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RESEARCH ARTICLE

Going beyond optimal distinctiveness: Strategic positioning for gaining an audience composition premium

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Abstract

Research Summary: A core question in strategy research is how firms should position themselves to gain favorable audience evaluations. Emphasizing the heterogeneity in audience predispositions, we propose that firms can gain an audience composition premium by strategically positioning themselves to gain more (less) attention from audiences with positive (negative) predispositions toward them. We argue that this approach to strategic positioning is more conducive for firms with high dispersion in their audience predispositions and that firms can increase their ability to gain an audience composition premium by engaging with audiences holding moderately diverse evaluative schemas. We employ recommender systems and topic modeling to analyze 152,312 firm-analyst-year observations from 1997 to 2018 and 297,931 earnings call transcripts of U.S. public firms and find strong support for our predictions.

Managerial Summary: A key question managers encounter is how to increase their firms' evaluations from external evaluators such as security analysts. In this study, we show that firms can increase their aggregate analyst recommendations by influencing the composition of analysts who opt to cover them and gaining evaluations from analysts who have more favorable predispositions toward them (i.e., by gaining an audience composition premium). Our findings also suggest that gaining an audience composition premium is more important for enhancing a firm's aggregate analyst recommendations when there is a higher dispersion in analyst predispositions toward the firm. To increase its ability to gain an audience composition premium, the firm should engage with analysts who exhibit a moderate degree of heterogeneity in their evaluative schemas.

KEYWORDS

audience heterogeneity, machine learning, optimal distinctiveness, recommender systems, strategic positioning

1 | INTRODUCTION

A robust stream of strategy scholarship has been concerned with firms' optimal positioning strategies for attaining positive audience evaluations (Zhao, Fisher, Lounsbury, & Miller, 2017). To investigate optimal positioning strategies, past scholarship has conceptualized audience evaluations of firms as following two sequential stages. First, audiences limit their consideration set to a manageable sample of comparable firms. Second, they sort through firms in the consideration set and evaluate them (Häubl & Trifts, 2000; Hsu, Roberts, & Swaminathan, 2012; Shocker, Ben-Akiva, Boccara, & Nedungadi, 1991; Zuckerman, 1999, 2017). This two-stage evaluation framework implies that firms should position themselves to advance through the two stages—screening and selection—sequentially and independently, vying for audience attention first and maximizing distinctiveness relative to other firms next. Scholars have argued that firms should conform to categorical benchmarks to pass through the first stage. Firms that defy categorical norms and expectations (e.g., firms that deviate from prototypes or straddle categories) are typically less successful in garnering audience attention (Hsu, 2006; Hsu, Hannan, & Koçak, 2009; Zuckerman, 1999). Accordingly, this stream of research has explored firms' optimal positioning strategies relative to commonly held categorical benchmarks, such as prototypes and exemplars (Barlow, Verhaal, & Angus, 2019; Zhao, Ishihara, Jennings, & Lounsbury, 2018).

More recently, scholars have highlighted heterogeneity and idiosyncrasies in audiences' evaluative schemas—that is, "the criteria used to arrive at overall quality judgments" (Hsu et al., 2012, p. 84). Specifically, audiences' evaluative schemas could be heterogeneous because they may have different theories of value (Lamont, 2012), different degrees of domain-relevant expertise (Falchetti, Cattani, & Ferriani, 2022), and varied preferences and perspectives (Pontikes, 2012). Even audiences of the same type may vary in how they evaluate firms due to their different calculative frames (Beunza & Garud, 2007), path-dependent evaluation routines (Theeke, Polidoro Jr, & Fredrickson, 2018), and goals and motivations (Bowers, 2020; Bowers & Prato, 2019; Glaser, Krikorian Atkinson, & Fiss, 2020). Such differences suggest that audiences could have varying *predispositions* toward a firm—that is, were they to evaluate a firm, the outcome of their evaluations may vary based on their preexisting evaluative schemas (Kovács & Sharkey, 2014; Yoo & Sarin, 2018).[1]

While the optimal distinctiveness thesis has made major advancements in informing firms' optimal positioning strategies (Zhao, 2022), our knowledge regarding firms' optimal positioning strategies in light of heterogeneous audience predispositions remains limited. Extant research has suggested that increasing their reach to different audiences helps firms pass through the first stage of evaluation and is thus universally beneficial to firms (e.g., Barlow et al., 2019). The premise of heterogeneous audience predispositions suggests instead that gaining an audience's attention may not necessarily benefit a firm but may actually harm it. Furthermore, research in this domain has often assumed that there are agreed-upon categorical benchmarks against which firms adjust their positioning strategies (e.g., Bu, Zhao, Li, & Li, 2022; Taeuscher & Rothe, 2021; Zhao et al., 2018). Moreover, past studies have often assumed that audiences within a category utilize a homogeneous set of evaluative schemas when assessing firms. For instance, Benner and Ranganathan (2017, p. 761) maintained that "evaluative schemas form a unified set of expectations for evaluating the performance of different firms within the category." Hsu et al. (2012), however, observed differences in the evaluative schemas of wine critics in the U.S. wine market and proposed that "more investigation is needed into the causes and consequences of this kind of divergence" (p. 93). Overall, optimal distinctiveness research has traditionally emphasized commonalities in audiences' evaluative schemas, posing the need for studies that directly and explicitly build upon the premise of heterogeneity within audiences.

To address these limitations, we need to examine firms' optimal positioning strategies while emphasizing heterogeneous audience predispositions. In other words, we must go beyond simply examining how firms can gain audience attention to exploring whose attention firms should aim to gain and how they can do so. In this study, we first propose an alternative approach to firms' optimal positioning strategy that incorporates heterogeneous audience predispositions. We contrast this approach with the traditional optimal distinctiveness thesis grounded in the two-stage evaluation framework. Next, we examine which firms benefit most from our proposed approach to strategic positioning. Finally, given the complexity of positioning relative to a multitude of audiences with heterogeneous predispositions, we ask, how can firms better understand the evaluative schemas behind their audiences' heterogeneous predispositions and gain the capability to optimally position themselves with this approach?

Our core contention is that when audiences have varying predispositions toward a firm, strategic positioning entails a selective approach to gaining audience attention (as opposed to broadly conforming to categorical norms to maximize audience attention). To gain attention from the right audience, a firm should influence its audience composition such that it is

[1]Evaluative schema and predisposition are two key concepts in this article. Evaluative schema captures the "how," whereas predisposition captures the (potential/predicted) "outcome." We use the term evaluative schema to refer to any type of idiosyncratic differences in how an audience member evaluates a firm that could potentially lead to different evaluation outcomes. Such differences could be due to differences in categorization schema, theories of value, path-dependent evaluation routines, calculative frames, or domain-relevant expertise. We use the term predisposition to refer to an audience member's evaluative outcome regarding a firm regardless of whether the outcome is positive or negative. The prefix "pre-" in the term predisposition captures our intention for referring to an audience member's latent evaluation regarding a firm even if that member is not actually evaluating the firm currently. The prefix "pre-" thus demonstrates a tendency that might or might not actualize in the future. In other words, an audience member's predisposition toward a firm is his/her ex ante evaluation of it.

evaluated mostly by audiences with favorable predispositions toward it (and less by those with unfavorable predispositions). By doing so, firms can gain an *audience composition premium*, which translates into more positive actual evaluations. Essentially, the concept of audience composition premium captures the increase in positive evaluations due to the composition of audiences evaluating a firm.

We further posit that positioning relative to specific audiences with the aim of gaining an audience composition premium is beneficial to firms to the extent that there is dispersion in the audience predispositions toward them. In the absence of such dispersion, firms might be better off formulating their positioning strategies relative to the commonly shared categorical benchmarks. When there is high dispersion in audience predispositions and much to be gained from positioning relative to specific audiences, firms need to discern the heterogeneous evaluative schemas underpinning these audience predispositions and adjust their narratives accordingly. This requires firms to have an efficient strategy for audience engagement—namely, the bidirectional communication between a firm and its audiences whereby the audiences express their evaluative schemas and concerns, and the firm explains its positioning. Since, in most contexts, firms are not able to engage with all of the audiences in the environment, they should select which audiences they engage with. We propose that by engaging with audiences holding moderately diverse evaluative schemas, firms can balance the need to expand their learning regarding their audiences (Leiponen & Helfat, 2011; Love, Roper, & Vahter, 2014; March, 1991) and the need to integrate and utilize the learned knowledge to strategically position and effectively communicate their narratives adjusted to a target audience group (Falchetti et al., 2022).

We test these theoretical predictions in the context of security analysts' investment recommendations of publicly listed U.S. firms. Employing recommender systems as a powerful family of machine learning models, we predict analysts' idiosyncratic predispositions toward firms. Specifically, we develop a predictive model using a machine learning algorithm that was one of the winners of the Netflix Prize competition for predicting users' ratings of movies and shows (Bennett & Lanning, 2007). To measure the heterogeneity in the evaluative schemas of audiences that firms engage with, we use transcripts data on firms' earnings calls to examine the type of questions that firms engage with during the question and answer (Q&A) segments. Our empirical analysis of a sample of 152,312 firm-analyst-year observations from 1997 to 2018 and 297,931 earnings call transcripts provides strong support for our predictions.

Our study makes four key contributions. First, we extend previous literature on firms' optimal positioning strategies by proposing a positioning approach that emphasizes heterogeneous audience predispositions. We theorize that instead of conforming to categorical norms to garner audience attention, firms need to strategically position themselves to garner attention selectively from audiences with favorable predispositions toward them. Second, by examining dispersion in audience predispositions as a moderator amplifying the benefits of gaining an audience composition premium, we highlight a key contextual factor that makes our proposed approach more suitable relative to traditional optimal distinctiveness positioning strategies. Third, by conceptualizing audience engagement as a two-directional communication channel between firms and audiences, we show how firms can balance learning about their audiences broadly and catering to certain audiences selectively by engaging with audiences with moderate heterogeneity in their evaluative schemas. Fourth, by introducing and showcasing a family of machine learning models, we advance the methodological frontier of strategy research and demonstrate how these methods can be used to make predictions regarding idiosyncratic audience predispositions.

2 | THEORETICAL DEVELOPMENT

2.1 | Strategic positioning through optimal distinctiveness

Drawing from marketing and consumer behavior research (e.g., Häubl & Trifts, 2000; Shocker et al., 1991), management scholars have suggested that audiences evaluate firms through a two-stage process. First, audiences screen firms to limit their consideration set to a manageable sample of comparable firms. Second, they sort through the consideration set to evaluate and rank the firms therein (Zuckerman, 1999, 2017). Following this logic, firms should aim to gain audience attention and pass through the first stage of the evaluation process and then differentiate to stand out and garner a high evaluation in the second stage (Zuckerman, 1999, 2017). In other words, firms should strategize to advance through the two stages—screening and selection—sequentially and independently, vying for attention first and maximizing distinctiveness relative to peers next.

Building on this two-stage evaluation framework, past research on strategic positioning has focused on firm positioning relative to categorical benchmarks. Early studies in this domain demonstrated that in order to receive audience attention, firms need to conform to their categories' norms and prototypes to be perceived as easier to classify and analyze (e.g., Hsu, 2006; Zuckerman, 1999). Accordingly, Hsu et al. (2012, p. 83) suggested that "in the first stage, producers vie for audience attention. Producers and products that locate clearly within established market categories are easier for audience members to identify and are therefore more likely to gain attention." According to this research, firms that defy such "categorical imperatives" receive less attention from audiences and thus face an "illegitimacy discount" (Zuckerman, 1999). Later studies went beyond the categorical imperative hypothesis, suggesting that, in some contexts, categorical boundaries could be blurry and ambiguous (Durand, Rao, & Monin, 2007; Rao, Monin, & Durand, 2005), thus enabling, and sometimes rewarding, firms that adopt an atypical market position (Negro, Koçak, & Hsu, 2010; Smith, 2011; Smith & Chae, 2017). More recent studies have explored the effects of conformity and differentiation vis-à-vis category exemplars. Via similarity to exemplars—namely, outstanding category members—firms can garner audience attention (Barlow et al., 2019; Zhao et al., 2018) while risking lower performance evaluations due to comparisons with outstanding firms.

These studies rest on the assumption that categories, as the "cognitive infrastructure" of markets (Schneiberg & Berk, 2010), are shared schemas among all members of an audience group. Based on this assumption, a typical audience member has a relatively clear expectation of what a category member should look like. This cognitive perception of a category member could be formed through a prototype view of the category, which entails categorization based on common attributes of all category members (Rosch, 1973), or through an exemplar view of the category, which refers to categorization based on similarity to outstanding category members (Nosofsky & Johansen, 2000). Either way, a common theoretical and empirical assumption (albeit implicit in most studies) is that conceptions of prototypes and exemplars are shared among audience members insofar as "category construction … involves gaining agreement within the audience about what it means to carry a label" (Hannan, Hannan, Pólos, & Carroll, 2007, p. 59).

Furthermore, researchers often examine audience members within the same category (e.g., analysts specialized in a specific industry) as a homogenous body that reacts uniformly to a firm's within-category positioning strategy. The argument here is that evaluative schemas are shared and uniform across audiences evaluating firms within a certain category (Benner & Ranganathan, 2017; Hsu et al., 2012). Assuming such within-category homogeneity in audiences' evaluative schemas, Hsu et al. (2012) measured between-category differences in wine critics' evaluative schema clarity. Similarly, Benner and Ranganathan (2017) investigated the evolution of the evaluative schemas that were commonly held by analysts who followed the telecommunications industry. In another instance, Litov, Moreton, and Zenger (2012) examined the negative effects of strategy uniqueness vis-à-vis industry averages on analyst coverage, implicitly assuming a similar reaction from all analysts in a firm's primary industry. In yet another study, analysts were assumed to react uniformly to firms that changed their market positions by undertaking major spinoffs (Feldman, 2016).

By emphasizing the commonalities in audiences' evaluative schemas, extant optimal distinctiveness research has tended to focus on the aggregate as opposed to the individual audience. Optimal distinctiveness research has primarily been concerned with identifying an abstract point of optimal distinctiveness within a category, paying limited attention to individual firms and audience idiosyncrasies, let alone individual firm-audience relationships (Durand & Haans, 2022). Furthermore, by highlighting institutional pressures and the need for conformity, early research often assumed that categorical expectations are imposed on firms, which have been regarded as passive entities subject to being categorized (or miscategorized). While recent optimal distinctiveness research has gone beyond this passive view (e.g., Zhao et al., 2018), firms' agency in strategic positioning is still considered to be confined within certain categorical expectations. For instance, according to Barlow et al.'s (2019) study, mobile apps' positioning strategies are limited to how far or close they position themselves relative to the exemplars and prototypes of the category they already belong to.

2.2 | Strategic positioning in light of heterogeneity in audience predispositions

More recently, scholars have started to theorize about important heterogeneities both within and across audiences (e.g., Beunza & Garud, 2007; Falchetti et al., 2022; Kim & Jensen, 2011; Kovács & Sharkey, 2014; Pontikes, 2012) due to differences in their theories of value (Lamont, 2012; Zuckerman & Rao, 2004), degrees of domain-relevant expertise (Falchetti et al., 2022), preferences and perspectives (Pontikes, 2012; Taeuscher, Zhao, & Lounsbury, 2022), calculative frames (Beunza & Garud, 2007), path-dependent evaluation routines (Theeke et al., 2018), and goals and motivations (Bowers, 2020; Bowers & Prato, 2019; Glaser et al., 2020). Therefore, when audiences evaluate a firm, they may embrace different categorization schemas, judge the firm through different lenses (Beunza & Garud, 2007; Pontikes, 2012), and compare the firm with different reference groups (Bowers, 2015; Goodman & Haisley, 2007; Smith & Chae, 2017), giving rise to different predispositions toward the firm.

The premise of heterogeneity in audience predispositions begets a deeper examination of optimal positioning strategies that maximize firm benefit. The two-stage evaluation framework indicates that audiences first screen through firms to determine whether each firm is worthy of their attention, deciding whether the firm passes through the initial screening, and only then they evaluate and confer a rating to it (Häubl & Trifts, 2000; Hsu et al., 2012; Shocker et al., 1991; Zuckerman, 1999, 2017). Given that audiences have varying predispositions when evaluating a firm, it is crucial to consider the interdependence between the two stages: what evaluation will an audience member give a firm (second stage) once he or she decides to evaluate it (first stage)? Depending on the predicted outcome of the second stage, a firm should strategize to influence the first stage. In other words, a firm should strategically influence its audience composition to gain favorable evaluations. We develop this contention in more detail below.

In virtually every important evaluation context, not every audience member evaluates every firm. Instead, each firm is evaluated by a limited number of audience members. As argued before, different audiences may come to different evaluations of the same firm. Consequently, any aggregate evaluation that a firm receives depends on the specific group of audiences that decide to evaluate it. In other words, the makeup of the audiences that evaluate a firm—namely, its audience composition—is an important determinant of the overall evaluation (Kovács & Sharkey, 2014).

Firms can adopt strategies to influence their audience compositions to receive higher aggregate evaluations. We term this gain in evaluations an *audience composition premium*.[2] To illustrate, consider the example of an evaluative landscape in Figure 1. As shown, there are a total of 10 evaluators in the environment. Were they all to evaluate the firm, they would give an average rating of 4 to the firm. However, as mentioned previously, in most contexts, only a select group of audiences evaluate each specific firm. Let us assume in our example that the firm receives evaluations from five out of the 10 evaluators in the environment. Depending on how it positions itself, the firm could gain an average rating of 4.5 in Position 1 or 3.5 in Position 2. We conceptualize the 0.5 points above the total average rating in Position 1 a premium gained through an optimal composition of audiences evaluating the firm.

We propose that firms can strive to achieve a favorable audience composition by strategically positioning themselves to maximize the likelihood of receiving attention from and being evaluated by only those audience members who have a favorable predisposition toward them. Let us illustrate this idea through the familiar example of the peer-review process, in which a manuscript functions as a candidate being evaluated by a specific audience group—namely, reviewers. A manuscript needs favorable evaluations from reviewers to be published. Reviewers, being scholars themselves, often come from different backgrounds and have distinctive evaluative schemas and may therefore have different predispositions toward a given manuscript (second stage of the evaluation process). Moreover, reviewers are likely to evaluate a manuscript only if it is positioned in or near their areas of expertise and research (first stage of the evaluation process). A manuscript's chance of publication thus depends on both stages of the evaluation process: it will be evaluated positively to the extent that it is positioned to attract the right reviewers.

This proposition stands in contrast with suggestions from prior optimal distinctiveness research (see a summary of these differences in Table 1). In contrast to past research, our proposition represents an alternative approach to the strategic positioning challenge by focusing on audience predispositions as opposed to categorical features and benchmarks. From this perspective, the strategic positioning challenge is rather about solving a matching problem,[3] bypassing the need for firms to navigate the concurrent and often complicated pressures to both belong to and stand out within their categories. Our proposed approach focuses on the evaluative

[2]Similarly, we can think of an *audience composition penalty*, which refers to a firm's loss in evaluations due to a suboptimal audience composition. We use the term audience composition premium to parsimoniously refer to this loss as well.

[3]We thank our anonymous reviewer for suggesting the idea of juxtaposing positioning based on the two-stage evaluation framework versus positioning as solving a matching problem.

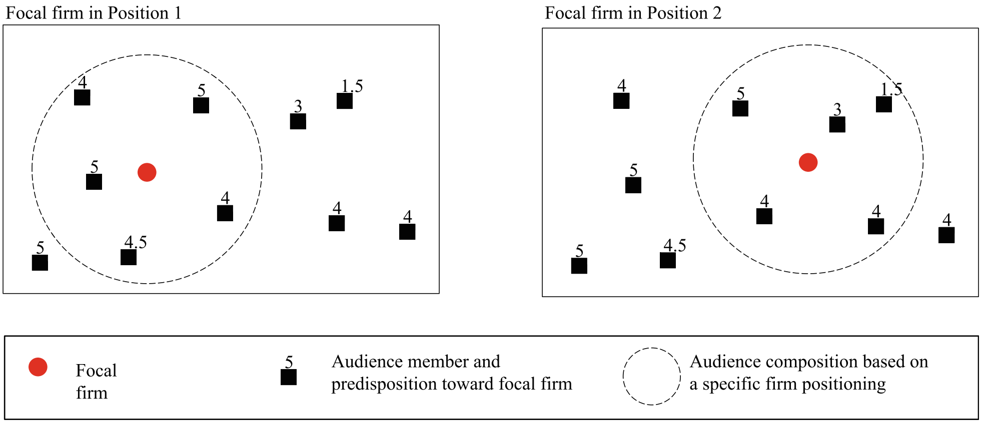

FIGURE 1 Illustration of an audience composition premium

relationship between a specific firm and specific audience members. In doing so, we shift attention to the study of heterogeneities and idiosyncrasies in how audiences evaluate a firm. Moreover, our approach emphasizes firms' agency in influencing how they are evaluated. Recent research has shed light on some aspects of firms' ability to influence audiences' evaluative schemas—for example, through category strategy (Pontikes, 2018; Pontikes & Rindova, 2020; Rindova & Courtney, 2020), which refers to affecting market categories to firms' advantage, or through linguistic framing strategies based on target audiences' mental construals (Falchetti et al., 2022). Our proposed approach complements these studies and introduces yet another way of influencing how a firm is assessed, not by changing specific audiences' evaluative schemas but by influencing who gets to evaluate the firm in the first place. According to the preceding arguments, we propose the following:

> **Hypothesis (H1).** *Firms can increase the evaluations they receive by strategically positioning themselves to attract audiences that have favorable predispositions toward them* (i.e., *by generating an audience composition premium).*

2.3 | The degree of dispersion in audience predispositions

Our proposed approach of aiming to gain a higher audience composition premium is most beneficial when there is a high degree of dispersion in audience predispositions toward a firm. Such dispersion could be caused by differences in evaluative schemas, resulting in varying (ex ante) evaluation outcomes based on similar information.[4] Specifically, in the context of security analysts' evaluations of firms, Zuckerman (2004) showed that some firms, more than others, are

[4]It is important to note that we are interested in the predispositions of all audiences in the evaluative environment toward the firm, whether they are currently evaluating the firm or not. In other words, our conceptualization of dispersion in audience predispositions aims to capture a characteristic of the firm rather than a specific group of audiences. Furthermore, we are interested in dispersion in predispositions as opposed to evaluative schemas because distinct evaluative schemas do not necessarily result in diverging predispositions.

TABLE 1 A comparative analysis between two distinctive positioning strategies

	Positioning based on the traditional optimal distinctiveness thesis	Positioning to gain an audience composition premium
Positioning benchmark	• Position relative to categorical benchmarks (prototypes or exemplars).	• Position relative to audiences.
Two-stage model	• The two-stage model (screening and selection) examined sequentially and independently. • Almost always beneficial to maximize attention.	• The two-stage model examined concurrently and interdependently. • Gain attention only selectively.
Idiosyncrasy vs. commonality	• Focus on the aggregate-level, common, and shared evaluative schemas and predispositions.	• Focus on the individual level, idiosyncratic, and heterogeneous evaluative schemas and predispositions.
Firm agency	• Firms have limited agency to strategically position themselves within certain categorical constraints.	• Firms have agency in influencing the evaluation lenses through which they are evaluated.

inherently likely to attract analysts who have varying industry specialties, use different evaluative models, interpret the same information differently, and—eventually—come to different evaluations of the same firm. He found that for firms that tend to attract analysts with different specialties, trade volume and volatility are higher after quarterly announcements because there is divergence in interpretation of the new information, resulting in distinctive evaluations of these firms.

This distinction in the degree of dispersion in audience predispositions can be illustrated by the example of a firm in Panels (a) and (b) of Figure 2. As shown, for the focal firm in Panel (a), there is a high degree of dispersion in audience predispositions (the standard deviation [*SD*] of audience predispositions is about 1.5). In contrast, there is a low degree of dispersion in audience predispositions for the focal firm in Panel (b) (the *SD* of audience predispositions is about 0.5). As the graphs suggest, the focal firm's gain from strategies to optimize the composition of audiences evaluating it depends on the degree of dispersion in audience predispositions. In Panel (a), where dispersion is high, the difference between the evaluations from the best audience composition (Position 1) and worst audience composition (Position 2) is 2.7. In contrast, in Panel (b), where there is a lower degree of dispersion, the difference in evaluations gained from the best and worst positioning is 0.7.

As we mentioned previously, extant research on optimal positioning strategies has focused on the aggregate and commonalities in audiences' evaluative schemas. This approach would be reasonable in contexts where audiences hold rather uniform schemas and converging predispositions toward a firm. Given a lack of significant variation in audience predispositions, there would be little benefit for selectively targeting specific audiences as the eventual evaluation garnered would essentially be the same. In such a context, the traditional optimal distinctiveness thesis grounded in the sequential two-stage model would be theoretically more suitable. However, when dispersion in audience predispositions toward a firm is higher, selectively gaining attention from audiences with more favorable predispositions will translate into a higher

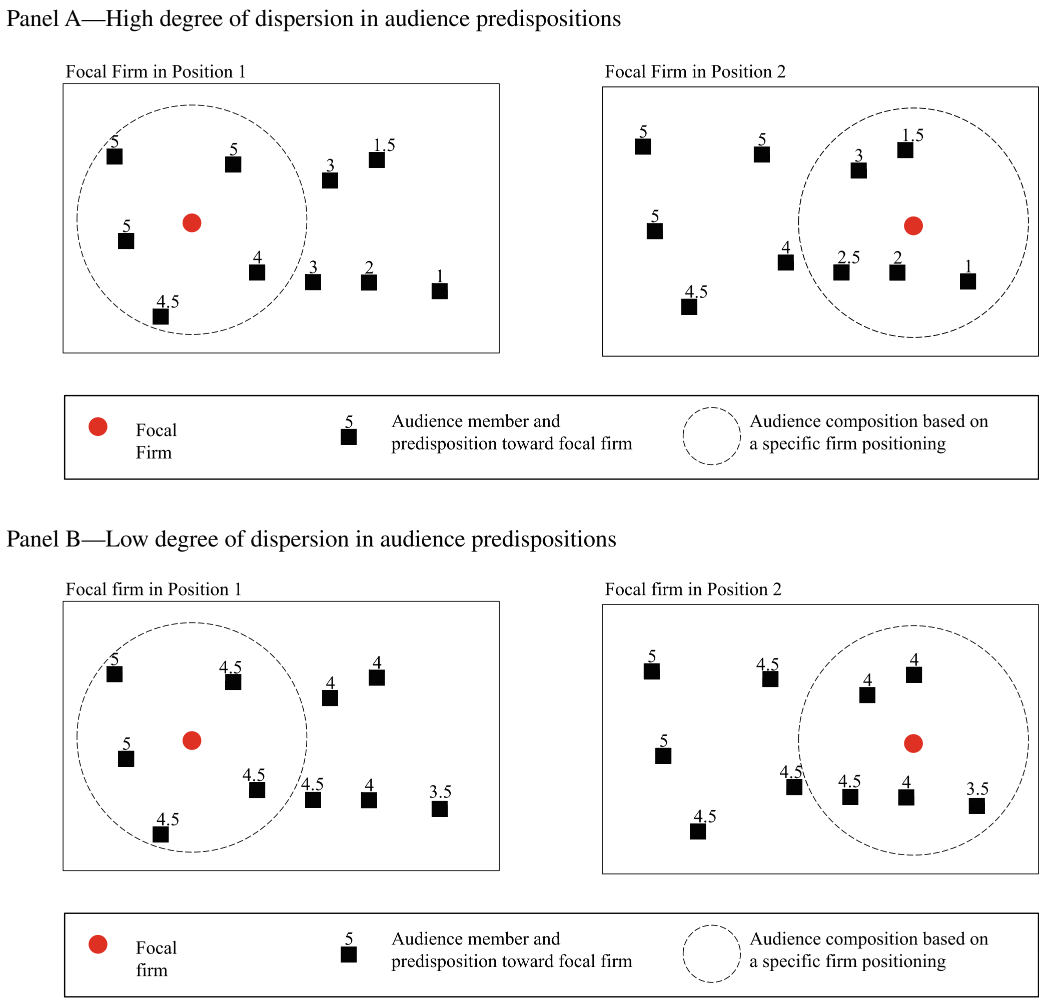

FIGURE 2 Illustration of a firm in two different contexts: in panel (a), there is a high level of dispersion in audience predispositions, whereas, in Panel (b), dispersion in audience predispositions is low

aggregate evaluation. In this case, we expect a stronger positive effect of audience composition premium on the aggregate evaluation that a firm receives. Accordingly, we propose the following:

> **Hypothesis (H2).** *The degree of dispersion in audience predispositions toward a firm positively moderates the relationship between the firm's audience composition premium and its aggregate evaluation.*

2.4 | Engagement with audiences holding diverse evaluative schemas

Gaining an audience composition premium entails learning how different audiences would evaluate a firm and being able to influence their attention strategically. To do so, firms need to go beyond estimating who views them negatively or positively to learning about how and why audiences arrive at specific assessments of them. As an example, for a paper to succeed through the peer-review process, its authors need to know about the evaluative schemas of scholars in their field (perhaps by engaging with various scholars in conferences, getting friendly reviews, giving talks, etc.) and frame their paper such that it is clearly and effectively positioned toward their targeted audiences. Accordingly, firms can strive to achieve a favorable audience composition through two steps: (1) learn about their audiences and their evaluative schemas and (2) strategically position and effectively communicate their positions to their select audiences.

Gaining an audience composition premium thus necessitates a process whereby firms can discern audiences' evaluative schemas, concerns and preferences and use that knowledge to cater to them effectively. Unlike categorical benchmarks, such as prototypes and exemplars, which are few, visible, and known, audiences' evaluative schemas can be multiplex, tacit, and evolving (Theeke et al., 2018). Firms are successful in optimizing their positioning relative to their heterogeneous audiences to the extent that they learn and become cognizant of audiences' distinctive evaluative schemas. Furthermore, to effectively garner attention from their targeted audiences, firms need to provide a narrative that is adjusted to and congruent with their specific audiences' evaluative schemas (Falchetti et al., 2022). Thus, to gain an audience composition premium, firms need to efficiently navigate a two-way communication channel: in one direction, firms need to gain knowledge about their audiences' evaluative schemas; in the other direction, firms need to supply information and narratives regarding their positioning adjusted to their target audiences. In other words, audience engagement—namely, the bidirectional communication between firms and their audiences—is key to gaining an audience composition premium.

Given that audiences hold heterogeneous evaluative schemas and that it is impossible for a firm to engage with all of its audiences in most contexts, a key question is which audiences a firm should engage with. We suggest that engaging with a group of audiences holding a moderate degree of heterogeneous evaluative schemas maximizes a firm's ability to gain an audience composition premium. The degree of heterogeneity in the evaluative schemas of the audiences that a firm engages with influences both steps needed to gain an audience composition: (1) learning about audiences and their evaluative schemas and (2) utilizing that knowledge to strategically position and effectively communicate a firm's position. As we elaborate in more detail below, the relationship between the degree of heterogeneity in the evaluative schemas of the audiences a firm engages with and the first step described above is positive, while that relationship is negative for the second step. We assume that the two effects combine in a multiplicative manner to influence the eventual outcome (Haans, Pieters, & He, 2016), which is the firm's ability to gain an audience composition premium. The outcome of these multiplicative effects is an inverted U-shaped relationship (as illustrated in Figure 3). The reason for our assumption is that contrary to an additive effect between two independent mechanisms, the eventual gain that a firm achieves through each of these steps depends on the other step. In other words, a firm's learning about its audiences is useful only as long as the firm can utilize it, and a firm can utilize its learning to enhance its positioning as long as it has a breadth of knowledge about its audiences. Our proposition of an optimal balance between the need for learning about audiences and the ability to use the knowledge gained to effectively implement positioning strategies is in line with the widely established arguments favoring a balance between the need for exploration, variation, and discovery, on the one hand, and exploitation, implementation, and efficiency, on the other hand (Benner & Tushman, 2002; Gupta, Smith, & Shalley, 2006; March, 1991; Uotila, Maula, Keil, & Zahra, 2009).

By maximizing engagement with audiences holding highly heterogeneous evaluative schemas, firms can increase the breadth of knowledge they learn regarding their audiences and their evaluative schemas. As the variance hypothesis suggests, variety seeking and exploration

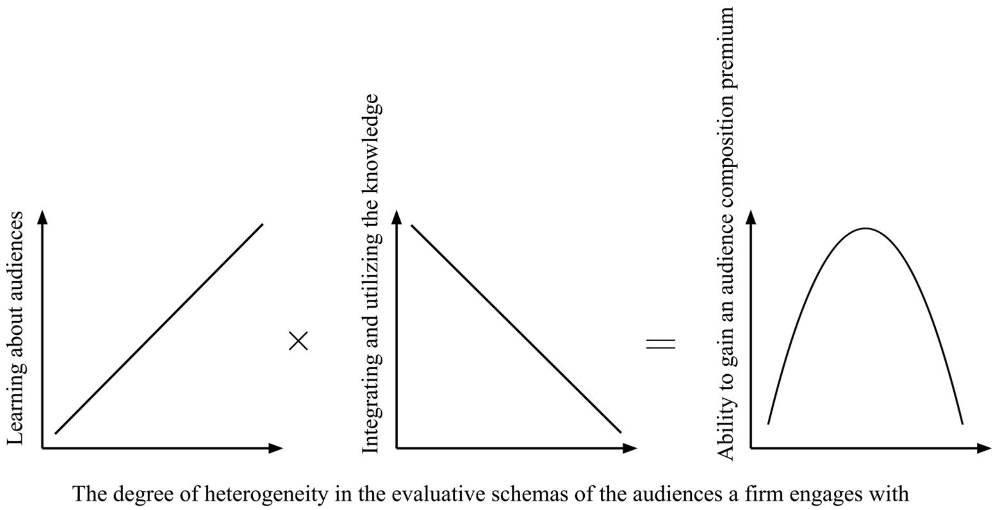

FIGURE 3 The multiplicative effects of (1) learning about audiences and (2) integrating and utilizing the knowledge gained from engagement with audiences on a firm's ability to gain an audience composition premium

enhance learning over time and help firms find optimal solutions to specific situations (Jeppesen & Lakhani, 2010; Laursen & Salter, 2006; Leiponen & Helfat, 2011; March, 1991). Firms that do not expand their learning through exploration and exposure to diverse sources of information risk being stuck with suboptimal equilibria (March, 1991). In the context of learning about audiences, firms that engage with a limited group of audiences with similar evaluative schemas and concerns may forego learning about audiences that would have evaluated them highly favorably were their attention attracted to them. Furthermore, the learning effect from interacting with audiences with heterogeneous evaluative schemas in one period carries over to the next period because a firm's learning capacity increases through its previous interactions (Love et al., 2014). Therefore, we propose there is a positive relationship between the heterogeneity in the evaluative schemas of the audiences that a firm engages with and the firm's knowledge and learning about its audiences and their evaluative schemas.

In contrast, there is a negative relationship between the heterogeneity in the evaluative schemas of the audiences a firm engages with and the firm's ability to successfully utilize the knowledge gained regarding its audiences to craft and deliver information and narratives adjusted to its select audience group. Organizational learning research has shown that while exposure to diverse knowledge can increase learning, it can also harm learning due to the difficulty of reconciling disparate combinations of knowledge (Cattani & Kim, 2021) and the opportunity cost associated with a broad external search (Dahlander, O'Mahony, & Gann, 2016). Thus, in the case of firms learning about their audiences, engaging with highly diverse audiences in terms of their evaluative schemas could dampen a firm's ability to integrate the knowledge gained regarding its audiences. Moreover, to effectively cater to each select audience, firms need to dedicate attention and resources to crafting a fitting narrative and explanation regarding their positions. As Flachetti et al. (2021, p. 6) argued, “because the availability and understandability of the information that is emphasized in a frame are likely to vary across audiences, frames must be ‘chosen with an audience in mind’ (Chong & Druckman, 2007, p. 117) to be effective (Fisher, Kuratko, Bloodgood, & Hornsby, 2017).” Engaging with audiences that are too diverse in terms of their evaluative schemas could hamper a firm's ability to utilize the knowledge gained from audience engagement to craft and deliver information suited to its target audience.

In our context, a key communication channel between analysts and firms is earnings conference calls (Brown, Call, Clement, & Sharp, 2019; Call, Sharp, & Shohfi, 2021). An earnings call is structured with a presentation by the focal company's top management team, followed by an interactive Q&A (discussion) segment with security analysts. Research has shown that the interactive Q&A segment is more informative and influential on analysts and stock market trade activity than the presentation segment (Matsumoto, Pronk, & Roelofsen, 2011). Earnings calls supplement written disclosures, such as 10-K filings, because these meetings are less formal and subject to less legal liability (Frankel, Johnson, & Skinner, 1999), and they also allow for direct two-way communication between analysts and firms' management teams (Matsumoto et al., 2011). Brown et al. (2019) did a survey of public firms' investor relations officers (IROs) and found that earnings calls are regarded as the main event allowing firms to manage their narratives. Therefore, while written reports, such as 10-K filings, are the formal medium for conveying information regarding a firm's positioning to the market, through these earnings calls, firms influence analysts' interpretation of the reports and manage their narratives. As the authors put it (p. 59), "public earnings conference calls are the single most important tool for conveying the company message to institutional investors, which helps explain the desire of company management to carefully manage every aspect of these calls." A survey respondent echoed this point, saying, "[earnings calls provide] a chance to spend the time that is required to explain what you're doing—and you have the full attention of the market at that point." Furthermore, a core function of these calls is to inform managers about analysts' and investors' perspectives regarding their firms. The feedback that analysts provide to firms regarding how they are perceived by the investment community helps firms more effectively manage their narratives (Brown et al., 2019). Indeed, one IRO regarded firms' relationships with security analysts as "communicating in two directions about how a company is performing in relation to its peers" (Brown et al., 2019, p. 66).

The Q&A segments of earnings calls are far from spontaneous. Before each call, most companies try to prepare a list of possible questions and answers and preapprove the list of participants who are prioritized to ask their questions (Bamber & Abraham, 2020; Brown et al., 2019; Cen, Chen, Dasgupta, & Ragunathan, 2016; Mayew, 2008). In other words, companies actively discriminate among analysts by choosing who gets to ask a question and, consequently, who they engage with. In their survey of IROs, Brown et al. (2019) found evidence that most companies do not select Q&A segment participants on a first-come, first-served basis.

Based on our arguments, a company's decisions regarding which analysts it engages with will influence its ability to garner a higher audience composition premium. Engagement with audiences with heterogeneous evaluative schemas allows a firm to gain a breadth of knowledge about its audiences. However, such engagement results in the firm's exposure to many disparate views, taking too much attention and effort for the firm to reconcile and hampering the firm's ability to utilize the knowledge gained to target a select group of audiences and efficiently communicate its narrative with them. The multiplicative interaction between these positive and negative effects results in an inverted U-shaped relationship. Accordingly, we propose the following:

> **Hypothesis (H3).** *There is an inverted U-shaped relationship between the degree of heterogeneity in the evaluative schemas of the audiences a firm engages with and the audience composition premium it gains.*

3 | METHODS

3.1 | Recommender systems: A machine learning approach to predicting audience predispositions

In management research, machine learning techniques have helped advance our methodological frontiers in two regards. First, machine learning algorithms have been utilized as exploratory data-analysis tools for theory building (Puranam, Shrestha, He, & von Krogh, 2020). Machine learning techniques can aid inductive and abductive theory building by discovering patterns in quantitative data that might otherwise go unnoticed by researchers (Choudhury, Allen, & Endres, 2021; Croidieu & Kim, 2018; Puranam et al., 2020; Sen & Puranam, 2022). For example, Tidhar and Eisenhardt (2020) combined machine learning and multicase methods to build a theory about the optimum revenue model in the App Store. Second, machine learning techniques have been used to reveal and measure theoretical constructs that are then used for hypothesis testing with traditional econometrics models (Choudhury, Wang, Carlson, & Khanna, 2019). An example following this approach is the use of topic modeling techniques, such as latent Dirichlet allocation (LDA) (Hannigan et al., 2019), to measure framing repertoires (Giorgi & Weber, 2015), knowledge-recombination characteristics (Kaplan & Vakili, 2015), and strategic differentiation (Haans, 2019).

In this article, we use recommender systems—a powerful class of machine learning models that are underutilized in management research—to predict the heterogeneous predispositions of audiences and use such predictions to study firms' positioning strategies.[5] A large body of research in computer science has focused on using machine learning algorithms to predict the fit between a product and an audience (e.g., Adomavicius & Tuzhilin, 2011; Goldberg, Roeder, Gupta, & Perkins, 2001; Quadrana, Cremonesi, & Jannach, 2018; Schafer, Konstan, & Riedl, 2001; Zhang, Yao, Sun, & Tay, 2019). With the exponential growth of the internet and e-commerce and the growing variety of product offerings, a pressing need emerged to filter which products were recommended to different customers (Ricci, Rokach, & Shapira, 2011). Recommender systems have been widely used to help firms better serve their customers by recommending products to them based on their individual preferences.

A specific event that further popularized recommender systems was the Netflix Prize competition (Bennett & Lanning, 2007). Netflix traditionally used its subscribers' ratings of movies they had previously watched to recommend new movies to them. The competition offered $1,000,000 to any team that could develop an algorithm to increase the accuracy of Netflix's previous model by 10% (in terms of predicted ratings of movies by users). Specifically, the database provided 100 million ratings for 17,000 movies by 500,000 users (on a 1–5 scale), and the task involved predicting user-movie ratings that were not in the database (8.5 billion possible user-movie combinations). Essentially, the task was to fill in the blank cells of a sparse matrix, where only about 1.2% of the cells contained a value. Some of the methods developed by the teams participating in this competition became cornerstones for further developments in recommender system research and application (Ricci et al., 2011). Today, companies like Amazon, Netflix, Spotify, and (Alphabet's) YouTube use sophisticated recommender system algorithms to predict customers' evaluations of merchandise, movies, music, and videos, respectively. Based on these predictions, they choose which products to recommend to a particular user (Lu, Wu,

[5]In Appendix A, we discuss the key differences between machine learning and standard statistical inference for making predictions.

	Features					Users		
	Genre1	Genre 2	Production Date	Runtime	Budget ($M)	Ava	James	Sophia
Avatar	Action	Fantasy	2009	162	237	5	2	3
Atonement	Drama	Romance	2007	123	30	2	4	?
Avengers: Age of Ultron	Action	Fantasy	2015	141	280	?	3	3
Accidental Love	Romance	Drama	2015	100	26	3	5	?
Toy Story 3	Animation	Family	2010	103	200	4	?	4

FIGURE 4 A content-based recommender system. In a content-based recommender system, a user's rating of an item is predicted by examining how the user previously rated items with similar features. For example, in the table above, Ava's rating of the movie *Avengers*: *Age of Ultron* is calculated using her ratings of movies with similar characteristics as *Avengers*: Action/fantasy movies with high budgets, long runtimes, and production dates around 2010 (e.g., Avatar)

Mao, Wang, & Zhang, 2015), often to a satisfactory result. For instance, it was estimated that in the mid-2010 s, more than 80% of the shows people watched on Netflix were attributed to the platform's recommender system (Plummer, 2017).

A recommender system uses users' previous ratings of items (in sample) to predict ratings for user-item pairs for which data are not available (out of sample). There are two basic approaches to developing a recommender system: content-based and collaborative filtering approaches (Aggarwal, 2016). A content-based approach utilizes users' previous ratings of items with specific features to predict their ratings of items with given combinations of features. For example, assume movies are coded based on various features, such as genre, date of production, runtime, budget, and so forth (see Figure 4). The problem here is to find patterns that would predict a user's rating of a movie with certain features given the user's previous ratings of other movies. For example, in Figure 4, to predict Ava's rating of the movie *Avengers*, we can use her rating of a movie like *Avatar*, which is similar to *Avengers* in the features' values. There are two major limitations to this approach: first, it requires coding each item's features, which is often an unreliable, daunting, or even impossible task; second, it does not take advantage of how users with similar preferences have previously rated a specific item. A collaborative filtering approach addresses these two limitations.

Collaborative filtering requires no data regarding the features or content of items. Instead, an algorithm predicts a user's rating of a focal item by examining how other users with similar preferences (i.e., those who have given similar ratings to the same items) previously rated the item. For instance, a collaborative filtering algorithm might predict a user's rating of a movie based on how users with similar preferences rated the movie before (e.g., in Figure 5, Ava's rating of the movie *Avengers* could be predicted based on Alex's previous ratings of the movie because Ava and Alex have demonstrated similar previous ratings). The advantage of a collaborative filtering algorithm is that it does not require explicit codification of each item's features. A major limitation of this approach, however, is the "cold start" problem—namely, making predictions for new users (or items) that have not rated (or been rated by) a large enough sample. In practice, companies sometimes address this issue by using another algorithm, such as a content-based recommender system, for newer users and items.

Multiple algorithms are available for developing a recommender system using a collaborative filtering approach. One of the most popular and efficient of these is FunkSVD

	Users				
	Ava	James	Sophia	Alicia	Alex
Avatar	5	2	3	1	5
Atonement	2	4	?	2	1
Avengers: Age of Ultron	?	3	3	2	5
Accidental Love	3	5	?	?	?
Toy Story 3	4	?	4	3	4
Up	?	2	5	1	5
The Elephant Man	?	5	2	4	?
A Marriage	2	?	?	4	2

FIGURE 5 A collaborative filtering recommender system. In a collaborative filtering recommender system, a user's rating of an item is predicted by examining how other users with similar previous ratings rated the item. For example, in the table above, Ava's rating of the movie *Avengers*: *Age of Ultron* could be estimated using similar users' ratings of the movie. In this case, Ava and Alex seem to have preferences that are relatively aligned

			Latent Feature 3	0.44	-0.17	0.02	0.18	-0.29
			Latent Feature 2	0.20	-0.20	0.08	-0.26	0.11
			Latent Feature 1	0.15	-0.07	-0.03	0.12	0.22
Latent Feature 3	**Latent Feature 2**	**Latent Feature 1**		**Ava**	**James**	**Sophia**	**Alicia**	**Alex**
0.08	0.18	0.10	**Avatar**	5	2	3	1	5
0.09	-0.13	-0.28	**Atonement**	2	4	?	2	1
-0.14	-0.18	0.03	**Avengers: Age of Ultron**	?	3	3	2	5
-0.08	-0.14	0.02	**Accidental Love**	3	5	?	?	?
-0.10	0.13	0.00	**Toy Story 3**	4	?	4	3	4
-0.19	0.15	-0.03	**Up**	?	2	5	1	5
-0.06	-0.31	0.00	**The Elephant Man**	?	5	2	4	?
0.14	-0.27	-0.04	**A Marriage**	2	?	?	4	2

FIGURE 6 The FunkSVD algorithm for a collaborative filtering recommender system. In the FunkSVD algorithm, the weight of each latent factor is estimated for each user and each item. These weights are estimated such that prediction accuracy is maximized. While the weights are estimated by training the model on the in-sample observations (i.e., user-item pairs for which we have data), they could be used to make predictions regarding out-of-sample pairs (i.e., user-item pairs for which we do not have data).

(Funk, 2006). This algorithm tied for third place in the aforementioned Netflix Prize competition and gained significant traction due to its simplicity and relatively low implementation cost.[6] Intuitively, this algorithm turns the high-dimensional user-item space into a latent lower-dimensional space. As Funk described in his blog[7] regarding his approach to the Netflix competition, "presumably there are some generalities to be found [in the data], something more

[6]Netflix never used the algorithm that won first place because it was overly complicated (Falk, 2019).
[7]https://sifter.org/~simon/journal/20061211.html.

concise and descriptive than 8.5 billion completely independent and unrelated ratings … A lot of the 8.5 billion ratings ought to be explainable by a lot less than 8.5 billion numbers." For instance, in the case of predicting movie ratings, the FunkSVD algorithm could be used to estimate each user's preferences and each item's attributes along 15–20 latent features. Thus, each user and each item would be assigned a vector of corresponding weights for the latent features. A user's predicted rating of an item could be calculated using the dot product between the user's and the item's feature weight vectors. In the example illustrated in Figure 6, to estimate Ava's rating of the movie *Avengers*, we can calculate the dot product between Ava's feature vector and *Avenger*'s feature vector (global, user, and item averages should be added after calculating the dot product between the user and item feature weight vectors). While the estimated features could correspond to interpretable variables, such as genre, budget, production year, and so forth, they are mathematical constructs built to optimize prediction accuracy and are not necessarily open to interpretation. There are various computational methods for estimating latent feature weights such that the errors between predicted ratings and observed ratings are minimized. Most of these methods, such as gradient descent or stochastic descent, start from some predefined initial parameters (e.g., all feature weights initiated randomly) before updating the parameters through rounds of iterations that aim at reducing some cost function (e.g., sum of squared errors). The algorithm stops once the parameters yield an error term below a prespecified value. We provide a more detailed overview of the FunkSVD algorithm in Appendix B.

3.2 | Predicting analysts' investment recommendations

We developed a model that predicts security analysts' investment recommendations of U.S. public firms using the Institutional Brokers' Estimate System's (IBES) Recommendations Detail dataset. Within the IBES dataset, we kept an analyst's latest investment recommendation on a firm in each calendar year (Westphal & Graebner, 2010). We reverse scored the IBES's standardized recommendations by subtracting it from 6 so that a higher score corresponds with a more favorable investment recommendation (5 being the most favorable and 1 being the least). We limited the sample to firms that had at least five analysts covering them in a given year and analysts who had covered at least 10 firms in their portfolios historically. In addition, we dropped unnamed analysts from our dataset. To construct a variable regarding firms' probability of being covered by specific analysts (as discussed later), we used firms' business descriptions in their 10-K filings. Therefore, we limited our sample to firms whose 10-K filings were available on the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. To construct control variables, we limited our dataset to firms with accounting data on Compustat. Our final sample consists of 152,312 firm-analyst-year observations.

3.2.1 | Model estimation

We developed a FunkSVD model to predict security analysts' investment recommendations regarding specific firms.[8] The FunkSVD algorithm takes input in the form of user, item, and rating. In our case, a user is an analyst's unique identifier, an item is a firm-year combination,

[8]We have publicly shared the code for our models and empirical analysis on a GitHub repository. Please see https://github.com/Majid-Majzoubi/Audience-Composition-Premium.

and the rating is the analyst's latest recommendation for that firm in the specific year.[9] To develop the FunkSVD model, we needed to determine three key hyperparameters: number of factors, learning rate, and regularization term (technical details explained in Appendix B). We randomly split our data into three segments: a training set (80% of the data), a validation set (10% of the data), and a test set (10% of the data). We trained our models using the training set and then tested the accuracy of the predictions against the data in the validation set to tune the model's hyperparameters. The test set was only used for a final test of the model's accuracy after tuning it. In Figure 7, we plot the mean squared error (MSE; the average squared difference between the predicted recommendations using the model trained on the training set and the actual recommendations in the validation set) for different numbers of factors (from 50 to 1,000, at 50-unit increments). Based on this plot, we set the number of factors to 400. We used a similar approach for determining the algorithm's learning rate and regularization term. Figures 8 and 9 illustrate the resulting MSE for different values of the learning rates and regularization terms, respectively. As shown, the lowest MSE is obtained when the learning rate is set to 0.005 and the regularization term is set to 0.2. We thus trained the FunkSVD model with 400 factors with a learning rate of 0.005 and a regularization term of 0.2.[10]

The trained model had high accuracy in predicting analysts' recommendations. We used the model trained with data from the training set to test how accurately it predicted recommendations for our sample in the test set (the test set was not used for training or tuning the model). The MSE between the predicted and actual recommendations is 0.734. Regressing the actual recommendations (y) against the predicted recommendations (x), the coefficient for predicted recommendations is 0.797 with a *p*-value of .000 (Table 2). The predicted recommendations are therefore strong predictors of the actual recommendations (Piñeiro, Perelman, Guerschman, & Paruelo, 2008). We graph the predicted ratings against actual ratings in Figure 10. The graph further illustrates the strong correlation between predicted recommendations and actual recommendations.

3.3 | Audience composition premium

We conceptualized audience composition premium as the difference between the evaluation that a firm would receive from an audience composition related to a specific market position and the average evaluation it would receive from all audiences. In our context, we operationalized the audience composition premium variable by subtracting the average predicted rating of all analysts from the average predicted rating of analysts who are likely to cover a firm based on its position.

To estimate the probability of a firm receiving coverage from each analyst based on its strategic positioning, we examined how close (similar) the firm is positioned to other firms in the specific analyst's portfolio. The assumption here is that a firm is more likely to receive coverage

[9]It is worthwhile to note that the FunkSVD algorithm is not a time-aware recommender system, meaning that it does not incorporate a time element in its modeling approach. The FunkSVD algorithm makes predictions by filling in the gaps in a two-dimensional user-item matrix. Hence, we use a firm-year combination as the unit of an item in our model. We discuss the advantages and disadvantages of this approach in the discussion section.

[10]Note that the algorithm uses a stochastic learning process, and therefore, the resulting models could be different each time they are trained on the same data. Hence, one might get slightly different results when tuning for hyperparameters. As robustness checks, we trained the FunkSVD model using different numbers of factors (200, 300, 500). Our results remain qualitatively unchanged.

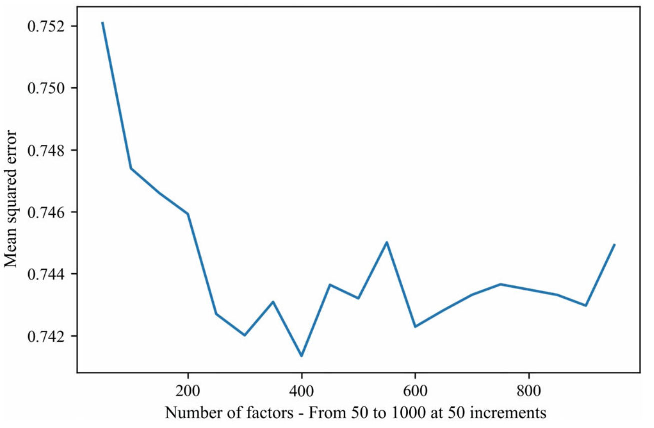

FIGURE 7 Mean squared error between predicted and actual recommendations for models with different numbers of factors

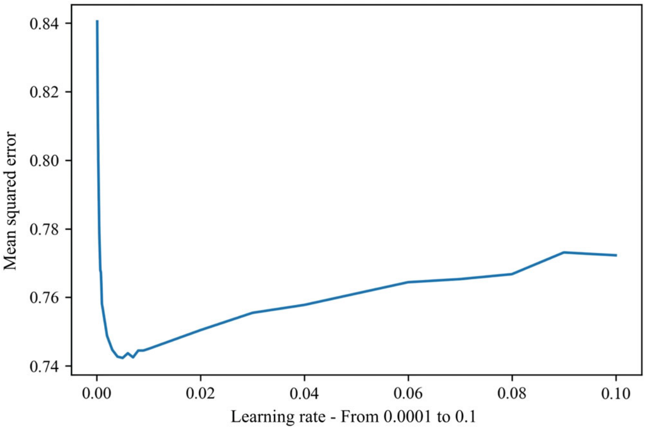

FIGURE 8 Mean squared error between predicted and actual recommendations for models with different values of learning rates

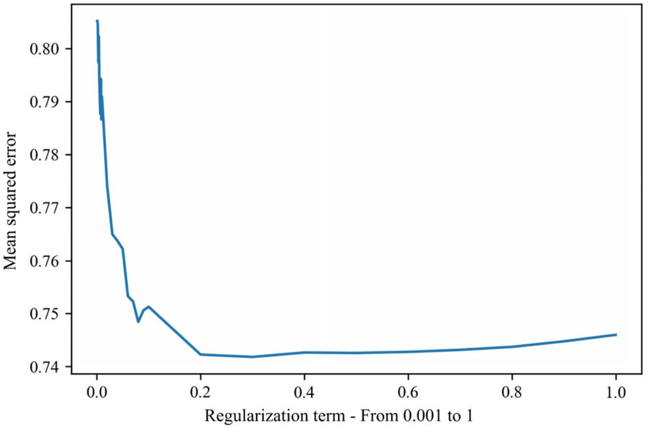

FIGURE 9 Mean squared error between predicted and actual recommendations for models with different regularization term values

TABLE 2 Regressing security analysts' actual recommendations on predicted recommendations of U.S. public firms

	Dependent variable: Actual recommendations			
	β	***p***	**Conf. Int. 0.025**	**Conf. Int. 0.975**
Predicted recommendations	.797	.000	0.763	0.830
Intercept	.724	.000	0.605	0.844
Number of observations	15,231			
R^2	.125			
F-statistic	2,183.0			
Prob (*F*-statistic)	.000			

(attention) from an analyst who covers similar and comparable other firms (Bowers, 2015). To measure the similarity between firms in an analyst's coverage portfolio, we applied a topic modeling algorithm to firms' business description sections in their 10-K reports. Topic modeling uses the statistical co-occurrence of words in documents to identify latent topics within a corpus (for a review, see Hannigan et al., 2019). We used the LDA (Blei, Ng, & Jordan, 2003) algorithm to discover the latent topics in our corpus of firms' business descriptions. The LDA algorithm assumes that each document includes a mixture of topics and that each topic itself includes a mixture of different words. Therefore, the algorithm finds an optimal solution for a two-layer distribution of topics within documents and terms within topics. To determine the appropriate number of topics in our model, we evaluated our model's log perplexity and coherence scores for different numbers of topics (results shown in Figure 11). Perplexity score is an evaluation metric for a model's generalizability, showing how well the model can predict a test sample that was not used in training the model (Blei et al., 2003). Coherence score measures semantic similarity between the top words in each topic (Syed & Spruit, 2017). As shown in Figure 11, both the perplexity and coherence scores point to an optimal outcome when setting the number of topics at 70.[11] Thus, we developed a topic model with the number of topics set at 70.[12] We then used Jensen–Shannon (JS) divergence[13] to measure the similarity between firms based on their topic weight vectors. We averaged the topic weight vectors of all firms covered by an analyst and measured each firm's distance to this averaged vector.

An exploratory analysis confirmed that there is a high degree of correlation between the probability of a firm being covered by an analyst and that firm's similarity to other firms in the analyst's coverage portfolio. In our sample, the mean similarity score between a firm and the portfolio of an analyst who covers it is .680 versus .232 for the similarity score between a firm and the portfolio of any analyst, regardless of whether the analyst covers the firm or not. This analysis corroborates our assumption that a firm's probability of being covered by an analyst is directly proportional to the similarity between that firm and all firms in the analyst's coverage portfolio:

[11]Our results are highly robust to the choice of number of topics for our topic model. We tested our main regression models using various numbers of topics (50, 100, 150, 200) and generated consistent results.

[12]Topic modeling using the LDA algorithm requires selecting two other key hyperparameters: alpha (document-topic density) and beta (topic-word density) values. We allowed Python's Gensim package to learn these two hyperparameters automatically.

[13]JS divergence is a preferred method for measuring differences between probability distributions. We thank our anonymous reviewer for bringing this to our attention.

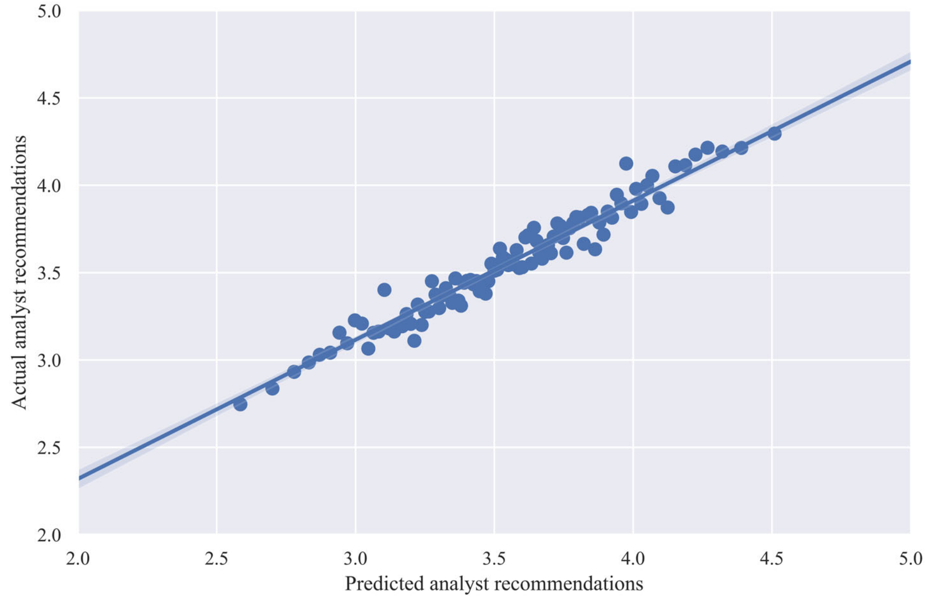

FIGURE 10 Analysts' recommendations on U.S. public firms: Predicted recommendations versus actual recommendations. For visual clarity, we have plotted the average of predicted recommendations and corresponding average actual recommendations for 100 bins, as represented by each circle in the graph

$$Pr_{ij} \propto \text{Similarity}_{ij},$$

where $Pr_{i\,j}$ is the probability that analyst j will cover firm i, and $\text{Similarity}_{i\,j}$ is the similarity between firm i and analyst j's coverage portfolio based on firms' business descriptions.

To estimate our measure of audience composition premium for each firm-year in our sample (15,567 observations), we calculated the probability of garnering coverage by each specific analyst and the predicted evaluation of the firm by that specific analyst. There were 32,106,812 such combinations in our sample.[14] We used our previously constructed FunkSVD model to estimate the predicted investment recommendation of each specific analyst toward a firm for all the firm-analyst-year combinations. We then used the formula below to calculate a firm's audience composition premium in each given year:

$$\text{Audience Composition Premium}_i = \frac{\sum_j Pr_{ij} * \text{Rating}_{ij}}{\sum_j Pr_{ij}} - \frac{\sum_j \text{Rating}_{ij}}{N},$$

where $Pr_{i\,j}$ is the similarity between firm i and analyst j's portfolio, $\text{Rating}_{i\,j}$ is the predicted rating of analyst j of firm i, and N is the total number of predicted ratings for firm i. Figure 12

[14]It is worth mentioning again that we had only 152,312 firm-analyst-year combinations in our dataset with actual investment recommendations. That is because in any given year, each analyst only covers a few firms, and each firm is covered by only a few analysts. In other words, the matrix containing actual firm-analyst data is a sparse matrix. A recommender system, however, is capable of generating predictions for all possible firm-analyst pairs in a given year. In other words, the matrix containing predicted firm-analyst data are a dense matrix. Thus, there is the observed difference between 152,312 actual recommendations and 32,106,812 predicted recommendations.

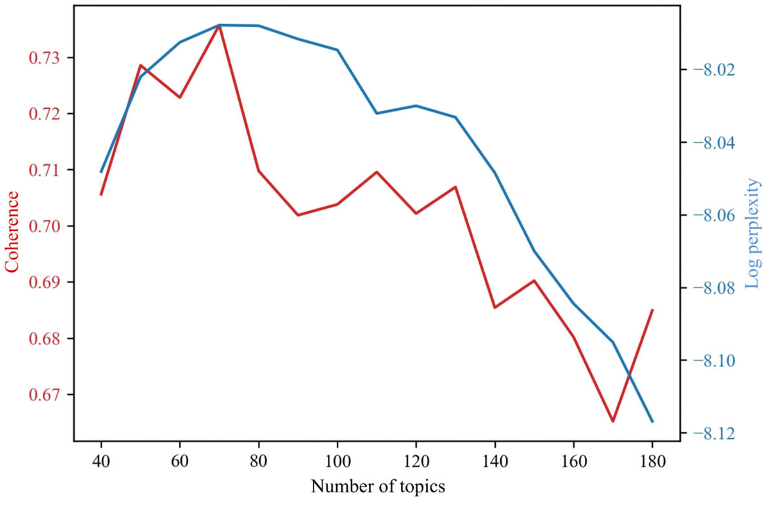

FIGURE 11 Evaluating the topic models on firms' 10-K filings based on different numbers of topics

shows the distribution of this variable. As shown, while some firms enjoy a positive audience composition premium, others experience a negative audience composition premium (alternatively, an audience composition penalty).

We tested the effect of audience composition premium on the aggregate investment recommendation a firm receives from the analysts who follow it, while controlling for other covariates established in prior research. In particular, we controlled for firm size using trade volume (log), for firm performance using return on equity (ROE) and market share, and for firm strategic resource allocation using advertising intensity and intangibles and depreciation as shares of total assets (Litov et al., 2012). We also controlled for merger and acquisition (M&A) activity using a mergers expenditure (log) variable since M&As have been shown to affect analyst coverage (Sibilkov, Straska, & Waller, 2013). We also controlled for the number of segments in which a firm reports sales (four-digit Standard Industrial Classification [SIC] codes) and firm typicality—namely, each firm's average similarity to other firms in its industry (four-digit SIC)—as these factors have been shown to affect audience evaluations (Smith, 2011; Zuckerman, 1999). Firm typicality was measured using the same LDA model previously implemented for measuring similarity between firms and analysts' portfolios. At the industry level, we controlled for the number of firms in the industry, industry concentration, and industry heterogeneity (Haans, 2019).[15]

3.4 | Dispersion in audience predispositions

To measure this construct, we took the *SD* of all analysts' predicted investment recommendations for a given firm in a given year.[16] A high value of this variable indicates that security analysts would come to highly divergent investment recommendations for the firm if they were to

[15]Please see Table 3 for more detailed descriptions of and measurement approaches for these variables.

[16]In the Section 4.1, we discuss an alternative approach for measuring dispersion in audience predispositions toward a firm. We specifically used the method developed by Zuckerman (2004) to measure the incoherence in the coverage networks of analysts, which has been shown to result in divergent evaluations of a firm by security analysts.

evaluate the firm. Conversely, a low number indicates a higher level of convergence in analysts' predicted recommendations.

3.5 | Heterogeneity in the evaluative schemas of the audiences a firm engages with

Public earnings calls are the primary channel for two-directional communication between firms and security analysts. Through these calls, a firm can both learn about analysts' and the market's evaluative schemas and manage its narrative in response to analysts' questions. Questions that are asked during these calls represent various views and evaluative concerns that analysts have regarding firms. Our approach in analyzing analysts' questions in the Q&A segments of earnings calls is similar to Benner and Ranganathan's (2017) study. As the authors mentioned, "our premise is that the language in these discourses reflects the cognitive representations that constitute analysts' evaluative schemas" (p. 761).

Firms carefully choose the questions to engage with during the Q&A segments of their calls (Bamber & Abraham, 2020). Therefore, the heterogeneity in the questions that are engaged with during earnings calls is a good proxy for whether a firm decides to engage with audiences that hold different evaluative schemas and concerns or whether it prefers to only engage with a narrow and specific group of audiences with similar concerns and questions. Therefore, we measured the heterogeneity in the evaluative schemas of the audiences a firm engages with during its earnings calls by investigating the heterogeneity in broad conceptual concerns raised in the questions the firm decided to engage with during its calls.

Data for earnings call conferences was collected from the Wharton Research Data Services Capital IQ Transcripts dataset. The data are only available from 2008. We identified 6,188,252 questions that were asked by analysts during a total of 297,931 earnings call events, with an average of 20.7 questions per event. The questions have 54 words on average.[17] We combined the questions asked during all events within a year for each firm. Next, we removed all stop words, numeric values, and words that are only one character. We created a bigram transformation of our texts and lemmatized all the words.

To identify the broad evaluative concerns and questions expressed during earnings calls by analysts, we applied LDA topic modeling to the corpus of all asked questions. Similar to our approach with 10-K filings, we used coherence and log perplexity metrics to evaluate our topic models while using different numbers of topics. As Figure 13 shows, we obtained the highest coherence value when setting the number of topics at 30. The log perplexity score is also almost at its optimum when the number of topics is set to 30.

We measured the heterogeneity in the topics of questions that were asked during earnings call events for a firm in a specific year. Specifically, we followed the formula used by Haans (2019) to construct a heterogeneity metric using topic modeling:

$$\text{Heterogeneity in the evaluative schemas of the audiences a firm engages with} \\ = \sum_{T=1}^{30} \frac{1}{N-1} \sum_{i=1}^{N} \left(\theta_{T,i} - \overline{\theta}_{T,I}\right)^2,$$

[17] We only had access to about the first 50 words (256 characters) of each question.

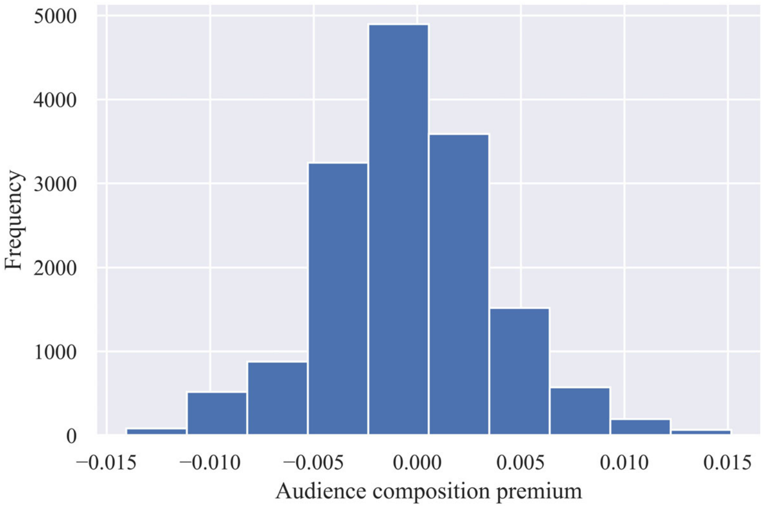

FIGURE 12 Distribution of the audience composition premium variable

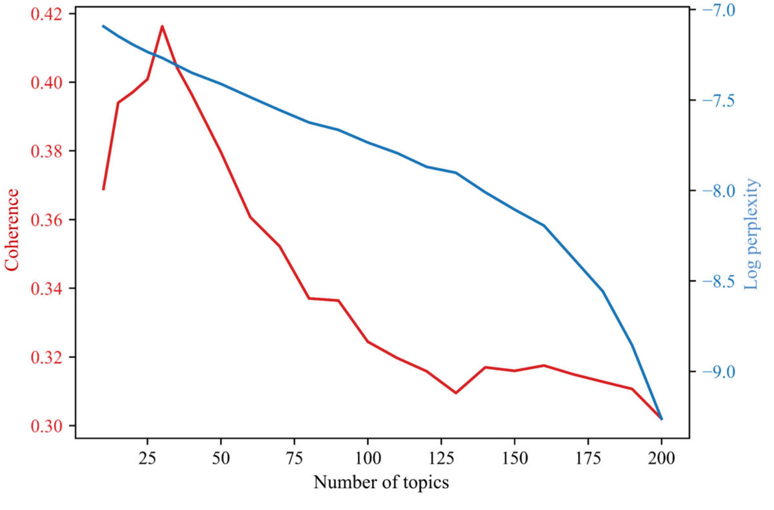

FIGURE 13 Evaluating the topic models on questions asked during earnings calls based on different numbers of topics

where N is the total number of questions asked for firm I in a given year; $\theta_{T,i}$ is the weight of topic T in question i; and $\overline{\theta}_{T,I}$ is the average weight of topic T for all questions asked during firm I's earnings calls in the given year.

Using the same data, we generated some control variables related to the earnings calls. For each firm in a given year, we counted the total number of questions; the total number of unique analysts asking questions; the total number of words in questions; the total number of words in the presentation segments; and the total number of words in the earnings calls, including the answers given by managers during the Q&A segments. We added 1 to each of these control variables and used their log transformation in our regression models.

TABLE 3 Descriptive statistics and measurement of variables

	Mean	*SD*	Description
Key variables			
Aggregate investment recommendations	3.673	0.388	The average of recommendations given to a firm in a given fiscal year by all analysts covering it. Only the latest recommendation is kept for each analyst.
Audience composition premium	−0.000	0.004	Developed a FunkSVD model using the training set. Used the model to predict ratings for all possible firm-analyst pairs in each year. Used the formula below to calculate the audience composition premium: $\frac{\sum_j Pr_{ij} * \text{Rating}_{ij}}{\sum_i Pr_{ij}} - \frac{\sum_j \text{Rating}_{ij}}{N}$.
Dispersion in audience predispositions	0.238	0.005	The *SD* of all the predicted investment recommendations (obtained using the FunkSVD model) for a firm in a given year.
Control variables			
Trade volume (log)	19.499	1.279	Log of total annual trade volume.
ROE	0.988	2.229	Return on equity. NI/(CSHO*PRCC_F) using Compustat variables.
Market share	0.105	0.166	Firm sales divided by total sales in a firm's primary industry (four-digit SIC).
Advertising intensity	0.015	0.038	Advertising expenditure divided by total operating expenditure.
Intangibles (share of total assets)	0.168	0.197	Intangibles as part of fixed assets divided by total assets.
Depreciation (share of total assets)	0.038	0.035	Total depreciation and amortization divided by total assets.
Mergers expenditure (log)	−9.777	129.024	Log of pre-tax merger or acquisition expenditure.
Number of segments	1.518	1.012	The number of business segments in which a firm reports sales (the number of unique four-digit SIC codes).
Firm typicality	0.498	0.166	Developed a topic model on firms' business descriptions. Measured the similarity between a firm's topic weight vector and that of its industry's average.
Number of firms in industry	76.292	90.563	The number of firms in a firm's industry (four-digit SIC).
Industry concentration	1,116.997	1,299.565	Industry concentration measured by the Herfindahl–Hirschman index.

TABLE 3 (Continued)

	Mean	*SD*	Description
Industry heterogeneity	0.071	0.028	Developed a topic model on firms' business descriptions. Measured the distance between a firm's topic model weight vector and that of its industry's average, summed the squared distances, and divided by the total number of firms.
Number of following analysts	15.915	6.639	The total number of analysts who issued investment recommendations for the firm in a given year.
Variables from earnings call transcripts			
Heterogeneity in the evaluative schemas of the audiences a firm engages with	0.407	0.026	Applied LDA topic modeling on the questions asked during firms' earnings calls. Next, used the topic weights to construct a measure of the heterogeneity in questions using the following formula: $\sum_{T=1}^{30} \frac{1}{N-1} \sum_{i=1}^{N} \left(\theta_{T,i} - \overline{\theta}_{T,I}\right)^2$.
Total number of questions	139.939	62.799	The number of questions that were asked during all earnings call events in a given year for a firm.
Total number of analysts asking questions	41.216	17.652	The number of unique analysts who asked questions during all the earnings call events in a given year for a firm.
Total number of words in questions	6,944.003	3,629.785	The total number of words in all the questions asked during all the earnings call events in a given year for a firm.
Total number of words in presentations	19,388.363	14,385.797	The total number of words in the presentation segments of all the earnings call events in a given year for a firm.
Total number of words in earnings calls	46,924.993	27,614.993	The total number of words spoken in all the earnings call events in a given year for a firm.

4 | RESULTS

In Table 3, we provide the descriptive statistics of our variables along with a brief overview of our measurement approaches. In our regression models, we first examine the relationship between audience composition premium and firms' aggregate recommendations. Since our dependent variable is a continuous variable, we used ordinary least squares regressions. Model 1 in Table 4 shows the effect of the audience composition premium variable on aggregate recommendations. Model 2 is similar to Model 1, except it controls for other covariates. The coefficient for analyst composition premium in Model 2 supports our Hypothesis (H1) that a firm that positions itself toward audiences with favorable predispositions will garner higher aggregate recommendations ($\beta = 28.902$; $p = .000$). The results suggest that a better positioning strategy resulting in an increase of 1 *SD* in audience composition premium could yield an increase of 0.30 *SD* in analyst recommendations.

Model 3 in Table 4 shows the moderation effect of dispersion in audience predispositions on the impact of audience composition premium on aggregate recommendations. As shown, while

TABLE 4 Effects of audience composition premium on aggregate investment recommendations of U.S. public firms

	Dependent variable: Aggregate investment recommendations					
	Model 1		**Model 2**		**Model 3**	
	β	***p***	***β***	***p***	***β***	***p***
Audience composition premium	26.070	.000	28.902	.000	−114.280	.007
Audience composition premium × dispersion in audience predispositions					602.452	.001
Dispersion in audience predispositions					−2.547	.000
Trade volume (log)			−.010	.010	−.010	.008
ROE			.0.018	.000	.017	.000
Market share			.101	.000	.104	.000
Advertising intensity			−.034	.725	−.056	.565
Intangibles (share of total assets)			.177	.000	.170	.000
Depreciation (share of total assets)			−.317	.005	−.288	.011
Mergers expenditure (log)			.000	.003	.000	.003
Number of segments			−.005	.238	−.004	.305
Firm typicality			−.071	.004	−.074	.002
Number of firms in industry			.000	.000	.000	.000
Industry concentration			.000	.003	.000	.005
Industry heterogeneity			−.093	.541	−.063	.678
Number of following analysts			−.003	.000	−.003	.000
Constant	3.687	.000	3.889	.000	4.504	.000
Number of observations	10,361		10,361		10,361	
R^2	.076		.104		.107	
F-statistic	852.266		86.094		77.164	
Prob (*F*-statistic)	.000		.000		.000	

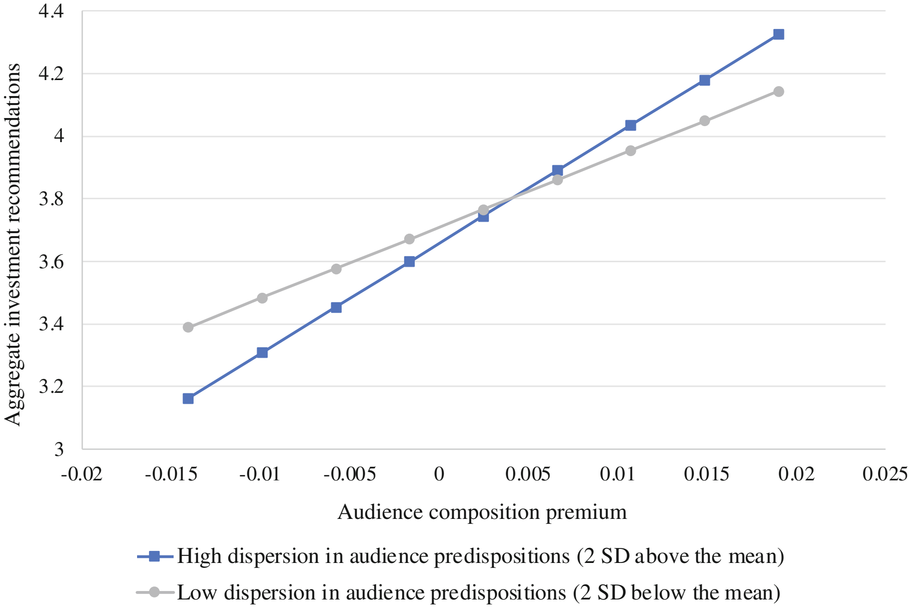

FIGURE 14 Effects of audience composition premium on analyst recommendations for low (2 *SD* below mean) and high (2 *SD* above mean) dispersion in audience predispositions based on the results from Model 3 in Table 4 (all other variables at their means)

the coefficient for audience composition premium becomes negative ($\beta = -114.280$; $p = .007$), the coefficient for the interaction between dispersion in audience predispositions and audience composition premium is positive and statistically significant ($\beta = 602.452$; $p = .001$), supporting our Hypothesis (H2). The results indicate that the positive effect of audience composition premium on analyst recommendations is stronger when there is a higher degree of dispersion in audience predispositions. Figure 14 illustrates the effects of audience composition premium for firms with low (2 *SD* below mean) and high (2 *SD* above mean) dispersion in audience predispositions. This result suggests that the positive effect of a 1 *SD* increase in audience composition premium is about 54% higher for a firm with high dispersion in audience predispositions (2 *SD* above mean) than the same effect for a firm with low dispersion (2 *SD* below mean).

In Models 4 and 5 in Table 5, we tested Hypothesis (H3), which proposes there is an inverted U-shaped relationship between the heterogeneity in the evaluative schemas of the audiences a firm engages with and the audience composition premium it garners. In Model 4, we regressed audience composition premium on heterogeneity in the evaluative schemas of audiences and its squared term. We created a 1-year lag between our independent and dependent variables. In Model 5, we included the control variables. As the results of Model 5 show, the coefficient for heterogeneity in the evaluative schemas of audiences is positive and significant ($\beta = 0.373$; $p = .000$), while the coefficient for its squared term is negative and significant ($\beta = -0.543$; $p = .000$). These results provide support for our Hypothesis (H3). The turning point of the curve is 0.343, which is well within the range of our heterogeneity in the evaluative schemas of audiences variable (min = 0.288, and max = 0.476). For ease of interpretation, we illustrate the results in Figure 15.

TABLE 5 Effects of heterogeneity in the evaluative schemas of the audiences a firm engages with on its audience composition premium

	Dependent variable: Audience composition premium			
	Model 4		**Model 5**	
	β	***p***	***β***	***p***
Heterogeneity in the evaluative schemas of the audiences a firm engages with	.449	.000	.373	.000
Heterogeneity in the evaluative schemas of the audiences a firm engages with (squared)	−.600	.000	−.543	.000
Total number of questions			−.003	.000
Total number of analysts asking questions			.000	0.814
Total number of words in questions			.003	.000
Total number of words in presentations			.001	.002
Total number of words in earnings calls			−.001	.391
Constant	−.083	.000	−.076	.000
Number of observations	2,164.000		2,164.000	
R^2	.037		.074	
F-statistic	41.138		24.705	
Prob (*F*-statistic)	.000		.000	

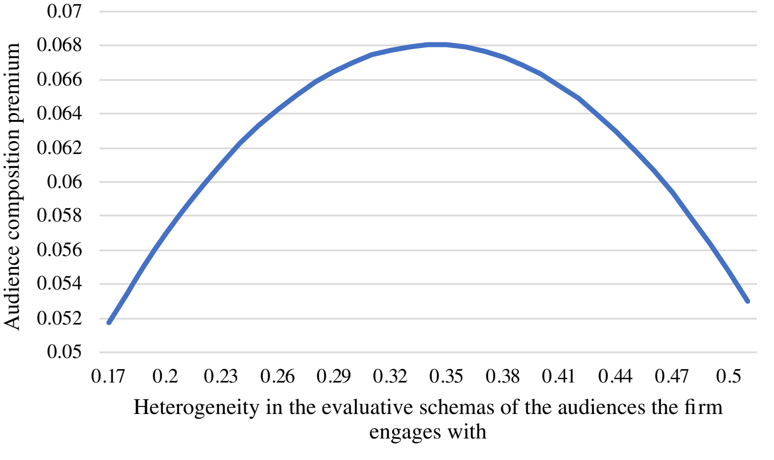

FIGURE 15 Effects of heterogeneity in the evaluative schemas of the audiences a firm engages with on audience composition premium based on the results from Model 5 in Table 5 (all other variables at their means, constant value not included)

4.1 | Additional analysis

We tested our moderation effect using an alternative operationalization of dispersion in audience predispositions. To measure the coherence of the network of analysts following a firm, Zuckerman (2004) examined the degree of overlap between the following analysts' coverage portfolios. The logic behind this metric is that the coverage portfolio of each analyst is a good proxy for his or her idiosyncratic, path-dependent, evaluative models and specializations. Therefore, an analyst covering Amazon, Netflix, and Twitter will likely have a different set of evaluative models than an analyst covering Amazon, Walmart, and Target.

We followed Zuckerman (2004) and used the following approach to calculate an alternative operationalization for a firm's dispersion in its audience predispositions. First, we measured the degree of portfolio overlap between two analysts in our sample by dividing the number of shared stocks by the number of stocks covered by the analyst with the larger portfolio. Next, we used the following formula to measure audience dispersion for each firm:

$$\text{Dispersion in audience predispositions}_i = -1 * \frac{\sum \text{Overlap}_{m,n}}{N(N-1)/2},$$

where $\text{Overlap}_{m,n}$ is the degree of portfolio overlap for analyst m and analyst n who follow the firm, and N is the total number of analysts covering firm i. There are $N(N\text{-}1)/2$ unique pairs of analysts m and n covering the firm.

Using this alternative measure for dispersion in audience predispositions, we reran the regression in Model 3. In our results, the coefficient for the interaction between dispersion in audience predispositions and audience composition premium was positive and statistically significant ($ß = 36.629$; $p = .009$), providing further support for our Hypothesis (H2). The effect size is comparable to what we found using our original measurement of dispersion in audience predispositions. Specifically, the positive effect of a 1 *SD* increase in audience composition premium is about 48% higher for a firm with high dispersion in audience predispositions (2 *SD* above mean) than the same effect for a firm with low dispersion in audience predispositions (2 *SD* below mean).

5 | DISCUSSION AND CONCLUSION

Extant research has conceptualized that audiences evaluate organizations through a sequential two-stage process: first, they screen for firms that are worthy of their attention, and second, they evaluate and rank the ones that pass the first stage (Häubl & Trifts, 2000; Hsu et al., 2012; Shocker et al., 1991; Zuckerman, 1999, 2017). As such, firms need to adopt strategies, such as conforming to category prototypes (Deephouse, 1999; Haans, 2019) or category exemplars (Barlow et al., 2019; Zhao et al., 2018), to garner audience attention and pass through the first stage of audience evaluations. Research has thus explored optimal positioning strategies vis-à-vis commonly held categorical benchmarks. More recently, studies have examined the heterogeneity in audiences' evaluative schemas and, as a consequence, heterogeneity in their predispositions (Beunza & Garud, 2007; Falchetti et al., 2022; Kim & Jensen, 2011; Kovács & Sharkey, 2014; Paolella & Durand, 2016; Pontikes, 2012).

The premise of heterogeneity in audience predispositions motivated us to revisit the traditional optimal distinctiveness thesis built around the two-stage evaluation model. We argued that firms could gain an audience composition premium if they influence the composition of the audiences evaluating them such that a larger proportion of evaluations are from audiences with a favorable predisposition toward them. In contrast to prior literature, our approach focuses on audiences instead of categorical benchmarks, emphasizes idiosyncrasies in predispositions and evaluative schemas as opposed to commonalities, conceptualizes the two-stage evaluation framework as interdependent as opposed to independent, and further highlights firms' agency in influencing the evaluation lenses through which they are evaluated.

Furthermore, we posited that the benefits of positioning with the aim of increasing the audience composition premium are amplified for firms that witness a high degree of dispersion in their audience predispositions. Moreover, given the relative complexity of learning about the diverse evaluative schemas underlying the heterogeneous predispositions of audiences and adjusting firm narratives accordingly, we explored how firms can improve their audience composition premium by engaging with audiences with heterogeneous evaluative schemas and concerns. We argued that engagement with audiences with heterogeneous evaluative schemas enhances firms' ability to learn about their audiences (Leiponen & Helfat, 2011; Love et al., 2014). However, a high degree of heterogeneity in the evaluative schemas of the audiences a firm engages with reduces the firm's ability to successfully integrate the diverse set of knowledge it has gained regarding its audiences and hampers the firm's ability to utilize the knowledge to adjust its narrative according to its target audience groups. Therefore, we posited an inverted U-shaped relationship between the heterogeneity in the evaluative schemas of the audiences a firm engages with and its audience composition premium.

We empirically tested our proposed approach to firm positioning in the context of investment recommendations that U.S. public firms received from security analysts between 1997 and 2018. Introducing a new family of machine learning models to management research, we showed how the predictive power of recommender systems could be utilized to predict security analysts' evaluations of firms. In addition to recommender systems, we used topic modeling on firms' corporate filings and analysts' questions during earnings calls to operationalize our measurements of audience composition premium and engagement with audiences holding heterogeneous evaluative schemas. The results of our empirical tests provide strong support for our theoretical arguments.

5.1 | Contributions

5.1.1 | Contributions to strategic positioning and audience evaluation research

First, we advance an alternative approach to strategic positioning that focuses on heterogeneous audience predispositions toward firms as opposed to commonly held categorical benchmarks. Our work thus answers the recent call by scholars to examine the role of heterogeneities within audiences in firms' optimal positioning strategies (Durand & Haans, 2022; Fisher, 2020; Pontikes, 2012; Zhao et al., 2017). We extend prior theories building on the two-stage evaluation model (Hsu et al., 2012; Zuckerman, 1999, 2017) and research exploring strategies firms could adopt to garner audience attention (e.g., Barlow et al., 2019; Deephouse, 1999; Navis & Glynn, 2011; Zhao et al., 2018). By bringing to the forefront the premise of heterogeneity in audience predispositions toward a firm, we show the importance of studying the interdependent effects of a firm's positioning strategy on both stages in the evaluation process. Specifically, we show that firms need to strategically influence a specific audience's attention (Stage 1) based on how the audience would evaluate them (Stage 2). Moreover, we argue that not all attention is (equally) positive; receiving attention from an audience member who has an unfavorable predisposition toward a firm could actually harm the firm's total evaluations.

Second, by exploring dispersion in audience predispositions as a moderator of the benefits of an audience composition premium, we show that it is specifically important for firms with a heterogeneous body of evaluators to aim at improving the composition of their audiences. Durand and Haans (2022, p. 7) suggest that "the thicker the boundaries separating categories, the higher the categorical contrast and the higher the penalty when spanning categories (Hsu et al., 2009)—enabling organizations to crisply define their direct competitors and subsequently optimize their positioning strategies." We suggest that optimal positioning relative to categorical benchmarks is beneficial and relevant for firms to the extent that their audiences are not heterogeneous in their evaluative schemas and predispositions toward them. Therefore, in the extreme scenario in which each individual audience of a firm holds its own idiosyncratic evaluative schema and predisposition toward the firm, an optimal positioning strategy involves focusing on the audience members as opposed to common categorical benchmarks in the environment. In the same vein, for the extreme scenario in which all audiences hold similar evaluative schemas and predispositions regarding a firm, the firm is better off focusing on optimizing its positioning relative to the commonly accepted benchmarks in its category.

Third, we extend prior literature by exploring learning and framing as precursors to accomplishing an optimal positioning strategy. By conceptualizing audience engagement as a two-directional communication channel between firms and audiences, we show the importance of engagement with a group of audiences holding diverse enough evaluative schemas so that firms can learn about their heterogeneous audiences but not too diverse so that firms can develop an integrated understanding and are able to adjust their narratives accordingly. Our theoretical development in this area is thus an answer to the call by Durand and Haans (2022) to explore factors that enable firms to pursue optimal positioning strategies. As the authors argued, an important factor preventing firms from finding optimal positioning could be a lack of knowledge regarding their key benchmarks. This problem becomes exacerbated if firms aim to position relative to a group of audiences holding highly divergent evaluative schemas and predispositions. Furthermore, our work complements recent work by Falchetti et al. (2022) that show the importance of framing and adjusting narratives in the presence of a heterogeneous audience group. We contribute to this research by articulating the importance of limiting the heterogeneity in the evaluative schemas of the audiences a firm engages with since a moderate level of focus allows firms to better fine-tune their narratives according to their audiences' evaluative schemas and concerns.

Fourth, we highlight the strategic agency of firms in influencing how they are evaluated and their audiences' categorical expectations. While the extant optimal positioning literature has emphasized the conformity pressure imposed on firms due to the categorical imperative, we highlight firms' ability to strategically target audiences that have specific evaluation schemas and predispositions toward them. By doing so, we bolster recent work proposing "a move toward a more agency-oriented approach, aiming to redirect scholarly emphasis away from thinking of categories largely as a constraint or as being ascribed ex ante and homogeneously to whole portions of the market, that is, producers, audiences, and intermediaries" (Durand & Khaire, 2017, p. 3). Our study thus joins recent scholarly works investigating firms' agency in shaping audience evaluations. While these works have emphasized how firms can alter specific audience groups' evaluative schemas through category strategy (Pontikes, 2018) or shape their evaluation outcomes by using framing strategies (Falchetti et al., 2022), our study sheds light on firms' agency in shaping how they are evaluated by influencing which audiences with what types of evaluative schemas get to evaluate them in the first place.

Fifth, our study extends the prior literature on audience evaluations by demonstrating that the evaluations a firm receives are not always an unbiased representation of the firm's performance and quality but are highly affected by the composition of audiences that opt to evaluate the firm. By coining the term *audience composition premium*, we conceptualize a parsimonious construct to refer to the gain that accrues to a firm due to the composition of audiences evaluating it. The importance of our theoretical conceptualization is even more tangible in the digitized platform markets that heavily rely on online ratings (Dellarocas, 2003). These online platforms often present the aggregate ratings of all users as unbiased quality signals. In these markets, the success or failure of a firm heavily depends on the evaluations it receives. For example, Luca (2016) showed that a one-star increase in ratings on Yelp results in a 10% increase in revenue. Our study shows the potential bias in these ratings and proposes strategies firms could adopt to maximize their ratings given such biases.

5.1.2 | Contributions to machine learning in strategy research

Our contributions related to the use of machine learning in strategy research are twofold. First, we demonstrate how recommender systems and topic modeling can be utilized together to operationalize theoretical conceptualizations of audience composition premium and the heterogeneity in the evaluative schemas of audiences a firm engages with. Particularly, we believe our study is the first in our field to showcase the use of collaborative filtering and, more broadly, recommender systems. This class of machine learning models is specifically useful for studies at the intersection of firms and their audiences. We thus advance the methodological frontiers of strategy research and enable future quantitative works that could reliably measure idiosyncratic audience predispositions toward products or firms.

Second, our study has strong prescriptive value (Bazerman, 2005). As Agrawal, Gans, and Goldfarb (2018a), Agrawal, Gans, and Goldfarb (2018b), and Agrawal, McHale, and Oettl (2018) mentioned (p. 17), "the most common question board members ask us is: 'How will AI affect our strategy?'" The question of how machine learning influences strategy is of great concern to managers. Indeed, recent studies have suggested that artificial intelligence and, more specifically, machine learning algorithms enable cheap, accurate, and generalizable predictions that can significantly influence firm strategy (Agrawal, Gans, & Goldfarb, 2017). Agrawal, Gans, and Goldfarb (2018a), Agrawal, Gans, and Goldfarb (2018b), and Agrawal, McHale, and Oettl (2018) illustrated the potential effect of accurate prediction on firm strategy through the following example. Amazon currently uses a shopping-then-shipping strategy. If, at some point, it could accurately predict what customers want to buy, it could transition to a shipping-then-shopping strategy, delivering products to customers before they make an order online. Machine learning algorithms could also impact innovation processes by facilitating the discovery of useful combinations in complex discovery spaces (Agrawal, Gans, & Goldfarb, 2018a; Agrawal, Gans, & Goldfarb, 2018b; Agrawal, McHale, & Oettl, 2018; Cockburn, Henderson, & Stern, 2018). In addition, Goldfarb, Gans, and Agrawal (2019) explored how machine learning can facilitate firms' ability to distinguish reliable partners, thus reshaping theories built on search inefficiencies and partner frictions in traditional economics.

We believe there is an opportunity to explore ways firms can use machine learning to make strategic decisions. Based on the insights from our study, the "what is the optimal positioning strategy" problem could be reformulated as a "how will the market and its key stakeholders react to a specific market position" problem. Given the availability of data and the sophistication of machine learning techniques, firms could predict how specific audience members would react to a given positioning strategy. Through the empirical investigation of security analysts' evaluations of U.S. public firms, we demonstrate how recommender systems could prove particularly useful for this purpose. Firms could use insights gained from the predictions made by machine learning models to optimize their positioning strategies and drive tangible performance outcomes. For instance, a restaurant that is planning to open a new branch in its city could use the insights from our paper to increase its success prospects. Specifically, the restaurant would need to apply our proposed machine learning methodology to Yelp data to identify locations where it could attract audiences with a favorable predisposition toward it and gain the highest audience composition premium.

5.2 | Limitations and future research directions

Our study has limitations that provide grounds for future research. First, we assumed that all firms are motivated and willing to adopt positioning strategies that aim at improving their audience evaluations. As Durand and Haans (2022) argued, some firms might decide not to pursue a short-term maximization of performance outcomes, such as analyst recommendations, but instead focus on other long-term goals. Building upon this insight, future studies could explore what factors within firms and their environments motivate them to give more attention to their positioning strategies and consequent audience evaluations. Furthermore, we only focused on positioning strategies aiming at gaining an aggregate positive evaluation. Firms might also pursue positioning and framing strategies to influence the composition of their evaluating audiences for other purposes. For instance, firms might aim to attract audiences that are less resistant to firm changes (Benner & Ranganathan, 2017; Theeke et al., 2018) or they might even intentionally and instrumentally attract audiences with extreme negative evaluations to engage in controversy and gain visibility (Roulet, 2020).

Second, for the sake of parsimony, we implemented theoretical arguments around our proposed positioning approach in isolation of a firm's positioning relative to categorical benchmarks. Future research could examine how firms could potentially adopt both strategies—that is, adopt a broad categorical strategy while also adapting to heterogeneities within various audience groups (Hsu, Kovács, & Koçak, 2019). A study in this domain would answer the call by Zhao et al. (2017) for optimal distinctiveness studies that incorporate the role of stakeholder multiplicity. A particularly interesting direction for future research in this line would be to explore optimal positioning strategies for hybrid organizations (Battilana & Lee, 2014; Zhao & Glynn, 2022) and multicategory firms (Hsu et al., 2009). Such firms could potentially have more heterogeneous audiences, increasing the need for a positioning strategy that focuses on heterogeneous audience predispositions in combination with categorical benchmarks.

Third, we assumed that firms' positioning and narratives are malleable such that firms can adjust them according to an optimal point. A particularly important factor affecting firms' ability to attract various groups of audiences is whether they are a niche player or a generalist. Future research could explore the tension between a specialist's ability to gain a higher audience composition premium for having a more targeted audience group and a generalist's ability to flexibly adjust its positioning and framing to garner the attention of a particular group of audiences. Furthermore, while we argued that the Q&A segments of earnings calls give firms an opportunity to manage their companies' narratives, we did not investigate the specific framing strategies that firms could use to influence analysts' evaluations. Empirically and in analyzing the transcript data from earnings calls, we focused on the audiences' evaluative concerns by examining the questions they asked. Future studies could go a step beyond this and conduct topic modeling and other natural language processing techniques on the answers provided by firm managers to analyst questions. Such investigations could elaborate on the nuances of how firms adjust their narratives in response to various analysts and how particular framings beget further concerns and questions by other analysts.

Fourth, while we emphasized the heterogeneity in audiences, we did not conduct a theoretical investigation into the change in audiences' preferences over time and the sudden discontinuities in firms' audience groups when firms go through various stages of their lifecycle (Fisher, 2020; Fisher, Kotha, & Lahiri, 2016). Future work could examine the change in a firm's audience composition as both the firm and its audiences evolve and change. Of particular importance is to examine the factors that enable firms to adapt to a changing landscape and adopt strategies that allow them to maintain an optimal and dynamic audience composition (Hsu et al., 2019).

Our study also has several empirical limitations. First, our study was conducted using archival data, so our inferences lack the causal strength of a randomized experiment. In future studies, a series of experimental studies similar to Falchetti et al.'s (2022) could be particularly useful to further corroborate insights from our study.

Second, our study was conducted in the context of large established firms being evaluated by an expert audience group—namely, security analysts. We could expect that in a context with de novo firms and novice audiences, audiences' evaluative schemas are less developed and more malleable and that their predispositions are less predictable. Future work could examine efficient positioning strategies relative to a heterogeneous group of audiences under such circumstances.

Third, our proposed methodology of using machine learning to predict audience evaluations limits our study to contexts in which big data on audiences' previous evaluations are available and accessible. More specifically, to develop a collaborative filtering recommender system, we need a context in which evaluators have rated multiple firms (or products), and firms (or products) have been rated multiple times. Thus, in the context of analysts' evaluations of public firms, we had to limit our sample to firms and analysts for which we had a certain minimum amount of data available. In the recommender systems domain, the problem of dealing with users and items with few previous ratings is known as the "cold start" problem (Aggarwal, 2016) and is usually addressed through more sophisticated algorithms, such as combinations of content-based and collaborative filtering methodologies. Future studies could explore such methodologies, including ensemble methods, and compare the accuracy of these methods against each other for different types of firms and audiences. More broadly, given that firms could utilize such machine learning modeling to gain insights into their audiences' preferences and adopt strategies accordingly, one could argue that access to big data are a source of competitive advantage (Ng, 2016). Future studies could therefore investigate the competitive dynamics that arise due to firms' varying degrees of access to audience evaluation data and explore how such competitive advantages could translate into more optimal positioning strategies. An interesting and related example is the competitive advantage that a platform firm like Amazon would have when producing and optimally positioning its own private-label products using the trove of user behavior data that it has.

Fourth, to use the FunkSVD algorithm to develop a collaborative filtering recommender system, evaluation data needs to be in a clean and structured format that is translatable into simple numeric ratings. While this type of data are conveniently available in digital platforms, such as the App Store, Airbnb, Yelp, and Grubhub, in many relevant contexts, such as venture capitalists' evaluations of startups, data might be more sparse and less structured. Such contexts require a more customized approach to developing context-specific machine learning models. For instance, in the context of Spotify, a user's evaluation of a song is not identified using a typical five-star rating system but rather through the user's behaviors, such as the length of listening to a song, time of the day that a song is played, how often the song is listened to on repeat, and so forth. The recommender systems developed for this setting are thus very context-specific and are based on an understanding of music-listening behaviors.

Fifth, since the FunkSVD algorithm is not a time-aware algorithm, we used firm-year combinations as our unit of an item. For example, Apple-2005 is an item different from Apple-2015 in our model. Our model makes predictions about a specific analyst's evaluation of a firm based on the evaluations the firm received from other analysts in that specific year. In doing so, we are essentially indicating a firm in year t and the same firm in year $t + 1$ as two separate items. In addition to the algorithmic limitations of FunkSVD, our reasoning for this approach is that there could be major changes in a firm and the environment within the 20-year time span of our data. Our model is robust to such temporal changes in a firm because it is trained on the basis of firm-year combinations. The cost of this approach, however, is that we do not exploit the interdependencies and patterns within the data from 1 year to the other (Xiang et al., 2010). Time-aware and context-aware recommender systems aim at identifying the temporal and contextual patterns in items and user preferences (e.g., Adomavicius & Tuzhilin, 2011; Baltrunas & Amatriain, 2009; Koren, 2009; for a review, see Campos, Díez, & Cantador, 2014). This limitation in our modeling approach opens avenues for future research to utilize other recommender system algorithms that are context and time aware. A more sophisticated modeling approach could include not only time and seasonality elements in the model but also contextual factors, such as macroeconomic indicators, stock market indices, the characteristics of the brokerage house where the analyst is employed, analysts' past forecast accuracy, and so forth.

Sixth, a fundamental limitation in any machine learning model is that it is trained using data that is, by definition, limited to something done in the past. Obviously, and critically, we do not have access to data on what has not yet happened. Using data to find patterns in audiences' evaluative tendencies prevents us from discovering possibilities not shown in past data. Henry Ford is famously quoted (perhaps mistakenly) for saying, "If I had asked people what they wanted, they would have said faster horses." A machine learning approach to understanding audiences based on past data would probably have resulted in a similar insight and would have fallen short of the imagination to envision a demand for cars in the future.

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DATA AVAILABILITY STATEMENT

Part of the data that support the findings of this study was derived from SEC's EDGAR system. The remainder of the data used in this study are available from Wharton Research Data Services (WRDS). Restrictions apply to the availability of these data, which were used under license for this study.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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