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Abstract

Publicly listed firms have the discretion to disclose (or not) advertising spending in their annual (10-K) reports. The disclosure of advertising spending can provide valuable information because advertising is a leading indicator of future performance. However, estimates of advertising spending are available from data providers, arguably mitigating the need for its formal disclosure. This study argues that firms' disclosure of advertising spending provides more complete and public information and therefore lowers investor uncertainty about future firm performance (idiosyncratic risk). Empirical analyses show this effect is largely driven by the negative effect of disclosure of advertising spending on analyst uncertainty. Consistent with agency theory, the negative effect of the disclosure of advertising spending on analyst uncertainty is stronger for firms with more financial resources, lower disclosure quality, and that are in more competitive industries. Additional analyses show that the disclosure of advertising spending has a significant positive effect on firm value in specific sectors. These results, therefore, identify an avenue for Chief Marketing Officers to play a greater role in managing investor relations. In addition, they suggest strong merit for the Securities and Exchange Commission and the Financial Accounting Standards Board to reconsider current regulations governing advertising spending disclosure.

Key words: disclosure, advertising spending disclosure, advertising, marketing information, marketing-finance interface

Advertising spending is a critical element of marketing decisions that triggers "the chain of marketing productivity" by helping firms build long-term assets such as brand and customer equity (Rust et al. 2004, p. 77). Research in marketing consistently shows that advertising spending is a leading indicator of firm performance (e.g., Sridhar et al. 2016). Current regulations, however, allow firms to make the judgement whether advertising spending is useful information for investors and only then disclose it (Financial Reporting Release No. 44 in SEC 1994). Crucially, several firms choose not to disclose their advertising spending, despite spending a considerable amount on advertising. For example, Apple Inc. increased its advertising spending from $933 million in 2011 to $1.8 billion in 2015, but stopped disclosing it from 2016 even though its 10-K report notes that it:

> "…believes ongoing investment in research and development ("R&D"), marketing and advertising is critical to the development and sale of innovative products and technologies". (Apple Inc. 10-K Report 2016)

Analysts and investors bemoaned Apple's decision. Analysts at Wells Fargo pointed out that this decision was "a shame as it was useful to track Apple's advertising expense..." (O'Reilly 2016). Apple Inc., however, is not the only firm that does not disclose its advertising spending. Most publicly listed firms do not disclose their advertising spending (see Web Appendix A1). Prominent examples include Campbell Soup Company that did not disclose its advertising spending for 1997-2009, and Eli Lily and Company that did not disclose its advertising spending till 2018. For investors and analysts, information about advertising spending is potentially useful because it allows them to have a better understanding of how the firm is achieving its financial performance. Indeed, research shows that firms can either cut advertising spending to meet earnings targets (Mizik 2010) or increase it to boost the current quarterly earnings at the expense of the subsequent earnings (Chapman and Steenburgh 2011). Indeed, firms can also increase advertising to raise their profile before Seasoned Equity Offerings (Lou 2014).

On one hand, the lack of disclosure of advertising spending is surprising because the Securities and Exchange Commission (SEC) and Financial Accounting Standards Board (FASB) mandate that firms provide disclosures that lower investor uncertainty about future financial performance of the firm as reflected in their idiosyncratic risk. Idiosyncratic risk reflects the investor uncertainty about future cash flows of the firm that is due to firm-specific factors and not due to overall stock market returns and the systematic risk factors (see Srinivasan and Hanssens 2009). Lowering idiosyncratic risk is vital because it indicates greater transparency and efficient functioning of capital markets (see FASB 2016). Idiosyncratic risk is also a critical concern for Chief Marketing Officers (CMO) because it represents the risk implications of their actions (Han, Mittal, and Zhang 2017), a performance dimension that is increasingly relevant for CMOs (see Marketing Week 2019; Wall Street Journal 2016). Indeed, recent research underscores the need for CMOs to understand and communicate the effects of their actions on idiosyncratic risk to other C-suite leaders (see Panagopoulos, Mullins, and Avramidis 2018, p. 86).

On the other hand, disclosure of advertising spending in 10-K reports is arguably unlikely to provide useful information because estimates of advertising spending are easily available from secondary data providers. In fact, prior research uses such estimates, not the actual expenses disclosed in 10-K reports, to examine the effect of advertising spending on firm value (e.g., Madsen and Niessner 2019). However, these estimates typically reflect the media buying costs and therefore do not offer a complete picture of the expenses incurred by the firm in conceptualizing and producing its advertisements (see Focke, Ruenzi, and Ungeheuer 2020). Against this background, this study makes two contributions.

First, we find that the disclosure of advertising spending in 10-K reports provides valuable information to both investors and analysts, above and beyond the estimates of advertising spending available from data providers. Specifically, an analysis of 2,285 publicly listed firms over 25 years shows that disclosure of advertising spending lowers the idiosyncratic risk by about 7%. Outlining the underlying mechanism, we also find that the negative effect of disclosure of advertising spending on idiosyncratic risk is partially mediated by its effect on lowering the divergence about future financial performance of the firm amongst financial analysts, i.e., analyst uncertainty (see Barron et al. 1998).

These findings are of direct relevance for Chief Marketing Officers (CMO) who face increasing calls to consider the risk implications of their actions and play a more prominent role in investor relations (see Wies et al. 2019). Indeed, the National Investor Relations Institute explicitly identifies the marketing function as a key pillar of investor relations management (NIRI 2003).[1] CMO participation in investor relations is critical as it allows for greater interaction with and influence on the CEO and CFO, a perennial challenge for marketing executives (see Koo and Lee 2018).

Second, we delineate specific conditions under which disclosure of advertising spending is more (or less) useful for financial analysts. Consistent with the arguments drawn from agency theory, we find that the firm's financial structure, overall disclosure quality, and competitive intensity moderate the negative effect of disclosure of advertising spending on analyst uncertainty. Importantly, these moderating effects are statistically and economically significant. Specifically, the negative effects of disclosure of advertising spending on analyst uncertainty are 41% greater for firms with high (vs low) liquidity and 34% greater for firms in more (vs. less) competitive industries. In addition, the negative effects of disclosure of advertising spending are 28% greater for firms with low (vs high) disclosure quality, and 20% greater for firms with low (vs high) leverage.

[1] "Investor relations is a strategic management responsibility that integrates finance, communication, marketing and securities law compliance to enable the most effective two-way communication between a company, the financial community, and other constituencies." (NIRI 2003; Chapman et al. 2022, p. 81)

The robust impact of disclosure of advertising spending on idiosyncratic risk and analyst uncertainty provides support for recent calls for greater disclosure of this metric by researchers (Chakravarty and Grewal 2011) and the Marketing Accountability Standards Board (Stewart and Gugel 2016). A potential concern, however, is that disclosure can reveal proprietary information and have an adverse effect on firm valuation (see Simpson 2008). Therefore, we examine the effect of disclosure of advertising spending on firm value. Results show that disclosure of advertising spending enhances firm value for firms in the Manufacturing and Business Services sectors. For firms in other sectors, disclosure of advertising does have significant negative effects on idiosyncratic risk and analyst uncertainty but weakly significant effects (i.e., High-Tech and Healthcare) or no significant effects on firm value. As such, we see strong merit for the SEC and FASB to reconsider current regulations for the disclosure of advertising spending.

Disclosure of Advertising Spending

Financial Reporting Release Number 44

In 1994, the SEC issued FRR 44 that amended regulations for a Supplementary Income Statement Information schedule (see SEC 1994). The objective of FRR 44 was to simplify financial reporting filings for publicly listed firms. The SEC concluded that certain items in supplementary income statements including advertising spending are not required to be disclosed.[2] Prior to FRR 44, firms were required to disclose their advertising spending if it exceeded more than 1% of sales (Heitzman, Wasley, and Zimmerman 2010). In their deliberation of the provisions of FRR 44, the SEC concluded that removal of disclosure requirements is appropriate because:

> "The Commission believed that eliminating this and other supplementary schedules would result in reduced costs of reporting by public companies

[2] FRR 44 also relaxed disclosures for maintenance and repairs expense, depreciation and amortization of the cost of intangible assets, pre-operating costs and similar deferred costs, taxes other than payroll, and royalties.

> without loss of material information necessary to protect investors." (Simpson 2008, p. 403-404)

Financial analysts raised concerns on the changed disclosure requirements, noting that:

> "the actual costs of providing this information is small, and... the reduced disclosures could lead to an increase in the costs of capital due to an increase in investor uncertainty" (as quoted in SEC 1994, p. 8).

Despite such objections, the SEC implemented FRR 44. Importantly, to the best of our knowledge, no empirical support was provided to assess potential implications of FRR 44. Indeed, little is known about its potential impact on idiosyncratic risk and analyst uncertainty. Currently, firms have to disclose their advertising spending if they consider it to be *material* information. The SEC (1999, p. 2-4) explains that "materiality concerns the significance of an item to users of a registrant's financial statements. A matter is 'material' if there is a substantial likelihood that a reasonable person would consider it important".

Idiosyncratic Risk and Disclosure

Examining idiosyncratic risk is critical not only for marketing managers but also for investors and regulators such as SEC and FASB. For marketing managers, idiosyncratic risk is critical because it provides a broader perspective on the impact of their decisions. Marketing managers that evaluate outcomes only in terms of returns are likely to adopt strategies that have "pernicious", i.e., subtle but harmful, effects (Han, Mittal, and Zhang 2017, p. 25) as focus only on returns can "mask" the financial risk (see Germann, Ebbes, and Grewal 2015, p 12). Idiosyncratic risk is also important for senior managers due to its negative impact on their compensation (e.g., Brown and Kapadia 2007), future capital investments (e.g., Panousi and Papanikolaou 2012), CEO turnover (e.g., Engel, Hayes, and Wang 2003), litigation risk (e.g., Kim and Skinner 2012), and working capital requirements (Rao and Bharadwaj 2008). For investors, higher idiosyncratic risk implies greater cost of capital, i.e., it serves as a signal of the financial soundness of a firm (Bartram, Brown, and Stulz 2016). For SEC and FASB, idiosyncratic risk is a critical concern because it represents investor information environment and high idiosyncratic risk represents lack of transparency and therefore lower efficiency of financial markets (FASB 2016).

As shown in Table 1 and Web Appendix A2, the marketing literature focuses on the effects of marketing outcomes (e.g., brand equity) and marketing actions (e.g., marketing alliances) on idiosyncratic risk. Scarce attention, however, is directed towards the effect of disclosure of marketing metrics on idiosyncratic risk. An exception is Bayer, Tuli, and Skiera (2017) who find that an index of 34 forward-looking disclosures of customer metrics has a negative impact on idiosyncratic risk. However, an aggregated index combining backward-looking disclosures of customer metrics including disclosure of advertising spending as one of the metrics does not have any effect on idiosyncratic risk. As such, it is not clear whether disclosure of advertising spending is likely to have an impact on idiosyncratic risk.

[Insert Table 1 about here]

Interestingly, the current literature focuses almost exclusively on the antecedents of disclosure of advertising spending. Simpson (2008) finds that a firm is more likely to disclose its advertising spending if it can enhance its valuation. Heitzman, Wasley, and Zimmerman (2010) find that firms with greater incentives for voluntary disclosure and those with higher prior advertising spending are more likely to disclose. More recently, Shi, Grewal, and Sridhar (2021) show that the disclosure of advertising spending is driven by the disclosures of industry peers. An exception is McAlister et al. (2016) who show that advertising spending has a positive effect on investor evaluation only for firms that follow a differentiation strategy as reflected in their disclosure of advertising spending. Little, therefore, is known about the effect of disclosure of advertising spending on idiosyncratic risk.

Disclosure of Advertising Spending, Idiosyncratic Risk, and Analyst Uncertainty

Figure 1 outlines the conceptual framework that identifies the direct effect of disclosure of advertising spending on idiosyncratic risk and analyst uncertainty, the mediating role of analyst uncertainty and the accompanying contingencies. Disclosure is likely to lower idiosyncratic risk if the disclosed information is both credible and useful (see Beyer et al. 2010). Therefore, we first establish that the information about advertising spending in 10-K reports is credible and likely to be useful for investors. Next, we build on the insight that analysts serve as information intermediaries between firms and investors to argue for the mediating role of analyst uncertainty (Edeling, Srinivasan, and Hanssens 2021). We complete the framework by drawing on agency theory to outline contingencies that moderate the effects of disclosure of advertising spending on analyst uncertainty.

[Insert Figure 1 about here]

Disclosure of Advertising Spending and Idiosyncratic Risk

Disclosure plays an important role in reducing the information asymmetry between managers and investors, therefore improving efficiency in financial markets (Healy and Palepu 2001). By providing relevant and credible information, disclosure can reduce the investors' uncertainty about the future performance of a firm (Leuz and Wysocki 2016). However, disclosure of information that is ambiguous, has low credibility, or requires higher costs of processing and interpreting may not help investors reduce uncertainty about future performance of a firm (see Kravet and Muslu 2013).

Advertising spending information disclosed in a firm's 10-K report is credible as it is formally reported by the senior management, certified by external auditors, and reviewed by the SEC. In addition, empirical research in marketing, accounting, and economics consistently shows that information about advertising spending level is relevant for investors to understand future cash flows of a firm (see Edeling and Fischer 2016). Indeed, information about advertising spending of a firm can allow investors to assess future sales as advertising has significant short and long-term sales elasticity (Sethuraman, Tellis, and Briesch 2011) across multiple channels (e.g., van Ewijk et al. 2021).

Arguably the information provided by the disclosure of advertising spending disclosures in 10-K reports can be substituted by information already available in financial reports or that from market research firms. For example, a firms' selling, general and administrative (SG&A) expenses can be viewed as marketing investments (see Mizik and Jacobson 2007). In addition, both analysts and institutional investors have considerable resources to evaluate advertising spending of firms by purchasing proprietary data sources that provide estimates of advertising spending.

However, it is important to note that SG&A is a highly aggregated metric that includes multiple items such as foreign exchange costs and retirement provisions (see Lim, Tuli, and Grewal 2020). In addition, the information contained in proprietary datasets reflects the estimates of costs of purchasing media space for advertising across different channels (e.g., Liaukonytė and Žaldokas 2022). Crucially, it does not include information about related costs of advertising such as production costs and creative costs that are likely to be significant for advertising (Focke, Ruenzi, and Ungeheuer 2020, p. 4687).[3] In addition, the proprietary databases are available only on a subscription basis at a significant cost. Therefore, even though some investors may be able to piece together other information to form approximations of a firm's advertising spending, these sources are unlikely to serve as a substitute for the advertising spending disclosed by the firm. Therefore, we expect:

H_1: Disclosure of advertising spending has a negative effect on idiosyncratic risk.

Disclosure of Advertising Spending and Analyst Uncertainty

Financial analysts play a critical role in capital markets as they draw on their expertise to provide valuable information in the form of earnings forecasts and stock recommendations

[3] Consistent with our argument we find that typically, the formally disclosed advertising spending is significantly higher than the estimates of advertising spending. For example, consider the following differences for 2017 based on estimates published in Advertising Age (2018): In 2017, Procter and Gamble (P&G) reported $7.1 billion of advertising spending in its 10-K report whereas Kantar Media estimated advertising spending of $2.7 billion. Similarly, Pfizer disclosed $3.1 billion as its advertising but the corresponding figure in Kantar Media is $1.6 billion. Amazon, in 2017, reported $6.3 billion as its advertising spending, but Kantar Media estimated it advertising spending to be $564 million.

(Huang et al. 2018). By doing so, analysts shape information environment in capital markets (Chakravarty and Grewal 2016). Higher dispersion amongst analysts forecasts about future earnings, that is, analyst uncertainty, therefore, is a critical concern that increases market friction and reduces market efficiency (FASB 2016; Beyer et al. 2010).

By providing relevant information on managerial actions, firm disclosures reduce the information asymmetry and enhance the analysts' ability to predict firm future cash flows (Beyer et al. 2010). Given that advertising has both short and long-term sales elasticity, information about advertising spending in 10-K reports of a firm can provide analysts with insights into future cash flows. Importantly, there are few alternative sources of this information. Advertising spending information typically provided by proprietary databases is based on media buying rates, estimated based on the time at which the advertisement is shown in a particular media channel, and does not include costs of producing the advertisements (see Focke, Ruenzi, and Ungeheuer 2020). Given that financial analysts need to estimate future earnings, complete information about costs related to advertising incurred by the firm is important. In addition, advertising spending disclosed in 10-K reports reflects the time at which the expense is incurred by the firm and is not based on the time at which the advertisement is shown on a specific channel. This precision in timing of the expense is also useful for analysts as they estimated and release forecasts for future earnings. Indeed, analysts' responses to both Apple's decision to stop disclosing its advertising spending (see O'Reilly 2016) and the SEC decision on FRR 44 (SEC 1994) show that information about advertising spending is relevant for them. Therefore, we expect:

H_2: Disclosure of advertising spending has a negative effect on analyst uncertainty.

Mediating Role of Analyst Uncertainty

In capital markets, financial analysts act as information intermediaries and play a central role in information transfer to investors and in shaping investor expectations about firms. Financial analysts are highly skilled in analyzing companies as they have access to and collect a variety of information that is not widely available (Brauer and Wiersema 2018). Based on skilled analyses and ability to collect information, analysts provide firm-specific information (e.g., stock recommendations and earnings forecasts) that shapes investor expectations (Kim, Lu, and Yu 2019). Importantly, information about analyst forecasts is widely disseminated through media and potentially reaches general investors. Indeed, consensus earnings forecasts among analysts are widely accepted as shaping and reflecting investor expectations about firm future earnings (Frankel and Lee 1998). Analysts, therefore, are critical to the functioning of capital markets as they serve as information intermediaries between firms and investors (see Edeling, Srinivasan, and Hanssens 2021).

Analyst uncertainty is likely to shape investor uncertainty as analyst forecasts are a valuable source of information for investors (Chakravarty and Grewal 2016). Given that analysts serve as critical information intermediaries in capital markets, the negative effect of disclosure of advertising spending on idiosyncratic risk is likely to be driven by the degree to which it lowers analyst uncertainty. Indeed, research shows that analysts clarify corporate disclosures to facilitate investors' understanding of firm future performance (Huang et al. 2018). By lowering analyst uncertainty, disclosure of advertising spending enriches the investors' information environment and lowers idiosyncratic risk. Therefore, we expect:

> *H_3: The negative effect of disclosure of advertising spending on idiosyncratic risk is mediated by analyst uncertainty.*

Contingency Framework: Agency Theory Perspective

Agency theory focuses on information asymmetry and conflict of interest between the principal and the agent (Eisenhardt 1989). Financial markets present a classical agency problem due to information asymmetry between investors (the principal) and managers (the agent). The principal, i.e., investors, faces a hidden action problem as it cannot completely and accurately monitor the actions taken by the agent, i.e., managers (see Bergen, Dutta, and Walker 1992). Financial analysts monitor managers' actions and report their opinions about the future performance of the firm, thereby seeking to reduce the agency costs incurred by investors (Jensen and Meckling 1976, p. 354-355). Analysts, therefore, serve as the eyes and ears of investors as their compensation is directly linked to providing accurate and credible insights about firms' future performance (Kim, Lu, and Yu 2019).

Importantly, there is a natural goal conflict between managers and analysts because managers are likely to be focused on their individual gains, whereas analysts are focused on assessing if the managerial actions maximize the long-term investor wealth. For example, managers can reduce investments in projects that have positive long-term effects if it means that they can meet their quarterly earnings target, even though such cuts are likely to have an adverse effect on long-term performance (see Graham, Harvey, Rajgopal 2005).

A key tenet of agency theory is that the principal will incur monitoring costs to ensure that the agent behaves in a manner that is consistent with her objectives (see Chakravarty and Grewal 2016). Monitoring costs refer to the resources that the principal needs to expend to ensure that the agent's efforts and behaviors are aligned with the principal's interests (see Eisenhardt 1989). For analysts, monitoring costs translate into efforts at collecting additional information about a firm and/or analyzing managers' decisions (see Bradley et al. 2017). Disclosures about managers' actions are more valuable for analysts in situations where they incur higher monitoring costs (see Hope and Lu 2020). This is because the value of the additional information provided by disclosures is greater when it is more difficult for analysts to identify and understand the actions of the managers. Consistent with this argument, Dhaliwal et al. (2011) find that disclosures of material weakness in a firm's operations is more valuable for firms for which banks and credit agencies face higher monitoring costs. In addition, Downar, Ernstberger, and Link (2018) find that the benefits of higher disclosure frequency are higher for firms that typically require more monitoring. Therefore, we propose that the value of disclosure of advertising spending for analysts is higher for firms with higher monitoring costs. Specifically, two sources of monitoring costs incurred by analysts are important to understand the value of disclosure of advertising spending.

First, monitoring costs are likely to be higher if there are more available resources at management disposal (Jensen and Meckling 1976). This is because greater availability of resources increases the incentives for managers to act in their own interests as opposed to those of investors. Prior research on agency theory suggests that monitoring costs are higher for firms with higher financial liquidity but lower leverage (see Jensen 1986; Kalcheva and Lins 2007). Financial liquidity refers to the extent to which a firm is able to convert its assets into cash. This allows for more resources that are immediately available to managers, which suggests higher operational flexibility and requires greater monitoring of managerial actions (Joseph and Richardson 2002). In contrast, leverage indicates the level of the firm's debt and reduces operational flexibility for managers as they are more focused on servicing the debt payments (see Malshe and Agarwal 2015). Indeed, Jensen (1986) identifies debt as a key instrument to lower the agency costs for shareholders, thereby indicating that the need for disclosures is likely to be higher for firms with lower financial leverage.

Second, monitoring costs are likely to be higher for firms with more opaque information environments that make it difficult to monitor and assess managerial actions (Armstrong, Balakrishnan, and Cohen 2012). As such, the overall quality of financial disclosures by the firm is a critical contingency because it provides a direct indicator of the information opacity of a firm. The level of competitive intensity faced by a firm is also an important contingency that indicates higher monitoring costs. Higher competitive intensity indicates higher level of complexity and unpredictability in the operating environment of the firm (Messersmith et al. 2014). As such, it is more difficult for investors and analysts to assess managerial actions for firms operating in more competitive industries.

Monitoring Costs Related to Level of Firm Financial Resources

Financial liquidity. Agency problems are more severe when more free cash flows are available to managers (Jensen 1986). Greater free cash flows provide managers with greater operational flexibility and leave more financial resources to be susceptible for wasteful investment. Indeed, Jensen (1986) suggests that managers tend to overinvest a firm's internal cash, and firms with greater cash bear greater agency costs. Financial liquidity indicates the level of cash or cash equivalents in a firm and high financial liquidity may allow for more financial resources that are readily available at management disposal (Kalcheva and Lins 2007). Thus, managers in firms with higher financial liquidity are likely to have more opportunities for the misuse of firm resources, and those firms may require greater degree of monitoring of managerial actions (i.e., higher monitoring costs).

Advertising spending informs analysts of the extent to which a manager allocates financial resources on advertising. This information is critical for firms with higher liquidity because "when firms are flush with cash, they tend to spend liberally on advertising, even beyond what seems necessary or desirable." (Tellis 1998, p. 396). Information about advertising spending for firms with high liquidity is also important as it allows analysts to assess whether the current cash holdings of a firm are due to either cuts in advertising spending to build up cash, or due to spikes in it to boost short-term earnings at the expense of long-term performance (Chapman and Steenburgh 2011). As such, disclosure of advertising spending is more valuable for analysts evaluating firms with higher liquidity. Formally,

H_4: The negative effect of disclosure of advertising spending on analyst uncertainty is stronger for firms with higher financial liquidity.

Financial leverage. Financial leverage indicates the degree to which a firm relies on debt to fund its activities (Malshe and Agarwal 2015). Agency theory suggests financial leverage can serve as a monitoring mechanism to mitigate agency problems (Jensen 1986). Specifically, high financial leverage lowers excess free cash flows and therefore is likely to have a disciplining effect on agency costs (see Williams 1987). Consistent with this argument, Ang, Cole, and Lin (2000) find that agency costs are lower for highly leveraged firms due to greater monitoring activities by debt holders. Similarly, Aivazian, Ge, and Qiu (2005) find that high leverage serves the purpose of a disciplining role in preventing an agency problem of overinvestment.

In other words, firms with lower financial leverage may incur higher agency costs due to greater need to monitor managerial actions. Importantly, prior research suggests that there is a greater need to carefully monitor advertising spending of firms with more resources at their disposal due to greater potential for wasteful or excessive spending (see Joseph and Richardson 2002). This suggests that information about advertising spending is more valuable for financial analysts following firms with low leverage as it provides them with valuable insights into how managers are using available resources. Therefore, we expect:

> *H_5: The negative effect of disclosure of advertising spending on analyst uncertainty is stronger for firms with lower financial leverage.*

Monitoring Costs Related to Information Opacity

Disclosure quality. Disclosure quality of a firm represents the level of relevant information available for analysts and investors (Chen, Miao, and Shevlin 2015). Disclosure quality reflects a firm's information environment and therefore the monitoring costs incurred by analysts to understand future firm performance (Bushman and Smith 2001; Hope and Thomas 2008). Higher disclosure quality indicates more transparent information environment for analysts and investors making it easier to monitor managerial actions (Huang and Zhang 2012). In contrast, lower disclosure quality reflects opaque information environment, and monitoring managers can be more costly because analysts need to gather more relevant information from alternative sources rather than from firm disclosures (Dhaliwal et al. 2012).

Disclosure of advertising spending provides analysts with insight about managerial deployment of financial resources on advertising activities. Information about advertising spending levels is especially critical for analysts assessing firms with lower quality disclosures as it provides them with an opportunity to assess if levels of advertising are being adjusted to meet earnings targets (see Graham, Harvey, and Rajgopal 2005). For analysts examining firms with higher disclosure quality, higher availability of more granular financial information makes it easier to carefully assess managerial actions related to earnings management. As such, the incremental benefit of information about advertising spending is lower for analysts following firms with higher disclosure quality. Therefore, we expect,

H_6: The negative effect of disclosure of advertising spending on analyst uncertainty is stronger for firms with lower disclosure quality.

Competitive intensity. Prior research consistently finds that analysts following firms in more competitive industries face higher monitoring costs due to more complex operating environment. Higher competitive intensity implies greater complexity of operating environment as multiple firms are likely to adopt different business models and strategies to engage the customers (Messersmith et al. 2014). Such complexity of operating environment increases the information asymmetry between managers and analysts (Ndofor, Wesley, and Priem 2015). Higher competitive intensity is also likely to make the information environment poorer for analysts. This is because in highly competitive industries, managers are likely to be more concerned about their competitors using the information provided by disclosures to compete more effectively (see Leuz and Wysocki 2016). Indeed, Verrecchia and Weber (2006) find that firms in more competitive industries are more likely to request the SEC to redact information in their disclosures. Ellis, Fee, and Thomas (2012) also find that firms in more competitive industries are less likely to disclose the names of their large customers.[4]

Highly competitive industries, therefore, are characterized by opaque information environment due to the complexity of operating environment and fewer voluntary disclosures. As a key competitive marketing action, advertising spending plays a significant role in securing stable cash flows (Bagwell 2007). As such, information about advertising spending of a firm is likely to be more important for analysts to evaluate future performance of a firm in a more competitive industry. Indeed, in more competitive environments, managers may have greater pressure on meeting performance targets and are more tempted to implement earnings management (Healy et al. 2014). Cutting advertising spending is often used for earnings management, which is ultimately harmful for shareholder value and is not in line with principals' interest (Mizik 2010). That is, empirical evidence on earnings management suggests that the required degree of monitoring managerial actions such as advertising spending could be greater in more competitive environments. As such, disclosure of advertising spending is likely to be more relevant and valuable for analysts in highly competitive environments. Accordingly, we expect:

> *H_7: The negative effect of disclosure of advertising spending on analyst uncertainty is stronger for firms in more competitive industries.*

Method

Data

We collect data on firm financials and stock prices from COMPUTSTAT and Center for Research in Stock Prices (CRSP), and data on Fama and French and the Momentum factor from Kenneth French's library. We obtain analysts' forecasts of Earnings Per Share

[4] Using an analytical model, Arya and Mittendorf (2007) show that in a Cournot Duopoly, it is possible that firms are likely to coordinate their actions and increase their mutually beneficial disclosures to increase analyst following "…as long as competition among the firms is not too cutthroat" (p. 323). As such, we control for level of analyst following in our model.

(EPS) from the Institutional Brokers' Estimate System (I/B/E/S). We obtain institutional ownership information from Thomson Reuters. We focus on the data starting from fiscal year 1995 as FRR 44 was implemented in 1994. In addition, we exclude firms in finance, insurance, and utilities industries because the financial reporting format for those firms is significantly different (e.g., Lim, Tuli, and Grewal 2020). As a result, our final sample consists of 2,285 firms and 15,297 firm-year observations over 25 years from 1995 to 2019.

Measures

Idiosyncratic risk. Idiosyncratic risk is the variability of the stock returns due to firm-specific factors, not systematic risk factors. To control for systematic risk factors, we use the Fama and French (1993) three-factor model augmented with the Carhart (1997) momentum factor (e.g., Chakravarty and Grewal 2016) and estimate the following equation:

$$(1)\qquad (R_{id} - R_{fd}) = \alpha + \beta_{mi} \times (R_{md} - R_{fd}) + \beta_{si} \times SMB_d + \beta_{hi} \times HML_d + \beta_{ui} \times UMD_d + \varepsilon_{id},$$

where R_{id} = daily return on stock of firm *i* on day *d*, R_{fd} = daily risk-free return on day *d*,
R_{md} = daily return on a value-weighted market portfolio on day *d*,
SMB_d = Fama-French size portfolio on day *d*,
HML_d = Fama-French market-to-book ratio portfolio on day *d*, UMD_d = the momentum factor on day *d*.

Idiosyncratic risk is the standard deviation of the residuals during the estimation period (see Han, Mittal, and Zhang 2017). To isolate the impact of disclosure of advertising spending, we estimate Equation 1 for each firm from the day of the release of a firm's 10-K report in year *t* and the day before the release of its 10-K report for year *t+1* (see Web Appendix A3).

Analyst uncertainty. We use the variation in analyst estimates of firms' future earnings (i.e., earnings per share) to measure analyst uncertainty (e.g., Chapman, Miller, and White 2019; Petacchi 2015). This measure, therefore, reflects the difference in analyst predictions of the future performance of firms (i.e., analyst forecast dispersion). Specifically, we measure analyst forecast dispersion by the natural logarithm of the standard deviation of analysts' earnings forecasts during the period between the day of the release of a firm's 10-K report in year *t* and the day before its release in year *t+1* (see Web Appendix A3).

Disclosure of advertising spending. We measure disclosure of advertising spending as a binary variable which is equal to 1 if a firm discloses advertising spending in its annual report and 0 otherwise (see Chen, Miao, and Shevlin 2015; Simpson 2008).

Financial liquidity and leverage. We use the ratio of current assets to current liabilities to measure financial liquidity (Han, Mittal, and Zhang 2017) and the total long-term debt, scaled by total assets to measure financial leverage (McAlister et al. 2016).

Disclosure Quality. Disclosure quality represents the quality of the information that a firm provides to its investors through its disclosures and firms with higher quality of financial disclosures provide more detailed and finer information for investors (see Sengupta 1998). We follow the recent work by Chen, Miao, and Shevlin (2015) and measure disclosure quality of a firm by using the level of disaggregation of disclosures in its annual report (also see Koo, Ramalingegowda, and Yu 2017). A firm's annual report (i.e., 10-K filing) has the hierarchical nesting feature such that one item consists of multiple disaggregated items. For example, current assets total includes inventory total and other seven second-level accounts. By using this nesting feature of a 10-K annual report, we calculate the ratio of non-missing items to the total items in the balance sheet and income statement. The theoretical premise in the measure is that finer information is of higher quality, and therefore firms that provide more granular disclosures have higher disclosure quality (see Web Appendix A4 for details).

Competitive intensity. To measure competitive intensity, we start by measuring the Herfindahl-Hirschman index (HHI), the sum of squares of firms' market shares in a four-digit North American Industry Classification System (NAICS4) industry. [5] As HHI indicates industry concentration, we subtract HHI from 1 to make higher values of the variable indicate higher competitive intensity (e.g., Deb, David, and O'Brien 2017).

[5] The North American Industry Classification System is the standard used by Federal statistical agencies in classifying business establishments for the purpose of collecting, analyzing, and publishing statistical data related to the U.S. economy.

Control variables. To isolate the impact of disclosure of advertising spending, we utilize a comprehensive set of control variables. At the firm level we account for variables that reflect financials (e.g., total assets, selling, general and administrative expense, earnings, cash flows), analyst following, institutional ownership, and firm age. Importantly, we also control for the level of the estimates of advertising spending by drawing on Kantar Media data. To isolate the impact of disclosure of advertising spending in 10-K reports, it is important to control for the level of advertising spending because such information is likely to be used by investors and analysts to evaluate firm's future performance. In addition, we control for industry growth and demand uncertainty (see Web Appendix A5 for the details). Table 2 outlines the descriptive statistics and correlations of the variables.

[Insert Table 2 about here]

Model Specification

We specify rich data models with an extensive set of control variables to account for the variance in our dependent variables driven by observable firm and industry factors (Germann, Ebbes, and Grewal 2015). To account for unobservable year effects, we include year-specific fixed effects. We also include a firm-specific random effect (i.e., the random-effects panel data model) to parsimoniously account for potential firm-level heterogeneity (Sridhar et al. 2016). Accordingly, to test H_1 and H_2, we estimate the following models:

$$(2) \qquad IR_{i,j,t} = \beta_0 + \beta_1 AD_{i,j,t-1} + \Delta' Controls_{i,j,t-1} + \sum_{k=1}^{K-1} \theta_k Year_t + \mu_i + \varepsilon_{i,j,t},$$

where $IR_{i,j,t}$ = idiosyncratic risk for firm *i* in industry *j* in fiscal year *t*,
$AD_{i,j,t-1}$ = disclosure of advertising spending by a firm, $Controls_{i,j,t-1}$ = the vector of control variables,
$Year_t$ = a year dummy, μ_i = a firm random effect, and $\varepsilon_{i,j,t}$ = the random error term.

$$(3) \qquad AU_{i,j,t} = \gamma_0 + \gamma_1 AD_{i,j,t-1} + \Lambda' Controls_{i,j,t-1} + \sum_{k=1}^{K-1} \lambda_k Year_t + \nu_i + \zeta_{i,j,t},$$

where $AU_{i,j,t}$ = analyst uncertainty for firm *i* in industry *j* in fiscal year *t*,
ν_i = a firm random effect, and $\zeta_{i,j,t}$ = the random error term.

To test H_3, we follow the prior literature (e.g., Steenkamp, van Heerde, and Geyskens 2010) and use Baron and Kenny (1986) sequential approach. First, we examine the effect of disclosure of advertising spending on idiosyncratic risk (i.e., β_1) and analyst uncertainty (i.e., γ_1) respectively. Second, we include the proposed mediator (i.e., analyst uncertainty) in the idiosyncratic risk model (i.e., Equation 2) and estimate the following model:

$$(4) \qquad IR_{i,j,t} = \beta_0 + \beta_m AU_{i,j,t} + \beta_1 AD_{i,j,t-1} + \Delta'Controls_{i,j,t-1} + \sum_{k=1}^{K-1}\theta_k Year_t + \mu_i + \varepsilon_{i,j,t}$$

Finally, to test the contingency framework (i.e., H_4-H_7), we estimate the following model:

$$\begin{aligned}(5) \qquad AU_{i,j,t} = {} & \gamma_0 + \gamma_1 AD_{i,j,t-1} \\ & + \gamma_2 AD_{i,j,t-1} \times Financial\ Liquidity_{i,j,t-1} + \gamma_3 AD_{i,j,t-1} \times Financial\ Leverage_{i,j,t-1} \\ & + \gamma_4 AD_{i,j,t-1} \times Disclosure\ Quality_{i,j,t-1} + \gamma_5 AD_{i,j,t-1} \times Competitive\ Intensity_{i,j,t-1} \\ & + \gamma_6 Financial\ Liquidity_{i,j,t-1} + \gamma_7 Financial\ Leverage_{i,j,t-1} \\ & + \gamma_8 Disclosure\ Quality_{i,j,t-1} + \gamma_9 Competitive\ Intensity_{i,j,t-1} \\ & + \Lambda'Controls_{i,j,t-1} + \sum_{k=1}^{K-1}\lambda_k Year_t + \nu_i + \zeta_{i,j,t.}\end{aligned}$$

Addressing Endogeneity

Disclosure of advertising spending. The disclosure of advertising spending is likely to be endogenous because managers may consider the potential proprietary costs and valuation benefits in making this decision (see Simpson 2008). For example, disclosure of advertising spending is arguably a strategic choice by managers as information about this metric can influence investor and analyst evaluation of the firm (see Heitzman, Wasley, and Zimmerman 2010). Such managerial foresight about investor and analyst evaluation about the firm is arguably correlated with not only the decision to disclose advertising spending, but also with the residuals in Equation 4 and 5 where the dependent variables are idiosyncratic risk and analyst uncertainty. Therefore, we use the method of two-stage residual inclusion (2SRI), a special case of the control function method for binary regressors to address the potential endogeneity of disclosure of advertising spending (e.g., Terza, Basu, and Rathouz 2008).

We draw on the recent literature that uses peer-based instruments for disclosure of advertising spending (e.g., Han, Mittal, and Zhang 2017) and advertising spending levels (e.g., Sridhar et al. 2016). A potential concern with the use of peer-based instruments is that whereas they are likely to be strong instruments, their validity is likely to be weak due to the close competitive interactions of the peers with the focal firm. As such, there is a natural trade-off between the strength and validity of peer-based instruments (see Papies, Ebbes, and van Heerde 2017). Accordingly, to strengthen our identification strategy, we use three types of peers, i.e., Industry, Sector, and Auditor peers, that represent different degrees of competitive proximity to the focal firm (see Web Appendix A6 for arguments and Web Appendix A7 for examples of Industry, Sector, and Auditor peers).

NAICS classification identifies an "Industry" as a specific category of firms that are a part of a broader "Sector". For example, Starbucks is a part of the NAICS 7225 Industry, "Restaurants and Other Eating Places", that is a part of NAICS 72 Sector, "Accommodation and Food Services". We leverage this structure to create two instruments. First, we identify Industry peers, i.e., firms in the same NAICS 4-digit industry as the focal firm. For Starbucks, this refers to all the firms that belong to NAICS 7725 other than Starbucks itself (e.g., Dunkin Brands and Wendy's Co). The weighted proportion of Industry peers that disclose their advertising spending serves as the first instrument. [6]

Second, we identify Sector peers, i.e., firms that belong to the same NAICS 2-digit sector but are not in the same NAICS 4-digit industry. For Starbucks, this means firms that are in Sector NAICS 72, but are not in Industry NAICS 7225. The Sector peers for Starbucks include firms such as Marriot Inc and Hyatt Hotels that belong to the same Sector but are not part of the same Industry. As such, Sector peers are more "distant" peers as compared to the Industry peers. The weighted proportion of Sector peers that disclose their advertising spending serves as the second instrument.

[6] To account for instrument granularity (Angrist 2014), we use weighted proportions as this allows the instrument to vary at the firm level as opposed to having a common instrument for all firms in an Industry. We assign weights based on firm characteristics such that similar peers have greater influence on the focal firm and, therefore, our peer-based instrument has the sufficient firm-level variation to predict an endogenous variable (see Web appendix A8 for details).

Third, we draw on the accounting literature which shows that firms with the same auditor are likely to have a similar style of financial statements (e.g., Johnston and Zhang 2021) and disclosure patterns (e.g., Brown and Knechel 2016) to identify the Auditor peers. We use the weighted proportion of Auditor peers (i.e., firms that share the same auditor but do not belong to the same industry as the focal firm) as an instrument. As advertising spending outside a focal industry has lower relevance for disclosure (Shi, Grewal, and Sridhar 2021), our use of Sector and Auditor peers provides us with more exogenous variation. Accordingly, in the first stage we estimate the following probit model:

$$(6)\quad \Pr(AD_{i,j,t-1} = 1)$$
$$= \Phi(\alpha_0 + \alpha_1 WIPD_{i,j,t-2} + \alpha_2 WSPD_{i,j,t-2} + \alpha_3 WAPD_{i,j,t-2} + \Psi' Controls_{i,j,t-1} + \textstyle\sum_{k=1}^{K-1}\rho_k Year_{t-1}),$$

Where, $WIPD_{i,j,t-2}$ = weighted proportion of Industry peers, other than firm *i*, that disclose advertising spending, $WSPD_{i,j,t-2}$ = weighted proportion of Sector peers, excluding industry peers, that disclose advertising spending, $WAPD_{i,j,t-2}$ = weighted proportion of Auditor peers, excluding industry peers, that disclose advertising spending for firm *i* in industry *j* at fiscal year *t-1*.

We include the probit residual of $AD_{i,j,t-1}$ (i.e., $\boldsymbol{PR\_AD_{i,j,t-1}}$) generated from Equation 6 as an additional covariate in Equations 2-5.

Estimated Advertising spending, analyst uncertainty & selection bias. Advertising spending is potentially endogenous because managers strategically plan and implement advertising (Sridhar et al. 2016). For example, managers may cut advertising spending to meet earnings targets (Mizik 2010) or increase their advertising spending to meet quarterly performance targets (Chapman and Steenburgh 2011). In addition, Equations 2-5 may suffer from a selection bias because Kantar Media's decision to estimate advertising spending of a firm could lead to a systematic difference between firms that are in the sample and those that are not. Finally, analyst uncertainty in the mediation model (i.e., Equation 4) is likely to be endogenous because it could be correlated with unobservable factors that are a part of the residuals. For example, firms' quality of investor relations management is a plausible omitted variable because it facilitates communication with investors and analysts and is associated with financial market outcomes (Chapman, Miller, and White 2019). Therefore, we control for endogeneity of estimated advertising spending and analyst uncertainty.

For identification, we use the weighted averages of estimated advertising spending and analyst uncertainty of both Industry and Sector peers as instruments for a focal firm's estimated advertising spending and its analyst uncertainty (for precedence see Sridhar et al. 2016). Similarly, we estimate a probit model to generate the inverse Mills Ratio to account for the potential selection bias due to Kantar Media coverage of firms (Frennea, Han, and Mittal 2019). Web Appendix A6 outlines the specific models we use to generate the control function for potential endogeneity of advertising spending ($\hat{\boldsymbol{\eta}}_{\mathbf{i,j,t-1}}$) and analyst uncertainty ($\hat{\boldsymbol{\upsilon}}_{\mathbf{i,j,t}}$), and the inverse Mills ratio to account for the potential selection bias ($\mathbf{IMR_{i,j,t-1}}$). We include the three endogeneity correction terms in Equation 2-5 and the additional endogeneity correction term (i.e., $\hat{\boldsymbol{\upsilon}}_{\mathbf{i,j,t}}$) for $AU_{i,j,t}$ in Equation 4 to estimate the following models:

$$\text{(7)}\quad IR_{i,j,t} = \beta_0 + \beta_1 AD_{i,j,t-1} + \Delta'Controls_{i,j,t-1} + \sum_{k=1}^{K-1}\theta_k Year_t + \beta_a \mathbf{PR\_AD_{i,j,t-1}} + \beta_b \hat{\boldsymbol{\eta}}_{\mathbf{i,j,t-1}} + \beta_c \mathbf{IMR_{i,j,t-1}} + \mu_i + \varepsilon_{i,j,t},$$

$$\text{(8)}\quad AU_{i,j,t} = \gamma_0 + \gamma_1 AD_{i,j,t-1} + \Lambda'Controls_{i,j,t-1} + \sum_{k=1}^{K-1}\lambda_k Year_t + \gamma_a \mathbf{PR\_AD_{i,j,t-1}} + \gamma_b \hat{\boldsymbol{\eta}}_{\mathbf{i,j,t-1}} + \gamma_c \mathbf{IMR_{i,j,t-1}} + \nu_i + \zeta_{i,j,t},$$

$$\text{(9)}\quad IR_{i,j,t} = \beta_0 + \beta_m AU_{i,j,t} + \beta_1 AD_{i,j,t-1} + \Delta'Controls_{i,j,t-1} + \sum_{k=1}^{K-1}\theta_k Year_t + \beta_a \mathbf{PR\_AD_{i,j,t-1}} + \beta_b \hat{\boldsymbol{\eta}}_{\mathbf{i,j,t-1}} + \beta_c \mathbf{IMR_{i,j,t-1}} + \beta_d \hat{\boldsymbol{\upsilon}}_{\mathbf{i,j,t}} + \mu_i + \varepsilon_{i,j,t},$$

$$\begin{aligned}\text{(10)}\quad AU_{i,j,t} = {} & \gamma_0 + \gamma_1 AD_{i,j,t-1} \\ & + \gamma_2 AD_{i,j,t-1}\times \text{Financial Liquidity}_{i,j,t-1} + \gamma_3 AD_{i,j,t-1}\times \text{Financial Leverage}_{i,j,t-1} \\ & + \gamma_4 AD_{i,j,t-1}\times \text{Disclosure Quality}_{i,j,t-1} + \gamma_5 AD_{i,j,t-1}\times \text{Competitive Intensity}_{i,j,t-1} \\ & + \gamma_6 \text{Financial Liquidity}_{i,j,t-1} + \gamma_7 \text{Financial Leverage}_{i,j,t-1} \\ & + \gamma_8 \text{Disclosure Quality}_{i,j,t-1} + \gamma_9 \text{Competitive Intensity}_{i,j,t-1} \\ & + \Lambda'Controls_{i,j,t-1} + \sum_{k=1}^{K-1}\lambda_k Year_t + \gamma_a \mathbf{PR\_AD_{i,j,t-1}} + \gamma_b \hat{\boldsymbol{\eta}}_{\mathbf{i,j,t-1}} + \gamma_c \mathbf{IMR_{i,j,t-1}} \\ & + \nu_i + \zeta_{i,j,t}.\end{aligned}$$

We use feasible generalized least squares with standard errors clustered at the firm level to account for possible correlations between errors of observations from the same firm (e.g., Han, Mittal, and Zhang 2017). Finally, we use 200 bootstrapping replications to correct standard errors of the estimated terms included in Equation 7-10 (see Petrin and Train 2010).

Results

Descriptive Statistics

We find a moderately decreasing trend of disclosure of advertising spending from 1996 to 1998, but after 1998, disclosure of advertising spending starts to increase and disclosure behavior of firms tends to be stable (i.e., about 50%) from 2006. Importantly, disclosure of advertising spending has significant cross-sectional variation such that 7,341 observations (i.e., 48% of the sample) are from 1,116 firms that disclose advertising spending. The remaining 7,956 observations (i.e., 52% of the sample) from 1,455 firms do not disclose their advertising spending. Among those firms, there are 286 firms that switch between disclosure and non-disclosure of advertising spending, resulting in 2,285 firms in our sample (i.e., 1,116 + 1,455 - 286 = 2,285). From a longitudinal perspective, 1,999 firms do not change disclosure of advertising spending, but 286 firms do so. Among 1,999 firms that do not change the disclosure of advertising spending, 830 firms disclose advertising spending and 1,169 firms do not disclose it within the panel. This predominantly cross-sectional variance in disclosure of advertising spending is consistent with the prior work which shows that firms tend to display similar disclosure behaviors across years (e.g., Simpson 2008).

Hypotheses Testing

Web Appendix A9-A12 outline the results of the first stage models, which are consistent with our expectations. The multivariate Sanderson-Windmeijer F-test also shows the instruments are strong for disclosure of advertising spending (= 708.75, $p < .001$), for estimated advertising spending (= 439.21, $p < .001$), and for analyst uncertainty (= 20.05, $p < .001$). Now, we outline the results of the hypotheses testing in Table 3.

[Insert Table 3 about here]

Consistent with H_1 and H_2, we find that disclosure of advertising spending has a significant negative impact on idiosyncratic risk (β_1 = -.0028, $p < .001$) and analyst uncertainty (γ_1 = -.0910, $p < .001$). In addition, given the significant negative effects of disclosure of advertising spending on idiosyncratic risk and analyst uncertainty, the positive and significant effect of analyst uncertainty on idiosyncratic risk indicates empirical support for the partial mediation of analyst uncertainty in the relationship between disclosure of advertising spending and idiosyncratic risk. That is, we find the effect of analyst uncertainty is positive and significant (β_m = .0196, $p < .001$) and the effect of disclosure of advertising spending on idiosyncratic risk is significant, but weaker (β_1 = -.0013, $p < .05$) in the model with the proposed mediator (i.e., Equation 4) than that (β_1 = -.0028, $p < .001$) in the model without it (i.e., Equation 2). The Wald test result suggests the model fit significantly improves ($\Delta\chi^2(1)$ = 361.23, $p < .001$) after including analyst uncertainty. To test the statistical significance of the partial mediating effect, we use Preacher and Hayes (2004) approach and draw 1,000 bootstrap samples to obtain the 95% confidence interval (CI) for the indirect effect of disclosure of advertising spending on idiosyncratic risk through analyst uncertainty (Malshe, Colicev, and Mittal 2020). We find the indirect effect (i.e., the product term of β_m and γ_1) is negative and significant (-.0018, $p < .001$, CI = [-.0023, -.0013]). That is, consistent with H_3, we find the partial mediation effect of analyst uncertainty in the relationship between disclosure of advertising spending and idiosyncratic risk.

In Table 3, the results of the full model provide strong support for the contingency framework. In the full model, the main effect of $AD_{i,j,t-1}$ on analyst uncertainty is still negative and significant (γ_1 = -.0911, $p < .001$). Results show the interaction of $AD_{i,j,t-1}$ and Financial $Liquidity_{i,j,t-1}$ is negative and significant (γ_2 = -.0042, $p < .01$). Therefore, H_4 is supported. We find that the interaction of $AD_{i,j,t-1}$ and Financial $Leverage_{i,j,t-1}$ is positive but marginally significant (γ_3 = .0332, $p < .10$). As such, H_5 is weakly supported. In addition, the interaction of $AD_{i,j,t-1}$ and Disclosure $Quality_{i,j,t-1}$ is positive and significant (γ_4 = .0798, p < .01). Therefore, H_6 is supported. Consistent with H_7, the interaction of $AD_{i,j,t-1}$ and Competitive $Intensity_{i,j,t-1}$ is negative and significant (γ_5 = -.0517, p < .05).

Robustness Analyses

Alternative measures of estimated advertising spending. Given that it is important to control for the estimates of advertising spending, we assess the sensitivity of our conclusions to the use of alternative measures of this metric. To do so, we use the estimated advertising spending scaled by sales (McAlister, Srinivasan, and Kim 2007), natural log of advertising spending scaled by sales and total assets (Sridhar et al. 2016). We also use alternative instruments for advertising spending based on alternative measures. As shown in Table 4 (see Model 2a – 4d), we continue to find empirical support for our hypotheses (i.e., H_1-H_7).

[Insert Table 4 about here]

Alternative instruments. Whereas we rely on instruments based on Industry, Sector, and Auditor peers, there is likely to be a natural trade-off between the strength and validity of peer-based instruments, which may not be objectively assessed by a formal test. Therefore, to examine if our conclusions are sensitive to the exclusion of a particular instrument, we estimate our models by individually excluding industry, sector, and auditor peers from the set of instruments. We also assess the effect of replacing industry peers with second-degree peers as instruments (Shi, Grewal, and Sridhar 2021). Web Appendix A13 outlines results of first stage models with alternative instruments. Furthermore, we test the sensitivity of the instruments for analyst uncertainty by using the Gaussian copula method to test H_3. The Gaussian copula directly models the joint distribution of the potentially endogenous variable and the error term through a control function term (Park and Gupta 2012). [7]

[7] The identifying assumption for the Gaussian copula method is that the potentially endogenous variable is not normally distributed. Both Shapiro-Wilk test (W = .7388, p < .001) and the normality test based on skewness and kurtosis (p < .001) indicate this assumption is met. We use 200 bootstrapping replications to correct standard errors, and the copula correction term for analyst uncertainty in the mediation model is significant (= .0018, p < .001). For this analysis, we use Sector and

As shown in Table 4 (models 5a-9d), we continue to find empirical support for the proposed H_1-H_7 with a few exceptions in the levels of significance if we use alternative instruments. First, the support for the mediating effect of analyst uncertainty is stronger in Models 5c, 6c, and 8c as the effect of disclosure of advertising spending on idiosyncratic risk is significant only at $p < .10$ (one-tailed) in Models 5c and 6c and is not significant in Model 8c. Second, whereas we continue to find support for the partial mediation effect of analyst uncertainty (H_3), the effect of disclosure of advertising spending on idiosyncratic risk is more significant in model 7c where we only use industry and sector peers as instruments.

Alternative industry classification. Since we use NAICS4 classification to measure competitive intensity and other industry variables, we assess the sensitivity of results to the use of the four-digit Standard Industry Classification (SIC4). As shown in Table 4, we find consistent and robust results for all hypotheses except the mediation effect of analyst uncertainty and the moderating effect of financial leverage. Considering Models 10a-10c, we find that analyst uncertainty completely mediates the effect of disclosure of advertising spending on idiosyncratic risk. In Model 10d, we do not find support for H_5 as the interaction between disclosure of advertising spending and financial leverage is not significant.

Accounting for the discussion of advertising. Firms are likely to vary in the extent to which they discuss their advertising spending in their 10-K reports and thereby provide additional information to analysts and investors. Accordingly, to assess the robustness of our results, we use text analysis of the 10-K reports to measure the extent to which a firm discusses advertising and include it as a control variable in our focal models (see Web Appendix A14 for the construction of the variable & Web Appendix A15 for the descriptive statistics). As shown in Web Appendix A16, we continue to find empirical support for H_1,

Auditor peer instruments for disclosure of advertising spending and Sector peer instruments for advertising spending levels and Kantar Media selection. The results of using Industry, Sector, and Auditor peers for disclosure of advertising spending and Industry and Sector peers for advertising spending levels and Kantar Media selection are qualitatively equivalent.

H_2, H_4-H_7. We do, however, find that the mediation effect of analyst uncertainty (H_3) is stronger in this specification as the direct effect of disclosure of advertising spending on idiosyncratic risk in presence of analyst uncertainty is significant only at $p < .10$.

Additional robustness analyses. We conduct three additional sensitivity analyses to assess the robustness of our results to the use of including industry-related fixed effects as control variables (Web Appendix A17), and alternative measures for investor and analyst uncertainty (Web Appendix A18 and A19). As shown in Web Appendices A17-A19, we consistently find support for H_1-H_7 when using these alternative specifications.

Discussion

Implications for the Extant Literature

The current study contributes to the literature on the disclosures of marketing metrics in four important aspects. First, whereas Bayer, Tuli, and Skiera (2017) focus on an aggregated index of 34 customer metrics disclosures, we focus on the disclosure of advertising spending. This focus on a specific metric is important not only because advertising spending is central for marketing, but also because it allows us to directly examine the impact of the specific regulation on the disclosure of advertising spending.

Bayer, Tuli, and Skiera (2017, p. 255) find disclosures of customer outcome metrics have significant negative effects on idiosyncratic risk and analyst uncertainty but do not find significant effects of the disclosures reflecting firm actions. In contrast, we find that the disclosure of advertising spending, a backward-looking customer metric reflecting a firm action, significantly lowers idiosyncratic risk and analyst uncertainty. As such, this study qualifies the findings of Bayer, Tuli, and Skiera (2017) that are based on an aggregated index of disclosures of customer metrics. A potential explanation for the difference between the results could be that the aggregation of disclosures of different types of customer metrics masks the potential heterogenous effects of disclosure of individual metrics. Indeed, in subsequent analyses, Bayer, Tuli, and Skiera (2017) find that there is significant heterogeneity in the investor response to information about different customer metrics.

Second, this study reveals an important mechanism by which disclosure of advertising spending lowers idiosyncratic risk. We find that disclosure of advertising spending lowers idiosyncratic risk by reducing analyst uncertainty and this indirect effect accounts for approximately 58.06% of the total effect. This significant proportion of the indirect effect indicates the important role of analysts in communicating marketing information to investors and therefore their relevance for senior marketing managers. Indeed, recent research shows that the appointment of an investor relations officer can lower analyst uncertainty by almost 15.5% (see Chapman, Miller, and White 2019). Comparatively, our estimates show that the disclosure of advertising spending can potentially lower analyst uncertainty by 8.70% (see Halvorsen and Palmquist 1980 for details). That is, the effect of the disclosure of advertising spending on analyst uncertainty is economically significant.

Third, drawing on agency theory, we identify contingencies for the negative impact of disclosure of advertising spending on analyst uncertainty. To visualize the moderating effects, we plot the marginal effects of disclosure of advertising spending on analyst uncertainty across the values of each moderating variable (see Figure 2). Importantly, the moderating effects are both statistically and economically significant. Specifically, the magnitude of the negative effect of advertising spending disclosure on analyst uncertainty is almost 41% stronger for firms with high vs. low liquidity, 34% stronger for firms in more vs. less competitive industries, 28% stronger for firms with low vs. high disclosure quality, and 20% stronger for firms with low vs high leverage (see Figure 2). By identifying critical firm and industry level contingencies, the current study provides a more nuanced view of the impact of disclosure of advertising spending.

[Insert Figure 2 about here]

Implications for Regulators and Managers

Should all managers disclose their advertising spending to investors? Table 3 shows that the disclosure of advertising spending is associated with a decrease of 0.0028 in idiosyncratic risk, which translates to an arc elasticity of 7% (see Allen and Lerner 1934; Fong, Fang, and Luo 2015). Disclosure of advertising spending, therefore, fulfils a key criterion of financial reporting: providing information to help investors assess the uncertainty of prospective cash flows (FASB 1978, Concept No. 1; also see Lev 2008, p. 686). However, for managers and regulators, it is also important to consider two more issues.

First, the firm bears the costs of collecting and disclosing its advertising spending. Second, advertising spending can be viewed as sensitive information and thus managers may be concerned about an adverse impact of such disclosures on firm performance (Beyer et al. 2010). These arguments suggest that the disclosure of advertising can lower firm value. Accordingly, we estimate the impact of disclosure of advertising spending on Tobin's q and Market Capitalization using the same modeling approach (see Web Appendix A20). For the pooled sample, we find that disclosure of advertising spending does not have a significant effect on Tobin's q and Market Capitalization. Estimating the effects across seven major sectors in our sample, however, shows that disclosure of advertising spending not only lowers idiosyncratic risk and analyst uncertainty, but also results in higher firm value for firms in the Manufacturing and Business Services (see Table 5). We also find weak empirical support for the positive effect of disclosure of advertising spending on firm value in High-Tech ($p < .10$, two-tailed) and in Healthcare ($p < .05$, two-tailed only for Market Capitalization). The positive impact of disclosure of advertising spending on firm value is consistent with the argument that lower idiosyncratic risk is likely to be reflected in higher valuation.[8] As such,

[8] From an asset pricing perspective, there is little consensus whether lower idiosyncratic risk is reflected in higher returns. Some studies argue that lower idiosyncratic risk is likely to result in higher valuation (see Babenko, Boguth, and Tserlukevich 2015), while others argue that idiosyncratic risk should not have an impact on stock returns (see Francis, Nanda, and Olsson 2008, p. 61). Reflecting on this issue, Rajgopal and Venkatachalam (2011, p. 3) conclude "Even if

CMOs in these major sectors should take a bigger role in investor relations and recommend disclosure of advertising spending in 10-K reports.

[Insert Table 5 about here]

We do not see a significant valuation effect of disclosure of advertising spending for firms in the Consumer Services, Information, and other major sectors, even though we do see significant negative effects on idiosyncratic risk and analyst uncertainty. A plausible reason could be that the valuation benefits due to lower idiosyncratic risk and analyst uncertainty are negated by investor concerns about proprietary costs due to disclosures of advertising spending (see Matsumura, Prakash, and Vera-Munoz 2014 for similar arguments).

In summary, we find that disclosure of advertising spending lowers idiosyncratic risk and analyst uncertainty, while either enhancing firm value or not having a significant effect on it for most firms in our sample. As it is common in the current regulatory environment for firms to not disclose advertising spending, our findings suggest that there is strong merit for SEC and FASB to reconsider the current regulations on disclosure of advertising spending. This is especially important as research does show that managers can manipulate advertising spending to meet short-term objectives at the expense of long-term performance, which is not consistent with interests of investors (e.g., Mizik 2010; Chapman and Steenburgh 2011).

Limitations and Future Research Directions

The current study focuses on the capital markets in the United States where firms have the option to disclose or not to disclose their advertising spending. Therefore, a natural limitation of our findings is that if all firms have to disclose their advertising spending or if there are specific thresholds for such disclosures, then the disclosure of advertising is unlikely to have a significant impact on analyst uncertainty and idiosyncratic risk. As such, future

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idiosyncratic risk were not priced in stock returns, we believe that documenting a link between deteriorating financial reporting quality and increasing stock return volatility is valuable, because increasing stock return volatility has important implications for arbitrage opportunities, portfolio diversification, and stock option pricing."

research can explore examining the consequences of disclosure of advertising spending by firms in other capital markets that have different regulations. Future research can also build on the current study to explore disclosure of other marketing assets such as brand equity because “firms benefit more from marketing assets than from advertising expenditure in terms of future revenues” as marketing assets are “much more sticky” than advertising expenditure (see Edeling and Fischer 2016, p. 520). A comparison of effects of disclosures of advertising spending and other marketing assets could, in turn, offer senior marketing managers valuable insights into the relative benefits of such disclosures.

The current study follows tradition in the prior literature on disclosures by testing hypotheses using secondary data along with an instrumental variable approach to identify the effects of disclosure of advertising spending. As such, it reflects the current disclosure practices of firms. Future research, therefore, can adopt experimental methods to explore alternative approaches to disclosures to identify more normative implications. For example, Martin and Moser (2016) conduct an experiment and find that investors favorably respond to disclosures of green investments positioned as societal benefits as opposed to costs of such investments. Future research, therefore, could utilize the experimental method to examine if investors are more favorably disposed to disclosures of advertising spending if they are positioned as investments into creating value for customers than if they are stated as costs.

The current study focuses on disclosure of dollar amount on advertising spending in 10-K reports but does not examine narrative discussion of this metric within the 10-K or in other channels such as social media that is emerging as an effective channel and is followed by investors and analysts (see for example, Colicev et al. 2018). As such, future research can build on the current study and use text analyses tools to identify different strategies firms might follow in discussing their advertising spending in the discussion section of 10-K reports and in social media and compare their effectiveness.

This study presents an initial step into examining the benefits of disclosures of marketing metrics by focusing on advertising spending. Future research can build on the theoretical and empirical approach in the current study to provide additional insights about disclosures of marketing metrics for regulators, senior managers, investors, and analysts.

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Table 1. The Literature on Marketing Outcomes, Actions, Disclosures and Idiosyncratic Risk

Study	Key Independent Variable	Dependent Variable(s): Idiosyncratic Risk	Dependent Variable(s): Analyst Uncertainty	Dependent Variable(s): Firm Value	Mechanism Studied	Moderator(s) Examined	Main Finding
Marketing Outcomes							
Rego, Billett, and Morgan (2009)	Customer Based Brand Equity (CBBE)	✓					CBBE enhances credit rating and lowers total, systematic, and idiosyncratic risk. CBBE has a stronger negative impact on idiosyncratic risk than systematic risk and downside systematic risk than upside systematic risk.
Bharadwaj, Tuli, and Bonfrer (2011)	Perceived Brand Quality	✓		✓		Earnings Industry Concentration	Unanticipated increase in brand quality results in higher stock returns and systematic risk, but lower idiosyncratic risk. Earnings and industry competition enhance (mitigate) the impacts of brand quality on stock returns (systematic risk).
Luo, Raithel, and Wiles (2013)	Brand Rating Dispersion (BRD) Brand Rating	✓		✓		Upside vs. Downside BRD BRD	BRD has a harmful effect on abnormal returns but reduces firm risk. Downside BRD has a stronger impact on abnormal returns than upside BRD, and the negative effect of brand rating on firm risk is mitigated by BRD.
Marketing Actions							
Panagopoulos, Mullins, and Avramidis (2018)	Sales Force Downsizing	✓				Product Market Fluidity Advertising Intensity Accruals Management CEO External Focus	Sales force reductions increase idiosyncratic risk, and this effect is stronger when competitive threats are high and firm financial reporting transparency is low. Advertising and CEO external focus mitigate these deleterious moderating effects.
Frennea, Han, and Mittal (2019)	Advertising Investments (AI) Receivable Investments (RI)	✓		✓		Firm Scope Interaction of AI and RI	Increasing AI (RI) has an adverse impact on the beneficial effect of RI (AI) on shareholder value. The negative interaction effect of AI and RI is weaker when firms have a broader business scope.
Dotzel and Shankar (2019)	B2B Service Innovations (SI) B2C SI	✓		✓		Number of Product Innovations Customer-Focused SI	B2B SIs have a positive effect on firm value, and this effect is greater than that of a B2C SI. The positive effect of B2B SIs on firm value is stronger for firms with more product innovations and weaker for firms with customer-focused SIs.
Josephson et al. (2019)	Business-to-Government (B2G) Relationship	✓		✓	Costs and Benefits of Government Customers	Government Customer Breadth Government Customer Depth	B2G relationships have a positive nonlinear effect on firm value and a positive effect on firm risk. While government customer breadth mitigates the positive nonlinear effect of B2G relationships on firm value and idiosyncratic risk, government customer depth alleviates the positive effects of B2G relationships on idiosyncratic risk and systematic risk.
Chakravarty, Zhou, and Sharma (2020)	Alliance Network Asymmetry	✓		✓		Innovation Quality Total Interdependence	Direct tie asymmetry has an inverted U-shaped effect on abnormal returns and a U-shaped effect on idiosyncratic risk. Indirect tie asymmetry has a U-shaped effect on idiosyncratic risk. Innovation quality and total interdependence weaken these curvilinear effects.

Table 1. The Literature on Marketing Outcomes, Actions, Disclosures and Idiosyncratic Risk (Cont'd)

Study	Key Independent Variable	Dependent Variable(s)			Mechanism Studied	Moderator(s) Examined	Main Finding
		Idiosyncratic Risk	Analyst Uncertainty	Firm Value			
Disclosure of Marketing Metrics							
Gou, Lev, and Zhou (2004)	Disclosure of Product-Related Information	✓					Disclosures of product-related information by biotech firms are determined by competitive disclosure costs proxied by the stage of product development, availability of patent protection, and venture capital backing. These disclosures have negative effects on bid-ask spread, quoted depth, and stock return volatility.
Simpson (2008)	Disclosure of Advertising Spending						Firms with high proprietary costs (valuation benefits) related with advertising are less (more) likely to disclose advertising spending.
Heitzman, Wasley, and Zimmerman (2010)	Disclosure of Advertising Spending						The materiality of advertising information and disclosure incentives such as future debt issues and litigation risk jointly affect disclosure of advertising spending.
Ellis, Fee, and Thomas (2012)	Nondisclosure of Customer Identities						The proprietary costs of customer information have a significant and positive effect on non-disclosure of information about major customer identities.
Merkley (2014)	Narrative R&D disclosure quantity		✓	✓			Managers adjust the quantity of narrative R&D disclosure based on current earnings performance to provide relevant information. Narrative R&D disclosure is informative because it has beneficial effects on analyst behavior and 10-K information content and lowers information asymmetry.
Bayer, Tuli, and Skiera (2017)	Aggregated Index of Backward & Forward Looking Disclosures of Customer Metrics	✓	✓				Forward-looking disclosures of customer metrics have a negative effect on investor and analyst uncertainty, but do not have an effect on future cash flows.
Shi, Sridhar, and Grewal (2021)	Disclosure of Advertising Spending						Firms follow industry peers' decisions to disclose advertising spending.
Current Research	*Disclosure of Advertising Spending (AD)*	✓	✓	✓	*Analyst Uncertainty*	*Financial Liquidity Financial Leverage Disclosure Quality Competitive Intensity*	*AD lowers* idiosyncratic risk *and analyst uncertainty, and the effect of AD on* idiosyncratic risk *is partially mediated by analyst uncertainty. The negative effect of AD on analyst uncertainty is stronger for firms with higher financial liquidity, those with lower financial leverage, those with lower disclosure quality, and those in more competitive industries. Finally, AD has a positive effect on firm value for firms in manufacturing, high-tech, wholesales and business services, and healthcare major sectors.*

Table 2. Descriptive Statistics and Correlation Matrix

Variable	*n*	*Mean*	*SD*	*Min*	*Max*	Correlation															
						1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*
1. Idiosyncratic Risk$_{i,j,t}$	15,297	.022	.012	.007	.070	1.00															
2. Analyst Uncertainty$_{i,j,t}$	15,297	.162	.174	.007	.971	**.11**	1.00														
3. AD$_{i,j,t-1}$	15,297	.480	.500	.000	1.000	**-.02**	**-.04**	1.00													
4. Estimated Adv Spending$_{i,j,t-1}$	15,297	.007	.019	.000	.133	**.04**	**-.06**	**.25**	1.00												
5. Financial Liquidity$_{i,j,t-1}$	15,297	2.390	1.622	.476	9.552	**.15**	**-.06**	*-.01*	**-.07**	1.00											
6. Financial Leverage$_{i,j,t-1}$	15,297	.187	.183	.000	.823	**-.06**	**.16**	**-.04**	**.02**	**-.26**	1.00										
7. Disclosure Quality$_{i,j,t-1}$	15,297	.715	.099	.464	.899	**-.29**	*.01*	**.21**	.00	**.10**	**-.14**	1.00									
8. Competitive Intensity$_{j,t-1}$	15,297	.815	.139	.270	.965	**.09**	-.01	**-.11**	**-.06**	**.15**	**-.04**	**-.07**	1.00								
9. Analyst Following$_{i,j,t-1}$	15,297	2.206	.890	.000	3.738	**-.30**	**.07**	**.04**	**.02**	**-.08**	**.10**	**.13**	**.04**	1.00							
10. Institutional Ownership$_{i,j,t-1}$	15,297	.700	.254	.020	1.151	**-.24**	**.06**	**.07**	**.02**	**.04**	**.09**	**.35**	**-.07**	**.41**	1.00						
11. Firm Age$_{i,j,t-1}$	15,297	2.959	.714	1.609	4.466	**-.35**	**.07**	**-.03**	**-.04**	**-.15**	**.06**	**.10**	**-.06**	**.13**	**.09**	1.00					
12. Firm Size$_{i,j,t-1}$	15,297	7.328	1.785	3.558	11.844	**-.51**	**.22**	**-.03**	**-.08**	**-.32**	**.28**	**.07**	**-.04**	**.59**	**.11**	**.43**	1.00				
13. SG&A$_{i,j,t-1}$	15,297	.274	.200	.012	1.014	**.28**	**-.15**	**.26**	**.16**	**.03**	**-.32**	**.03**	**-.06**	**-.19**	**-.09**	**-.17**	**-.43**	1.00			
14. ROA$_{i,j,t-1}$	15,297	.043	.100	-.445	.267	**-.37**	**-.07**	**.02**	**.06**	.00	**-.11**	**.03**	**-.03**	**.17**	**.09**	**.16**	**.20**	**-.16**	1.00		
15. Cash Flows$_{i,j,t-1}$	15,297	.104	.084	-.210	.334	**-.28**	**-.06**	**.08**	**.10**	**-.07**	**-.10**	**.05**	.01	**.21**	**.09**	**.09**	**.15**	**-.02**	**.66**	1.00	
16. Industry Growth$_{j,t-1}$	15,297	.044	.132	-.424	.507	**.02**	.00	**-.03**	.00	.00	**-.04**	**-.07**	**.04**	**.03**	**-.02**	**-.04**	.00	.00	**.09**	**.02**	1.00
17. Demand Uncertainty$_{j,t-1}$	15,297	.136	.090	.025	.461	**.18**	**.04**	**-.12**	**-.02**	-.01	**-.03**	**-.22**	**-.07**	**-.03**	**-.07**	**-.10**	**-.07**	**-.04**	**-.02**	*-.01*	**.24**

Notes: a. We winsorize all continuous variables at 1% to rule out the influence of outliers.
b. Correlations in bold are significant at $p < .05$ (two-tailed) and in italic at $p < .10$ (two-tailed).
c. SD = standard deviation; AD$_{i,j,t-1}$ is disclosure of advertising spending; SG&A$_{i,j,t-1}$ is selling, general, and administrative expense (excluding estimated advertising spending), scaled by total assets; ROA$_{i,j,t-1}$ is return on assets for firm *i* in industry *j* in fiscal year *t-1*; n = the number of firm-year observations.

Table 3. The Results of Hypotheses Testing

	Main Effect Model				*Mediation Model*		*Full Model*		
	Idiosyncratic Risk		*Analyst Uncertainty*		*Idiosyncratic Risk*		*Analyst Uncertainty*		
Variable	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*	*Coef.*	*SE*	
$AD_{i,j,t-1}$	-.0028	(.0006)****			-.0013	(.0006)**			*H_1 (-): Supported*
			-.0910	(.0120)****			-.0911	(.0124)****	*H_2 (-): Supported*
Analyst Uncertainty$_{i,j,t}$					.0196	(.0010)****			
Indirect Effect ($\beta_m \times \gamma_1$)					-.0018	(.0002)****			*H_3 (-): Supported*
$AD_{i,j,t-1}$ × Financial Liquidity$_{i,j,t-1}$							-.0042	(.0016)***	*H_4 (-): Supported*
$AD_{i,j,t-1}$ × Financial Leverage$_{i,j,t-1}$							.0332	(.0183)*	*H_5 (+): Weakly Supported*
$AD_{i,j,t-1}$ × Disclosure Quality$_{i,j,t-1}$							.0798	(.0249)***	*H_6 (+): Supported*
$AD_{i,j,t-1}$ × Competitive Intensity$_{j,t-1}$							-.0517	(.0241)**	*H_7 (-): Supported*
Financial Liquidity$_{i,j,t-1}$	-.0001	(.0001)**	.0017	(.0011)	-.0002	(.0001)***	.0037	(.0013)***	
Financial Leverage$_{i,j,t-1}$	.0032	(.0006)****	.0294	(.0108)***	.0026	(.0006)****	.0124	(.0150)	
Disclosure Quality$_{i,j,t-1}$	-.0033	(.0016)**	-.0598	(.0340)*	-.0018	(.0019)	-.0967	(.0380)**	
Competitive Intensity$_{j,t-1}$	.0018	(.0008)**	-.0258	(.0153)*	.0022	(.0007)***	.0047	(.0195)	
Estimated Adv Spending$_{i,j,t-1}$	.0067	(.0065)	-.1746	(.0991)*	.0097	(.0053)*	-.1799	(.0987)*	
Analyst Following$_{i,j,t-1}$	-.0004	(.0002)**	-.0056	(.0028)**	-.0002	(.0002)	-.0054	(.0029)*	
Institutional Ownership$_{i,j,t-1}$	-.0030	(.0005)****	.0258	(.0083)***	-.0035	(.0005)****	.0259	(.0091)***	
Firm Age$_{i,j,t-1}$	-.0023	(.0002)****	-.0094	(.0035)***	-.0021	(.0002)****	-.0093	(.0034)***	
Firm Size$_{i,j,t-1}$	-.0025	(.0001)****	.0417	(.0024)****	-.0032	(.0001)****	.0418	(.0024)****	
SG&A$_{i,j,t-1}$	.0032	(.0008)****	.0945	(.0147)****	.0017	(.0008)**	.0948	(.0145)****	
ROA$_{i,j,t-1}$	-.0177	(.0013)****	-.0249	(.0175)	-.0172	(.0013)****	-.0246	(.0181)	
Cash Flows$_{i,j,t-1}$	-.0084	(.0014)****	.0117	(.0216)	-.0085	(.0013)****	.0092	(.0222)	
Industry Growth$_{j,t-1}$	-.0014	(.0005)***	-.0041	(.0101)	-.0013	(.0005)***	-.0042	(.0101)	
Demand Uncertainty$_{j,t-1}$	.0077	(.0009)****	.0316	(.0146)**	.0069	(.0008)****	.0297	(.0144)**	
$PR\_AD_{i,j,t-1}$	.0027	(.0007)****	.0911	(.0122)****	.0012	(.0006)*	.0926	(.0129)****	
$\hat{\eta}_{i,j,t-1}$	-.0101	(.0114)	.3694	(.1643)**	-.0155	(.0101)	.4311	(.1659)***	
IMR$_{i,j,t-1}$	-.0017	(.0009)*	-.0022	(.0179)	-.0018	(.0009)**	-.0018	(.0175)	
$\hat{\upsilon}_{i,j,t}$					-.0063	(.0013)****			
Intercept	.0014	(.0011)	-.0005	(.0190)	.0018	(.0009)**	-.0020	(.0197)	
Wald χ^2 (df)	11,900.86 (40)****		3,155.74 (40)****		21,640.46 (42)****		3,948.59 (44)****		

Notes: a. # of observations (# of firms) = 15,297 (2,285); DV = dependent variable; SE = standard error. b. $AD_{i,j,t-1}$ is disclosure of advertising spending; SG&A$_{i,j,t-1}$ is selling, general, and administrative expense (excluding estimated advertising spending) scaled by total assets; ROA$_{i,j,t-1}$ is return on assets; IMR$_{i,j,t-1}$ is the inverse Mills ratio generated from the probit model to control for sample selection due to the inclusion of estimated advertising spending; *$PR\_AD_{i,j,t-1}$* is the probit residual of $AD_{i,j,t-1}$ for firm *i* in industry *j* in fiscal year *t-1*; $\hat{\eta}_{i,j,t-1}$ and $\hat{\upsilon}_{i,j,t}$ are the control function correction terms for Adv Spending$_{i,j,t-1}$ and Analyst Uncertainty$_{i,j,t}$. c. We use the clustered robust standard errors of estimates at the firm level and use 200 bootstrapping replications to calculate the standard errors. The models include year fixed effects. d. We mean center all continuous variables; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed).

Table 4. Robustness Analyses

	Model 1a Focal Model	Model 2a Alternative Measure of Est. Adv (1)	Model 3a Alternative Measure of Est. Adv (2)	Model 4a Alternative Measure of Est. Adv (3)	Model 5a Alternative Instrument (1): No IP	Model 6a Alternative Instrument (2): No SP	Model 7a Alternative Instrument (3): No AP	Model 8a Alternative Instrument (4): 2DP	Model 9a Copula Correction for AU	Model 10a Alternative Industry Classification
DV = Idiosyncratic Risk$_{i,j,t}$										
H_1 (-): $AD_{i,j,t-1}$	-.0028****	-.0029****	-.0028****	-.0028****	-.0028***	-.0021***	-.0041****	-.0027***	n/a	-.0016***
DV = Analyst Uncertainty$_{i,j,t}$	Model 1b	Model 2b	Model 3b	Model 4b	Model 5b	Model 6b	Model 7b	Model 8b	Model 9b	Model 10b
H_2 (-): $AD_{i,j,t-1}$	-.0910****	-.0893****	-.0908****	-.0893****	-.0974****	-.0819****	-.1055****	-.0985****	n/a	-.0574****
DV = Idiosyncratic Risk$_{i,j,t}$	Model 1c	Model 2c	Model 3c	Model 4c	Model 5c	Model 6c	Model 7c	Model 8c	Model 9c	Model 10c
Analyst Uncertainty$_{i,j,t}$	.0196****	.0197****	.0196****	.0197****	.0188****	.0195****	.0194****	.0188****	.0062****	.0204****
$AD_{i,j,t-1}$	-.0013**	-.0013**	-.0013**	-.0013**	-.0011*	-.0010*	-.0022***	-.0010	-.0016**	-.0006
H_3 (-): Indirect Effect ($\beta_m \times \gamma_1$)	-.0018****	-.0018****	-.0018****	-.0018****	-.0018****	-.0016****	-.0021****	-.0019****	-.0006****	-.0012****
DV = Analyst Uncertainty$_{i,j,t}$	Model 1d	Model 2d	Model 3d	Model 4d	Model 5d	Model 6d	Model 7d	Model 8d	Model 9d	Model 10d
$AD_{i,j,t-1}$	-.0911****	-.0895****	-.0910****	-.0895****	-.0976****	-.0823****	-.1072****	-.0987****	n/a	-.0571****
H_4 (-): $AD_{i,j,t-1}$ × Financial Liquidity$_{i,j,t-1}$	-.0042***	-.0041***	-.0042***	-.0041***	-.0041***	-.0041***	-.0042**	-.0041***	n/a	-.0040***
H_5 (+): $AD_{i,j,t-1}$ × Financial Leverage$_{i,j,t-1}$	.0332*	.0344**	.0332**	.0341**	.0321**	.0330**	.0339**	.0324**	n/a	.0236
H_6 (+): $AD_{i,j,t-1}$ × Disclosure Quality$_{i,j,t-1}$	.0798***	.0801***	.0795***	.0794***	.0780***	.0802****	.0839***	.0815***	n/a	.0746***
H_7 (-): $AD_{i,j,t-1}$ × $COMP_{j,t-1}$	-.0517**	-.0515**	-.0518**	-.0512**	-.0504**	-.0513***	-.0509**	-.0503**	n/a	-.0342**
# of Observations	15,297	15,297	15,297	15,297	15,297	15,297	15,297	15,263	15,297	14,403
(# of Firms)	(2,285)	(2,285)	(2,285)	(2,285)	(2,285)	(2,285)	(2,285)	(2,282)	(2,285)	(2,205)

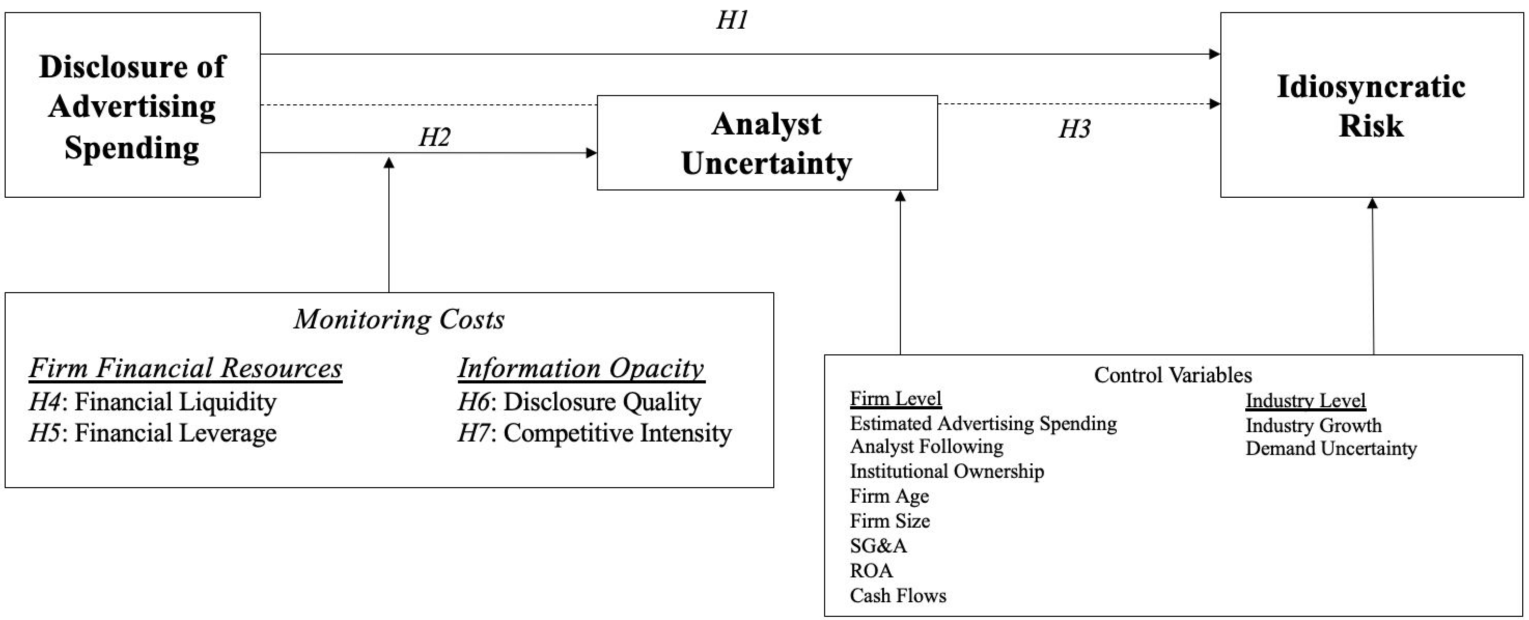
Notes: a. $AD_{i,j,t-1}$ is disclosure of advertising spending for firm *i* in industry *j* in fiscal year *t-1*; IP = industry peer instruments; SP = sector peer instruments; AP = auditor peer instruments; 2DP = the second degree peer instruments; AU = analyst uncertainty. b. We use alternative measures for estimated advertising spending for Model 2a-4d (i.e., estimated advertising spending scaled by sales for Model 2a-2d, natural log of estimated advertising spending scaled by total assets for Model 3a-3d, and natural log of estimated advertising spending scaled by sales for Model 4a-4d) ; We use alternative instruments for Model 5a-8d; We use the copula correction term to control for the endogeneity of AU for Model 9c and the copula correction term is significant (=.0018, $p < .001$); We use the four-digit Standard Industry Classification (SIC4) as an alternative industry classification for Model 10a-10c. To identify the business sector, we use the 10 divisions in SIC excluding non-classifiable. c. We use the clustered robust standard errors of the estimates at the firm level and use 200 bootstrapping replications to calculate the standard errors. d. We mean center all continuous variables. DV = dependent variable; COMP = competitive intensity. e. * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed for Model 1a-1d; one-tailed for the robustness analyses models 2a to 10d); All models are significant at $p < .001$.

Table 5. The Marginal Effects of Disclosure of Advertising Spending on Financial Market Performance for Major Sectors

DV				Idiosyncratic Risk$_{i,j,t}$		Analyst Uncertainty$_{i,j,t}$		Tobin's q$_{i,j,t}$		Market Capitalization$_{i,j,t}$	
Major Sectors	*N*	*n*	*% AD*	*dy/dx*	SE	*dy/dx*	SE	*dy/dx*	SE	*dy/dx*	SE
Manufacturing	4,664	602	45.09%	-.0018	(.0008) **	-.1007	(.0161) ****	.4502	(.1051) ****	.2591	(.0739) ****
High Tech	4,246	662	43.33%	-.0056	(.0008) ****	-.0996	(.0151) ****	.2166	(.1115) *	.1209	(.0801) *
Consumer Services	2,070	252	81.59%	-.0017	(.0010) *	-.0827	(.0158) ****	.1734	(.1220)	.0377	(.0909)
Business Services	1,214	185	26.69%	-.0060	(.0012) ****	-.1389	(.0181) ****	.4712	(.1397) ***	.2575	(.0961) ***
Healthcare	1,230	219	44.47%	-.0030	(.0012) **	-.0764	(.0192) ****	.3105	(.1901)	.2078	(.1025) **
Information	891	173	68.01%	-.0031	(.0011) ***	-.1040	(.0181) ****	.0861	(.1649)	.1449	(.1053)
Others	982	192	23.63%	-.0031	(.0019)	-.1141	(.0242) ****	-.0218	(.1508)	-.1530	(.1319)
# of Observations (# of Firms)	15,297	2,285	47.99%								

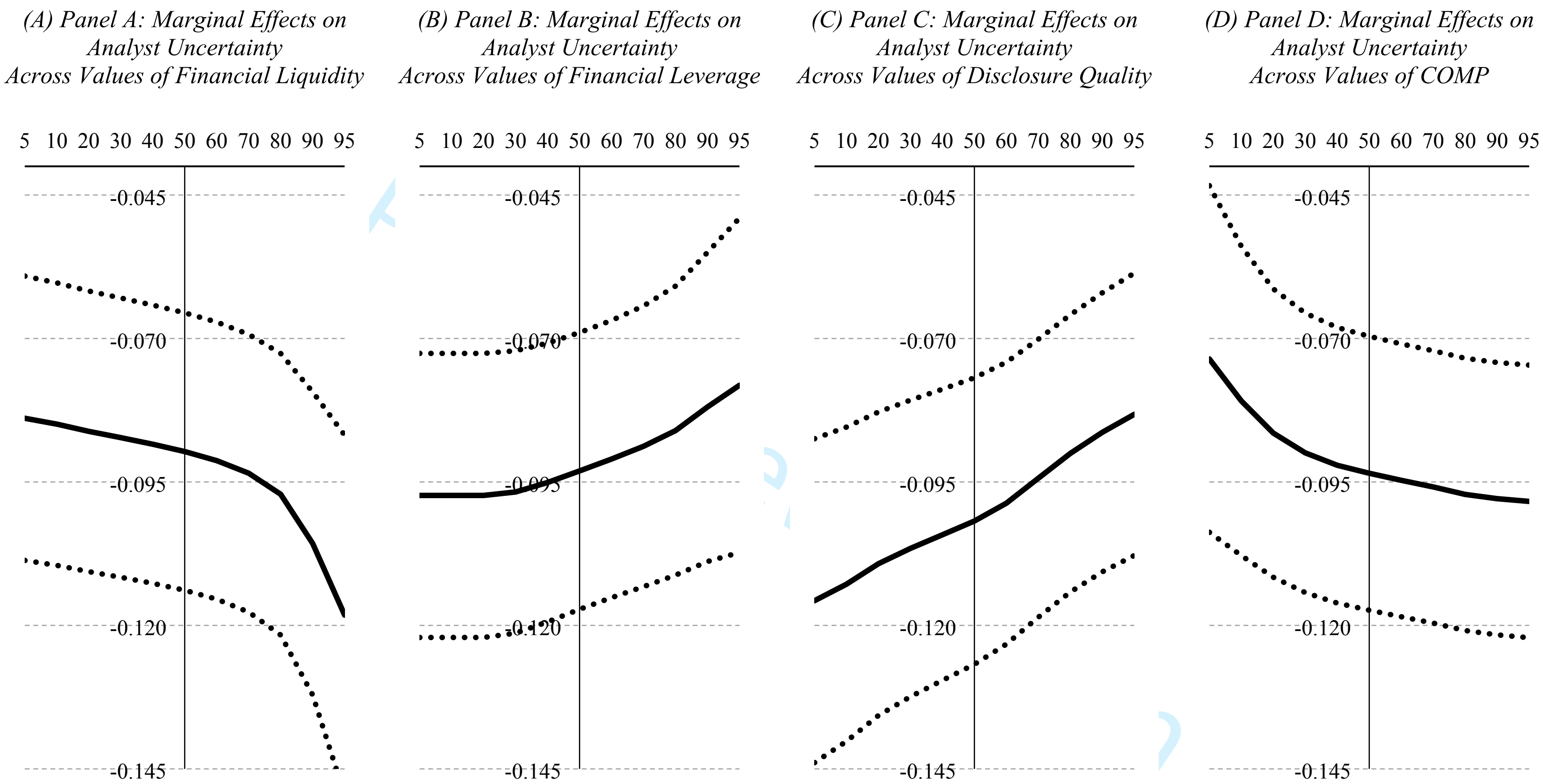
Notes:
a. DV = dependent variable; N = firm-year observations; n = unique firms; %AD = percentage of firm-year observations for which advertising spending is disclosed; *dy/dx* = estimated marginal effect of disclosure of advertising spending; SE = standard error
b. In our sample, Manufacturing includes manufacturing firms (NAICS2 31-33) except High Tech firms and Healthcare firms. High Tech includes firms producing technology goods and providing high-tech services in NAICS4 3341, 3342, 3344, 3345, 3364, 5112, 5179, 5181, 5182, 5413, 5415, and 5417 (see Decker et al. 2020) except Healthcare firms. Decker et al. (2020) include NAICS4 3254 and 5161 to classify High Tech firms, and we do not observe in our sample and include NAICS4 3254 in Healthcare. Consumer Services include firms in Retail Trade (NAICS2 42 & 45), in Leisure and Hospitality (NAICS2 71 & 72), and Personal and Laundry Services (NAICS3 811). Business Services include firms in Wholesale Trade (NAICS2 42) and Professional and Business Services (NAICS2 54-56). Healthcare includes firms pharmaceutical and medical firms, and healthcare service firms in NAICS4 3254, 3391, and NAICS2 62. Information includes firms in Information (NAICS2 51) except High Tech firms. Others include firms in Mining, Quarrying, and Oil and Gas Extraction (NAICS2 21), Construction (NAICS2 23), Transportation and Warehousing (NAICS2 48-49), Real Estate and Rental and Leasing (NAICS2 53), and Educational Services (NAICS 61). Web Appendix A20 outlines the construction of 7 major sectors in more detail.
c. **** $p < .001$, *** < $p < .01$, ** $p < .05$, * $p < .10$ (two-tailed).

Figure 1. Conceptual Framework



Notes: SG&A = Selling, general, and administrative expense; ROA = Return on assets; Dotted line = Mediation effect of analyst uncertainty

Figure 2. Marginal Effects of Disclosure of Advertising Disclosure on Analyst Uncertainty



Notes:
a. The horizontal axis is the range of each moderating variable from the value at the 5th percentile to the 95th percentile in the COMPUSTAT sample.
b. The vertical axis is the marginal effect of disclosure of advertising spending on analyst uncertainty.
c. The dotted lines represent 95% confidence intervals; COMP = competitive intensity.

Web Appendices

Does Disclosure of Advertising Spending Help Investors and Analysts?

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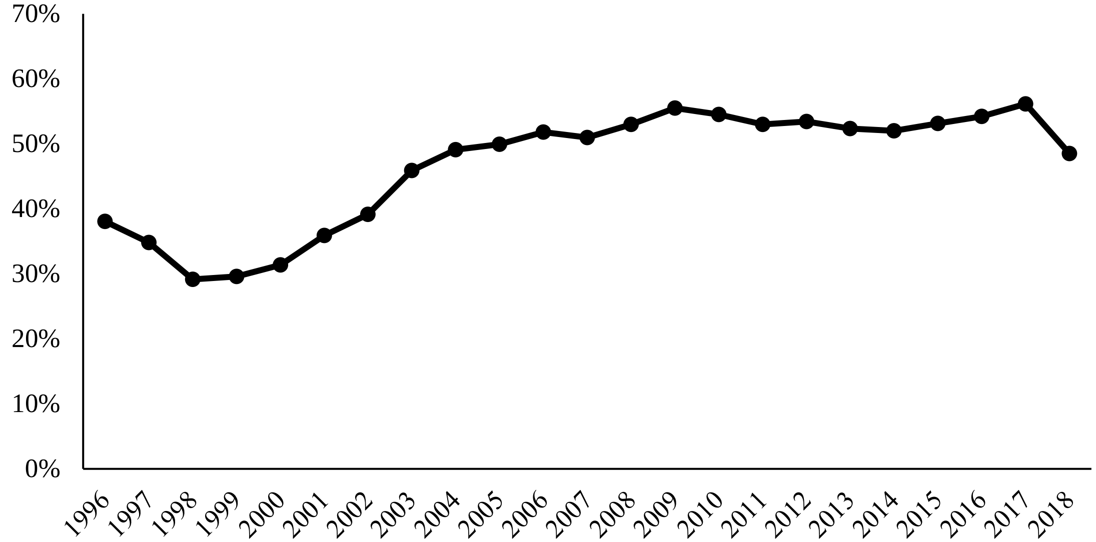
Web Appendix A1

Disclosure of Advertising Spending by Publicly Listed Firms in the Sample over Years



Notes:

a. The vertical axis represents the percentage of firms that disclose advertising spending in our sample.

b. Given our empircal models have the lag structures in the first stage models and focal models, the focal models exploit the variation of disclosure of advertising spending from fiscal year 1996 to 2018.

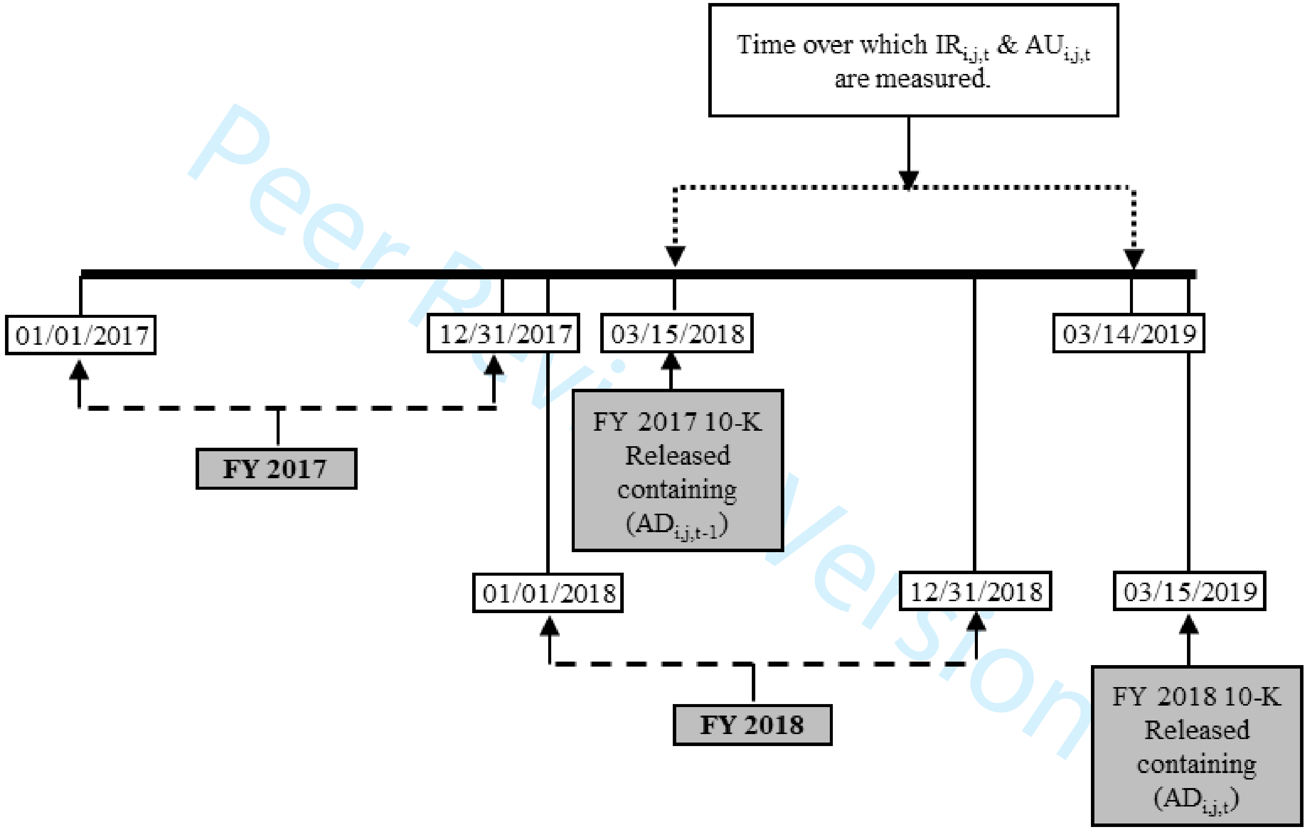
Web Appendix A2. The Literature on Marketing Outcomes, Actions, and Idiosyncratic Risk

Study	Key Independent Variable	Dependent Variable(s): Idiosyncratic Risk	Dependent Variable(s): Analyst Uncertainty	Dependent Variable(s): Firm Value	Mechanism Studied	Moderator(s) Examined	Main Finding
Marketing Outcomes							
Sorescu and Spanjol (2008)	Breakthrough Innovation Incremental Innovation	✓		✓		Interaction of Incremental and Breakthrough Innovation	Breakthrough innovation is associated with increases in Tobin's q, abnormal stock returns, and idiosyncratic risk whereas incremental innovation is associated with an increase in Tobin's q only.
Tuli and Bharadwaj (2009)	Customer Satisfaction	✓					Customer satisfaction lowers not only overall systematic and idiosyncratic risk but also downside systematic and idiosyncratic risk.
Luo, Homburg, and Wieseke (2010)	Customer Satisfaction	✓		✓	Analyst Stock Recommendation (ASR) & ASR Dispersion	Product Market Competition Financial Market Uncertainty	Positive changes in customer satisfaction improve ASR and lower ASR dispersion. These effects are stronger when product markets are more competitive and financial markets are more uncertainty.
Marketing Actions							
Osinga et al. (2011)	Direct-to-Consumer Advertising (DTCA) Direct-to-Physician (DTP) Marketing	✓		✓		Relaxation of Regulation	DTCA increases stock returns (the strongest effect after the regulation relaxation) and idiosyncratic risk and lowers systematic risk. In contrast, DTP marketing has modest positive effects on stock returns and idiosyncratic risk.
Fang, Palmatier, and Grewal (2011)	Customer and Innovation Asset Configuration	✓		✓		Industry Dynamism	A configuration strategy using deep customer and broad innovation assets or deep innovation and broad customer assets has a positive effect on firm performance. In contrast, deep-deep or broad-broad asset configurations decrease firm performance variability. These effects of configuration strategies are stronger in more dynamic industry environments.
Dotzel, Shankar, and Berry (2013)	Internet-Enabled Service Innovativeness (EI) People-Enabled Service Innovativeness (PI)	✓		✓	Customer Satisfaction	Types of Service Innovations Human-Dominated Industry	EI has a positive and direct effect on firm value and PI has an overall positive effect on firm value through its positive effect on customer satisfaction only in human-dominated industries. In addition, whereas EI & PI have positive effects on idiosyncratic risk, PI indirectly lowers idiosyncratic risk by increasing customer satisfaction in human-dominated industries.

Web Appendix A2. The Literature on Marketing Outcomes, Actions, and Idiosyncratic Risk (Cont'd)

Study	Key Independent Variable	Dependent Variable(s)			Mechanism Studied	Moderator(s) Examined	Main Finding
		Idiosyncratic Risk	Analyst Uncertainty	Firm Value			
Marketing Actions							
Thomaz and Swaminathan (2015)	Marketing Alliances Firm Network Density Partner Network Density	✓				Repeat Partnership	Marketing alliances reduce firm risk only for a new partnership. At high levels, a firm's network density increases idiosyncratic risk, and a partner's network density increases systematic risk.
McAlister et al. (2016)	Advertising Spending			✓		Disclosure of Advertising Spending	Advertising increases sales regardless of firm strategy but increases firm value only for differentiators.
Han, Mittal, and Zhang (2017)	Relative Strategic Emphasis	✓				Relative Performance Demand Instability	Relative strategic emphasis on value appropriation reduces idiosyncratic risk. This effect is weaker when firms have larger positive or negative relative performance, and the contingent effects are stronger if industry demand instability is high.
Colicev et al. (2018)	Earned Social Media (ESM) Owned Social Media (OSM)	✓		✓	Customer Satisfaction Purchase Intent Brand Awareness		ESM improves customer mindset metrics, whereas OSM increases customer satisfaction and brand awareness. Purchase intent and customer satisfaction enhance shareholder value.

Web Appendix A3
Timeline for Measuring Disclosure, Analyst Uncertainty, and Idiosyncratic Risk



FY = Fiscal Year
$AD_{i,j,t-1}$ = Disclosure of Advertising Spending for FY t-1
$IR_{i,j,t}$ = Idiosyncratic Risk between release of 10-K of FY t-1 and FY t
$AU_{i,j,t}$ = Analyst Uncertainty between release of 10-K of FY t-1 and FY t

Web Appendix A4
Construction of Disclosure Quality

Consistent with Chen, Miao, and Shevlin (2015), we start by counting the non-missing items in both the firm's balance sheet and its income statement. A firm's annual report (i.e., 10-K filing) has the hierarchical nesting feature such that one item consists of multiple disaggregated items. For example, *current assets total* includes *inventory (IVT) total* and other seven second-level accounts, and *IVT total* includes four more disaggregated accounts, *IVT raw material*, *IVT work-in-progress*, *IVT finished goods*, and *IVT other*. By using this nesting feature of a 10-K annual report, we calculate the ratio of non-missing items to the total items in the balance sheet and income statement. For the balance sheet, we identify 11 groups, which are associated with 25 second-level items and 93 subaccounts. We count the non-missing items in 93 subaccounts for the balance sheet and generate the value-weighted ratio of the non-missing items for each group based on the magnitude of the group over the total assets. For the income statement, we generate the equal-weighted ratio of the non-missing items to the total items. Note that we do not include the item of advertising spending in calculating the ratio of the non-missing items to the total items in the income statement to avoid the possibility that disclosure quality takes into account disclosure of advertising spending. Then, we use the average of the ratios for the balance sheet and income statement as disclosure quality of a firm. The higher the level of disaggregation of the annual report of a firm, the greater is the information available to investors, and therefore, the greater is the quality of its financial disclosures (see Chen, Miao, and Shevlin 2015 for detailed discussion on the construction of the measure and its validity).

Web Appendix A5
Measures, Data Sources, and the Supporting Literature for Control Variables

Variable	*Measure*	*Data Source*	*The Supporting Literature*
Estimated Adv Spending$_{i,j,t-1}$	Kantar Media advertising spending estimates, scaled by total assets	Kantar Media	Ramani and Srinivasan (2019) Wies et al. (2019)
Analyst Following$_{i,j,t-1}$	Natural log of the number of analysts reporting earnings forecasts of a firm between the day of the release of the firm's annual report and the day before the release of the firm's annual report in the following year	I/B/E/S	Lehavy, Li, and Merkley (2011) Lang and Lundholm (1996)
Institutional Ownership$_{i,j,t-1}$	Percentage of outstanding shares owned by institutional investors	Thomson Reuters	Bayer, Tuli, and Skiera (2017)
Firm Age$_{i,j,t-1}$	Natural log of number of years since the firm stock's first listing	CRSP	McAlister, Srinivasan, and Kim (2007)
Firm Size$_{i,j,t-1}$	Natural log of the total assets of a firm	COMPUSTAT	Rego, Billett, and Morgan (2009)
SG&A$_{i,j,t-1}$	Selling, general, and administrative expense, scaled by total assets	COMPUSTAT	Chakravarty and Grewal (2016) Ptok, Jindal, and Reinartz (2018)
ROA$_{i,j,t-1}$	Income before extraordinary items, scaled by total assets	COMPUSTAT	Kurt and Hulland (2013) Rego, Billett, and Morgan (2009)
Cash Flows$_{i,j,t-1}$	Net operating cash flows, scaled by total assets		Gruca and Rego (2005) Bayer, Tuli, and Skiera (2017)
Industry Growth$_{j,t-1}$	Natural log of sales of an industry in the current fiscal year less natural log of sales of an industry in the prior year	COMPUSTAT	Dotzel, Shankar, and Berry (2013)
Demand Uncertainty$_{j,t-1}$	The standard deviation of 5-year industry sales, scaled by the average of 5-year industry sales.	COMPUSTAT	Fang, Palmatier, and Steenkamp (2008)

Note: We deduct estimated advertising spending in the calculation of SG&A$_{i,j,t-1}$.

Web Appendix A6
Identification Strategies

Relevance and Validity of Proposed Instruments for Disclosure of Advertising Spending

Arguments for Industry and Sector Peers. Industry and Sector peer instruments are conceptually relevant because peer firms' disclosures arguably reflect the industry and sector norms that are followed by firms either due to learning (Han, Mittal, and Zhang 2017) or to gain legitimacy (Sine, Haveman, and Tolbert 2005). Indeed, prior research shows that firms are likely to follow their industry and sector norms for decisions such as advertising spending (Sridhar et al. 2016) or disclosure of advertising spending (Shi, Grewal, and Sridhar 2021). Importantly, sector and industry peer disclosures are unlikely to be related to omitted variables in the error term. For example, consider the unobserved managerial foresight. Decisions guided by managerial foresight may be correlated with advertising spending disclosure and also idiosyncratic risk. However, it is highly unlikely that instruments based on sector and industry peers correlate with managerial foresight for a specific firm. First, it is very difficult for peer firms to observe and measure a focal firm's managerial foresight. Even if a peer firm is able to observe an individual manager's foresight, it is highly unlikely that all peer firms can observe it and even more improbable that all peers will be able to collectively and strategically act on it (also see Germann, Ebbes, and Grewal 2015).

Arguments for Auditor Peers. We also propose that the proportion of disclosures of advertising spending by Auditor Peers is also a relevant and valid instrument. Firms rely on auditors to make accounting- and disclosure-related decisions (e.g., Glendening, Mauldin, and Shaw 2019). Auditors have particular structured processes and internal rules of conducting an audit that characterize a particular audit style (Francis, Pinnuck, and Watanabe 2014). The particular audit style, in turn, may act as norms not only for auditing and but also for accounting decisions such as information disclosures, resulting in similar financial statements of client firms sharing the same auditor (Johnston and Zhang 2021). Indeed, empirical studies suggest that firms sharing the same auditor show similar disclosure patterns (e.g., Brown and Knechel 2016). Therefore, we expect that a firm's disclosure of advertising spending is positively related to those of its auditor peers.

Auditor peer disclosure of advertising spending, however, is unlikely to be correlated with the potential omitted variables (e.g., managerial foresight). Given business confidentiality, an auditor is unlikely to share its clients' decision rules shaped by managerial foresight that may influence disclosure decisions. Therefore, there is no reason to expect the auditor peer instrument for disclosure of advertising spending correlates with unobservable omitted variables. To strengthen the identification of the proposed econometric approaches, we construct auditor peers as firms which hire the same auditor as the focal firm but do not operate in the same industry as the focal firm (i.e., non-overlapping peers).

Potential Endogeneity of Estimated Advertising Spending

Advertising spending is likely to be endogenous because managers strategically plan and implement advertising. For example, managers may spend more on advertising if firm sales are expected to decline. It is also possible that managers may cut advertising budgets to meet earnings expectation in the short-term (Mizik 2010). Thus, there may be unobservable factors that influence both idiosyncratic risk and analyst uncertainty, and advertising spending decisions. Accordingly, we adopt the control function approach and use the weighted averages of estimated advertising spending levels of both industry and sector peers as instruments for a focal firm's estimated advertising spending (for precedence see Sridhar et al. 2016). We estimate the following auxiliary regression:

$$\text{Est. Adv Spending}_{i,j,t\text{-}1} = \kappa_0 + \kappa_1\text{WIPAS}_{i,j,t\text{-}2} + \kappa_2\text{WSPAS}_{i,j,t\text{-}2} + \boldsymbol{\Theta}'\textbf{Controls}_{\mathbf{i,j,t\text{-}1}} + \sum_{k=1}^{K-1}\pi_k\text{Year}_{t\text{-}1} + \xi_i + \eta_{i,j,t\text{-}1},$$

where Est. Adv Spendingi,j,t-1 = Kantar Media estimates of advertising spending scaled by total assets, $\text{WIPAS}_{i,j,t\text{-}2}$ = weighted average of estimated advertising spending scaled by total assets of industry peers other than firm *i*, and $\text{WSPAS}_{i,j,t\text{-}2}$ = weighted average of estimated advertising spending scaled by total assets of sector peers excluding industry peers in industry *j* at fiscal year *t-2*; ξ_i = a firm random effect, and $\eta_{i,j,t\text{-}1}$ = the random error term.

After estimating the model, we generate the residual, $\hat{\eta}_{i,j,t\text{-}1}$, and include it in the final models to address potential endogeneity of estimated advertising spending.

Potential Selection Bias for the Inclusion of Estimated Advertising Spending

Equation 2-5 may face a selection bias due to the inclusion of Est. Adv $\text{Spending}_{i,j,t\text{-}1}$, which requires data from Kantar Media. The coverage of firms by Kantar Media to estimate advertising spending, in turn, could create a potential selection bias (see Frennea, Han, and Mittal 2019). To account for this potential selection bias, we need to identify exclusion restrictions that predict the probability of coverage by Kantar Media but do not have an impact on the error terms related to idiosyncratic risk and analyst uncertainty. Consistent with our instrumentation approach, we adapt the approach followed by Han, Mittal, and Zhang (2017) and use the weighted proportion of both industry and sector peers covered by Kantar Media as exclusion restrictions. Specifically, in the first stage, we estimate the following probit model:

$$\Pr(\text{KM}_{i,j,t\text{-}1} = 1) = \Phi(\omega_0 + \omega_1\text{WIPKM}_{i,j,t\text{-}1} + \omega_2\text{WSPKM}_{i,j,t\text{-}1} + \boldsymbol{\Omega}'\textbf{Controls}_{\mathbf{i,j,t\text{-}1}} + \sum_{k=1}^{K-1}\varphi_k\text{Year}_{t\text{-}1}),$$

where $\text{KM}_{i,j,t\text{-}1}$ = Kantar Media advertising coverage (i.e., one if a firm is covered by kantar media and zero otherwise), $\text{WIPKM}_{i,j,t\text{-}2}$ = weighted proportion of industry peers other than firm *i* whose Kantar Media advertising spending is available, and $\text{WSPKM}_{i,j,t\text{-}2}$ = weighted proportion of sector peers excluding industry peers whose Kantar Media advertising spending is available in industry *j* at fiscal year *t*.

After estimating the probit model, we generate the inverse Mills ratio (i.e., $\mathbf{IMR}_{\mathbf{i,j,t\text{-}1}}$) and include it in the final models to control for the selection bias.

Potential Endogeneity of Analyst Uncertainty

Analyst uncertainty in the mediation model (i.e., Equation 4) is likely to be endogenous because the control variables in the model may not be able to capture all unobservable factors that can influence analysts' and investors' ability to predict firm future performance. Therefore, we apply the control function approach to account for the potential endogeneity of analyst uncertainty and use the weighted averages of sector and industry peers' analyst uncertainty as instruments. The proposed instruments are likely to be relevant and valid. Financial analysts tend to specialize in a specific industry or business sector and incorporate industry analysis in publishing the research reports. Industry expertise is one of the important aspects of analyst research (Brown et al. 2015) and comparison of firms within an industry is an important part of valuing stocks (Boni and Womack 2006). "Financial analysis textbooks commonly recommend the use of peer firms in valuation" (Healy and Palepu 2007; De Franco, Hope, and Larocque 2015, p. 84). When forecasting a firm's future performance, analysts incorporate their industry knowledge and their interpretation of industry specific information, i.e., intra-industry information transfer (Piotroski and Roulstone 2004). Thus, analyst uncertainty of a firm may correlate with those of its industry and sector peers.

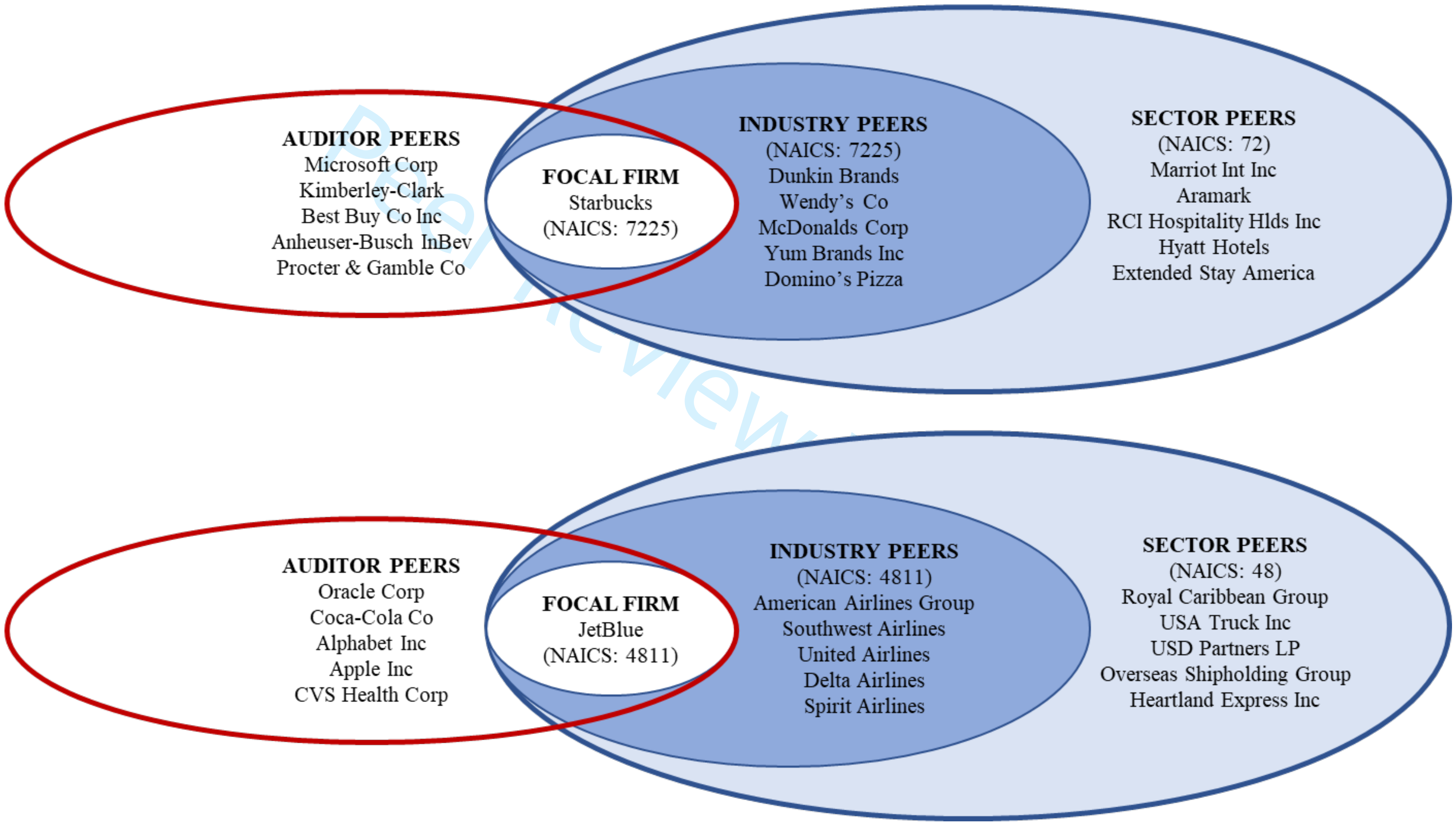
The proposed instruments are unlikely to be correlated with the error term in the idiosyncratic risk model because we control for a wide range of time varying industry factors that take into account the competitive conditions, growth, and uncertainty of demand. Therefore, we estimate the following model to obtain the residual term:

$$AU_{i,j,t} = \delta_0 + \delta_1 WIPAU_{i,j,t} + \delta_2 WSPAU_{i,j,t} + \boldsymbol{\Phi' Controls_{i,j,t-1}} + \sum_{k=1}^{K-1} \sigma_k Year_t + \varsigma_i + \upsilon_{i,j,t},$$

where $AU_{i,j,t}$ = analyst uncertainty; $WIPAU_{i,j,t}$ = weighted average of analyst uncertainty of industry peers other than firm *i* and $WSPAS_{i,j,t}$ = weighted average of analyst uncertainty of sector peers excluding industry peers in industry *j* at fiscal year *t*; ς_i, = a firm random effect; and $\upsilon_{i,j,t}$ = the random error term.

Then, we include $\hat{\upsilon}_{i,j,t}$ as an additional covariate in the final model to test the mediating effect of analyst uncertainty.

Web Appendix A7
Examples of Firms Included in Industry, Sector, and Auditor Peers to Calculate Instruments



Web Appendix A8
Estimation of the Weights for Peers

We follow Lim, Tuli, and Grewal (2020) to estimate the weights for sector, industry, and auditor peers. Using the classical multidimensional scaling method (MDS), we first draw a positioning map with two dimensions based on firms' similarity for each sector based on the two-digit NAICS, each industry based on the four-digit NAICS, and each auditor in each fiscal year. We estimate firms' similarity based on several important firm characteristics. To account for firms' similarity reflected in firm size and profitability, we include natural log of sales and return on assets. In addition, we include financial leverage (long-term debt scaled by total assets) to capture a firm's capital structure. Next, in the positioning maps generated by MDS, we calculate the Euclidean distances between all firms in each sector, industry, and for each auditor in each fiscal year. The Euclidean distance between a pair of firms represents dissimilarity between firms. Thus, as a next step, we measure the weights as follows:

$$\text{Weight}_{i,p,j,t} = (\text{Total Distance}_{i,j,t} - \text{Distance}_{i,p,j,t} \,/\, \text{Total Distance}_{i,j,t}),$$

where Total $\text{Distance}_{i,j,t}$ = the total Euclidean distance between the focal firm and all its peers in sector *j*, industry *j*, or auditor *j*; Distance = the Euclidean distance between the focal firm and its peer *p* in fiscal year *t*.

Finally, taking into account the weight, we measure the instruments as follows:

$$\text{Weighted Peer Instrument}_{i,j,t\text{-}2} = \frac{\sum_{i,p}^{N} w_{i,p,j,t\text{-}2} \times \text{Peer Variable}_{p,j,t\text{-}2}}{\sum_{i,p}^{N} w_{i,p,j,t\text{-}2}}$$

where $w_{i,p,j,t\text{-}2}$ = weight of the similarity between firm *i* and peer *p* in the sector, industry, or auditor *j* at fiscal year *t-2*; and Peer $\text{Variable}_{p,j,t\text{-}2}$ = a relevant peer variable for instruments (e.g., disclosure of advertising spending or estimated advertising spending level).

Web Appendix A9
Results of the First Stage Probit Model for Disclosure of Advertising Spending

Dependent Variable = $AD_{i,j,t-1}$		
Independent Variables	*Coef.*	*SE*
Weighted Industry Peer Disclosure$_{i,j,t-2}$	1.630	(.190) ****
Weighted Sector Peer Disclosure$_{i,j,t-2}$	1.133	(.251) ****
Weighted Auditor Peer Disclosure$_{i,j,t-2}$	3.817	(.578) ****
Financial Liquidity$_{i,j,t-1}$	.036	(.018) **
Financial Leverage$_{i,j,t-1}$	.354	(.166) **
Disclosure Quality$_{i,j,t-1}$	1.918	(.455) ****
Competitive Intensity$_{j,t-1}$	.090	(.268)
Analyst Following$_{i,j,t-1}$	-.038	(.045)
Institutional Ownership$_{i,j,t-1}$	.116	(.134)
Firm Age$_{i,j,t-1}$	.005	(.052)
Firm Size$_{i,j,t-1}$	.078	(.029) ***
SG&A$_{i,j,t-1}$	1.569	(.177) ****
ROA$_{i,j,t-1}$	.071	(.232)
Cash Flows$_{i,j,t-1}$	.676	(.303) **
Industry Growth$_{j,t-1}$	-.175	(.097) *
Demand Uncertainty$_{j,t-1}$	-.536	(.258) **
Intercept	1.273	(.176) ****
Year Fixed Effects	Yes	
Number of Firm-Year Observations (Number of Firms)	15,297 (2,285)	
Wald χ^2 (df)	667.65 (38) ****	
Log Pseudolikelihood	-8,481.26	

Notes:
a. $AD_{i,j,t-1}$ is disclosure of advertising spending for firm *i* in industry *j* in fiscal year *t-1*.
b. Weighted Industry Peer Disclosure$_{i,j,t-2}$ is the weighted proportion of industry peer firms that disclose advertising spending, Weighted Sector Peer Disclosure$_{i,j,t-2}$ is the weighted proportion of sector peer firms that disclose advertising spending, and Weighted Auditor Peer Disclosure$_{i,j,t-2}$ is the weighted proportion of auditor peer firms that disclose advertising spending in fiscal year *t-2*. SG&A$_{i,j,t-1}$ represents selling, general, and administrative expense (excluding estimated advertising spending), scaled by total assets for firm *i* in industry *j* in fiscal year *t-1*. ROA$_{i,j,t-1}$ is return on assets for firm *i* in industry *j* in fiscal year *t-1*.
c. The result of Wald test for joint significance of Weighted Industry Peer Disclosure$_{i,j,t-2}$, Weighted Sector Peer Disclosure$_{i,j,t-2}$, and Weighted Auditor Peer Disclosure$_{i,j,t-2}$ is 239.41 ($p < .001$).
d. We use the clustered robust standard errors of the estimates at the firm level; We mean center all continuous variables.
e. SE = standard error; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed).

Web Appendix A10
Results of the Auxiliary Regression Model for Estimated Advertising Spending

Dependent Variable = Est. Adv Spending$_{i,j,t-1}$		
Independent Variables	*Coef.*	*SE*
Weighted Industry Peer Est. Adv Spending$_{i,j,t-2}$	.106	(.024) ****
Weighted Sector Peer Est. Adv Spending$_{i,j,t-2}$	.059	(.016) ****
Financial Liquidity$_{i,j,t-1}$	-.000	(.000)
Financial Leverage$_{i,j,t-1}$	.001	(.002)
Disclosure Quality$_{i,j,t-1}$	-.018	(.006) ***
Competitive Intensity$_{j,t-1}$	.009	(.004) **
Analyst Following$_{i,j,t-1}$	-.000	(.000)
Institutional Ownership$_{i,j,t-1}$	.004	(.002) ***
Firm Age$_{i,j,t-1}$	-.002	(.001) **
Firm Size$_{i,j,t-1}$	-.003	(.000) ****
SG&A$_{i,j,t-1}$	.001	(.004)
ROA$_{i,j,t-1}$	.000	(.002)
Cash Flows$_{i,j,t-1}$	-.000	(.004)
Industry Growth$_{j,t-1}$	-.000	(.001)
Demand Uncertainty$_{j,t-1}$	-.002	(.002)
IMR$_{i,j,t-1}$	-.012	(.003) ****
Intercept	.009	(.003) ***
Year Fixed Effects	Yes	
Number of Firm-Year Observations (Number of Firms)	15,297 (2,285)	
Wald χ^2 (df)	123.38 (38) ****	

Notes:
a. Est. Adv Spending$_{i,j,t-1}$ is Kantar Media (KM) estimates of advertising spending scaled by total assets for firm *i* in industry *j* in fiscal year *t-1*.
b. Weighted Industry Peer Est. Adv Spending$_{i,j,t-2}$ is the weighted average of industry peer firms' KM advertising spending scaled by total assets and Weighted Sector Peer Adv Spending$_{i,j,t-2}$ is the weighted average of sector peer firms' KM advertising spending scaled by total assets at fiscal year *t-2*. SG&A$_{i,j,t-1}$ represents selling, general, and administrative expense (excluding KM advertising spending), scaled by total assets for firm *i* in industry *j* in fiscal year *t-1*. ROA$_{i,j,t-1}$ is return on assets for firm *i* in industry *j* in fiscal year *t-1*. IMR represents the inverse Mills ratio to correct for a selection bias of KM coverage of firms.
c. The result of Wald test for joint significance of Weighted Industry Peer Adv Spending$_{i,j,t-2}$ and Weighted Sector Peer Adv Spending$_{i,j,t-2}$ is 36.91 (p < .001).
d. We use the clustered robust standard errors of the estimates at the firm level; We mean center all continuous variables.
e. SE = standard error; * p < .10, ** p < .05, *** p <.01, **** p < .001 (two-tailed).

Web Appendix A11
Results of the Selection Model for Estimated Advertising Spending

Dependent Variable = $KM_{i,j,t-1}$		
Independent Variables	*Coef.*	*SE*
Weighted Industry Peer $KM_{i,j,t-1}$	.772	(.113) ****
Weighted Sector Peer $KM_{i,j,t-1}$	1.005	(.213) ****
Financial $Liquidity_{i,j,t-1}$	-.005	(.007)
Financial $Leverage_{i,j,t-1}$	.144	(.080) *
Disclosure $Quality_{i,j,t-1}$	1.905	(.223) ****
Competitive $Intensity_{j,t-1}$	-.365	(.130) ***
Analyst $Following_{i,j,t-1}$	.148	(.022) ****
Institutional $Ownership_{i,j,t-1}$	.025	(.022)
Firm $Age_{i,j,t-1}$	.208	(.027) ****
Firm $Size_{i,j,t-1}$	.113	(.015) ****
$SG\&A_{i,j,t-1}$	.683	(.088) ****
$ROA_{i,j,t-1}$	.038	(.068)
Cash $Flows_{i,j,t-1}$	.462	(.111) ****
Industry $Growth_{j,t-1}$	.025	(.048)
Demand $Uncertainty_{j,t-1}$	-.138	(.123)
Intercept	-3.494	(.207) ****
Year Fixed Effects	Yes	
Number of Firm-Year Observations (Number of Firms)	36,817 (5,091)	
Wald χ^2 (df)	1,110.17 (38) ****	
Log Pseudolikelihood	-22,570.66	

Notes: a. $KM_{i,j,t-1}$ is Kantar Media advertising coverage (i.e., one if a firm is covered by Kantar Media and zero otherwise) for firm *i* in industry *j* in fiscal year *t-1*.
b. Weighted Industry Peer $KM_{i,j,t-1}$ is the weighted proportion of industry peer firms covered by Kantar Media and Weighted Sector Peer $KM_{i,j,t-1}$ is the weighted proportion of sector peer firms covered by Kantar Media. $SG\&A_{i,j,t-1}$ represents selling, general, and administrative expense, scaled by total assets. $ROA_{i,j,t-1}$ is return on assets for firm *i* in industry *j* in fiscal year *t-1*.
c. The result of Wald test for joint significance of Weighted Sector Peer $KM_{i,j,t-1}$ and Weighted Industry Peer $KM_{i,j,t-1}$ is 91.92 ($p < .001$).
d. We use the clustered robust standard errors of the estimates at the firm level.
e. SE = standard error; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed).

Web Appendix A12
Results of the Auxiliary Regression Model for Analyst Uncertainty

Dependent Variable = Analyst Uncertainty$_{i,j,t}$		
Independent Variables	*Coef.*	*SE*
Weighted Industry Peer Analyst Uncertainty$_{i,j,t}$	.005	(.002) ***
Weighted Sector Peer Analyst Uncertainty$_{i,j,t}$	.003	(.001) **
Financial Liquidity$_{i,j,t-1}$	.001	(.001)
Financial Leverage$_{i,j,t-1}$	.016	(.015)
Disclosure Quality$_{i,j,t-1}$	-.122	(.032) ****
Competitive Intensity$_{j,t-1}$	-.022	(.025)
Analyst Following$_{i,j,t-1}$	-.005	(.003)
Institutional Ownership$_{i,j,t-1}$	.022	(.013) *
Firm Age$_{i,j,t-1}$	-.008	(.004) *
Firm Size$_{i,j,t-1}$	.040	(.003) ****
SG&A$_{i,j,t-1}$	.039	(.015) ***
ROA$_{i,j,t-1}$	-.029	(.017) *
Cash Flows$_{i,j,t-1}$	-.010	(.021)
Industry Growth$_{j,t-1}$	.002	(.010)
Demand Uncertainty$_{j,t-1}$	.048	(.018) ***
Intercept	-.043	(.010) ****
Year Fixed Effects	Yes	
Number of Firm-Year Observations (Number of Firms)	15,297 (2,285)	
Wald χ^2 (df)	997.74 (37) ****	

Notes:
a. Weighted Industry Peer Analyst Uncertainty$_{i,j,t}$ is the weighted average of industry peer firms' analyst uncertainty and Weighted Sector Peer Analyst Uncertainty$_{i,j,t}$ is the weighted average of sector peer firms' analyst uncertainty in fiscal year *t*. SG&A$_{i,j,t-1}$ represents selling, general, and administrative expense (excluding estimated advertising spending), scaled by total assets. ROA$_{i,j,t-1}$ is return on assets for firm *i* in industry *j* in fiscal year *t-1*.
b. The result of Wald test for joint significance of Weighted Industry Peer Analyst Uncertainty$_{i,j,t}$ and Weighted Sector Peer Analyst Uncertainty$_{i,j,t}$ is 11.83 ($p < .01$).
c. We use the clustered robust standard errors of the estimates at the firm level; We mean center all continuous variables.
d. SE = standard error; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed).

Web Appendix A13
Results of First Stage Models with Alternative Instruments

	Alternative Instruments (1) Removing Industry Peers	*Alternative Instruments (2) Removing Sector Peers*	*Alternative Instruments (3) Removing Auditor Peers*	*Alternative Instruments (4) Second Degree Peers*
DV = AD$_{i,j,t-1}$				
Variable	*Coef SE*	*Coef SE*	*Coef SE*	*Coef SE*
Weighted Industry Peer Disclosure$_{i,j,t-2}$		2.1245 (.1548)****	1.5427 (.1891)****	
Weighted Sector Peer Disclosure$_{i,j,t-2}$	2.3250 (.2039)****		1.1117 (.2521)****	2.2596 (.2082)****
Weighted Auditor Peer Disclosure$_{i,j,t-2}$	3.3789 (.5681)****	3.7760 (.5754)****		3.3814 (.5690)****
Second Degree Peer Disclosure$_{i,j,t-2}$				.5315 (.5798)
Joint Sig. χ^2 (df)	156.46 (2)****	213.64 (2)****	202.76 (2)****	155.51 (3)****
Wald χ^2 (df)	586.55 (37)	660.56 (37)	620.08 (37)	587.33 (38)
Obs	15,297 (2,285)	15,297 (2,285)	15,297 (2,285)	15,263 (2,282)
DV = Est. Adv Spending$_{i,j,t-1}$				
Weighted Industry Peer Est. Adv Spending$_{i,j,t-2}$		.1100 (.0244)****		
Weighted Sector Peer Est. Adv Spending$_{i,j,t-2}$	.0669 (.0157)****			.0657 (.0155)****
Second Degree Peer Est. Adv Spending$_{i,j,t-2}$				.0148 (.0318)
Joint Sig. χ^2 (df)	18.26 (1)****	20.40 (1)****		18.35 (2)****
Wald χ^2 (df)	127.42 (37)	116.41 (37)****		128.90 (38)
Obs	15,297 (2,285)	15,297 (2,285)		15,263 (2,282)
DV = KM$_{i,j,t-1}$				
Weighted Industry Peer KM$_{i,j,t-1}$		.9259 (.1088)****		
Weighted Sector Peer KM$_{i,j,t-1}$	1.4794 (.2026)****			1.4213 (.2075)****
Second Degree Peer KM$_{i,j,t-1}$				.3363 (.4490)
Joint Sig. χ^2 (df)	53.34 (1)****	72.36 (1)****		52.46 (2)****
Wald χ^2 (df)	1,144.50 (37)	1,090.14 (37)		1,149.83 (38)
Obs	37,340 (5,137)	37,340 (5,137)		37,230 (5,130)
DV = AU$_{i,j,t}$				
Weighted Industry Peer AU$_{i,j,t}$		.0045 (.0017)***		
Weighted Sector Peer AU$_{i,j,t}$	.0025 (.0013)*			.0025 (.0013)*
Second Degree Peer AU$_{i,j,t}$				.0013 (.0015)
Joint Sig. χ^2 (df)	3.75 (1)*	7.29 (1)***		4.59 (2)†
Wald χ^2 (df)	994.82 (36)	990.13 (36)		996.43 (37)
Obs	15,297 (2,285)	15,297 (2,285)		15,263 (2,282)

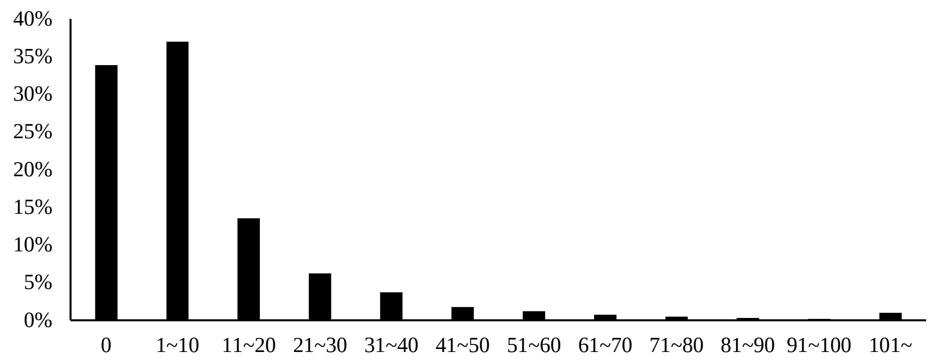
Notes: a. AU$_{i,j,t}$ = analyst uncertainty; AD$_{i,j,t-1}$ = disclosure of advertising spending; KM$_{i,j,t-1}$ = information availability of Kantar Media advertising spending for firm *i* in industry *j* in fiscal year *t-1*. b. We use the clustered robust standard errors of estimates at the firm level. c. We mean center all continuous variables; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed); † $p < .10$ (one-tailed). d. All models are significant at $p < .001$ and include year fixed effects. e. For alternative instruments (3), we report the results of the first stage model for AD$_{i,j,t-1}$ only as the rest of the first stage models are equivalent to those in the main analyses.

Web Appendix A14
Constructing the Word Count of Advertising in 10-K Reports of Firms

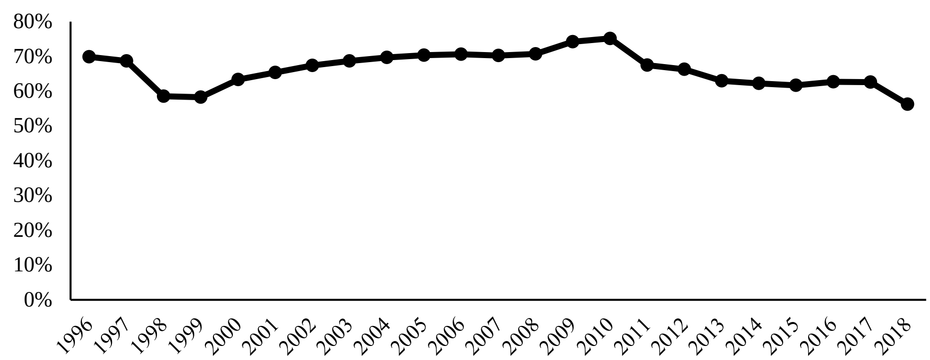
To account for the extent to which a firm qualitatively mentions its advertising in its 10-K report in our empirical models, we analyze the 10-K reports of firms and collect the textual data on the frequency of the occurrence of the word, "*advertising*". First, we use the Text Parse Macro (i.e., TEXTPARSE.SAS) provided by the WRDS SEC Analytics Suite (see Lim, Tuli, and Grewal 2020 for a recent application) and extract 300 characters preceding the matched line that includes the key word, "*advertising*". Next, we count the number of "*advertising*" mentioned in each extracted text (i.e., 300 characters) and calculate the sum of its frequency for each 10-K report. Then, we divide the raw word count of advertising in each 10-K report by its industry mean to generate the variable of the word count of advertising, i.e., Adv Word Count$_{i,j,t-1}$ for firm i in industry j in fiscal year $t-1$ (Kim et al. 2021). We include Adv Word Count$_{i,j,t-1}$ in the focal models as an additional control variable to account for the extent to which a firm qualitatively mentions its advertising in its 10-K report (see Web Appendix A14 for the descriptive statistics and A15 for the results).

Web Appendix A15
Distribution and Descriptive Statistics of the Word Count of Advertising

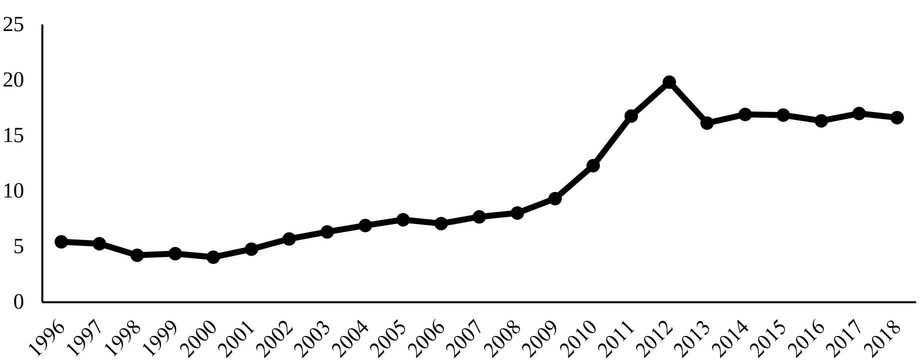
Panel A: Distribution of the Word Count of Advertising



Panel B: Percentage of Firms Mentioning Advertising in 10-K Reports



Panel C: The Average of the Word Count of Advertising over Years



Notes: a. The variable is the word count of advertising mentioned in the 10-K reports of firms in the sample before scaling it by its industry mean. B. # of Obs (# of firms) = 15,297 (2,285); Mean = 10.880; SD = 25.978; Min = 0; Max = 1,087. C. Given our empircal models have the lag structures in the first stage models and focal models, the models exploit the variation of the variable from fiscal year 1996 to 2018.

Web Appendix A16
Additional Analyses for the Word Count of Advertising

Variable	*DV = Idiosyncratic Risk$_{i,j,t}$* *Coef SE*	*DV = Analyst Uncertainty$_{i,j,t}$* *Coef SE*	*DV = Idiosyncratic Risk$_{i,j,t}$* *Coef SE*	*DV = Analyst Uncertainty$_{i,j,t}$* *Coef SE*	
$AD_{i,j,t-1}$	-.0018 (.0005) ****		-.0008 (.0004) *		*H_1 (-): Supported*
		-.0547 (.0090) ****		-.0560 (.0098) ****	*H_2 (-): Supported*
Analyst Uncertainty$_{i,j,t}$			.0196 (.0010) ****		
Indirect Effect ($\beta_m \times \gamma_1$)			-.0011 (.0002) ****		*H_3 (-): Supported*
$AD_{i,j,t-1}$ × Financial Liquidity$_{i,j,t-1}$				-.0041 (.0016) ***	*H_4 (-): Supported*
$AD_{i,j,t-1}$ × Financial Leverage$_{i,j,t-1}$				.0349 (.0182) *	*H_5 (+): Weakly Supported*
$AD_{i,j,t-1}$ × Disclosure Quality$_{i,j,t-1}$				.0846 (.0248) ***	*H_6 (+): Supported*
$AD_{i,j,t-1}$ × Competitive Intensity$_{j,t-1}$				-.0528 (.0242) **	*H_7 (-): Supported*
Financial Liquidity$_{i,j,t-1}$	-.0001 (.0001) **	.0011 (.0011)	-.0002 (.0001) ***	.0031 (.0012) **	
Financial Leverage$_{i,j,t-1}$	.0029 (.0006) ****	.0207 (.0104) **	.0025 (.0006) ****	.0028 (.0148)	
Disclosure Quality$_{i,j,t-1}$	-.0038 (.0016) **	-.0806 (.0332) **	-.0019 (.0018)	-.1203 (.0368) ***	
Competitive Intensity$_{j,t-1}$	.0016 (.0008) **	-.0297 (.0150) **	.0021 (.0007) ***	.0014 (.0196)	
Adv Word Count$_{i,j,t-1}$	.0003 (.0001) ****	.0084 (.0015) ****	.0002 (.0001) ***	.0089 (.0014) ****	
Est. Adv Spending$_{i,j,t-1}$	.0044 (.0065)	-.2136 (.1012) **	.0082 (.0053)	-.2177 (.0992) **	
Analyst Following$_{i,j,t-1}$	-.0003 (.0002) **	-.0050 (.0027) *	-.0002 (.0002)	-.0049 (.0028) *	
Institutional Ownership$_{i,j,t-1}$	-.0031 (.0005) ****	.0227 (.0084) ***	-.0036 (.0005) ****	.0227 (.0090) **	
Firm Age$_{i,j,t-1}$	-.0023 (.0002) ****	-.0082 (.0035) **	-.0021 (.0002) ****	-.0082 (.0033) **	
Firm Size$_{i,j,t-1}$	-.0024 (.0001) ****	.0423 (.0023) ****	-.0032 (.0001) ****	.0425 (.0024) ****	
SG&A$_{i,j,t-1}$	.0025 (.0007) ***	.0713 (.0136) ****	.0015 (.0007) **	.0714 (.0135) ****	
ROA$_{i,j,t-1}$	-.0177 (.0013) ****	-.0250 (.0172)	-.0171 (.0013) ****	-.0246 (.0179)	
Cash Flows$_{i,j,t-1}$	-.0085 (.0013) ****	.0067 (.0211)	-.0086 (.0013) ****	.0041 (.0219)	
Industry Growth$_{j,t-1}$	-.0013 (.0005) ***	-.0016 (.0098)	-.0013 (.0005) ***	-.0017 (.0100)	
Demand Uncertainty$_{j,t-1}$	.0080 (.0009) ****	.0405 (.0139) ***	.0071 (.0008) ****	.0385 (.0139) ***	
$PR\_AD_{i,j,t-1}$	.0014 (.0005) ***	.0531 (.0094) ****	.0005 (.0005)	.0559 (.0104) ****	
$\hat{\eta}_{I,j,t-1}$	-.0082 (.0114)	.4067 (.1679) **	-.0143 (.0101)	.4676 (.1668) ***	
IMR$_{i,j,t-1}$	-.0012 (.0009)	.0117 (.0169)	-.0014 (.0009) *	.0114 (.0164)	
$\hat{\upsilon}_{i,j,t}$			-.0063 (.0013) ****		
Intercept	.0003 (.0010)	-.0338 (.0172) **	.0013 (.0009)	-.0343 (.0168) **	
# of observations (# of firms)	15,297 (2,285)	15,297 (2,285)	15,297 (2,285)	15,297 (2,285)	
Wald $\chi 2$ (df)	12,449.61 (41)	3,392.18 (41)	21,661.30 (43)	4,210.56 (45)	

Notes: a. DV = dependent variable; SE = standard error. b. $AD_{i,j,t-1}$ is disclosure of advertising spending; Adv Word Count$_{i,j,t-1}$ is the word count of advertising mentioned in the 10-K report of a firm; SG&A$_{i,j,t-1}$ is selling, general, and administrative expense (excluding estimated advertising spending) scaled by total assets; ROA$_{i,j,t-1}$ is return on assets; IMR$_{i,j,t-1}$ is the inverse Mills ratio to control for sample selection due to the inclusion of estimated advertising spending; *$PR\_AD_{i,j,t-1}$* is the probit residual of $AD_{i,j,t-1}$ for firm *i* in industry *j* in fiscal year *t-1*; $\hat{\eta}_{i,j,t-1}$ and $\hat{\upsilon}_{i,j,t}$ are the control function correction terms for Adv Spending$_{i,j,t-1}$ and Analyst Uncertainty$_{i,j,t}$. c. We use the clustered robust standard errors of estimates at the firm level and use 200 bootstrapping replications to calculate the standard errors. d. We mean center all continuous variables; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed); e. All models include year fixed effects and are significant at $p < .001$.

Web Appendix A17
Accounting for Industry Fixed Effects

It would be possible to argue that accounting for industry effects is important because advertising spending disclosure practices vary across different industries (Shi, Grewal, and Sridhar 2021) and firms in different industries are likely to have different levels of financial market risks. Though our empirical models do include industry-level control variables and use industry- and sector-based peers as instruments, we test if our conclusions remain consistent after accounting for industry-fixed effects. To account for unobservable industry-related effects, we include industry fixed effects and estimate the models. Specifically, we conduct two robustness checks, one using NAICS2 dummies and the other using 7 major sector dummies (see Table A18.1 in Web Appendix A18 for the definition of 7 major sectors).

As shown in Table A16.1 and Table A16.2, both robustness analyses accounting for industry fixed effects provide support for our hypotheses H_1-H_7. We note that, the mediation effect of analyst uncertainty is stronger in the model accounting for NAICS2 fixed effects as we find the main effect of disclosure of advertising spending is significant only at $p < .10$ (one-tailed). In addition, the moderating effect of competitive intensity is weaker as the interaction of disclosure of advertising spending and competitive intensity is significant only at $p < .10$ (one-tailed) in the model accounting for NAICS2 fixed effects. Table A16.1 outlines the results of the models accounting for NAICS2 fixed effects and Table A16.2 outlines those accounting for 7 major sector fixed effects.

Table A17.1

Robustness Analyses Accounting for Industry Fixed Effects (1)

	DV = Idiosyncratic Risk$_{i,j,t}$ Coef SE	*DV = Analyst Uncertainty$_{i,j,t}$* Coef SE	*DV = Idiosyncratic Risk$_{i,j,t}$* Coef SE	*DV = Analyst Uncertainty$_{i,j,t}$* Coef SE	
AD$_{i,j,t-1}$	-.0028 (.0009) ***		-.0013 (.0009) †		*H_1 (-): Supported*
		-.0925 (.0158) ****		-.0915 (.0164) ****	*H_2 (-): Supported*
Analyst Uncertainty$_{i,j,t}$			.0190 (.0011) ****		
Indirect Effect ($\beta_m \times \gamma_1$)			-.0018 (.0003) ****		*H_3 (-): Supported*
AD$_{i,j,t-1}$ × Financial Liquidity$_{i,j,t-1}$				-.0038 (.0017) **	*H_4 (-): Supported*
AD$_{i,j,t-1}$ × Financial Leverage$_{i,j,t-1}$				.0350 (.0189) *	*H_5 (+): Weakly Supported*
AD$_{i,j,t-1}$ × Disclosure Quality$_{i,j,t-1}$				.0731 (.0234) ***	*H_6 (+): Supported*
AD$_{i,j,t-1}$ × Competitive Intensity$_{j,t-1}$				-.0345 (.0213) †	*H_7 (-): Weakly Supported*
Financial Liquidity$_{i,j,t-1}$	-.0002 (.0001) **	.0011 (.0012)	-.0002 (.0001) ***	.0030 (.0013) **	
Financial Leverage$_{i,j,t-1}$	.0031 (.0006) ****	.0228 (.0109) **	.0027 (.0005) ****	.0044 (.0161)	
Disclosure Quality$_{i,j,t-1}$	-.0043 (.0019) **	-.0864 (.0374) **	-.0022 (.0019)	-.1228 (.0364) ***	
Competitive Intensity$_{j,t-1}$	.0021 (.0009) **	-.0422 (.0170) **	.0028 (.0008) ***	-.0204 (.0200)	
Est. Adv Spending$_{i,j,t-1}$	.0045 (.0067)	-.2472 (.1007) **	.0087 (.0067)	-.2545 (.1029) **	
Analyst Following$_{i,j,t-1}$	-.0007 (.0002) ***	-.0108 (.0033) ***	-.0004 (.0002) **	-.0107 (.0033) ***	
Institutional Ownership$_{i,j,t-1}$	-.0029 (.0005) ****	.0306 (.0084) ****	-.0035 (.0005) ****	.0305 (.0088) ***	
Firm Age$_{i,j,t-1}$	-.0027 (.0002) ****	-.0178 (.0047) ****	-.0024 (.0002) ****	-.0179 (.0042) ****	
Firm Size$_{i,j,t-1}$	-.0026 (.0001) ****	.0389 (.0029) ****	-.0033 (.0001) ****	.0389 (.0027) ****	
SG&A$_{i,j,t-1}$	.0019 (.0010) **	.0868 (.0187) ****	.0008 (.0010)	.0855 (.0166) ****	
ROA$_{i,j,t-1}$	-.0177 (.0013) ****	-.0158 (.0176)	-.0174 (.0013) ****	-.0159 (.0169)	
Cash Flows$_{i,j,t-1}$	-.0093 (.0014) ****	-.0111 (.0220)	-.0090 (.0013) ****	-.0143 (.0214)	
Industry Growth$_{j,t-1}$	-.0015 (.0005) ***	-.0050 (.0101)	-.0014 (.0005) ***	-.0051 (.0101)	
Demand Uncertainty$_{j,t-1}$	.0079 (.0009) ****	.0414 (.0151) ***	.0070 (.0009) ****	.0402 (.0166) **	
PR_AD$_{i,j,t-1}$	.0026 (.0009) ***	.0929 (.0159) ****	.0011 (.0009)	.0931 (.0165) ****	
$\hat{\eta}_{i,j,t-1}$	-.0096 (.0116)	.4496 (.1660) ***	-.0164 (.0113)	.5055 (.1696) ***	
IMR$_{i,j,t-1}$	-.0036 (.0014) **	-.0381 (.0266)	-.0029 (.0014) **	-.0397 (.0227) *	
$\hat{\upsilon}_{i,j,t}$			-.0056 (.0013) ****		
Intercept	.0082 (.0022) ****	.1158 (.0386) ***	.0062 (.0020) ***	.1149 (.0337) ***	
Wald $\chi 2$ (df)	14,032.18 (57) ****	3,819.56 (57) ****	22,164.32 (59) ****	4,273.94 (61) ****	
Year and Industry Fixed Effects	Yes	Yes	Yes	Yes	

Notes: a. # of observations (# of firms) = 15,297 (2,285); DV = dependent variable; SE = standard error. b. AD$_{i,j,t-1}$ is disclosure of advertising spending; SG&A$_{i,j,t-1}$ is selling, general, and administrative expense (excluding estimated advertising spending) scaled by total assets; ROA$_{i,j,t-1}$ is return on assets; IMR$_{i,j,t-1}$ is the inverse Mills ratio generated from the probit model to control for sample selection due to the inclusion of estimated advertising spending; *PR_AD$_{i,j,t-1}$* is the probit residual of AD$_{i,j,t-1}$ for firm *i* in industry *j* in fiscal year *t-1*; $\hat{\eta}_{i,j,t-1}$ and $\hat{\upsilon}_{i,j,t}$ are the control function correction terms for Adv Spending$_{i,j,t-1}$ and Analyst Uncertainty$_{i,j,t}$. c. The models include industry fixed effects using NAICS2 dummies. We use the clustered robust standard errors of estimates at the firm level and use 200 bootstrapping replications to calculate the standard errors. d. We mean center all continuous variables; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed); † $p < .10$ (one-tailed).

Table A17.2
Robustness Analyses Accounting for Industry Fixed Effects (2)

	DV = Idiosyncratic Risk$_{i,j,t}$ *Coef SE*	*DV = Analyst Uncertainty$_{i,j,t}$* *Coef SE*	*DV = Idiosyncratic Risk$_{i,j,t}$* *Coef SE*	*DV = Analyst Uncertainty$_{i,j,t}$* *Coef SE*	
$AD_{i,j,t-1}$	-.0036 (.0008) ****		-.0020 (.0008) ***		*H_1 (-): Supported*
		-.0997 (.0144) ****		-.0989 (.0151) ****	*H_2 (-): Supported*
Analyst Uncertainty$_{i,j,t}$			.0203 (.0010) ****		
Indirect Effect ($\beta_m \times \gamma_1$)			-.0020 (.0003) ****		*H_3 (-): Supported*
$AD_{i,j,t-1}$ × Financial Liquidity$_{i,j,t-1}$				-.0042 (.0017) **	*H_4 (-): Supported*
$AD_{i,j,t-1}$ × Financial Leverage$_{i,j,t-1}$				.0356 (.0189) *	*H_5 (+): Weakly Supported*
$AD_{i,j,t-1}$ × Disclosure Quality$_{i,j,t-1}$				.0774 (.0233) ***	*H_6 (+): Supported*
$AD_{i,j,t-1}$ × Competitive Intensity$_{j,t-1}$				-.0483 (.0214) **	*H_7 (-): Supported*
Financial Liquidity$_{i,j,t-1}$	-.0001 (.0001) *	.0020 (.0011) *	-.0002 (.0001) ***	.0040 (.0013) ***	
Financial Leverage$_{i,j,t-1}$	.0032 (.0006) ****	.0236 (.0110) **	.0027 (.0006) ****	.0049 (.0161)	
Disclosure Quality$_{i,j,t-1}$	-.0029 (.0018)	-.0529 (.0366)	-.0013 (.0017)	-.0898 (.0350) **	
Competitive Intensity$_{j,t-1}$	.0014 (.0008) *	-.0153 (.0165)	.0015 (.0008) *	.0142 (.0196)	
Est. Adv Spending$_{i,j,t-1}$	.0049 (.0066)	-.2929 (.0996) ***	.0102 (.0056) *	-.3028 (.1020) ***	
Analyst Following$_{i,j,t-1}$	-.0005 (.0002) ***	-.0058 (.0030) *	-.0003 (.0002) *	-.0055 (.0031) *	
Institutional Ownership$_{i,j,t-1}$	-.0029 (.0005) ****	.0293 (.0083) ****	-.0035 (.0005) ****	.0293 (.0087) ***	
Firm Age$_{i,j,t-1}$	-.0023 (.0002) ****	-.0128 (.0039) ***	-.0020 (.0002) ****	-.0129 (.0037) ***	
Firm Size$_{i,j,t-1}$	-.0024 (.0001) ****	.0407 (.0026) ****	-.0032 (.0001) ****	.0408 (.0024) ****	
SG&A$_{i,j,t-1}$	.0033 (.0009) ****	.1044 (.0163) ****	.0016 (.0008) *	.1039 (.0145) ****	
ROA$_{i,j,t-1}$	-.0176 (.0013) ****	-.0252 (.0175)	-.0169 (.0013) ****	-.0252 (.0171)	
Cash Flows$_{i,j,t-1}$	-.0086 (.0014) ****	.0046 (.0220)	-.0086 (.0014) ****	.0017 (.0214)	
Industry Growth$_{j,t-1}$	-.0015 (.0005) ***	-.0020 (.0101)	-.0015 (.0005) ***	-.0020 (.0102)	
Demand Uncertainty$_{j,t-1}$	.0077 (.0009) ****	.0309 (.0149) **	.0068 (.0008) ****	.0293 (.0165) *	
$PR\_AD_{i,j,t-1}$	.0034 (.0008) ****	.0995 (.0144) ****	.0018 (.0008) **	.1002 (.0151) ****	
$\hat{\eta}_{i,j,t-1}$	-.0084 (.0115)	.4987 (.1668) ***	-.0162 (.0109)	.5633 (.1691) ***	
IMR$_{i,j,t-1}$	-.0020 (.0012) *	-.0098 (.0217)	-.0019 (.0011) *	-.0104 (.0186)	
$\hat{\upsilon}_{i,j,t}$			-.0070 (.0013) ****		
Intercept	.0009 (.0013)	.0277 (.0222)	.0008 (.0012)	.0274 (.0209)	
Wald $\chi 2$ (df)	12,487.37 (46) ****	3,476.09 (46) ****	15,593.07 (48) ****	3,272.05 (50) ****	
Year and Industry Fixed Effects	Yes	Yes	Yes	Yes	

Notes: a. # of observations (# of firms) = 15,297 (2,285); DV = dependent variable; SE = standard error. b. $AD_{i,j,t-1}$ is disclosure of advertising spending; SG&A$_{i,j,t-1}$ is selling, general, and administrative expense (excluding estimated advertising spending) scaled by total assets; ROA$_{i,j,t-1}$ is return on assets; IMR$_{i,j,t-1}$ is the inverse Mills ratio generated from the probit model to control for sample selection due to the inclusion of estimated advertising spending; *$PR\_AD_{i,j,t-1}$* is the probit residual of $AD_{i,j,t-1}$ for firm *i* in industry *j* in fiscal year *t-1;* $\hat{\eta}_{i,j,t-1}$ and $\hat{\upsilon}_{i,j,t}$ are the control function correction terms for Adv Spending$_{i,j,t-1}$ and Analyst Uncertainty$_{i,j,t}$. c. The models include industry fixed effects using major sector dummies. We use the clustered robust standard errors of estimates at the firm level and use 200 bootstrapping replications to calculate the standard errors. d. We mean center all continuous variables; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed).

Web Appendix A18
Alternative Measurement Windows for Analyst Uncertainty and Idiosyncratic Risk

Our empirical model to test H_3 (i.e., the mediating effect of analyst uncertainty) assumes that investors are affected by analyst uncertainty simultaneously as we measure both of the variables in the same measurement window. To establish the casual effect of analyst uncertainty on idiosyncratic risk, it is important to assure that analyst uncertainty precedes idiosyncratic risk. To address this timing issue, we use alternative measurement windows to measure analyst uncertainty and idiosyncratic risk such that analyst uncertainty precedes idiosyncratic risk in the mediation model. First, we measure analyst uncertainty for the time window between the day following the release of a firm's annual report (i.e., 10-K) at fiscal year *t-1* and the day before its release of a quarterly report for the first quarter of fiscal year *t*. Then, we measure idiosyncratic risk after this period, i.e., the time window between the day following the release of a firm's quarterly report for the first quarter of fiscal year *t* and the day before its release of the annual report for fiscal year *t*. We replace the dependent variables used in the models with these alternative measures for analyst uncertainty and idiosyncratic risk.

As outlined in Table A17.1 we consistently find support for H_1-H_7 and our substantive conclusions are not sensitive to the alternative measurement windows for analyst uncertainty and idiosyncratic risk. However, we note that the mediating effect of analyst uncertainty is stronger in this additional analysis as the main effect of disclosure of advertising spending is marginally significant at $p < .10$ (two-tailed). Further, the moderating effect of competitive intensity is also weakly supported as the interaction of disclosure of advertising spending and competitive intensity is significant only at $p < .10$ (two-tailed) in this analysis (see Table A17.1).

Table A18.1
Alternative Measures of Idiosyncratic Risk and Analyst Uncertainty Accounting for Measurement Timing

	DV = Idiosyncratic Risk$_{i,j,t}$			*DV = Analyst Uncertainty$_{i,j,t}$*			*DV = Idiosyncratic Risk$_{i,j,t}$*			*DV = Analyst Uncertainty$_{i,j,t}$*			
	Coef	*SE*		*Coef*	*SE*		*Coef*	*SE*		*Coef*	*SE*		
$AD_{i,j,t-1}$	-.0024	(.0007)	***	-.0703	(.0086)	****	-.0012	(.0007)	*	-.0703	(.0084)	****	*H_1 (-): Supported* *H_2 (-): Supported*
Analyst Uncertainty$_{i,j,t}$							.0221	(.0012)	****				
Indirect Effect ($\beta_m \times \gamma_1$)							-.0016	(.0002)	****				*H_3 (-): Supported*
$AD_{i,j,t-1}$ × Financial Liquidity$_{i,j,t-1}$										-.0036	(.0013)	***	*H_4 (-): Supported*
$AD_{i,j,t-1}$ × Financial Leverage$_{i,j,t-1}$										.0387	(.0145)	***	*H_5 (+): Supported*
$AD_{i,j,t-1}$ × Disclosure Quality$_{i,j,t-1}$										.0551	(.0191)	***	*H_6 (+): Supported*
$AD_{i,j,t-1}$ × Competitive Intensity$_{j,t-1}$										-.0319	(.0184)	*	*H_7 (-): Weakly Supported*
Financial Liquidity$_{i,j,t-1}$	-.0001	(.0001)		.0021	(.0009)	**	-.0002	(.0001)	**	-.1999	(.0825)	**	
Financial Leverage$_{i,j,t-1}$	.0030	(.0007)	****	.0376	(.0080)	****	.0021	(.0006)	****	.0032	(.0026)		
Disclosure Quality$_{i,j,t-1}$	-.0046	(.0018)	**	-.0153	(.0215)		-.0034	(.0016)	**	-.0020	(.0069)		
Competitive Intensity$_{j,t-1}$	.0020	(.0008)	**	-.0215	(.0124)	*	.0021	(.0007)	***	-.0067	(.0028)	**	
Est. Adv Spending$_{i,j,t-1}$	.0070	(.0064)		-.1980	(.0774)	**	.0094	(.0064)		-.0392	(.0243)		
Analyst Following$_{i,j,t-1}$	-.0003	(.0002)	*	.0029	(.0025)		-.0004	(.0002)	**	.0353	(.0018)	****	
Institutional Ownership$_{i,j,t-1}$	-.0022	(.0005)	****	-.0022	(.0073)		-.0023	(.0005)	****	.0918	(.0105)	****	
Firm Age$_{i,j,t-1}$	-.0022	(.0002)	****	-.0069	(.0027)	**	-.0021	(.0002)	****	-.0691	(.0163)	****	
Firm Size$_{i,j,t-1}$	-.0023	(.0001)	****	.0351	(.0019)	****	-.0030	(.0001)	****	.0572	(.0187)	***	
SG&A$_{i,j,t-1}$	.0031	(.0008)	****	.0914	(.0099)	****	.0019	(.0008)	**	.0175	(.0111)		
ROA$_{i,j,t-1}$	-.0155	(.0014)	****	-.0691	(.0159)	****	-.0138	(.0014)	****	.0039	(.0010)	****	
Cash Flows$_{i,j,t-1}$	-.0085	(.0014)	****	.0591	(.0163)	****	-.0097	(.0015)	****	-.0024	(.0168)		
Industry Growth$_{j,t-1}$	-.0017	(.0005)	***	-.0014	(.0071)		-.0016	(.0005)	***	-.0012	(.0076)		
Demand Uncertainty$_{j,t-1}$	.0082	(.0008)	****	.0532	(.0121)	****	.0067	(.0008)	****	.0514	(.0113)	****	
$PR\_AD_{i,j,t-1}$	.0021	(.0007)	***	.0735	(.0087)	****	.0009	(.0007)		.0747	(.0086)	****	
$\hat{\eta}_{i,j,t-1}$	-.0027	(.0116)		.3262	(.1181)	***	-.0060	(.0113)		.3713	(.1247)	***	
IMR$_{i,j,t-1}$	-.0018	(.0010)	*	.0248	(.0122)	**	-.0025	(.0010)	**	.0260	(.0121)	**	
$\hat{\upsilon}_{i,j,t}$							-.0129	(.0017)	****				
Intercept	.0018	(.0011)		-.0212	(.0133)		.0028	(.0011)	**	-.0231	(.0133)	*	
Wald $\chi2$ (df)	11,535.05 (40) ****			3,070.20 (40) ****			12,855.85 (42) ****			3,166.77 (44) ****			

Notes: a. # of observations (# of firms) = 13,585 (2,090); DV = dependent variable; SE = standard error. For this robustness analysis, we use alternative windows to measure AU and IR. Specifically, we measure AU using the time window between the day following the release of a firm's annual financial report at fiscal year *t-1* and the day before its release of a quarterly report in the first quarter of fiscal year *t*. We measure IR using the time window between the day following the release of a firm's quarterly report in the first quarter of fiscal year *t* and the day before its release of the annual report at fiscal year *t*. b. $AD_{i,j,t-1}$ is disclosure of advertising spending; SG&A$_{i,j,t-1}$ is selling, general, and administrative expense (excluding estimated advertising spending) scaled by total assets; ROA$_{i,j,t-1}$ is return on assets; IMR$_{i,j,t-1}$ is the inverse Mills ratio generated from the probit model to control for sample selection due to the inclusion of estimated advertising spending; *$PR\_AD_{i,j,t-1}$* is the probit residual of $AD_{i,j,t-1}$ for firm *i* in industry *j* in fiscal year *t-1*; $\hat{\eta}_{i,j,t-1}$ and $\hat{\upsilon}_{i,j,t}$ are the control function correction terms for Adv Spending$_{i,j,t-1}$ and Analyst Uncertainty$_{i,j,t}$. c. We use the clustered robust standard errors of estimates at the firm level and use 200 bootstrapping replications to calculate the standard errors. d. We mean center all continuous variables; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed).

Web Appendix A19
Using Stock Return Volatility as a Measure of Investor Uncertainty

In this study, we examine disclosure of advertising spending lowers uncertainty faced by investors about firm future performance that is reflected in idiosyncratic risk. It is well established in academic research on disclosure that disclosure and more transparent financial reporting reduce investor uncertainty (see Billing, Jennings, and Lev 2015, p. 161), and investor uncertainty is a fundamental concern for senior managers, analysts, and regulators (see Huang et al. 2021; Bayer, Tuli, and Skiera 2017; SEC 2017; FASB 2013). Both stock return volatility and idiosyncratic risk are widely used to measure investor uncertainty in the accounting literature (see Barth et al. 2020; Huang et al. 2021). Therefore, we use stock return volatility to test the robustness of the results estimated from models in which the dependent variable is idiosyncratic risk. We consistently find support for all of our hypotheses in which the dependent variable is idiosyncratic risk (i.e., H_1 and H_3).

Variable	*DV = Stock Return Volatility$_{i,j,t}$* Coef	SE	*DV = Stock Return Volatility$_{i,j,t}$* Coef	SE
Analyst Uncertainty$_{i,j,t}$			.0211	(.0010)****
AD$_{i,j,t-1}$	-.0043	(.0007)****	-.0026	(.0007)****
Financial Liquidity$_{i,j,t-1}$	.0000	(.0001)	.0000	(.0001)
Financial Leverage$_{i,j,t-1}$	.0024	(.0006)****	.0017	(.0006)***
Disclosure Quality$_{i,j,t-1}$	-.0054	(.0018)***	-.0037	(.0019)*
Competitive Intensity$_{j,t-1}$	.0021	(.0009)**	.0025	(.0007)***
Est. Adv Spending$_{i,j,t-1}$	-.0053	(.0066)	-.0024	(.0061)
Analyst Following$_{i,j,t-1}$	-.0004	(.0002)**	-.0002	(.0002)
Institutional Ownership$_{i,j,t-1}$	-.0015	(.0005)***	-.0021	(.0005)****
Firm Age$_{i,j,t-1}$	-.0026	(.0002)****	-.0024	(.0002)****
Firm Size$_{i,j,t-1}$	-.0023	(.0001)****	-.0031	(.0001)****
SG&A$_{i,j,t-1}$	.0026	(.0009)***	.0011	(.0008)
ROA$_{i,j,t-1}$	-.0190	(.0014)****	-.0183	(.0014)****
Cash Flows$_{i,j,t-1}$	-.0087	(.0015)****	-.0088	(.0014)****
Industry Growth$_{j,t-1}$	-.0016	(.0006)***	-.0015	(.0006)***
Demand Uncertainty$_{j,t-1}$	.0114	(.0010)****	.0105	(.0009)****
PR_AD$_{i,j,t-1}$	.0039	(.0007)****	.0023	(.0007)***
$\hat{\eta}_{I,j,t-1}$	-.0005	(.0122)	-.0060	(.0111)
IMR$_{i,j,t-1}$	-.0038	(.0010)****	-.0038	(.0010)****
$\hat{\upsilon}_{i,j,t}$			-.0065	(.0013)****
Intercept	.0024	(.0012)**	.0029	(.0011)***
# of observations (# of firms)	15,297 (2,285)		15,297 (2,285)	
Wald $\chi 2$ (df)	14,337.51 (40)		17,423.64 (42)	

Notes: a. DV = dependent variable; SE = standard error. Stock Return Volatility is the standard deviation of stock returns and we measure Stock Return Volatility$_{i,j,t}$ following the release of a firm's annual report at fiscal year *t-1* and before its release of the annual report at fiscal year *t*. b. AD$_{i,j,t-1}$ is disclosure of advertising spending; SG&A$_{i,j,t-1}$ is selling, general, and administrative expense (excluding estimated advertising spending) scaled by total assets; ROA$_{i,j,t-1}$ is return on assets; IMR$_{i,j,t-1}$ is the inverse Mills ratio to control for sample selection due to the inclusion of estimated advertising spending; *PR_AD$_{i,j,t-1}$* is the probit residual of AD$_{i,j,t-1}$ for firm *i* in industry *j* in fiscal year *t-1*; $\hat{\eta}_{i,j,t-1}$ and $\hat{\upsilon}_{i,j,t}$ are the control function correction terms for Adv Spending$_{i,j,t-1}$ and Analyst Uncertainty$_{i,j,t}$. c. We use the clustered robust standard errors of estimates at the firm level and use 200 bootstrapping replications to calculate the standard errors. d. We mean center all continuous variables; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed); e. All models include year fixed effects and are significant at $p < .001$.

Web Appendix A20

Estimating the Nuanced Effects of Disclosure of Advertising Spending for 7 Major Sectors

To provide the nuanced implications of disclosure of advertising spending, we classify firms into more aggregated industry groups. Specifically, we construct the following 7 major sectors: Manufacturing, High Tech, Consumer Services, Business Services, Healthcare, Information, and Others (see Table A19.1 for the details). Then, to account for sector-specific nuanced effects, we include the major sector dummies and interact them with $AD_{i,j,t-1}$ (i.e., disclosure of advertising spending) in the main effects models. Specifically, the following model is used to estimate the nuanced effects of disclosure of advertising spending for each major sector:

$$\begin{aligned} DV_{i,j,t} = {} & \beta_0 + \beta_1 AD_{i,j,t-1} \\ & + \beta_2 AD_{i,j,t-1} \times \text{Hi Tech}_g + \beta_3 AD_{i,j,t-1} \times \text{Consumer Services}_g + \beta_4 AD_{i,j,t-1} \times \text{Business Services}_g \\ & + \beta_5 AD_{i,j,t-1} \times \text{Healthcare}_g + \beta_6 AD_{i,j,t-1} \times \text{Information}_g + \beta_7 AD_{i,j,t-1} \times \text{Others}_g \\ & + \beta_8 \text{Hi Tech}_g + \beta_9 \text{Consumer Services}_g + \beta_{10} \text{Business Services}_g + \beta_{11} \text{Healthcare}_j + \beta_{12} \text{Information}_g + \beta_{13} \text{Others}_g \\ & + \Delta' \text{Controls}_{i,j,t-1} + \textstyle\sum_{k=1}^{K-1} \theta_k \text{Year}_t \\ & + \beta_a \mathbf{PR\_AD_{i,j,t-1}} + \beta_b \hat{\boldsymbol{\eta}}_{\mathbf{i,j,t-1}} + \beta_c \mathbf{IMR_{i,j,t-1}} + \mu_i + \varepsilon_{i,j,t}, \end{aligned}$$

where, $DV_{i,j,t}$ = Idiosyncratic $risk_{i,j,t}$, Analyst $Uncertainty_{i,j,t}$, Tobin's $q_{i,j,t}$, or Log of Market $Capitalization_{i,j,t}$,

Hi $Tech_g$ = high tech sector dummy, Consumer $Services_g$ = consumer service sector dummy,

Business $Services_g$ = business service sector dummy, $Healthcare_g$ = pharmaceutical and healthcare sector dummy,

$Information_g$ = information sector dummy, $Others_g$ = other sector dummy,

$\mathbf{PR\_AD_{i,j,t-1}}$ = the probit residual of disclosure of advertising spending,

$\hat{\boldsymbol{\eta}}_{\mathbf{I,j,t-1}}$ = the control function correction term for advertising spending,

$\mathbf{IMR_{i,j,t-1}}$ = the inverse Mills ratio to control for the sample selection due to the inclusion of estimated advertising spending.

We use $Manufacturing_g$ as a baseline whose effect is captured by β_1 in the specified model above. The models are estimated using the procedures outlined in the methods section to estimate the impact of disclosure of advertising spending on idiosyncratic risk and analyst uncertainty. Table A19.1 outlines the construction of 7 major sectors, and Table A19.2-A19.3 outline the results of the models used to estimate marginal effects of disclosure of advertising spending on idiosyncratic risk, analyst uncertainty, Tobin's q, and log of market capitalization for each major sector (see Table 5 in the main manuscript).

Table A20.1 Construction of 7 Major Sectors

Major Sector	Construction
Manufacturing	Manufacturing (NAICS2 31-33) except High Tech and Healthcare firms.
High Tech	Computer and Peripheral Equipment Manufacturing (NAICS4 3341) Communications Equipment Manufacturing (NAICS4 3342) Semiconductor and Other Electronic Component Manufacturing (NAICS4 3344) Navigational, Measuring, Electromedical, and Control Instruments Manufacturing (NAICS4 3345) Aerospace Product and Parts Manufacturing (NAICS4 3364) Software Publishers (NAICS4 5112) Other Telecommunications (NAICS4 5179) Internet Service Providers and Web Search Portals (NAICS4 5181) Data Processing, Hosting, and Related Services (NAICS4 5182) Architectural, Engineering, and Related Services (NAICS4 5413) Computer Systems Design and Related Services (NAICS4 5415) Scientific Research and Development Services (NAICS4 5417)
Consumer Services	Retail Trade (NAICS2 42 & 45) Leisure and Hospitality (NAICS2 71 & 72) Personal and Laundry Services (NAICS3 811).
Business Services	Wholesale Trade (NAICS2 42) Professional and Business Services (NAICS2 54-56).
Healthcare	Pharmaceutical and Medicine Manufacturing (NAICS4 3254) Medical Equipment and Supplies Manufacturing (NAICS4 3391) Ambulatory Health Care Services (NAICS 621) Hospitals (NAICS 622) Nursing and Residential Care Facilities (NAICS 623)
Information	Information (NAICS2 51) except High Tech
Others	Mining, Quarrying, and Oil and Gas Extraction (NAICS22 21) Construction (NAICS2 23) Transportation and Warehousing (NAICS2 48-49) Real Estate and Rental and Leasing (NAICS2 53) Educational Services (NAICS 61).

Note: Decker et al. (2020) include NAICS4 3254 and 5161 to classify High Tech firms. We do not observe firms in NAICS4 5161 in our sample and define NAICS4 3254 as Healthcare.

Table A20.2
The Nuanced Effects of Disclosure of Advertising Spending on Idiosyncratic Risk and Analyst Uncertainty for Major Sectors

DV = Idiosyncratic Risk$_{i,j,t}$ *Variable*	*Major Sector Fixed Effects* *Coef*	 *SE*	*Interactions with Major Sector Fixed Effects* *Coef*	 *SE*
$AD_{i,j,t-1}$	-.0036	(.0008)****	-.0018	(.0008)**
$AD_{i,j,t-1}$ × Hi Tech$_g$			-.0038	(.0005)****
$AD_{i,j,t-1}$ × Consumer Services$_g$			.0001	(.0007)
$AD_{i,j,t-1}$ × Business Services$_g$			-.0042	(.0008)****
$AD_{i,j,t-1}$ × Healthcare$_g$			-.0012	(.0009)
$AD_{i,j,t-1}$ × Information$_g$			-.0013	(.0008)
$AD_{i,j,t-1}$ × Others$_g$			-.0013	(.0019)
Industry Fixed Effects	Yes		Yes	
Year Fixed Effects	Yes		Yes	
Wald $\chi 2$ (df)	12,487.37 (46)****		12,948.92 (52)****	
DV = Analyst Uncertainty$_{i,j,t}$ *Variable*	*Major Sector Fixed Effects* *Coef*	 *SE*	*Interactions with Major Sector Fixed Effects* *Coef*	 *SE*
$AD_{i,j,t-1}$	-.0997	(.0144)****	-.1007	(.0161)****
$AD_{i,j,t-1}$ × Hi Tech$_g$			.0011	(.0087)
$AD_{i,j,t-1}$ × Consumer Services$_g$			.0180	(.0105)*
$AD_{i,j,t-1}$ × Business Services$_g$			-.0382	(.0112)***
$AD_{i,j,t-1}$ × Healthcare$_g$			.0243	(.0152)
$AD_{i,j,t-1}$ × Information$_g$			-.0033	(.0149)
$AD_{i,j,t-1}$ × Others$_g$			-.0134	(.0227)
Industry Fixed Effects	Yes		Yes	
Year Fixed Effects	Yes		Yes	
Wald $\chi 2$ (df)	3,476.09 (46)****		3,654.57 (52)****	

Notes:
a. # of observations (# of firms) = 15,297 (2,285); DV = dependent variable; SE = standard error.
b. $AD_{i,j,t-1}$ is disclosure of advertising spending for firm *i* in industry *j* in fiscal year *t-1*. To account for unobservable industry-related effects, we use fixed effects for the 7 major sectors.
c. We use the clustered robust standard errors of estimates at the firm level and use 200 bootstrapping replications to calculate the standard errors.
d. We mean center all continuous variables; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed).

Table A20.3
The Nuanced Effects of Disclosure of Advertising Spending on Tobin's q and Log of Market Capitalization for Major Sectors

DV = Tobin's $q_{i,j,t}$ Variable	*Major Sector Fixed Effects* Coef	SE	*Interactions with Major Sector Fixed Effects* Coef	SE
$AD_{i,j,t-1}$	.2674	(.0984)***	.4502	(.1051)****
$AD_{i,j,t-1}$ × Hi $Tech_g$			-.2336	(.0688)****
$AD_{i,j,t-1}$ × Consumer $Services_g$			-.2767	(.0805)****
$AD_{i,j,t-1}$ × Business $Services_g$			.0211	(.1063)
$AD_{i,j,t-1}$ × $Healthcare_g$			-.1397	(.1749)
$AD_{i,j,t-1}$ × $Information_g$			-.3640	(.1230)***
$AD_{i,j,t-1}$ × $Others_g$			-.4720	(.1238)****
Industry Fixed Effects	Yes		Yes	
Year Fixed Effects	Yes		Yes	
Wald χ2 (df)	4,147.78 (46)****		4,395.45 (52)****	

DV = Log of Market $Capitalization_{i,j,t}$ Variable	*Major Sector Fixed Effects* Coef	SE	*Interactions with Major Sector Fixed Effects* Coef	SE
$AD_{i,j,t-1}$	.1490	(.0663)**	.2591	(.0739)****
$AD_{i,j,t-1}$ × Hi $Tech_g$			-.1382	(.0408)***
$AD_{i,j,t-1}$ × Consumer $Services_g$			-.2214	(.0580)****
$AD_{i,j,t-1}$ × Business $Services_g$			-.0016	(.0613)
$AD_{i,j,t-1}$ × $Healthcare_g$			-.0513	(.0701)
$AD_{i,j,t-1}$ × $Information_g$			-.1142	(.0697)
$AD_{i,j,t-1}$ × $Others_g$			-.4121	(.1145)****
Industry Fixed Effects	Yes		Yes	
Year Fixed Effects	Yes		Yes	
Wald χ2 (df)	35,036.94 (46)****		30,033.61 (52)****	

Notes:
a. # of observations (# of firms) = 15,292 (2,282); DV = dependent variable; SE = standard error.
b. $AD_{i,j,t-1}$ is disclosure of advertising spending for firm *i* in industry *j* in fiscal year *t-1*. To account for unobservable industry-related effects, we use fixed effects for the 7 major sectors.
c. We use the clustered robust standard errors of estimates at the firm level and use 200 bootstrapping replications to calculate the standard errors.
d. We mean center all continuous variables; * $p < .10$, ** $p < .05$, *** $p < .01$, **** $p < .001$ (two-tailed).

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