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Organizational Herding in Advertising Spending Disclosures: Evidence and Mechanisms

Huanhuan Shi, Rajdeep Grewal, and Hari Sridhar

Abstract

As firms use advertising to gain product market advantages and increase their valuation in financial markets, disclosing their advertising spending is influential—whether it erodes organizational competitive advantages in product markets or signals quality in financial markets. The authors argue that firms learn from peers' decisions to reduce the uncertainty in their own advertising disclosure, and they empirically investigate information-based organizational herding in the context of advertising spending disclosure, where a 1994 reporting rule made advertising spending disclosures voluntary in the United States. The authors examine whether a firm relies on information from benchmark leaders or similar peers to resolve disclosure uncertainty. A novel identification strategy, which uses partially overlapping strategic groups to mitigate simultaneity and correlated unobservables, shows robust evidence for herding effects among peer firms in the same strategic group. Moreover, firms are more likely to resolve disclosure uncertainty from similar peers rather than from benchmark leaders. The authors discuss how firms can use knowledge of competitors' predicted advertising disclosure decisions conditional on their disclosure to their strategic advantage in product and financial markets.

Keywords

advertising spending, financial markets, herding, product markets, voluntary disclosure

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A recent story in *Business Insider* reports Apple's decision to stop disclosing how much it spends on advertising (O'Reilly 2016). In the article, an analyst from Wells Fargo considers Apple's decision disappointing, as information on advertising spends is useful from an analyst's perspective (especially because Apple's advertising expenses had risen by 50% during the previous year). However, the article goes on to say that the motivation behind Apple's decision might be a desire to not want to "share that kind of data with competitors." Clearly, disclosing advertising spending amounts is a strategic organizational decision with ramifications for both financial-market (information is useful for analysts) and product-market (fear of sharing data with competitors) perspectives.

So should firms disclose[1] the amount they spend on advertising? The U.S. Securities and Exchange Commission (SEC) Financial Reporting Release 44 (FRR44) in 1994 transformed the previously mandatory disclosure of advertising spending to a voluntary one.[2] As we show in Figure 1, before 1994, 32.81%–40.61% firms reported advertising expenses on an annual basis; that proportion dropped to 15.84% in the 1994 fiscal year, followed by another slight drop (of .79%) in the 1995 fiscal year. The percentage of firms reporting advertising expenses subsequently increased from 1996 to 2006, reaching 38.61% in 2006. This upward trend indicates a correlation

[1] "Disclosure" refers to the organizational decision to reveal the annual amount spent on advertising in annual reports.

[2] In a voluntary disclosure regime, firms choose whether to disclose their advertising spending. Prior to 1994 (mandatory disclosure regime), firms did not have this choice, which imposed higher regulatory costs on policy makers. If herding causes firms to disclose their advertising spending voluntarily, public policy makers can avoid the regulatory costs associated with monitoring compliance with mandatory disclosure rules.

Huanhuan Shi is Assistant Professor of Marketing, Mays Business School, Texas A&M University, USA (email: hshi@mays.tamu.edu). Rajdeep Grewal is Townsend Family Distinguished Professor of Marketing, Kenan-Flagler Business School, University of North Carolina at Chapel Hill, USA (email: grewalr@unc.edu). Shrihari Sridhar is Joe Foster '56 Chair in Business Leadership and Professor of Marketing, Mays Business School, Texas A&M University, USA (email: ssridhar@mays.tamu.edu).

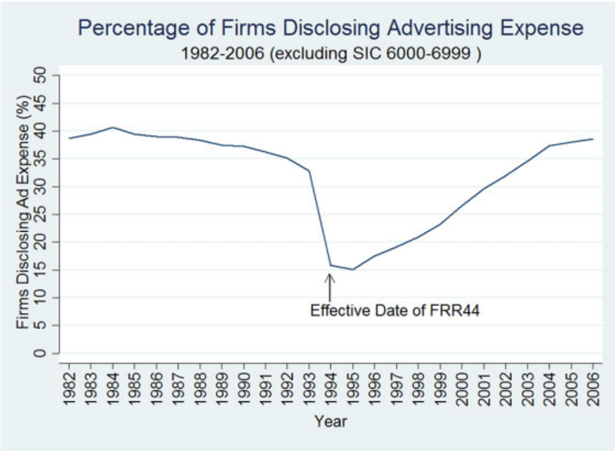

Figure 1. Percentage of firms disclosing advertising spending.
Notes: FRR44 became effective on December 13, 1994. Before 1994, 32.81%–40.61% of firms reported their advertising expenses. The proportion dropped to 15.84% for fiscal year 1994, followed by a slight drop (.79%) in fiscal year 1995 and then a notable increase. Before 1994, firms may not have disclosed advertising spending if their advertising spending was below the threshold of materiality. That is, a decision not to disclose certain information may reflect that the amounts involved are too small to make a difference (they are not material). Firms develop their own model of the judgement of materiality by taking into account many variables (see pp. 7, 56–57 of Statement of Financial Accounting Concepts No. 2 issued by FASB, accessible at https://www.fasb.org/pdf/con2.pdf).

among firms' reporting behaviors toward disclosure. As we discuss subsequently, it is important from both a managerial and policy perspective to understand the relationship between firms' reporting behaviors. Thus, we consider two key questions: (1) Is the observed relationship among firms' advertising disclosure decisions caused by herding triggered by the uncertainty of disclosure outcome, or is it a result of common factors that influence all firms (e.g., disclosure environment, industry-wide shocks)? (2) What information sources do firms rely on to resolve the uncertainty in their disclosure decisions?

Understanding these two research questions is important from product-market, financial-market, and public policy perspectives. From a product-market perspective, advertising spending is critical for gaining a competitive advantage (Bagwell 2007) and building market-based assets (Srivastava, Shervani, and Fahey 1998), but disclosing advertising spending might erode organizational ability to build and sustain a competitive edge, by revealing organizational "secrets."[3] From a financial-market perspective, advertising spending disclosures enable investors to compare and evaluate competing firms, using spending amount as a quality signal (Simpson 2008). Finally, from a public policy perspective, regulators aim to promote fair competition and help investors make informed decisions such that they confront a trade-off in the costs and benefits of requiring marketing information disclosures. Considering product-market and financial-market trade-offs, organizational advertising spending disclosure decisions are complex, which may prompt competing firms to examine each other's (past) decisions as information for making their own decisions, suggesting a possible herding explanation for the data patterns in Figure 1.

Quantifying causal herding effects in organizational contexts is notoriously difficult though, due to the presence of simultaneity and unobserved correlated factors (Manski 1993). To address this methodological problem we apply a novel identification strategy originating from social network literature (Bramoullé, Djebbari, and Fortin 2009; De Giorgi, Pellizzari, and Redaelli 2010), which takes advantage of partially overlapping groups of peers.[4,5] That is, firms belong to multiple strategic groups and compete with different sets of peer firms in each group (DeSarbo and Grewal 2008), deviating from the majority of organizational research, which forms peer groups on the basis of a single strategic group (e.g., a firm's primary industry [Kedia, Koh, and Rajgopal 2015] or geographic region [Miller and Tucker 2009]). Partially overlapping peer groups feature firm-specific peer groups and second-degree linked peers, which help resolve key identification issues in our research setting.

To explain herding, we use an information cascading lens to study the temporal process of firms' disclosure decisions. Disclosure decisions around discretionary advertising spending represent a quintessential setting for information-based herding for three interrelated reasons (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992). First, the product- and financial-market consequences of disclosing advertising spending are uncertain. In product markets, firms cannot accurately predict whether their advertising disclosure is likely to deter competitors from advertising, spur competitors to increase advertising, or incentivize competitors to free ride. In financial markets, investors may have different interpretations of a firm's nondisclosure (e.g., hiding negative information, concealing proprietary information). Even when a firm discloses advertising spending, investors' response to the favorableness of this disclosure depends on many factors external to the firm and thus is difficult to predict. Because of these complications, there is substantial uncertainty concerning the net effect of advertising spending disclosure. This uncertainty should

[3] Firms have the discretion of revealing advertising spending as a separate item or just masking the amount in selling, general and administrative (SG&A) expenses.

[4] We use "peers" and "competitors" interchangeably because peers are defined as firms that compete with a focal firm in at least one industry.

[5] Groups are partially overlapping if the sets of peers of two peer firms do not perfectly coincide. For example, Apple operated in three Standard Industrial Classification (SIC) industries 3571, 3661, and 5734; Dell operated in 3571 and 3577 in the data period. Apple and Dell are peers because both competed in 3571. Part of the two firms' peers are overlapping (e.g., Fujitsu, which has business in 3571). Each of the two firms also has its own peers that are different from each other. For example, Best Buy is in Apple's peer group but not in Dell's because Best Buy operated in 5734 but not in any of Dell's sectors (3571, 3577); similarly, NetWolves is in Dell's peer group but not in Apple's because NetWolves operated in 3577 but not in any of Apple's sectors (3571, 3661, and 5734). More details are in Figure 2.

motivate a firm to turn to its peers to learn their practices, as these peers likely face similar challenges. Second, conditional on disclosure, peers are likely to reveal the correct amount they spent on advertising (to avoid potential litigation costs; e.g., Lennox and Li 2014) so that a firm can rely on them as a credible information source. Third, given the uncertainty in disclosure outcome and the presence of a new credible information source, we reason that a rational firm will update its prior belief by leveraging new information specifically from benchmark leaders or peers in similar market positions to resolve its decision uncertainty.

Our results indicate a robust herding effect; if peer disclosure increases by 10%, a firm's disclosure probability increases by 4.8%–8.9%. Our finding provides evidence that the upward trend of disclosures (as shown in Figure 1) after the removal of the mandatory disclosure regulation were at least partially due to peer effects. To study how firms resolve the decision uncertainty (e.g., learn from benchmark leaders or similar peers), we estimate the relative strengths of the influences from four subgroups, based on firms' key characteristics (i.e., size, profitability, and market value): high-influence subgroup, similar-peer subgroup, low-influence subgroup, and dissimilar-peer subgroup. We find evidence for a dominant influence from size-based similar peers, indicating that firms believe that similar-sized peers, rather than benchmark leaders, provide information to resolve uncertainty concerning advertising spending disclosure. Our analysis of the relative importance of their similarity in business scope and financial standing further shows that peer groups with high financial standing similarity have relatively stronger influences on a firm's disclosure decision than do peer groups with low financial standing similarity. In contrast, the business scope similarity of peers does not seem to influence the advertising spending disclosure decision.

Our work departs from prior research in organizational herding and the literature on marketing information disclosure in several key respects. First, although others have applied information cascading theories to understand the adoption of new organizational practices (e.g., Angst et al. 2010; Gaba and Meyer 2008), ours is one of the first studies to examine temporal aspects of the contagion process in firms' strategic information disclosure decisions. In this context, a firm needs to decide on the disclosure of its own private information, which has multifaceted implications for product-market competitors and financial-market investors. Second, although prior research has examined the voluntary disclosure of marketing strategic information (e.g., Ellis, Fee, and Thomas 2012; Simpson 2008), it has not considered whether peers' disclosure decisions affect a firm's own decision, limiting its ability to understand the dynamics of disclosure decisions. Third, from a methodological perspective, we quantify causal herding effects in organizational behaviors using a novel identification strategy of partially overlapping peers. Constructing partially overlapping peer groups not only represents the marketplace reality that firms belong to multiple strategic groups and compete with different sets of peer firms in each group but also addresses challenges related to simultaneity and correlated unobservables that may bias the estimation of herding effect.

In terms of implications for firms, we find that a firm can strategically use advertising disclosure to shape the marketing information environment dynamically. For example, if a firm is similar in size and financial standing to its competitor, the firm can infer the likelihood that the competitor will disclose advertising spending conditional on its own advertising disclosure. Firms can use knowledge of competitors' predicted advertising disclosure decisions (conditional on their disclosure) to their strategic advantage in product markets and financial markets. In product markets, firms know that revealing proprietary advertising information creates an information advantage for competitors. When only a few competitors disclose advertising spends, a nondisclosing firm may seek more advertising information and can pressure disclosure from nondisclosing competitors by disclosing its own advertising information. For a nondisclosing firm, the existence of herding effects makes it possible to estimate whether the cost of revealing one's own information offsets the gains from increased disclosure from nondisclosing competitors. In financial markets, investors and analysts infer the value implication of a firm's disclosure decision by benchmarking against competing firms' decisions. With the existence of herding effects, a firm would expect that its own disclosure decision is part of the influence that shapes the peer group's disclosure level, which in turn changes analysts' responses toward the competing firms. Thus, a firm can shape analysts' responses to its future disclosure decisions by shaping the competing peer group's disclosure level.

Our findings have implications for the SEC because herding-induced voluntary disclosure affects the costs incurred to mandate disclosure regulations and rules. The total enforcement cost for all disclosure regulations and security laws amounts to $994.8 million (69% of the SEC's annual spending in 2014), prompting this agency to seek ways to increase efficiencies and minimize regulatory costs while still meeting its compliance targets. The evidence of herding that we provide herein suggests that the SEC could leverage herding momentum to reduce the regulatory costs associated with mandatory disclosure requirements without comprising disclosure quality. The SEC could further improve disclosure regulation efficiencies by leveraging industry heterogeneity in herding effects and focusing mandatory disclosure regulations on industries with little herding effects.

Finally, our research relates directly to the goals of the Marketing Accountability Standards Board (MASB), namely, to encourage or require public firms to disclose critical marketing metrics, which in turn empowers chief marketing officers and enhances firms' marketing effectiveness and efficiency. Our findings related to herding and the underlying uncertainty resolution mechanism suggest that MASB could rely on voluntary disclosures and take advantage of herding momentum to increase the transparency of marketing metrics.

For the remainder of this article, we first discuss relevant literature to ground our research. Then, we describe the institutional setting and data, model setup, and identification strategies. After we outline our methods, we present the results and discuss their implications.

Literature Review

Information-Based Herding: Relevant Background

Herding occurs among a group of economic agents when an individual agent's utility of adopting a practice increases with the proportion of others who adopt that practice (for reviews, see Chamley [2004], Hirshleifer and Teoh [2003], and Lieberman and Asaba [2006]). When others' adoption adds direct economic or social payoff to the agent's utility, the manifest herding is denoted as a network externality (e.g., a telephone adopter's utility increases as the number of other adopters grow), or social conformity (e.g., a student drinks alcohol to gain social acceptance among friends who do so). When others' adoption does not add direct economic payoff but reduces the level of uncertainty in the decision outcome, the manifest herding represents information-based herding (e.g., newcomers to a town choose the restaurant with more local consumers).[6]

In the context of voluntary advertising spending disclosure, it is unlikely that the disclosure of advertising spending by peers directly increases a firm's utility of advertising disclosure. Instead, we focus on understanding whether a firm appears to benefit from peers' advertising disclosure decisions by lowering its own disclosure uncertainty. Thus, we focus on information-based herding in the context of advertising spending disclosure.

Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992) laid a theoretical foundation for an information-based herding, suggesting that agents reduce their decision uncertainty by incorporating information from other agents' decisions in a Bayesian updating manner. This stream of theoretical work provides three conditions under which information-based herding is likely to happen.

- **Motivation condition:** This condition implies that uncertainty associated with a decision outcome motivates an agent to seek new information. As suggested by Berger and Calabrese (1975, p. 103), "High levels of uncertainty cause increases in information seeking behavior. As uncertainty levels decline, information seeking behavior decreases." In essence, if an agent has relatively precise private information about the outcome of a decision (e.g., .95 probability that restaurant A is better than restaurant B), they are less motivated to gather information from peers than when they have uncertain private information (e.g., .51 probability that restaurant A is better than restaurant B).
- **Opportunity condition:** This condition implies that peers' observable decisions truthfully reveal their preference; thus, these decisions serve as a credible source of information. The underlying assumption is that an agent believes that peers have no incentive to make an out-of-equilibrium ("incorrect") move to try to influence peers (Bikhchandani, Hirshleifer, and Welch 1992). In the example of restaurant choice, a newcomer to the town believes that locals patronize a restaurant because of its quality, as opposed to locals patronizing the restaurant to mislead the newcomer.
- **Ability condition:** The final condition implies that agents are able to update their beliefs/knowledge on the basis of the information contained in peers' decisions. When the information inferred from peers' decisions dominates private signals, agents place lower emphasis on their private signals and greater emphasis on peers' behaviors (Bikhchandani, Hirshleifer, and Welch 1992). In the restaurant example, newcomers would update their beliefs about restaurants based on patronage of locals.

Empirical Examples of Information-Based Herding

Extant literature documents several instances of information-based herding in individual agents' decisions. Bollinger and Gillingham (2012) documented information-based herding by showing how neighbors influence individual adoption of solar photovoltaic panels. Information-based herding manifests for Bollinger and Gillingham (2012) because of the (1) motivation condition—uncertainty associated with new solar technology is a substantial barrier for risk-averse potential consumers to adopt the technology; thus, potential consumers are motivated to gather information; (2) opportunity condition—neighbors' adoption credibly reveals their belief that installation increases their utility by reducing energy bills and/or carbon footprint; and (3) ability condition—rational potential consumers are able to update their beliefs/knowledge about solar panels based on the information inferred from neighbors' adoption. Other such examples of information-based herding have been shown in the context of physicians' new drug prescriptions (Nair, Manchanda, and Bhatia 2010) and loan decisions (Zhang and Liu 2012).

Relatively sparse causal evidence exists on information-based herding for organizational decisions, the context of our research. Angst et al. (2010) revealed herding effect in hospitals' information technology innovation adoption, caused by (1) uncertainty associated with the value of the decision, (2) peers investing significant amount of financial and human resources to implement new information technology systems and thereby truthfully revealing their perceived payoff, and (3)

[6] We might observe instances of more than one source of benefit in the same adoption scenario (Iyengar, Van den Bulte, and Choi 2012). For example, information-based herding occurs when an agent adopts a video game console after their friend tells them how the console works. Network externality occurs when an agent adopts the game console because they enjoy playing together with their friends; more friends playing increases enjoyment. Social conformity occurs when an agent adopts a game console because they want to fit in their social circle in which most of their peers own a console. In the latter two cases, the agent is sure about the utility-increasing outcome of the adoption as the number of peers that adopt the product increases. In the information-based herding, the agent's utility is not directly contingent on the numbers previously adopted; rather, the information provided by peers reduces decision uncertainty.

the possibility of direct contact among peers enabling information flow.[7]

The majority of the evidence on information-based herding focuses on the adoption of new technologies or new practices by either individuals or organizations. Research on herding effects for repeated strategic organizational decisions, such as strategic information disclosure concerning disclosure of private information, is nonexistent. From a theoretical perspective, strategic information disclosure has multifaceted implications for both peers and nonpeer outsiders such as competitors and investors; thus, these differences warrant a theoretical discussion concerning the validity of the information-based herding conditions in the context of advertising disclosure.

Voluntary Disclosure of Advertising Spending

Publicly traded firms collapse advertising spending into SG&A expenses. They have the discretion of revealing advertising spending as a piece of information supplemental to SG&A expenses (disclosure of SG&A expenses is mandatory) or not revealing advertising spending, according to the voluntary disclosure regulation FRR44 (details in the subsequent section). Revealing advertising spending as a separate item sends a clear signal about how much a firm has spent on advertising. In contrast, if a firm does not disclose advertising spending, information users are uncertain whether the firm spends a minimal/trivial amount on advertising that is not worth disclosing or whether the firm spends significantly but is withholding information for strategic reasons.

Voluntary disclosure literature in the field of accounting documents empirical evidence concerning firms' motives for strategically disclosing marketing-related information to achieve product-market and financial-market goals.[8] Pertinent to advertising spending voluntary disclosure, Simpson (2008) proposed that firms face a trade-off between the costs of aiding competitors by revealing proprietary advertising spending information (proprietary cost motive) and the benefits of reducing information asymmetry with financial market participants (valuation benefit motive). However, Simpson (2008) did not consider the temporal changes in these motives and assumed temporally fixed costs and benefits of disclosures for firms. Simpson's perspective cannot explain the observed changes in aggregate disclosure level shown in Figure 1. Accordingly, we explore the plausibility of uncertainty-induced herding. We argue that firms are uncertain about the consequence of disclosure and seek information from peers. Thus, we build the case for information-based herding in voluntary advertising disclosure.

Plausibility of Information-Based Herding in Advertising Spending Disclosure

We organize the arguments for information-based herding in voluntary advertising disclosure alongside the three main conditions for information-based herding (i.e., motivation, opportunity, and ability conditions). We focus on each of these in the following subsections.

Motivation condition: payoffs from voluntary disclosure of advertising are uncertain

Uncertainty of disclosure consequence in product markets. Advertising spending information of a firm could possibly be valuable for competitors to decide their own advertising budgets to gain a competitive edge (e.g., Vardanyan and Tremblay 2006). By revealing private information, the firm incurs proprietary cost due to potential loss of competitive edge. There are at least three sources for the uncertainty in evaluating how competitors may use disclosed information.

First, the cross-firm advertising spillover effect (or how competitors change advertising in response to knowledge about a focal firm's advertising spending) is complicated and hard to predict without extensive market knowledge. Research on these spillovers in marketing and economics has theorized and documented different possibilities (Bagwell 2007). For example, Vardanyan and Tremblay (2006) find the existence of both negative and positive advertising spillovers for different beer brands, Shapiro (2018) documents positive advertising spillover in drug advertising, and Sahni (2016) relies on a field experiment to document positive advertising spillover on competitors' sales for online restaurant orders. Second, firms typically have incomplete knowledge of their competitors' advertising budgeting approach (e.g., Blasko and Patti 1984; Corfman and Lehmann 1994), which contributes to the uncertainty in evaluating the proprietary cost of disclosure. Third, information about advertising spending serves as a barrier for potential entrants (Bagwell and Ramey 1990). The magnitude of the deterrence of advertising spending information adds uncertainty to the payoff of voluntary advertising disclosure.

In summary, there is substantial uncertainty in evaluating the value of disclosing advertising spending to competitors because of the myriad ways in which this spending information could be of value to competitors. Thus, it is evident that the product-market consequences of advertising spending are unclear.

Uncertainty of disclosure consequence in financial markets. Advertising spending information is useful for investors in

[7] Correlational evidence suggests that similar information-based mechanisms are relevant in other strategic organizational decision contexts, such as production capability expansions (Gilbert and Lieberman 1987), acquisitions (Haunschild 1993), and international expansions (Gimeno et al. 2005).

[8] Firms tend to (1) hide information that reveals their competitive secrets, known as proprietary cost motive (e.g., firms withhold information about big customers; Ellis, Fee, and Thomas 2012) or highly profitable segments (Berger and Hann 2007); (2) withhold information that may reveal unresolved agency problems and induce greater external monitoring, often referred to as agent cost motive (e.g., firms withhold information of low-profit segments; Berger and Hann 2007); and (3) reveal information that could potentially reduce information asymmetry between firms and investors, called financial-market valuation motive (e.g., firms disclose segment-level information to lower their capital cost; Botosan and Harris 2000).

their efforts to value a firm (e.g., Joshi and Hanssens 2010). Yet how investors respond to nondisclosed or disclosed advertising amounts remains uncertain for at least two reasons.

First, uncertainty concerning investor reactions to nondisclosure of advertising spending information emanates from firms' lack of knowledge concerning investor reactions to this nondisclosure. Investors are likely to view the nondisclosure decision of a firm relative to the disclosure decision of the firm's peers. If peers disclose advertising spending, it indicates that a nondisclosing firm is likely to possess valuable information (e.g., spends a substantial amount on advertising) but has decided not to disclose it (Dye and Sridhar 1995). If investors think that this nondisclosure decision is due to the intention of hiding negative information (e.g., poor advertising efficiency), the investors would devalue the firm. In contrast, if investors believe that the nondisclosure is due to a firm's intention of keeping proprietary information private to prevent competitive gains, investors should reward the firm. Second, uncertainty stems from investors' interpretation of the disclosed amount of advertising spending. Extant marketing literature shows that the valence of the stock market reaction to changes in advertising spending depends on many complex factors such as firm's market share, financial leverage, and product-market profile (e.g., Srinivasan, Lilien, and Sridhar 2011). In summary, in recognizing uncertainty concerning investor reactions to disclosure and nondisclosure of advertising spending information, we find that the benefits from this disclosure decision are unclear.

Opportunity condition: peers' advertising disclosures are credible. For information-based herding to occur, an agent must believe that peers' disclosures truthfully reveal their preferences and therefore are a credible source of information for the agent to update prior beliefs. Firms that disclose advertising spending are legally bound to reveal their spending truthfully. A public firm is likely to face penalties and litigations if it attempts to mitigate negative payoffs by misreporting advertising spending (Lennox and Li 2014). The SEC may bring charges against public firms for various types of reporting errors. For example, in 2016,[9] the retailer Cabela's wrongly treated promotion fees and settled the litigation by paying $1 million penalty; Phoenix Companies, an insurance holding company, paid $.6 million penalty for dozens of accounting errors in valuating products; and PowerSecure, a utility company, paid $.47 million for not correctly identifying its business segments. The litigation cost and reputation damage from reporting errors ensure that the disclosed information is credible.

Ability condition: firms update beliefs on the basis of peers' disclosures. Abundant evidence in organizational science shows that firms learn from one another (e.g., Gilbert and Lieberman 1987; Gimeno et al. 2005; Haunschild 1993). If a firm is uncertain about the advertising spending disclosure outcome, and peers' decisions are observable, it is natural for the firm to draw inferences from peers' decisions. Following the reasoning that herding motives involve deriving information from peers' decisions, we argue for two plausible information sources on which a rational firm may rely: (1) the disclosure behaviors of benchmark leaders and (2) the disclosure behaviors of similar peers.

Information gleaned from behaviors of benchmark leaders. Because of the uncertainty concerning the consequences of advertising spending disclosure, a firm may choose to adopt the decisions of peers that occupy a leading position from a product-market or financial-market perspective. It is likely that firms that are successful and experienced in product markets (e.g., large firms, profitable firms) are knowledgeable about the product-market effects of advertising spending because their success may result from their marketing capabilities and market knowledge (Vorhies and Morgan 2005). In addition, firms leading in financial markets (e.g., firms with substantial market valuation) are probably perceived as knowledgeable with regard to how investors would respond to disclosed information and are skilled at managing financial-market valuation compared with average firms.

Information gleaned from behaviors of similar peers. For a firm, the level of similarity in terms of market position and financial profile varies across peer firms. For example, both Dell and Zoom Technologies were peers of Apple Inc. in 2006 because they operated in one of Apple's sectors: Dell in Electronic Computers (SIC 3571) and Zoom Technologies in Household Audio and Video Equipment (SIC 3651). Yet Dell is more similar to Apple than Zoom Technologies because of the similar market position (i.e., leading players in the sector) and financial profile (i.e., *Fortune* 500 companies). Firms may find it beneficial to learn from similar peers because similar peers occupy comparable positions on some important product-market dimensions. Specifically, a firm may perceive that the private information of similar peers is more relevant for its decisions than such information from disparate firms. For example, peers that resemble the firm in terms of product market position serve similar customers and face similar market challenges. Therefore, they are likely to be similar in terms of the size of advertising spending and may face comparable consequences to disclosing advertising spending.

Furthermore, similar peers' disclosures are relevant in the financial market because comparison with similar firms can drive investor expectations of disclosures. When more similar firms disclose, investors are more likely to expect the focal firm to disclose; if the firm does not disclose, investors tend to revise stock prices downward for the nondisclosing firm (Dye 1985; Jung and Kwon 1988). Recognizing investors' reasoning processes, a firm should be more likely to follow the disclosures of similar peers to avoid a severe discount on its market value.

[9] See https://www.sec.gov/litigation/litreleases/litrelarchive/litarchive2016.shtml (accessed January 2019).

Table 1. Variable Descriptions.

Variables	Description
Disclosure	Advertising expense disclosure decision of firm i, equal to 1 if the firm discloses advertising expenses in its 10-K report in time period t, and 0 otherwise
Peer behavior	Fraction of peer firms (excluding focal firm i) that report advertising expenses
Size	Natural logarithm of firm total assets
SG&A dummy	Equals 1 if SG&A expense is reported; otherwise 0
SG&A amount	Selling, general and administrative expenses (XSGA) minus R&D expenses (Mizik and Jacobson 2007) and divided by sales (SALE).
ROA	Net income adjusted for common/ordinary stock, divided by total assets (NIADJ/AT)
R&D	Ratio of R&D expenses to sales
Auditor dummies	Six dummy variables (Arthur Andersen, Ernst & Young, Deloitte & Touche, KPMG, PwC, and Coopers & Lybrand), each representing one of the big-six accounting firms; equal to 1 if firm i uses that auditor
Ind_HHI	Sales-based Hirschmann–Herfindahl index, calculated at the primary four-digit-SIC-code level for the firm
Ind_Turbulence	Regression covering years $t-1, t-2, \ldots, t-5$, in which SALES for firm i's primary four-digit SIC industry is the dependent variable and the YEAR is a predictor variable. Industry turbulence is the standard error of YEAR's estimated regression coefficient, divided by industry sales average for years $t-5$ to $t-1$ (Cannella, Park, and Lee 2008)
Tobin's Q	Ratio of the market value of assets to the book value of assets, measured at each year end. The market value of assets is estimated by (book value of debt + book value of preferred stock + market value of common stock) (Daines 2001)

Notes: This table lists the definitions of firm-level variables. A variable name such as XX_Peer_Avg (e.g., Size_Peer_Avg) represents the average characteristics (e.g., size) of the focal firm's peers. A variable name such as XX_2nd_Peer (e.g., Size_2nd_Peer) represents the average characteristics (e.g., size) of a focal firm's second-degree peers (firm i's peer's peer, which is not firm i's peer).

Institutional Setting and Data

SEC Financial Reporting Release FRR44

We investigate publicly traded firms listed on the NASDAQ, NYSE, or AMEX exchanges between 1982 and 2006. Our study window spans two regimes, each with different disclosure regulations regarding advertising spending. Before 1994, the SEC (51211 Rule 12–11) required firms to disclose, in the notes to their income statements, advertising spending, amortization of intangibles, maintenance and repairs, and several other expense items that are material (e.g., exceeded 1% of sales). In the interest of integrating U.S. with international requirements, the SEC eliminated this requirement in a December 13, 1994, financial reporting release (FRR44), "Financial Statements of Significant Foreign Equity Investments and Acquired Foreign Business of Domestic Issuers and Financial Schedules." As a result, advertising spending and several other expenses no longer were mandatory disclosure items in firms' 10-K forms. (In the Web Appendix, we provide a relevant excerpt from FRR44 that details the change.)

Although FRR44 was intended to simplify the quantitative disclosures of firms that conducted foreign business, it applies to all firms, except for banks and financial institutions (McAlister et al. 2016; Simpson 2008). Because the release of FRR44 is an exogenous change, not under the control of any individual firm, it provides a natural experiment through which we can study marketing spending disclosures before and after its release.

Advertising Disclosure and Financial Data

We collect advertising disclosure and financial data from Compustat fundamentals for firms listed on the NASDAQ, NYSE, or AMEX exchanges between 1982 and 2006 to form observation periods 12 years before (1982–1993) and after (1995–2006) the issuance of FRR44. We excluded all banks and financial institutions in SIC codes 6000–6999, because they are regulated by different disclosure rules. We also excluded observations with missing sales and stock price data to ensure that all firms are in business and are actively traded.

We measured firms' advertising disclosure decisions according to whether there was a nonmissing or nonzero value for the firm's advertising expense item (McAlister et al. 2016; Simpson 2008). A positive value for advertising expenses in a particular year meant that the firm disclosed advertising spending that year. We report the variable definitions in Table 1. To eliminate extreme outliers, we followed extant literature and Winsorized the continuous accounting variables at the 1% and 99% levels (Berger and Hann 2007; Ellis, Fee, and Thomas 2012; Simpson 2008).

Industry Segment Data and Peer Group Construction

We obtained the four-digit primary and secondary SIC codes associated with the business segments of each firm from Compustat's segment file. Because 72.7% of firms participate in multiple industries, we can construct partially overlapping groups of peers. Our definition of peers (or first-degree peers) refers to firms operating in at least one common industry. An underlying assumption is that firms with business in the same industries interact intensively due to competition for the customer base and financial-market resources, as well as the potential for cooperation or mutual learning achieved through their similar business nature. Our definition of second-degree peers refers to all the firms that are not firm i's peers but are

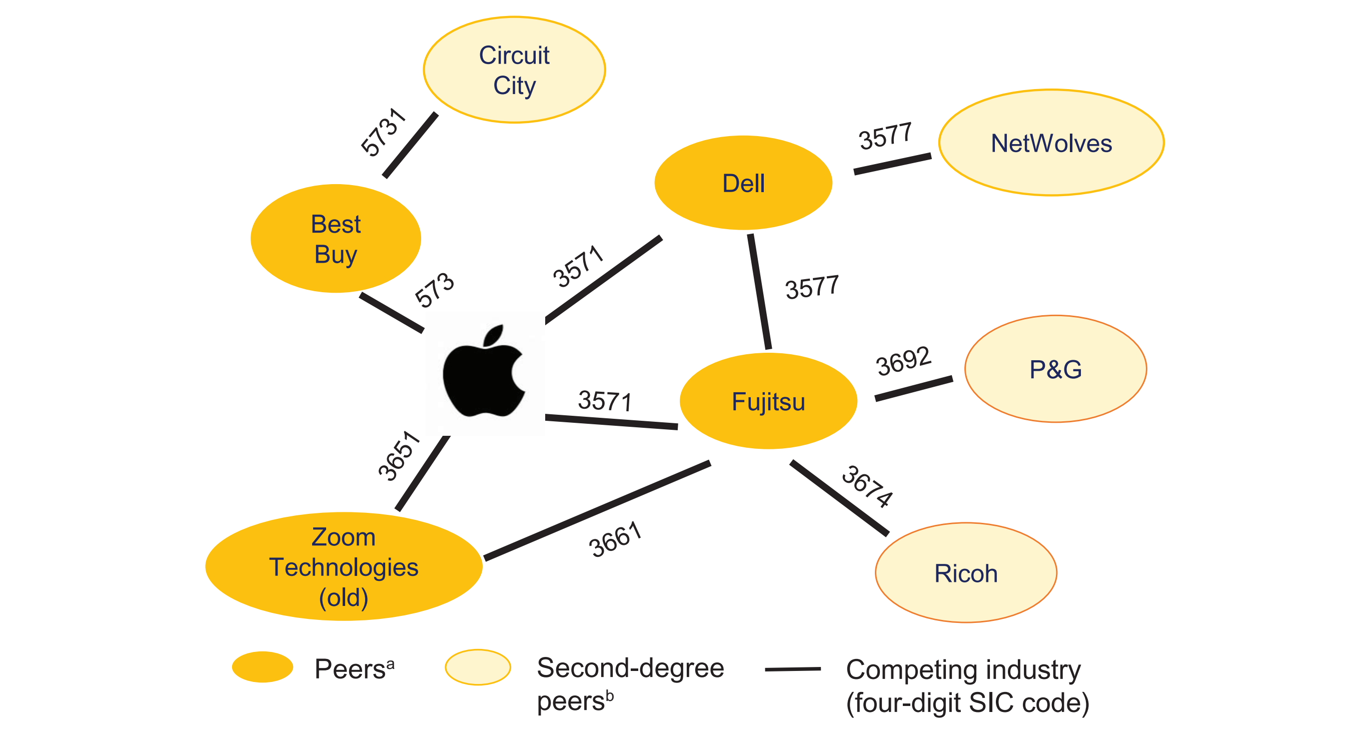

Figure 2. Illustration of partially overlapping peer groups.
We use Apple as a focal firm to illustrate the concepts of partially overlapping peer groups, peers, and second-degree peers.
[a]Peers of Apple: Apple Inc. operated in three industries: 3571 (Electronic Computers), 5734 (Computer and Computer Software Stores), and 3651 (Household Audio and Video Equipment). Firms that have business in any of these three industries are Apple's peers. In this illustration, four companies are Apple's peers: Dell and Fujitsu compete with Apple in 3571; Best Buy in 5734; and Zoom Technologies in 3651.
[b]Second-degree peers: Circuit City, NetWolves, P&G and Ricoh Global are Apple's second-degree peers. They are peers of Apple's peers (i.e., Dell, Fujitsu, Best Buy, or Zoom Tech), but they do not directly compete with Apple.
Notes: Regarding partially overlapping peer groups, we provide two examples. Example 1: Apple and Dell are peers to each other because both compete in 3571. Part of the two firms' peers are overlapping (e.g., Fujitsu, which has business in 3571). Each of the two also has its own peers that are different from each other (e.g., Best Buy is in Apple's peer group but not in Dell's, NetWolves is in Dell's peer group but not in Apple's). Example 2: Apple and Fujitsu are peers to each other. Part of the two firms' peers are overlapping (e.g., Dell and Zoom Tech are their common peers). Each of the two also has its own peers. Fujitsu has P&G and Ricoh Global as peers while Apple has Best Buy. In this figure, we include a subset of the industries in which each firm operates for the purpose of illustration.

peers of firm i's peers (De Giorgi, Pellizzari, and Redaelli 2010). We illustrate peer group construction in Figure 2 using Apple (operating in SIC industries 3571, 3651, and 5734) as a focal firm. In this illustration, Dell is Apple's peer and NetWolves is Apple's second-degree peer. Dell (in 3571, 3577) directly competes with Apple in 3571, so Dell is Apple's first-degree peer; NetWolves (in 3577) competes with Dell in 3577 and is not in any of Apple's sectors, so NetWolves is Apple's second-degree peer. We construct a peer group and a second-degree peer group for each firm. Figure 3 shows the distribution of peer-group size ($M = 159.9$, $SD = 163.6$) and Figure 4 shows the distribution of second-degree peer-group size ($M = 1752.5$, $SD = 805.5$).

We deleted firms with only one year of data (1.46% of the sample)[10] because we rely on within-firm variation in one of the specifications to identify herding effects. We also deleted observations with no peers or second-degree peers (.52% of the sample). The working sample thus consists of 6,298 firms (48,509 firm-year observations).[11] Table 2 provides the variable correlations and descriptive statistics for this sample, and Table 3 contains the descriptive statistics for the average characteristics of the peer group for each observation.

Identification Strategies

Perils of Perfectly Overlapping Peer Groups

Organizational herding literature often defines peer groups on the basis of a single attribute (e.g., firms' primary industry; Kedia, Koh, and Rajgopal 2015) or geographic region (Miller and Tucker 2009), resulting in perfectly overlapping peer

[10] These firms are included when we construct the peer disclosure variable.

[11] Among the firms that existed in both 1993 and 2001, 269 firms (12.83% out of the 2,097 firms) disclosed in 1993 but did not disclose in 2001. These firms did not switch back to disclosure. Therefore, nondisclosure, instead of disclosure, seemed to be in their best interest. Two hundred seventy firms (12.88%) did not disclose in 1993 but did disclose in 2001. For these firms, disclosure seems to be in their best interest.

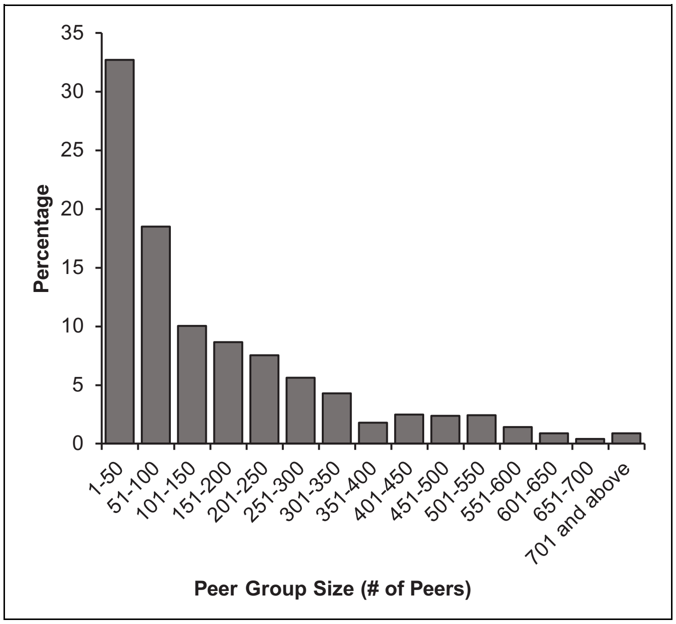

Figure 3. Distribution of peer group size.
Notes: The average size of the first-degree peer group is 159.9, with a standard deviation of 163.6. The minimum number of the first-degree peers is 1, and the maximum number is 1,197.

groups. That is, if firms i and j are in the same group, their peers coincide.[12] We show that perfectly overlapping peer groups fail to identify peer influence (Angrist 2014).

For every year, we observe whether firms disclose their advertising spending in their annual reports; for firm i at time (year) t, we denote this decision d_{it}, such that $d_{it} = 1$ if the firm discloses advertising spending and $d_{it} = 0$ if not. Consistent with the notations in the peer influence literature (e.g., Bollinger and Gillingham 2012; De Giorgi, Pellizzari, and Redaelli 2010; Manski 1993), d_{it} is formulated as a linear function:

$$d_{it} = \alpha + \beta E[d|G_i, t] + \boldsymbol{\gamma} E[\mathbf{x}|G_i, t] + \boldsymbol{\delta}\mathbf{x_{it}} + u_{it}, \quad (1)$$

where G_i is firm i's peer group, $E[d|G_i, t]$ is the average disclosure decision of G_i at time t,[13] $E[\mathbf{x}|G_i, t]$ is a vector of the average characteristics of G_i at time t (we use bold notations to represent vectors hereinafter), $\mathbf{x_{it}}$ is a vector of firm i's time-varying characteristics, and u_{it} represents the error component. In this specification, β is supposed to assess the endogenous social interaction among peers. However, this specification, at best, would identify a correlation coefficient between firm i's decision and the average peer group decision.

[12] To be more precise, if firms i and j are in the same group, their peers nearly coincide because firm i's peers include firm j and the rest of the firms in the group, while firm j's peers include firm i and the rest of the firms. Because the difference is minimal and negligible, especially when the group size is large, we overlook this difference in our discussion.

[13] In empirical estimation, we operationalize $E[d|G_i, t]$ as the average of the observed disclosure of i's peers at time t: $\left(\sum_{j=1}^{N_{G_i}} d_{jt}\right)/N_{G_i}, \forall j \in G_i$ for N_{G_i} as the number of firms in G_i. Similarly, $E[\mathbf{x}|G_i, t]$ is operationalized as the average of the characteristics of i's peers at time t.

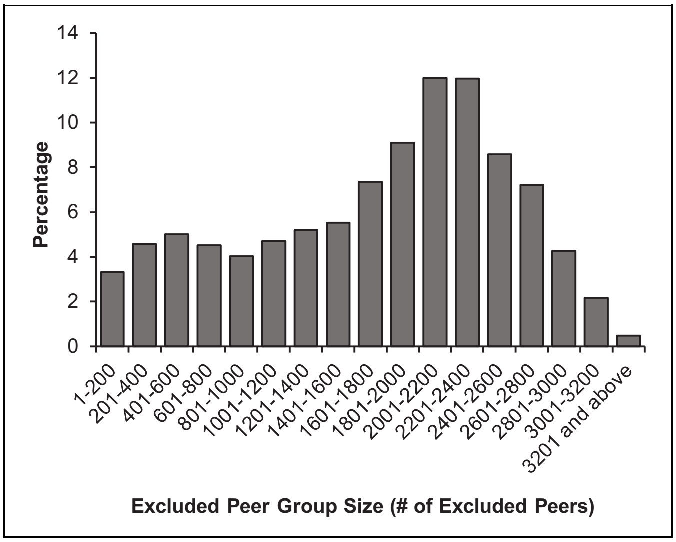

Figure 4. Distribution of second-degree peer group size.
Notes: The average size of the second-degree peer group is 1,752.5 with a standard deviation of 805.5. The minimum number of the second-degree peers is 1, and the maximum number is 3,580.

With perfectly overlapping peer groups, if firms i and j are in the same group, their peers coincide. Therefore, G_i and G_j are the same. Drawing on Equation 1, we write disclosure decisions of firms i and j as Equations 2a and 2b, respectively:

$$d_{it} = \alpha + \beta E[d|G_i, t] + \boldsymbol{\gamma} E[\mathbf{x}|G_i, t] + \boldsymbol{\delta}\mathbf{x_{it}} + u_{it}, \quad (2a)$$

$$d_{jt} = \alpha + \beta E\left[d|G_j, t\right] + \boldsymbol{\gamma} E\left[\mathbf{x}|G_j, t\right] + \boldsymbol{\delta}\mathbf{x_{jt}} + u_{jt}. \quad (2b)$$

Because G_i and G_j are the same, we can rewrite Equation 2b as follows:

$$d_{jt} = \alpha + \beta E[d|G_i, t] + \boldsymbol{\gamma} E[\mathbf{x}|G_i, t] + \boldsymbol{\delta}\mathbf{x_{jt}} + u_{jt}. \quad (2c)$$

Equations 2a and 2c show that firms i and j have the same components of $E[d|G_i, t]$ and $E[\mathbf{x}|G_i, t]$ on the right side of the decision equations. If we take the average of the decision equations of all firms in G_i (i.e.,$\forall j \in G_i$), we obtain the following equation (for similar specification, see De Giorgi, Pellizzari, and Redaelli [2010]):

$$E[d|G_i, t] = \alpha + \beta E[d|G_i, t] + \boldsymbol{\gamma} E[\mathbf{x}|G_i, t] + \boldsymbol{\delta} E[\mathbf{x}|G_i, t] + E[u|G_i, t]. \quad (3)$$

Here, we assume no unobserved common group shocks, such that $E[u|G_i, t] = 0$. We relax this assumption when we discuss correlated unobservables subsequently. Rearranging Equation 3, we can see that $E[d|G_i, t]$ is a linear combination of the other independent variables:

$$E[d|G_i, t] = \left(\frac{\alpha}{1-\beta}\right) + \left(\frac{\gamma + \delta}{1-\beta}\right) E[\mathbf{x}|G_i, t]. \quad (4)$$

Due to the linear dependence between the endogenous peer variable $E[d|G_i, t]$ and exogenous peer characteristics

Table 2. Sample Correlations and Descriptive Statistics.

	Correlations															
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
1. Disclosure choice	1.000															
2. Peer disclosure	.450	1.000														
3. Size	.039	.013	1.000													
4. SG&A dummy	.163	.195	−.061	1.000												
5. SG&A amount	−.005	−.002	−.031	.019	1.000											
6. ROA	.031	−.006	.331	.166	−.050	1.000										
7. R&D	−.071	−.032	−.191	−.299	.055	−.434	1.000									
8. Arthur Andersen	−.116	−.132	.006	−.030	−.005	.022	−.028	1.000								
9. Ernst & Young	.118	.029	.045	.003	−.007	−.020	.082	−.188	1.000							
10. Deloitte & Touche	−.031	.042	.082	−.003	.002	.047	−.046	−.152	−.222	1.000						
11. KPMG	−.034	.020	.021	−.004	−.001	−.004	.013	−.157	−.230	−.185	1.000					
12. PwC	−.001	.007	.142	.007	−.007	.024	−.014	−.179	−.262	−.211	−.219	1.000				
13. Coopers & Lybrand	−.039	−.093	−.015	−.010	−.003	.026	−.007	−.066	−.097	−.078	−.081	−.092	1.000			
14. Ind_HHI	.015	.052	−.034	.150	−.011	.078	−.084	−.025	−.001	−.007	−.007	.014	−.015	1.000		
15. Ind_Turbulence	−.061	−.080	−.010	.002	.002	−.002	−.037	.002	−.017	.006	.013	.009	−.015	.169	1.000	
16. Tobin's q	.008	.011	−.123	−.062	.014	−.168	.104	−.009	−.008	−.017	.000	−.008	−.004	−.043	.002	1.000
Summary Statistics (N = 48,509)																
Mean	.274	.273	5.703	.855	.440	−.030	.191	.114	.216	.152	.161	.200	.033	.243	.033	1.887
SD	.446	.208	2.062	.353	9.615	.244	.783	.317	.411	.359	.368	.400	.178	.198	.043	5.247
Min	.000	.000	.501	.000	−22.819	−1.392	.000	.000	.000	.000	.000	.000	.000	.000	.000	−.871
Max	1.000	1.000	10.587	1.000	1688	.297	5.920	1.000	1.000	1.000	1.000	1.000	1.000	1.000	5.760	644.925

Notes: The descriptive statistics and correlations are based on the final sample in our main analysis. The variable definitions are in Table 1.

Table 3. Descriptive Statistics for Peer Average Variables.

Variables	Mean	SD	Min	Max
Size_Peer_Avg	5.942	.978	2.307	10.587
SG&A Dummy_Peer_Avg	.843	.179	.000	1.000
SG&A Amount_ Peer_Avg	.368	.911	.000	42.435
ROA_ Peer_Avg	−.029	.091	−.734	.224
R&D_ Peer_Avg	.196	.369	.000	2.497
Arthur Andersen_ Peer_Avg	.885	.076	.000	1.000
Ernst & Young_ Peer_Avg	.114	.113	.000	1.000
Deloitte & Touche_ Peer_Avg	.216	.090	.000	1.000
KPMG_ Peer_Avg	.151	.080	.000	1.000
PWC_ Peer_Avg	.159	.069	.000	1.000
Coopers & Lybrand_ Peer_Avg	.210	.096	.000	1.000
Ind_HHI_ Peer_Avg	.034	.065	.000	1.000
Ind_Turbulence_ Peer_Avg	.230	.094	.050	1.000

Notes: A variable name such as XX_Peer_Avg (e.g., Size_Peer_Avg) indicates the average characteristics (e.g., Size) of the peer group of each observation (firm-year) in our sample.

$E[\mathbf{x}|G_i, t]$, when peers perfectly overlap, β cannot be identified; only a composite parameter $(\gamma + \delta)/(1 - \beta)$ can be estimated. Next, we discuss how partially overlapping peer groups solve this issue.

Partially Overlapping Peer Groups

To break down the linear dependence between endogenous and exogenous peer variables, we rely on partially overlapping peer groups, which vary at the individual firm level. Firm i's peer group G_i is different from its peer firm j's peer group G_j. Therefore, for firm i and its peer j's disclosure decision equations, the peer disclosure variable of firm i ($E[d|G_i, t]$) in Equation 2a is different from that of firm j ($E[d|G_j, t]$). Similarly, the peer average characteristics for firms i and j (i.e., $E[\mathbf{x}|G_i, t]$ and $E[\mathbf{x}|G_j, t]$) are different. Therefore, we cannot write Equation 2a as Equation 2b.

Because each peer firm j has its unique peer group G_j, the components of $E[d|G_j, t]$ and $E[\mathbf{x}|G_j, t]$ in the right side of Equation 2b are unique for each peer firm j. If we take expectation of the decision equations of all firms j in G_i (i.e.,$\forall$ j $\in G_i$), we obtain Equation 5. The expectation of $E[d|G_j, t]$ and $E[\mathbf{x}|G_j, t]$ across all firms j in G_i can be written as $E[E(d|G_j, t]|G_i, t)$ and $E[E(\mathbf{x}|G_j, t)|G_i, t]$, respectively. In the latter two terms, the inner expectation represents the average disclosure or average characteristics for peers of one peer firm j which is a peer of firm i, while the outer expectation represents the average of peer disclosure or peer characteristics for all firms that are peers of firm i (i.e., belong to G_i).

$$E(d|G_i, t) = \alpha + \beta E\Big[E\Big(d|G_j, t\Big)|G_i, t\Big] + \gamma E\Big[E\Big(\mathbf{x}|G_j, t\Big)|G_i, t\Big] + \boldsymbol{\delta} E(\mathbf{x}|G_i, t) + E(u|G_i, t). \tag{5}$$

In turn, the linear dependence between $E[d|G_i, t]$ and $E[\mathbf{x}|G_i, t]$ arising from nearly perfectly overlapping peer groups does not hold in Equation 5[14] when peer groups vary at the individual firm level. Therefore, partially overlapping peer groups enable us to separate endogenous peer influence from exogenous peer effects. In our context, we leverage the fact that the majority of the firms operate in multiple industries and rely on the assumption that a firm learns from peers that operate in at least one industry as itself and does not restrict the learning to peers that are in exactly the same set of industries as itself.

Rationale of Learning Mechanisms

In learning from partially overlapping peer groups, a focal firm identifies its peer group, or firms whose decision contains relevant information, as peer firms in one or more industries (labeled overlapping industries) in which the focal firm operates. The focal firm knows that peer firms' decision are likely influenced by competitors in their overlapping industries as well as industries outside the focal firm's business scope but within some the scope of some of the peers. Firms learn from peers' decisions in order to resolve some uncertainty in their own decision to disclose, to the extent that peers' decision basis (i.e., competitors in the overlapping industries) is relevant to the focal firm itself.

We illustrate the learning mechanism using a stylized example of Apple and Dell. Suppose Dell operates in two industries (computer hardware and cybersecurity system) and Apple in two industries (computer hardware and household audio/video equipment). Dell and Apple have partially overlapping peer groups with one overlapping industry (computer hardware). When Apple observes Dell's disclosure decisions, it knows that its peers likely influence Dell's decision in both computer hardware and cybersecurity systems. To the extent that at least some of Dell's peers (i.e., those in the computer hardware industry) are relevant to Apple, Dell's disclosure decision will resolve the uncertainty in Apple's decision.

An implicit assumption in this learning mechanism is that firms mainly look to other firms in overlapping industries for advertising disclosure information, and lack the motivation to look to firms outside their industry boundaries. Prior research supports this notion. In financial markets, investors and analysts evaluate firms' market value benchmarked against other firms within industries (Dye and Sridhar 1995). Analysts follow firms by industry and their research reports rank firms in the same industry (Boni and Womack 2006). Financial information users infer the long-term financial impact of advertising spending by industry (e.g., firms in the same industry are recommended to use the same amortization rate of advertising expenditure; Falk and Miller 1977; Peles 1970). Moreover, firms tend to mimic financial reporting behavior of other firms in the same industries even when they have access to financial

[14] $E[E(d|G_j, t)|G_i, t]$ will not be reduced to $E[d|G_i, t]$, the left side of the equation. $E[d|G_j, t]$ represents the average disclosure behavior of firm j's peer group. Firm j is one of firm i's peers, and each of firm i's peers has its own peer group. $E[\bullet|G_i, t]$ represents the average disclosure behavior of firm i's peer group.

reporting of firms outside the industry (e.g., earning restatement in Kedia, Koh, and Rajgopal [2015] and frequency of management forecasts in Seo [2017]).

In product markets, advertising spending outside industry boundaries has little relevance for disclosure purposes. Prior literature has shown that the sources of product-market uncertainty for disclosure decisions (e.g., advertising spillover, budgeting models) vary considerably across industries (Bagwell 2007; Blasko and Patti 1984; Corfman and Lehmann 1994). In firms' search for the most appropriate benchmarks, they first need to ensure that the link of action–performance in benchmarks also applies to themselves. As there is no evidence showing that the market reaction to advertising disclosure is homogenous across industries, firms are unlikely to benefit from imitating the actions of firms outside industry boundaries.

Correlated Unobservables

Identification issue could arise due to correlated unobservables. Context-specific, correlated, unobservable variables (e.g., unobservable group shocks) that affect both the focal firm and its peers bias the estimate of endogenous peer effects. To solve the endogeneity problem due to correlated unobservables, we use a two-pronged strategy: (1) an instrumental variable approach, in which instruments are naturally available in the setting of partially overlapping peers, and (2) a rich set of covariates and fixed effects (e.g., Bollinger and Gillingham 2012; Nair, Manchanda, and Bhatia 2010; Shriver, Nair, and Hofstetter 2013).

Instrument variable strategy. We use instruments that naturally arise in the framework of partially overlapping peer groups, reflecting the average characteristics (i.e., average of $\mathbf{x_{it}}$) of the second-degree peers, defined as the peers of firm i's peers that are not in firm i's own peer group. Suppose that firm i's second-degree peer group is XG_i at time t. Then $E[\mathbf{x}|XG_i,\ t]$ are theoretically valid instruments that meet both exclusion restriction and instrument relevance requirements. This strategy has been documented and empirically implemented in peer influence research (Bramoullé, Djebbari, and Fortin 2009; De Giorgi, Pellizzari, and Redaelli 2010). The exclusion restriction is satisfied due to the nature of the second-degree peer groups such that firms in XG_i are not in firm i's peer group. Therefore, their characteristics ($E[\mathbf{x}|XG_i,\ t]$) plausibly must be uncorrelated with unobservable shocks that affect firm i's disclosure decision (beyond time fixed effects). As illustrated in Figure 2, NetWolves' characteristics (part of $E[\mathbf{x}|XG_i,\ t]$) should have no direct impact on Apple's advertising disclosure decisions other than through the instrument relevance condition. Because NetWolves is not in Apple's peer group, the unobservables that affect the disclosure decisions of Apple and its peers are unlikely to affect NetWolves' characteristics (e.g., NetWolves' size, profit, SG&A spending, auditors). The exclusion restriction condition is further ensured with two pieces of evidence. First, the spurious herding effect in the mandatory disclosure regime (when causal herding should not be identified, as disclosure is not discretionary) is eliminated when instrument variables are used. Details are in Table W1 of the Web Appendix. Second, we also test overidentifying restrictions because we have four instruments, which is more than we need to identify one endogenous variable equation. With three more instruments, we can test whether the additional instruments are valid in the sense that they are uncorrelated with the error terms from the second-stage estimations when using the full set of instruments (Wooldridge 2002, p. 122). The Hansen J-statistic for the two-stage specification (Column 3 in Table 4) is 4.54 with $p > .10$. This test fails to reject the null hypothesis that at least one of the instruments is exogenous (Miller and Tucker 2009), suggesting no overidentifying issue.

Furthermore, instrument relevance is satisfied by the direct interaction between the peers and second-degree peers of a focal firm. Using Apple as the focal firm (Figure 2), one of its peers is Dell and one of its second-degree peers is NetWolves. NetWolves' characteristics (part of $E[\mathbf{x}|XG_i,\ t]$) affect its own disclosure decision, which in turn influences Dell's disclosure (part of $E[d|G_i,\ t]$) through within-group interaction. As a result, $E[\mathbf{x}|XG_i,\ t]$ is correlated with $E[d|G_i,\ t]$. That is, second-degree peer groups' characteristics provide a vector of potential instruments $E[\mathbf{x}|XG_i,\ t]$ to correct for the endogeneity issue due to unobservable time-varying group shocks.

Covariates

We include a rich set of variables in the firm characteristics vector ($\mathbf{x_{it}}$), average characteristics of peers, as well as industry $\times$ year fixed effects. Specifically, we include firm characteristics that may affect a firm's disclosure decision. Specifically, $\mathbf{x_{it}}$ includes (1) firm size (natural logarithm of the firm's total assets), (2) SG&A dummy (= 1 if firms reported nonzero selling, general and administrative expenses; although SG&A is a mandatory item to report, firms may not report it when the amount is not material), (3) SG&A amount (selling, general, and administrative expenses minus research-and-development [R&D] expenses [Mizik and Jacobson 2007], divided by sales), (4) profitability (net income adjusted for common/ordinary stock, divided by total assets), (5) R&D expenses (divided by sales), (6) auditor dummies, (7) primary industry competition (sales-based Hirschmann–Herfindahl index), and (8) primary industry turbulence[15] (Cannella, Park, and Lee 2008). See Table 1 for details.

We include the characteristics of the peer group as well. The group characteristics are the average characteristics of all peers, where these variables include all variables in $\mathbf{x_{it}}$. Specifically, we use the mean of peer firms' size, SG&A dummy,

[15] We follow a procedure suggested by Cannella, Park, and Lee (2008) such that we ran regressions in which sales for the firm's primary four-digit SIC industry was the dependent variable and the cumulative time period [$t-1, t-2, \ldots, t-5$] was a predictor variable, and then we measured the standard error of cumulative time period's estimated regression coefficient, divided by the industry sales average, for years $t-5$ to $t-1$.

Table 4. Herding Main Effect Analyses.

Dependent Variable: Ad Spending Disclosure	(1) Correlational Evidence	(2) Exogenous Peer Characteristics	(3) 2SLS[a]	(4) Falsification Test
Peer disclosure	.912***	.927***	.483***	.016
	(.009)	(.011)	(.186)	(.011)
Size	.010***	.012***	.010***	.010***
	(.001)	(.001)	(.001)	(.001)
SG&A dummy	.089***	.103***	.101***	.104***
	(.005)	(.006)	(.007)	(.008)
SG&A amount[b]	−.109	−.102	−.137	−.154*
	(.078)	(.081)	(.091)	(.083)
ROA	−.001	.003	.006	.003
	(.009)	(.009)	(.010)	(.012)
R&D	−.023***	−.026***	−.024***	−.027***
	(.002)	(.002)	(.002)	(.003)
Arthur Andersen (yes = 1)	−.126***	−.134***	−.134***	−.131***
	(.007)	(.008)	(.008)	(.008)
Ernst & Young (yes = 1)	.038***	.033***	.034***	.034***
	(.007)	(.007)	(.008)	(.009)
Deloitte & Touche (yes = 1)	−.109***	−.114***	−.127***	−.128***
	(.007)	(.007)	(.008)	(.008)
KPMG (yes = 1)	−.096***	−.100***	−.113***	−.112***
	(.007)	(.007)	(.008)	(.008)
PwC (yes = 1)	−.062***	−.067***	−.065***	−.066***
	(.007)	(.007)	(.008)	(.008)
Coopers & Lybrand (yes = 1)	−.049***	−.056***	−.057***	−.060***
	(.011)	(.011)	(.012)	(.012)
Ind_HHI index	−.042***	−.071***	N.A.	N.A.
	(.010)	(.012)		
Ind_turbulence	−.229**	−.182**	N.A.	N.A.
	(.099)	(.091)		
Size_PeerAvg		−.010***	.001	−.008***
		(.003)	(.005)	(.003)
SG&A dummy_PeerAvg		−.065***	.000	.025*
		(.012)	(.042)	(.015)
SG&A amount_PeerAvg		.001	.003**	.000
		(.001)	(.001)	(.002)
ROA_PeerAvg		−.065*	−.133	−.0245
		(.037)	(.089)	(.032)
R&D_PeerAvg		.014	−.019	−.005
		(.009)	(.025)	(.008)
Arthur Andersen_PeerAvg		.052*	−.238***	−.123***
		(.030)	(.088)	(.030)
Ernst & Young_PeerAvg		−.092***	−.237***	−.064*
		(.035)	(.057)	(.038)
Deloitte Touche_PeerAvg		.105***	−.169***	−.115***
		(.036)	(.059)	(.037)
KPMG_PeerAvg		.083**	−.252***	−.132***
		(.038)	(.059)	(.039)
PWC_PeerAvg		.003	−.126**	−.142***
		(.035)	(.062)	(.035)
Coopers Lybrand_PeerAvg		−.006	−.091	−.050
		(.039)	(.079)	(.041)
Ind_HHI index_PeerAvg		.168***	.119***	−.041*
		(.026)	(.040)	(.022)
Ind_turbulence_PeerAvg		−.344**	−.276	−.130
		(.161)	(.392)	(.146)
Industry × Year fixed effects	No	No	Yes	Yes
Year fixed effects	Yes	Yes	No	No
R-square/pseudo R-square	.23	.23	.33	.33
Number of observations	48,509	48,509	48,509	48,509

*$p < .10$.
**$p < .05$.
***$p < .01$.
[a]For the IV regressions in Columns 3, the Hansen J-statistic (overidentification test of all instruments) is 4.54 ($p > .10$), indicating that the model is not overidentified.
[b]The variable "SG&A amount" is rescaled by multiplying .001 so that the estimates after the third decimal digit can be shown; without rescaling, estimates are shown as .000 in the table. The rescaling does not affect the quantity of other coefficients and model fitness.
Notes: N.A. = not applicable. We calculate the R-squares of Columns 3 and 4 using the predicted dependent variables (d_{it}) that consist of the linear prediction and fixed-effect components.

SG&A amount, profitability, R&D, auditor dummies, industry competition, and industry turbulence to describe the characteristics of firm i's peer group.

We also include industry × year fixed effects to capture industry-specific, time-varying unobservables. We define industry as the firm's primary SIC industry. For example, industry × year fixed effects captures the effects of the Fair Disclosure Regulation of 2000 and Sarbanes–Oxley Act of 2002 on disclosure decisions. They also capture the effects of time-varying industry-wide shocks on firms' disclosures, such as the possible effect of internet advertising targeting technology on firms' disclosures decisions.[16]

Other Identification Issues

Reference group determination and contextual effects might also bias estimates of peer influence (Manski 1993). Reference group determination implies that researchers use observations of behavior to identify individual reference groups (Manski 1993). In our research context, it could imply that (1) firms choose their peer group (industry) on the basis of other firms' disclosure behavior, which is highly unlikely, or (2) the industry entry decision and disclosure decision are affected by common shocks. We alleviate this concern by evaluating the correlation of these two decisions in one of our robustness tests.

Contextual effects instead are "caused by the specific context in which the data arise" (Manchanda, Xie, and Youn 2008, p. 963) and can be excluded by replicating the study in another context (e.g., another geographic area in Manchanda, Xie, and Youn 2008). Because we include most industries, instead of picking a few to study, contextual effects should not be an issue.

Model Specifications and Estimation

Main Specification

To implement the identification strategies, we estimate the following specification:

$$d_{it} = \alpha + \beta\,\text{Peer Disclosure}_{it} + \delta\mathbf{x_{it}} + \gamma\mathbf{PEERGROUP_{it}} + \text{Industry} \times \text{Year} + \varepsilon_{it}, \tag{6}$$

where d_{it} is firm i's disclosure at time t ($d_{it} = 1$ if the firm discloses advertising spending and $d_{it} = 0$ if not), and α is the intercept. The second component ($\beta\text{PeerDisclosure}_{it}$) captures the endogenous peer effects. $\text{PeerDisclosure}_{it}$ is the fraction of firm i's peers (excluding firm i) that disclose advertising expense at time t, equal to

$$\frac{\sum_{j=1}^{N_{G_i}} d_{jt}}{N_{G_i}}, \forall j \in G_i \text{ for } N_{G_i} \text{ as the number of firms in } G_i. \tag{7}$$

$\mathbf{x_{it}}$ is a vector of firm characteristics including the variables defined in Table 1 and discussed in the "Covariates" subsection: size, SG&A dummy, SG&A amount, return on assets (ROA), R&D, and six auditor dummies, each representing one of the six big auditors (Arthur Andersen, Ernst & Young, Deloitte & Touche, KPMG, PwC, and Coopers & Lybrand, with the baseline category being firms using non–big six auditors), and Ind_HHI index, Ind_turbulence representing industry competition and turbulence respectively.

$\mathbf{PEERGROUP_{it}}$ is a vector that describes peer group characteristics. The elements in this vector take the average of the characteristics ($\mathbf{x_{it}}$) of each peer. It is calculated as the average characteristics of firm i's peers:

$$\frac{\sum_{j=1}^{N_{G_i}} x_{jt}}{N_{G_i}}, \forall j \in G_i \text{ for } N_{G_i} \text{ as the number of firms in } G_i. \tag{8}$$

Specifically, the variables in $\mathbf{PEERGROUP}_{it}$ are Size_PeerAvg, SG&A dummy_PeerAvg, SG&A amount_PeerAvg, ROA_PeerAvg, R&D_PeerAvg, and auditor variables (Arthur Andersen_PeerAvg, Ernst & Young_PeerAvg, Deloitte Touche_PeerAvg, KPMG_PeerAvg, PWC_PeerAvg, Coopers Lybrand_PeerAvg), Ind_HHI_PeerAvg, and Ind_turbulence_PeerAvg. Industry × year is a set of dummies each representing one combination of industry and year, and ε_{it} is the error term.

Instrument Variables

We need to instrument $\text{PeerDisclosure}_{it}$ to correct for correlated unobservables. The instrument variable vector $\mathbf{PEER\_2nd}_{it}$ ($E[\mathbf{x}|XG_i, t]$ in a previous discussion) is the average characteristics of firm i's second-degree peers:

$$\frac{\sum_{k=1}^{N_{XG_i}} x_{kt}}{N_{XG_i}}, \forall k \in XG_i \text{ for } N_{XG_i} \text{ as the number of firms in } XG_i. \tag{9}$$

We include four variables: Size_2nd_Peer (average size of second-degree peers), SG&A_2nd_Peer (average SG&A dummy of second-degree peers), ROA_2nd_Peer (average ROA of second-degree peers), and BigAudit_2nd_Peer (average big auditor dummy of second-degree peers). We choose these four variables because the corresponding variables in firm characteristics $\mathbf{x_{it}}$ (i.e., firm size, SG&A dummy, ROA, and BigAudit_dummy) have significant effects on disclosure decisions, which is necessary to establish the instrument relevance criterion.

[16] For example, internet marketing technology (e.g., targeting technology) improves over time, which benefits some industries more than others (e.g., Amazon and eBay benefit more from internet advertising than P&G and Unilever). If Amazon and eBay start to disclose advertising around the same time for this reason, the spurious correlation can be picked up in industry × year fixed effects.

We use a standard two-stage least squares (2SLS) regression to estimate herding effects. In the first stage, we estimate the following equation:

$$\begin{aligned}\text{Peer Disclosure}_{it} = \boldsymbol{\theta}_1 \textbf{PEER\_2nd}_{it} + \boldsymbol{\theta}_2 \mathbf{x_{it}} \\ + \text{Industry} \times \text{Year} + \omega_{it}.\end{aligned} \tag{10}$$

We then obtain the fitted values ($\widehat{\text{PeerDisclsoure}_{it}}$) from Equation 10 and replace $\text{PeerDisclosure}_{it}$ in Equation 6 with it.

Identifying Uncertainty Resolution Mechanisms

How firms resolve the disclosure uncertainty (i.e., gleaning information from benchmark leaders or similar peers) predicts different sources of peer influence. Firms are likely to be influenced by highly influential peers if firms perceive that benchmark leaders have information that is more valuable; they are likely to be influenced by similar peers if they perceive similar peers have information that is more valuable. In an ideal experimental setting, we would randomly assign firms to four conditions, such that firms in each condition are only informed about the disclosure decisions of one type of peer group: (1) high-influence peers, (2) similar peers, (3) low-influence peers, or (4) dissimilar peers. Then we could assess peer influence by the condition-specific correlation between participating firms' decisions and peers' decisions. If learning from benchmark leaders were the resolution mechanism, we would find the correlation for high influence peers, but if learning from similar peers were the resolution mechanism, we would see the correlation for similar peers.

However, in reality, firms may be exposed to the disclosure decisions of all their peer firms, irrespective of their type. Therefore, we exploit the variability in firms' characteristics within their peer group to mimic a randomized peer influence to the extent possible by dividing each firm i's peer group into four subgroups based on one of their key characteristics (i.e., size, profitability, or market value): high-influence subgroup G_i^h, similar-peer subgroup G_i^s, low-influence subgroup G_i^l, and dissimilar-peer subgroup G_i^{ds}. We then construct corresponding peer disclosure variables: PeerHigh, PeerSimilar, PeerLow, and PeerDissimilar. Next, we use the following firm-fixed effect specification (α_i represents firm-specific fixed effects) to estimate the relative strength of influences from the four subgroups:

$$\begin{aligned}d_{it} = \alpha_i + \beta^h \text{PeerHigh}_{it} + \beta^s \text{PeerSimilar}_{it} \\ + \beta^l \text{PeerLow}_{it} + \beta^{ds} \text{PeerDissimilar}_{it} + \boldsymbol{\delta} \mathbf{x_{it}} \\ + \gamma \textbf{PEERGROUP}_{it} + \text{Year} + \varepsilon_{it},\end{aligned} \tag{11}$$

where for firm i, one of its key characteristics (size, profitability, and market value) is in the range between deciles 4 and 7 among G_i at time t. We then construct high-influence peers G_i^h (deciles 8–10), similar peers G_i^s (deciles 4–7), low-influence peers G_i^l (deciles 1–3), and dissimilar peers G_i^{ds} (deciles 1, 2, 9, and 10). By this construction, similar peers G_i^s, high-influence peers G_i^h, and low-influence peers G_i^l are mutually exclusive; dissimilar peers G_i^{ds} mix part of G_i^h and G_i^l.

The reason that we use a subsample of firms from the middle range (deciles 4–7) of the key characteristics (size, profitability, or market value) instead of the entire sample is to ensure variability across peer groups. The identification for the different mechanisms comes from across-firm variation in the composition of the four peer groups (G_i^h, G_i^l, G_i^s, and G_i^{ds}). Such variation is not uniform across all firms; for example, if we use firm size to divide a focal firm's peer groups into G_i^h, G_i^l, G_i^s, and G_i^{ds}, and the focal firm's size locates in decile 10 among the group, the firm's G_i^h is the same as its G_i^s, and its G_i^l is the same as its G_i^{ds}; similarly, if the focal firm's size locates in decile one among the group, the firm's G_i^l is the same as its G_i^s, and its G_i^h is the same as its G_i^{ds}. Therefore, when the focal firm's size locates in the top and bottom ranges within the group, we cannot obtain sufficient differences in G_i^h, G_i^l, G_i^s, and G_i^{ds}.

Results

Correlational Evidence

We first show initial evidence of a herding effect. Because we construct peer behavior variables using partially overlapping peer groups, we are able to separate the endogenous herding effect and the effect of exogenous peer group characteristics. We add independent variables progressively to evaluate their impact on advertising disclosure decisions. Column 1 of Table 4 shows the results when we run a linear probability model with the regressors $\text{PeerDisclosure}_{it}$ and the vector of firm characteristics $\mathbf{x_{it}}$. The estimated effect of peer behavior is positive and statistically significant ($\beta = .912$, $p < .01$). We then add the exogenous peer effects by entering the peer group characteristic, variable $\textbf{PEERGROUP}_{it}$. As we report in Column 2 of Table 4, exogenous peer characteristics are significant, including the group average selling expense dummy (SG&A dummy_PeerAvg), group average profitability (ROA_PeerAvg), four of the six group average auditor dummies, group average profitability industry competition (Ind_HHI_PeerAvg), and group average industry turbulence (Ind_turbulence_PeerAvg). However, the endogenous herding effect estimate does not change much ($\beta = .927$, $p < .01$).

Correction for Correlated Unobservable Variables

We use a two-pronged approach to account for unobservable correlated effects: (1) apply instrumental variables to account for time-varying group shocks, then (2) add industry × year fixed effects along with firm characteristics $\mathbf{x_{it}}$ and group characteristics $\textbf{PEERGROUP}_{it}$. As we discussed previously, a set of instruments is naturally available in a setting marked by partially overlapping peer groups (i.e., the average characteristics of second-degree peers $\textbf{PEER\_2nd}_{it}$). We use size, the SG&A dummy, ROA, and the BigAudit dummy to construct

Table 5. First-Stage 2SLS.

Dependent Variable: Peer Behavior	First-Stage Estimates of 2SLS Results of Column 3 in Table 4
Exclusion restriction variables:	
Size_2nd_Peer	.020***
	(.007)
SG&A_2nd_Peer	.147***
	(.027)
ROA_2nd_Peer	.063
	(.061)
BigAudit_2nd_Peer	−.776***
	(.109)
Control variables (firm and peer average characteristics)[a]	Yes
Industry × Year fixed effects	Yes
Year fixed effects	No
R-square/pseudo R-square	.37
Number of observations	48,509

***$p < .01$.
[a]Control variables include firm average characteristics (size, SG&A dummy, SG&A amount, ROA, R&D, six auditor dummies, Ind_HHI index and Ind_turbulence) and peer averages of these variables.

PEER_2nd$_{it}$. Specifically, we average these variables across the second-degree peer group XG_i and denote them as Size_2nd_Peer, SG&A_2nd_Peer, ROA_2nd_Peer, and BigAudit_2nd_Peer. These four variables have significant effects on disclosure decision d_{it} (see Columns 3 and 4 of Table 4), and therefore instrument relevance is established.

We use 2SLS estimation. In the first stage, we regressed the endogenous variable (PeerDisclosure) on the four instrument variables, along with all other control variables (i.e., firm characteristics, peer group characteristics, and industry × year dummies). The results from the instrumental variable regression are in Column 3 of Table 4, and the first-stage output is in Column 1 of Table 5. As we report in Column 3 of Table 4, the herding effect is statistically significant ($\beta = .483$, $p < .01$). Because we have multiple instruments, we conducted overidentification tests too, and the Hansen J-statistic of 4.54 ($p > .1$) indicates that our study does not suffer from overidentification issues.

The first-stage regression in Table 5 shows that three of four instruments have significant effects on the endogenous variable PeerDisclosure. The R-square of the first-stage regression is .37; the joint significance test for the instrumental variables is significant ($F(4, 44{,}027) = 29.23$, $p < .01$). These statistics indicate that we do not have a problem of weak instruments, and instrument relevance is satisfied.

Falsification Test

As falsification, we test the assertion that a firm should not learn from firms that are outside its peer group. To construct a "false" peer group, we randomly assign firms to peer groups. We then run a regression with industry × year fixed effects where all peer related variables are constructed based on the "false" peer groups.[17] We find no herding effect ($\beta = .016$, $p > .10$), as detailed in Column 4 of Table 4 (i.e., a null effect lends credibility to our argument that firms are not learning from all firms whose disclosure decisions are observable).

Ruling Out Alternative Explanations and Reviewing for Robustness

We conducted additional analyses to exclude alternative explanations (summarized in Table 6). In addition, we performed robustness tests to confirm the causal effect of herding (results shown in Table 7).

Analyst expectation or scrutiny. Analysts serve as the external governance mechanism for investors through monitoring firms' financial disclosure (Chen, Harford, and Lin 2015; Chakravarty and Grewal 2016). When more peers disclose, firms that do not disclose face higher pressure from analysts and may eventually choose to disclose advertising spending. To test the plausibility of this explanation, we collected analyst coverage data from I/B/E/S and created a set of variables describing how likely analysts are to scrutinize a firm's financial disclosure. These variables include whether the firm is followed by any analyst (yes = 1) and, if it is covered, the consensus of the EPS forecasts (median of the forecasts), the disparity in the forecasts (standard deviation of the forecasts), the difference between the actual EPS and the forecast, and whether the firm has negative earnings surprise (yes = 1). We find robust herding effect after controlling for analyst variables (Column 1 of Table 7).

Advertising spending. Because we observe firms' advertising spending only when they choose to disclose, there is a possibility that nondisclosed advertising spending may bias herding effects. To assess this possibility, we imputed nondisclosed advertising spending for firms that disclosed in some but not all years after 1994. We first calculated a firm-specific advertising-to-SG&A ratio averaged across disclosing years and then approximated the advertising spending for the firm's nondisclosing years by multiplying the ratio and SG&A amount of nondisclosing years. We then construct an advertising spending variable by using disclosed advertising spending (for disclosing firm-year) and imputed nondisclosed advertising spending (for nondisclosing firm-year). For firms that never disclosed, we assume the advertising spending and year-to-year changes are zeros. We add the advertising spending variable and the changes in this variable to the 2SLS regression with industry × year fixed effects. We also add an interaction between advertising spending and PeerDisclosure to test how the herding

[17] Because the peer groups are randomly assigned to each firm, 2SLS instrument variable regression is not appropriate for the falsification test. The random assignment removes the correlation between unobservables and the variable PeerDisclosure.

Table 6. Ruling Out Alternative Explanations.

Alternative Explanation	Tests and Results
Firms have incentives to disclose in equilibrium, and all firms eventually disclose.	Not all firms eventually disclose: 269 firms that disclosed in 1993 did not switch back to disclosure in 2001; 334 firms switched from disclosure to nondisclosure in 1995–2006. Pressure from analysts is one specific form of market incentives. As one supplemental test, we show that herding effects manifest after controlling for analyst scrutiny (Column 1, Table 7).
Time-varying unobservable incentives lead to upward trend of disclosure.	We obtained significant herding effects after including industry $\times$ year fixed effects (Column 3 in Table 4).
As more firms disclose, analysts' belief about nondisclosing firms may change, pressuring those firms to disclose overcoming the costs of disclosure.	We created a set of variables describing how likely analysts may scrutinize a firm's financial disclosure. We obtained significant herding effects after controlling for analyst scrutiny, as we show in Column 1, Table 7.
Advertising spending amount and changes affect firms' decision to disclose.	First, advertising spending amount is included in SG&A amount regardless of whether firms disclose ad spending. Second, we still find significant herding effects (Column 2, Table 7) after adding ad-spending variables. The herding effect attenuates as the advertising level increases. The slope of PeerDisclosure is positive and significant ($p < .05$) when advertising level is lower than 1.5 SD above mean (98.08% of the observations).
Unobserved factors affect both industry entry (i.e., endogenous reference group issue) and disclosure decisions; for example, firms enter markets based on the changing attractiveness of the market.	We evaluated whether industry entry correlate with the change in disclosure decisions. If unobserved factors affect both industry entry and disclosure, these two decisions should correlate. We find that the two decisions do not correlate ($\chi^2_1 = .207, p > .649$). We add the binary industry entry variable as an additional covariate in our model. We still find a robust herding effect (Column 3, Table 7).

effect changes at different levels of advertising spending.[18] We found that the coefficient of PeerDisclosure is positive and significant (coefficient $= .505$, $p < .01$, Column 2 of Table 7). The interaction between advertising spending and PeerDisclosure is negative and significant (coefficient $= -.498$, $p < .01$), indicating that herding effect attenuates as the advertising level increases. To see the existence of herding effects at high levels of advertising spending, we calculate the herding effect (i.e., the slope of PeerDisclosure) when the advertising levels are at mean, one standard deviation above mean, one and a half standard deviations above the mean, and two standard deviations above the mean. The effect sizes are .490 ($p < .01$), .391 ($p < .05$), .341 ($p < .05$), and .291 ($p < .10$), respectively, providing evidence for heterogeneity in herding across advertising spending levels.

Endogenous industry entry. We construct a firm's peer group based on the industry membership. It is likely that a firm's industry entry decision is correlated to its disclosure decision, which may bias the herding effect estimates. We first examine whether the binary disclosure decision is correlated to the binary industry entry decision. We cross-tabulate the two decisions and conduct the chi-square test. The analysis shows that the two decisions are not correlated ($\chi^2_1 = .207$, $p > .64$). We then add the binary industry entry variable as an additional covariate and run the instruments corrected regression with industry $\times$ year fixed effects. We still find robust herding effect (Column 3 of Table 7).

Habitual reporting behavior. We conduct two robust tests to alleviate the concern that a firm's habitual reporting behavior (i.e., a tendency to adopt the same disclosure decision as the last year) causes the issues of autocorrelation and state dependence[19] and thus biases the estimation of herding effects. First, we run a two-stage instrumental variable regression with firm fixed effects. Firm fixed effects remove firms' time-invariant characteristics, including their inherent predisposition of disclosing or withholding advertising spending. We obtain robust herding effects even after adding firm fixed effects ($\beta = .888$, $p < .01$, Column 4 in Table 7). Second, we examine whether the effects of learning from peers exist when firms report annual financial statements for the first time. First-time reporters are

[18] We also roughly evaluated the correlation between the instruments and advertising spending amount. Using the sample of firms that disclose advertising spending for 1995–2006, we regress the reported advertising spending on the four instruments along with all the covariates in Equation 6 and find the coefficients of four instruments are not statistically significant. This evidence indicates that for firms that disclose advertising spending, their advertising spending level is not correlated to the instruments.

[19] In our main analyses, we cluster standard errors at firm level to take into account the correlation of error terms for the same firm across years and use a firm-specific effect (either through fixed-effect or random-effect estimation) to account for firm-specific unobservables that persist over time.

Table 7. Robustness Analyses.

Dependent Variable: Ad Spending Disclosure	(1) Analyst Scrutiny	(2) Advertising Spending	(3) Industry Entry[c]	(4) Habitual Reporting (Firm Fixed Effects)	(5) Habitual Reporting (First-Time Reporter)[d]	(6) Probit IV	(7) Un-Winsorized Variables	(8) Dropping SG&A Variables
Peer disclosure	.477***	.505***	.346**	.888***	.740***	3.749***	.455**	.487***
	(.186)	(.184)	(.179)	(.298)	(.136)	(.210)	(.185)	(.186)
Analyst coverage (yes = 1)	−.011**							
	(,004)							
Median of analyst forecasts[a]	.100***							
	(.032)							
SD of analyst forecasts[a]	.170							
	(.955)							
Difference of forecasted and actual EPS[a]	−.140							
	(.088)							
Negative EPS surprise	−.006							
	(.005)							
Ad spending[b]		.548***						
		(.036)						
Change in estimated ad		−.002***						
Spending		(.000)						
Peer disclosure × Ad spending		−.498***						
		(.082)						
Industry entry (yes = 1)			.006					
			(.006)					
Control variables (firm and peer average characteristics)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	No	No	No	Yes	Yes
R-square/pseudo R-square	.33	.35	.33	.77	.35	.10	.33	.33
Number of observations	48,509	48,509	44,677	48,509	2,464	48,509	48,509	48,509

[a]We rescale median of analyst forecasts (EPS), SD of analyst forecasts, and difference of forecasted and actual EPS by multiplying them by .001 so that the estimates after the third decimal digit can be shown; without rescaling, estimates are shown as .000 in the table. The rescaling does not affect the quantity of other coefficients and model fitness.
[b]We rescale advertising spending is rescaled by multiplying it by .001 so that the estimates after the third decimal digit can be shown.
[c]The sample size of column 3 is smaller than main analysis because the data from 1995 are not in the model; 1996 is the first year when we can see whether a firm in our sample enters new industries.
[d]For column 5, we used industry and year fixed effects instead of industry × year fixed effects because the sample is cross-sectional.
Notes: All models in this table are IV-corrected. The R-squares of all columns except column 6 are calculated using the predicted dependent variables (d_{it}) that consist of the linear prediction and fixed-effect components.

not influenced by habitual behaviors, as past behaviors are nonexistent, but they may still be influenced by peer behaviors. Therefore, the existence of peer learning effects for first-time reporters can confirm herding effects without the issue of habitual reporting behaviors. In our sample, we have 2,464 first-time reporters from 1995 to 2006. We run a two-stage instrumental variable regression with industry and year fixed effects. We obtain a positive and significant herding effect ($\beta = .740$, $p < .01$, Column 5 in Table 7).

Difference in market position. To determine whether market position confounds herding effects, we create leader × year fixed effects so leader firms have their own disclosure dynamics. We categorized leader versus nonleader firms in four possible ways. Leader firms can be large firms (firm size in the top two deciles in an industry), profitable firms (ROA in the top two deciles in an industry), high-market-value firms (Tobin's q in the top two deciles in an industry), or highly visible firms (*Fortune* 500 or S&P 500 firms). With leader × year fixed effects, the herding effects remain significant (large firms: .480, $p < .01$; profitable firms: .479, $p < .05$; high-market-value firms: .473, $p < .05$; *Fortune* 500/S&P 500 firms: .486, $p < .01$; see Table W3 in the Web Appendix).

Other robustness tests. We conduct four other robustness tests, and all confirm a significant herding effect: (1) We investigate the robustness of our results to alternative model specification (i.e., probit instrumental variable regression; Miller and Tucker 2009; Column 6, Table 7). (2) We test the robustness of our results to for un-Winsorized variables (Column 7, Table 7). (3) We test whether our results hold after dropping the SG&A dummy and amount variables (Column 8, Table 7). (4) We estimate the herding effect by constructing a weighted average of PeerDisclosure variable by placing a higher weight on peers in the same primary industry (Table W3 in the Web Appendix).[20] Our robustness tests could not completely rule out the alternative mechanism of firms learning from market reactions to past disclosure and could exclude only certain forms of learning from market reactions.[21]

Resolution to Uncertainty: Benchmark Leaders and Similar Peers

We estimate Equation 11 to determine how a firm resolves the uncertainty in disclosure of advertising spending—whether it infers information from the behavior of benchmark leaders or similar peers. We rank-order firms within their peer group on the basis of size, and we keep the firms with size in the middle range (deciles 4 to 7)[22] as focal firms. We then categorize each focal firm's peers into four groups G_i^h, G_i^l, G_i^s, and G_i^{ds} on the basis of firm size and create four peer disclosure variables: PeerHigh, PeerSimilar, PeerLow, PeerDissimilar. We estimate Equation 11 and report the results in Column 1 of Table 8. The effect of the similar peer group is highest ($\beta^s = .193$, $p < .01$), followed by low-influence ($\beta^l = .121$, $p < .01$), high-influence ($\beta^h = .059$, $p < .05$), and dissimilar peers (β^{ds} is n.s.). The Wald test for the difference between the β^s and β^l is statistically significant (F-statistic $= 3.81$, $p < .05$).

Because the four groups G_i^h, G_i^l, G_i^s, and G_i^{ds} are simply subgroups of G_i, the four peer disclosure variables (PeerHigh, PeerSimilar, PeerLow, PeerDissimilar) should have the same endogenous source (i.e., correlated unobservables) as the variable PeerDisclosure, and the same set of instrumental variables (i.e., $\mathbf{PEER\_2nd_{it}}$) that we used in the main analysis should be able to correct for the issue of correlated unobservables. We implement a control function approach in which we regress PeerDisclosure on $\mathbf{PEER\_2nd_{it}}$ and other variables ($\mathbf{x_{it}}$ and $\mathbf{PEERGROUP_{it}}$) in the first stage and add the error terms from the first stage to Equation 11 as endogeneity correction terms. The endogeneity-corrected estimates (Column 2 of Table 8) remain robust, indicating that similar-sized peers G_i^s have the highest influence among the four peer groups.

As a robustness check, we estimated four 2SLS specifications, each including one of the four peer variables, as detailed in Columns 3–6 of Table 8. We find that only the effect of similar peer groups G_i^s is significant and positive ($\beta^s = .559$, $p < .05$), whereas those of dissimilar peers G_i^{ds}, high influence peers G_i^h, and low influence peers G_i^l are not significant. Finally, as a comparison, we repeated the main analyses on this subsample. The 2SLS regression produces a peer effect of .852 ($p < .05$, Column 7 in Table 8), similar to the results based on our full sample (.888, $p < .01$; Column 4 in Table 7), indicating that the subsample is similar to the full sample in herding behaviors.

Next, we categorize peers into four groups according to their profitability and market value and repeat the analyses. Similar peers in terms of profitability or market value have the highest

[20] When looking for information from peers, firms may not give equal weight to the disclosure decision of each peer. Firms in the same primary industry compete more intensively and are more similar with respect to products, customers, and financial data users (e.g., investors, analysts). It is likely that firms put higher weight on decisions of firms in the same primary industries. The peer influence increases from .483 ($p < .01$) to .532 ($p < .05$) when the ratio of weight on primary industry peers to nonprimary industry peers is 2:1 and decreases to .504 ($p < .10$) if the ratio is 3:1. The results indicate that firms may put a moderately higher weight on the information from primary industry peers.

[21] Because firms in the same industry all observe the market reaction, the market reaction becomes a type of industry-wide common knowledge that the industry × year fixed effects pick up in the form of control variables while focusing our research question on the peer effects. One of our robustness test (Column 5, Table 7) examines whether a firm learns from peers when it reports annual financial statements for the first time. The existence of a herding effect for first-time reporters shows that learning from own disclosure in the past may not be the dominant mechanism.

[22] We did this because these firms have relatively distinct peer groups for the similar, dissimilar, high-influence, and low-influence peers. In contrast, firms in the top deciles have the same firms for their similar and high-influence peers, and those in the bottom deciles have the same firms for their similar and low-influence peers, which leaves the differential peer effects unidentified. Because we focus on a subsample, we rely on firm-fixed-effect specification for mechanism analyses rather than industry × year fixed effects because only a few firms in each industry are included.

Table 8. Firm-Size-Based Uncertainty Resolution Mechanisms.

Dependent Variable: Ad Spending Disclosure	(1) Four Types of Peers	(2) Four Types of Peers (Control Function)	(3) Similar Peers (2SLS)	(4) Dissimilar Peers (2SLS)	(5) High-Influence Peers (2SLS)	(6) Low-Influence Peers (2SLS)	(7) Baseline: All Peers (2SLS)
PeerSimilar	.193***	.239***	.559**				
	(.021)	(.072)	(.259)				
PeerDissimilar	.025	.025		.265			
	(.039)	(.039)		(.296)			
PeerHigh	.059**	.096			.597		
	(.025)	(.059)			(.544)		
PeerLow	.121***	.161**				.375	
	(.029)	(.066)				(.272)	
Peer disclosure							.852**
							(.391)
Control variables (firm and peer average characteristics)[a]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	18,810	18,810	18,810	18,810	18,810	18,810	18,810
R-square/pseudo R-square[b]	.839	.839	.835	.837	.832	.837	.836

**$p < .05$.
***$p < .01$.
[a]Control variables include firm characteristics (size, SG&A dummy, SG&A amount, ROA, R&D, six auditor dummies, Ind_HHI index, and Ind_turbulence) and the peer average of these variables. Table W2 in the Web Appendix provides the full output of these estimations
[b]The R-squares are calculated using the predicted dependent variables (d_{it}) that consist of the linear prediction and fixed-effect components.

influence. However, its difference from the second-highest influence is not statistically significant (see Table W2, Panel B, in the Web Appendix). Overall then, our results suggest that firms are more likely to seek information from similar-sized peers to resolve the uncertainty in disclosure of advertising spending.

Additional Analysis: Business Scope Similarity and Financial Standing Similarity

Table 8 shows that firms are more likely to be influenced by similar-sized peers. We next investigate how the similar-sized peer influence varies, depending on those peers' business scope and financial standing. Firms may tend to mimic peers that are more similar in business scope because they likely exhibit greater similarity in their product and service offerings, so their information is relevant and useful to a focal firm. Moreover, because investors are more likely to anticipate that these firms are more similar in terms of their advertising spending, firms come under pressure to disclose their advertising spending if other firms, similar in their business scope, have already disclosed. Alternatively, firms may tend to mimic peers that are more similar in their financial standing, as reflected in their efficient revenue generation, profitability, or leverage ratios, because they possess comparable financial resources and constraints. Thus, firms similar in their financial standing seemingly should employ similar marketing resource allocations. We test in turn for the relative importance of business scope and financial standing similarity in driving similar-sized peer influence.

To define similar-sized peers, we divide a focal firm's peer group into five strata based on size and retain firms in the same stratum as similar-sized peers. We describe each similar-sized peer along the two dimensions of business scope similarity and financial standing similarity to the focal firm. We measure business scope similarity using a Jaccard similarity coefficient, or the ratio of the number of common business segments to the total nonduplicated segments. We measure financial standing similarity using the Euclidean distance of three financial metrics: sales-to-asset ratio, to measure efficiency in sales revenue generation; ROA, to measure profitability; and the debt-to-asset ratio, to measure financial leverage.

In turn, we divide the similar-sized peers of firm i into four groups, using median splits of the two similarity dimensions, such that we obtain the following subgroups: a group with high business scope similarity and high financial standing similarity (high BS, high FS) $G_i^{b,\,f}$; a group with low business scope similarity and high financial standing similarity (low BS, high FS) $G_i^{-b,\,f}$; a group with high business scope similarity and low financial standing similarity (high BS, low FS) $G_i^{b,-f}$; and a group with low business scope similarity and low financial standing similarity (low BS, low FS) $G_i^{-b,-f}$. We retain firms that have at least 20 similar-sized peers in the analyses so that each subgroup has at least five peers. We then construct four peer variables by calculating the disclosure fraction for each group. By estimating a firm-fixed-effect model, we can investigate the relative importance of the influences of these four peer variables.

Table 9. Business Scope (BS) Versus Financial standing (FS) Similarity.

Dependent Variable: Ad Spending Disclosure

Panel A		**Panel B**		
	(1)		**(2)**	**(3)**
Peer disclosure (high BS, high FS)	.023**	Peer disclosure (high FS)	.132***	
	(.010)		(.020)	
Peer disclosure (high BS, low FS)	.015	Peer disclosure (low FS)	.022	
	(.010)		(.019)	
Peer disclosure (low BS, high FS)	.084***	Peer disclosure (high BS)		.052***
	(.018)			(.015)
Peer disclosure (low BS, low FS)	−.006	Peer disclosure (low BS)		.069***
	(.017)			(.025)
Control variables (firm and peer average characteristics)	Yes		Yes	Yes
Year fixed effects	Yes		Yes	Yes
Firm fixed effects	Yes		Yes	Yes
Number of observations	21,146		21,146	21,146
R-square/pseudo R-square[a]	.79		.78	.78

[a]The R-squares are calculated using the predicted dependent variables (d_{it}) that consist of the linear prediction and fixed-effect components.

Notes: The Wald test indicates that the difference in the coefficients of high-FS versus low-FS peer disclosure variables is statistically significant ($F(1, 17{,}563) = 14.89$, $p < .01$). Another Wald test shows that the difference in the coefficients of high-BS versus low-BS peer disclosure variables is not statistically significant ($F(1, 17{,}563) = .30$, $p > .10$).

As Table 9 shows, peer groups with high financial standing similarity exert relatively stronger influences on the firm's disclosure decision than do those with low financial standing similarity. Panel A reveals that the coefficients of $G_i^{b,f}$ and $G_i^{-b,f}$ peer disclosure are both positive and significant. In contrast, the coefficients of $G_i^{b,-f}$ and $G_i^{-b,-f}$ peer disclosure do not have significant impacts on a firm's disclosure decision. Therefore, herding effects seem to be differentiated mainly along the financial standing similarity dimension rather than along the business scope similarity dimension.

To confirm the differential effects of financial standing similarity, we group similar-sized peers into two groups: those high on financial standing similarity (G_i^{f}) and those low on financial standing similarity (G_i^{-f}). Column 2 of Table 9 shows that the coefficient of G_i^{f} peer disclosure has a positive and significant effect, but G_i^{-f} peer disclosure has no significant effect. The Wald test indicates a significant difference in the coefficients of peer disclosure for the high versus low financial standing similarity subgroups ($F(1, 17{,}563) = 14.89$, $p < .01$). Column 3 of Table 9 confirms that the influences from the high versus low business scope similarity groups do not differ significantly. In summary, we find evidence that, on average, firms mimic peers that are similar in financial standing more so than peers that are similar in business scope.

Discussion

We find causal evidence for herding in advertising spending disclosure decisions. Moreover, firms seem to rely more on the disclosure of similar peers than benchmark leaders. We discuss the managerial and policy implications of our findings.

Implications for Firms

Our results provide prima facie evidence that firms could strategically use their own advertising disclosure decisions to shape the marketing information environment in a dynamic manner. From the model estimates, a firm can predict whether a competitor is likely to disclose its advertising decision, conditional on its own advertising disclosure. Our results show that firms look to similar-sized peers rather than benchmark leaders to resolve advertising disclosure uncertainty, and within similar-sized peers, they are more influenced by those with similar financial standing (similar ROA and debt-to-asset ratio) than those with similar business scope (proportion of common business segments). Thus, if a firm is similar in size and financial standing to its competitor, the firm can infer the likelihood that the competitor will disclose its advertising spending conditional on the firm disclosing its advertising spends. As we discuss next, firms can use knowledge of a competitor's predicted likelihood of advertising disclosure (conditional on their disclosure) to their strategic advantage in product markets and financial markets.[23]

23 Firms may impute advertising spending as we did to infer competitors' advertising levels. However, firms' ability to impute expected advertising levels does not undermine the implications of herding for firms that collectively shape the marketing information environment. First, the imputed advertising levels rely on the ratio of ad spending to SG&A in disclosing years. It may not be accurate enough for firms that need more precise information about the actual spending of direct competitors. Second, when firms switch from disclosing to not disclosing, investors/analysts may suspect that firms might be concealing unexpected changes in advertising spending. Because imputation may not fully capture the unexpected changes, self-disclosed advertising spending has its informational value beyond imputed ad spending. Third, the imputation approach works better for firms that disclose

In product markets, firms know that revealing proprietary advertising information creates an information advantage for competitors. Therefore, an ideal situation for a firm is to maximize information asymmetry by concealing its own information and learning the information of all competing firms. In reality, when only few competitors disclose information, it is might be beneficial for a nondisclosing firm to seek more advertising information by disclosing its own advertising information first. For a nondisclosing firm, the existence of herding effects could result in a situation in which the cost of revealing one's own information is offset by the gain of more information from competing peers.[24] Therefore, knowing the magnitude of herding effects help firms better understand the information ramifications of their advertising disclosures in product markets.

In financial markets, investors and analysts infer the value implication of a firm's disclosure decision by benchmarking competing firms' decisions. With the existence of herding effects, a firm would expect that its own disclosure decision is part of the influence that shapes the competing peer group's disclosure level. Through the effect of its own disclosure on the subsequent disclosures of the peer group, a firm may change analysts' responses to the disclosure decisions for all firms in the group. For example, Apple initially chose to disclose advertising spending. If Apple could have known the existence of herding effects, it would expect that analysts' negative response to nondisclosing firms years later would be larger than if it chose not to disclose initially, as more firms in the peer group would herd to disclose because of Apple's disclosure. Therefore, it is useful for Apple to know that its initial disclosure decision changes the disclosure level of its peer group that may loop back to affect analysts' response to a subsequent disclosure decision (i.e., Apple's nondisclosure decision in 2016).

Implications for Policy Makers

The presence of herding effects suggests that the seemingly lenient policy of voluntary disclosures actually promotes the acceptance of disclosures through the interaction among firms. To evaluate the impact of herding at the aggregate disclosure level that is of interest to policy makers, we compared the predicted disclosure level based on our endogeneity-corrected model with that of a baseline model where we restricted the coefficient of peer disclosure to zero, ceteris paribus.[25] It suggests that 51.1% of the firms among all firms that disclose at the end of the observation period are doing so due to peer influence. This evidence helps policy makers (e.g., SEC, MASB) evaluate the potential savings in regulatory cost by using voluntary disclosure as opposed to mandatory disclosure. Our finding on peer influence from similar-sized peers implies that if the objective is to achieve a certain level of disclosure with speed, regulators should encourage middle-sized firms to disclose so that the effects ripple out toward larger and smaller firms. Thus, policy makers can use this finding to design effective strategies to promote disclosures.

Our approach also enables policy makers to explore targeted regulation of information disclosure by exploiting heterogeneity in herding effects at the industry level. We modify our model by adding the interactions of peer disclosure variable and industry dummy variables to the two-stage firm-fixed effects regression.[26] We find a high degree of heterogeneity in industry-specific herding effects, with 37 of 57 industries having positive and significant herding effects (see the output in Table W4 of the Web Appendix; the remaining 20 effects were statistically nonsignificant). This finding indicates that if policy makers want to achieve market-wide information transparency while minimizing regulatory cost, they can require mandatory disclosure for industries with significant advertising spending but null herding effects and adopt voluntary disclosure for other industries with a positive herding effect.

In summary, we show that uncertainty created by these contrasting benefits and costs of voluntary advertising spending disclosure decisions prompts firms to look to their peers' behaviors, providing ripe ground for herding. Further research could extend our findings to uncover other mechanisms as well as apply our identification framework to other voluntary disclosure decisions.

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adverting levels in some years to obtain the ratio of ad spending to SG&A. For firms that never disclose, the imputed values are not available, as one cannot obtain a reliable ad-to-SG&A ratio.

[24] For example, Nevsun Resources Ltd was in a ten-firm group in which none of its nine peer firms disclosed in 1995. If Nevsun Resources could have known the existence of herding effects, it would expect that if it started to disclose in 1996, half of the firms in the group would disclose by 2006. This expectation gives Nevsun Resources the option of keeping its own information private and not knowing that of any competing firms' versus revealing its own information and knowing the information of half of its competitors.

[25] Given our sample and estimates from instrumental variable regression, we predict that 37.4% firms disclose advertising in 2006. If we constrain peer influence to be 0, 18.3% firms disclose advertising.

[26] $d_{it} = \alpha_i + \beta\widehat{\text{PeerDisclosure\_it}} + \sum \delta_j \text{Industry}_j \times \widehat{\text{PeerDisclosure\_it}} + \delta\mathbf{x_{it}} + \gamma\widehat{\mathbf{PEERGROUP}}_{\mathbf{it}} + \text{Year} + \varepsilon_{it}$, where α_i represents firm fixed effects, $\widehat{\text{PeerDisclosure\_it}}$ is the predicted value of PeerDisclosure_it from the first-stage regression with instrument variables, Industry_j represents industry dummies, and $(\beta + \delta_j)$ represents herding effects in industry j.

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ORCID iD

Rajdeep Grewal https://orcid.org/0000-0003-4467-2717

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