The Double-Edged Sword of Exemplar Similarity

Provisional Accept, *Organization Science*

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We investigate how a firm's positioning relative to category exemplars shapes security analysts' evaluations. Employing a two-stage model of evaluation (initial screening and subsequent assessment), we propose that exemplar similarity enhances a firm's recognizability and legitimacy, increasing the likelihood that it passes the initial screening stage and attracts analyst coverage. However, exemplar similarity may also prompt unfavorable comparisons with exemplar firms, leading to lower analyst recommendations in the assessment stage. We further argue that category coherence, distinctiveness, and exemplar typicality influence the impact of exemplar similarity on firm evaluation. Leveraging Natural Language Processing (NLP) techniques to analyze a sample of 7,603 US public firms from 1997 to 2022, we find robust support for our predictions. By highlighting the intricate role of strategic positioning vis-à-vis category exemplars in shaping audience evaluations, our findings have important implications for research on positioning relative to category exemplars, category viability, optimal distinctiveness and security analysts.

1. Introduction

Firms frequently frame themselves relative to category exemplars – those outstanding, high-performing organizations within a category (Smith and Medin 1981, Cohen and Basu 1987, Zhao et al. 2018, Barlow et al. 2019, Younger and Fisher 2020). Management scholars have examined the effects of positioning near category exemplars, primarily highlighting the benefits of *exemplar similarity*. Exemplar similarity increases a firm's recognizability and legitimacy, facilitating its categorization and evaluation by audiences (Zhao et al. 2018, Barlow et al. 2019, Younger and Fisher 2020, Gouvard and Durand 2023). It also shapes audience beliefs about a firm's expected quality and performance, as audiences may presume that firms sharing characteristics with successful exemplars are likely to achieve similar levels of success (Gouvard and Durand 2023). Empirical evidence has demonstrated the positive effect of exemplar similarity on outcomes including app downloads (Barlow et al. 2019), video game sales (Zhao et al. 2018), and resource acquisition on crowdfunding platforms (Soublière and Gehman 2020).

However, a predominantly positive perspective on exemplar similarity may overlook the complexities of audience evaluations, and the potential unintended consequences of exemplar similarity. While exemplar similarity can enhance recognizability, it also invites comparison. Audiences evaluate similar firms relative to one another, with expectations of comparable quality and performance (Smith and Chae 2017). Such comparisons may not always yield positive outcomes. For example, Bowers (2015) found that comparisons among firms covered by an analyst could lead to unfavorable evaluations for those seen as underperforming relative to their counterparts. The case of Cava, a fast-casual Mediterranean restaurant, highlights the double-edged nature of exemplar similarity. The company's attempt to position itself as "the next Chipotle" garnered attention and legitimacy. For example, a *Wall Street Journal* article described "striking similarities" between the two companies, stating that "Like Chipotle, Cava sits a half step above fast food, allowing it to charge more for custom meals using quality ingredients, but without expensive table service." However, this positioning also invited an unfavorable comparison: the same article argued that, compared to Chipotle in its early days, Cava's stock might be overpriced because Chipotle was profitable with 450 restaurants in its initial surge, while Cava had 263 restaurants and wasn't yet profitable (Jakab, 2023). However, studies have not yet systematically examined both the benefits and costs of exemplar similarity for audience evaluations.

To develop a nuanced understanding of the impact of exemplar similarity, we investigate its effects in the context of security analysts' evaluations of public firms. These evaluations significantly shape market perceptions and investment decisions. By examining two distinct stages of audience evaluation – *screening* followed by *assessment* (Shocker et al. 1991; Zuckerman 1999, 2017; Haubl and Trifts 2000) – we isolate the countervailing effects of exemplar similarity. Screening involves narrowing down to a manageable set of comparable firms. Assessment involves evaluating and ranking the firms within the consideration set. In our context, screening determines analyst coverage (i.e., whether a firm is covered by an analyst), signaling a firm's legitimacy and reduceing agency costs by disseminating information about the firm to the market (Chung and Jo 1996, Zuckerman 1999, Jensen 2004). In turn, assessment comprises analyst recommendations (i.e., whether an analyst provides a favorable assessment of a firm), providing additional information about a firm's stock valuation and significantly impacting stock prices (Womack 1996, Barber et al. 2001). Both stages and their outcomes have implications for a firm's stock performance (Zhang et al. 2020). But because each stage is characterized by different evaluation criteria, the impact of exemplar similarity may vary across them (Soublière et al. 2022). Examining the effects of exemplar similarity on each evaluation stage, therefore, allows for a comprehensive understanding of the impact of exemplar similarity on audience evaluations in complex decision-making scenarios.

Specifically, we propose that exemplar similarity enhances a firm's chances of passing through the initial screening stage by signaling similarity to the exemplar (Zhao et al. 2018, Barlow et al. 2019), thus contributing to broader analyst coverage (Zuckerman 1999, Litov et al. 2012). However, exemplar similarity can also result in unfavorable comparisons during the assessment stage (Smith and Chae 2017), leading to lower investment recommendations (Meitner 2006, Bowers 2015). Therefore, the effects of exemplar similarity on firm evaluation may be positive in the first stage but negative in the second stage.

Additionally, we propose that the impact of exemplar similarity is moderated by category characteristics – coherence and distinctiveness – as well as the exemplars' position within the category. Categories with high coherence, characterized by strong resemblance among constituent members (Rosch 1978, Mervis and Rosch 1981), provide a robust framework for analysts to process complex information. This enhances the relevance of the category exemplars in the eyes of an audience (Haans 2019, Lo et al. 2020, Soublière et al. 2022), thus influencing both evaluation stages. In highly coherent categories, a firm positioned near the exemplar can benefit from increased analyst coverage, but the negative effect of exemplar similarity on analyst recommendations will likely be more pronounced. A category's distinctiveness reflects its unique position within a larger classification system (Lo et al. 2020). A category that overlaps excessively with its neighboring categories loses its distinctiveness and, consequently, its utility as an independent category. This can impact the two stages of evaluation and thus moderate the relationship between exemplar similarity and audience evaluations (Soublière et al. 2022). We expect category distinctiveness to amplify the positive effect of exemplar similarity on analyst coverage, as the exemplars serve as more valuable reference points in more distinct categories. Category distinctiveness can also intensify the negative effect of exemplar similarity on analyst recommendations due to limited comparison benchmarks.

We also account for the fact that exemplars can occupy distinct spaces within a category. In some categories, exemplar firms may align with category prototypes, defined as the typical attributes of most firms within that category (Durand and Paolella 2013, Taeuscher et al. 2021). However, exemplars can also deviate from the category prototype, because high-performing firms possess legitimacy buffers enabling them to deviate from established industry norms (Fisher et al. 2016). We propose that *exemplar typicality* influences the effect of exemplar similarity on audience evaluations. When exemplars are representative and align closely with category attributes, exemplar similarity will have a more positive relationship with analyst coverage. However, it can also intensify the negative effect of exemplar similarity on analyst recommendations because more typical exemplars are perceived as more valid and relevant referent points for comparison.

We tested our predictions using a sample of 7,603 US public firms from 1997 to 2022. To quantify the similarity between firms, we employed Natural Language Processing techniques on the 'Description of Business' section extracted from firms' 10-K reports. In particular, we utilized an advanced pre-trained model, grounded in Google's BERT language model. This model leverages the transformer architecture (Vaswani et al. 2017) and is known for its exceptional ability to convert text into numerical vectors, also known as embeddings. Applying this model, we transformed the textual data of each firm's document into a 768-dimensional vector space and used the vectors to measure the pairwise similarity between firms as well as various category characteristics. Our regression analyses and supplementary tests provide strong evidence supporting our predictions.

Our study makes several important contributions. It extends the literature on category exemplars by establishing that the impact of positioning a firm near a category exemplar results in varying assessments of that firm across different evaluation stages, and is contingent upon category characteristics and exemplar typicality. Relatedly, our study expands category viability research by highlighting the importance of category characteristics (category coherence and distinctiveness) for firms' within-category positioning strategies. It also adds important insights into the growing literature on optimal distinctiveness examining the effects of positioning relative to various categorical benchmarks such as exemplars. Finally, our study contributes to security analyst research by investigating how a crucial firm strategy – conformity versus differentiation relative to prominent firms within the category – differentially influences two key analyst outcomes.

2. Theory

2.1. Exemplar Similarity's Effect on Audience Evaluations

Audiences evaluate firms relative to benchmarks. Recent studies on the exemplar-based model of evaluation have proposed that audiences might evaluate targets relative to specific firms or products that are salient or prominent in their market category (Smith and Kemler 1984, Cohen and Basu 1987). The exemplar model is based on the psychological premise that "people represent categories by storing individual exemplars in memory and classify objects on the basis of their similarity to these stored exemplars” (Nosofsky and Johansen 2000: 375). An exemplar refers to a category member that embodies the exceptional and noteworthy features of the category (Smith and Zarate 1992). Studies in cognitive psychology have demonstrated that exemplars generate a “halo effect” by amplifying the visibility and credibility of category members that resemble them (Smith and Zarate 1992). For example, Gilovich (1981) conducted an experiment where participants were presented with descriptions of imaginary football players alongside a highly accomplished real football player. Participants tended to assign higher ratings to the potential success of the fictional players who shared certain characteristics with the exemplar player, even when there was no logical connection between those similarities (e.g., originating from the same hometown) and the potential for professional success.

Management scholars have referred to a category’s most outstanding and successful firm as its exemplar. For instance, Apple serves as an exemplar in the smartwatch category due to its widely recognized and top-performing product. For audiences, comparison with a category exemplar eliminates the need for cognitively taxing pairwise comparisons with all firms in a category (Glynn and Navis 2013). For firms, utilizing exemplars as a basis for strategic positioning creates the advantage of having clear reference points for anchoring and benchmarking within the market (Younger and Fisher 2020). Recent research by organizational scholars has highlighted the advantages that firms can attain by leveraging exemplar similarity. For instance, Zhao et al. (2018) found that during the initial stages of a category’s emergence, video games sharing features with successful predecessors were more favorably evaluated and achieved better market performance. Similarly, Barlow et al. (2019) observed that new apps on Google Play resembling top-performing apps attracted more downloads. These findings underscore the attention and recognition that can be garnered through exemplar similarity. However, they do not account for the potentially distinct effects of exemplar similarity on the two stages of audience evaluation: screening and assessment.

2.2. Security Analyst Evaluations Through the Two-Stage Model

To unravel the nuanced effects of exemplar similarity, we focus on firm evaluations by security analysts. In markets where valuation is complex, intermediaries like analysts play a crucial role in filtering information and influencing investment decisions (Zuckerman 1999, Zhao et al. 2018). Their role is especially evident in stock markets, where stock prices are often influenced by market consensus rather than explicit calculations of intrinsic value (Zuckerman 1999, 2000). Security analysts, as key intermediaries in stock exchange markets (Chung and Jo 1996, Zuckerman 1999, Jensen 2004, Litov et al. 2012), provide investors with valuable information through their analysis and reporting and leverage their specialized skills to enhance market efficiency (Healy and Palepu 2001). Consequently, analysts play a pivotal role in shaping investment decisions and determining a firm's market value (Litov et al. 2012).

Analysts' evaluations occur in two stages: screening and assessment[1] (Zuckerman 1999, 2017; Majzoubi and Zhao 2023). In the screening stage, firms are categorized into meaningful groups of comparable entities. Analyst coverage – that is, inclusion in a set of comparable firms in this stage – enhances a firm's market value by increasing awareness among the investment and business community. Moreover, through the dissemination of information regarding a firm's prospects and managerial effectiveness, analyst coverage and reports mitigate agency costs arising from the separation between ownership and control (Jensen and Meckling 1976, Chung and Jo 1996), bolstering the demand for a firm's stocks. Firms that do not receive specialized analyst coverage within their industry experience diminished demand for their stock (Zuckerman 1999, 2004).

Once a firm successfully passes the initial screening stage and receives coverage, the second stage of evaluation involves assessment: assessing the firm's performance in comparison to similar firms and issuing an investment recommendation. While analyst coverage indicates that a firm meets the fundamental criteria for inclusion within its primary category and possesses some level of legitimacy (Zuckerman 1999), investment recommendations provide deeper insights into a firm's stock valuation. The impact of buy or sell recommendations on a firm's stock price is significant: Womack's (1996) study

[1] The two-stage model was originally developed in marketing research to describe consumers' purchasing behavior as a screening stage followed by a selection stage (Shocker et al. 1991). We adopt the language of "screening" for the first stage where analysts determine coverage, and "assessment" for the second stage where analysts evaluate and judge firms to produce an investment recommendation. Other scholars have used terms like "categorization and valuation" (Gouvard and Durand 2023), "gaining attention and evaluation" (Hsu 2006), or "classification and valuation" (Soublière et al. 2022) to highlight the distinct nature of each stage.

of stock reactions to analyst recommendations during the 1989–1991 period revealed that sell recommendations were followed by a negative drift of -9.1 percent in stock price over six months. Similarly, Barber et al. (2001) demonstrated that, from 1985 to 1996, a portfolio of highly recommended stocks yielded an average annual abnormal gross return of 4.13 percent, while a portfolio of least recommended stocks yielded an abnormal return of -4.91 percent.

2.2.1. Exemplar Similarity and Analyst Coverage

We propose that exemplar similarity distinctly influences the screening and assessment stages in analyst evaluations. Consistent with prior research, we suggest that exemplar similarity enhances screening by affecting security analysts' decisions to cover a firm. Analysts strive for accurate financial forecasts (Litov et al. 2012), which they achieve by employing evaluation routines to analyze a firm's financial, operational, and competitive landscape information (Theeke et al. 2018). These routines are then applied to multiple firms with similar characteristics (Litov et al. 2012, Feldman 2016). As a result, analysts tend to specialize by industry (Zuckerman 1999, 2000) and primarily cover firms that are recognizable and familiar (Bhushan 1989). Research has indicated that when firms adopt new and uncertain knowledge combinations, hence increasing the cognitive effort required for analysis, security analysts tend to reduce coverage (Theeke et al. 2018). For example, Benner (2010) found that during technological transitions in an industry, security analysts exhibited a preference for firms adhering to existing technologies rather than those embracing new technologies.

A firm's resemblance to a prominent exemplar has the potential to increase its visibility and familiarity, thereby enhancing its legitimacy among analysts. Analysts dedicate significant effort to developing evaluation routines for covering exemplar firms. High-profile firms are of particular interest to analysts as they are highly visible within the investment community, and covering them can generate media attention while potentially boosting an analyst's professional status and career prospects (Hong and Kubik 2000, 2003). The increase in coverage resulting from exemplar similarity can be attributed to the concept of cognitive economy (Zuckerman 1999, Litov et al. 2012), as analysts prefer utilizing their existing knowledge and evaluation routines instead of expending additional time and effort to create new ones for each firm (Fiske and Taylor 1991). With pre-established routines for exemplars, firms exhibiting similarities can be analyzed more efficiently and with minimal additional effort. This cognitive economization enables analysts to cover a wider range of firms with less cognitive burden, making it easier to cover firms similar to the exemplar. Based on this rationale, we hypothesize that exemplar similarity can enhance a firm's recognizability and legitimacy, leading to broader analyst coverage. Hence, we propose:

Hypothesis 1a. *There is a positive relationship between exemplar similarity and the breadth of analyst coverage.*

2.2.2. Exemplar Similarity and Analyst Recommendations

While exemplar similarity is theorized to positively impact screening and result in broader coverage of a firm, we propose that, for firms that pass through the screening threshold, exemplar similarity will have a different impact on subsequent assessment.[2] In the second stage of evaluation, analysts assess the performance of covered firms and provide recommendations regarding whether to buy, hold, or sell its stock based on whether it appears under- or over-valued (Westphal and Clement 2008, Feldman 2016). Two primary valuation methods used by analysts are absolute and relative valuation. Absolute valuation involves conducting comprehensive net present value calculations using discounted future cash flows, whereas relative valuation involves comparing a firm's performance to that of a comparable set. The latter, also known as the indirect valuation or comparable valuation method, is widely used in practice. This method relies on multiples, which are ratios between a financial variable, such as the company's market price or enterprise value, and an accounting metric like earnings, sales, or book value (Stickney et al. 2007, Janda 2019). Asquith et al. (2005) examined 1,126 analyst reports and discovered that 99% of the sell-side analysts used multiples in their valuation methods to determine target price estimates, while

[2] Importantly, firms that do not pass the initial screening stage will not undergo assessment in the second stage, as analysts do not issue recommendations for non-covered firms. Systematic differences may exist between covered and non-covered firms; for instance, a firm with negligible sales/revenues may not gain coverage regardless of exemplar similarity. Thus, our arguments around exemplar similarity's effects on recommendations pertain only to covered firms. We address the potential selection bias empirically, but clarify here that our theorizing focuses on post-screening effects.

only 12.8% used a discounted cash flow model. Similarly, Pinto et al. (2019) found that 92.8% of a sample of 1,980 equity analysts used the market multiples approach. The prevalence of the indirect valuation method among practitioners can be attributed to its convenience, comprehensiveness, and its comparable accuracy compared to direct valuation methods (Dechow et al. 1999, Asquith et al. 2005, Bancel and Mittoo 2014, Pinto et al. 2019, Janda 2019).

The first step in the relative market valuation method involves selecting a firm or a group of firms to serve as benchmarks for the focal firm (Knudsen et al. 2017). This decision regarding comparison firms can exert a significant influence on analysts' recommendations (Bowers 2015). The selection process often relies on assessing the similarity between firms (Bhojraj and Lee 2002; Meitner 2006; Hoberg and Phillips 2010, 2016, 2018; Lee et al. 2015; Eaton et al. 2022). Similar firms often occupy similar product market spaces with related offerings, target analogous customer segments, and are subject to comparable innovation risks, life cycle dynamics, and competitive pressures. They are therefore likely to face similar risks and growth opportunities (Eaton et al. 2022), enhancing the likelihood and reliability of their comparison (Bhojraj and Lee 2002; Meitner 2006). As an example, in their November 2022 report for Cummins Inc., a leading manufacturer of diesel engines and power train-related component products, analysts from SADIF Investment Analytics identified a list of comparables and assigned a similarity score to each one. They explicitly stated: "The company's closest competitor, Genuine Parts Co, has a similarity index of 72.00% […]. This similarity index is enough to consider this competitor fully relevant for comparable analysis."

Accordingly, firms exhibiting high exemplar similarity are more likely to be compared to the exemplar.[3] In cases where a focal firm is compared to an exceptionally high-performing exemplar, its

[3] We acknowledge that sometimes exemplar similarity might not result in comparison with the exemplar. For example, some analysts might be more likely to focus on industry median metrics when conducting their assessments (Bhojraj and Lee 2002) and may deliberately avoid comparing a firm to an exemplar to provide a more balanced assessment. Furthermore, some analysts may eschew peer comparison methods in favor of absolute valuation techniques, such as discounted cash flow analysis (Nissim 2013). Our argument is that high exemplar similarity increases, but does not guarantee, the chances of a comparison being made, on average and across analysts. A more comprehensive examination of specific analyst evaluation approaches merits future analysis but is beyond this study's scope. We thank a reviewer for encouraging us to address this nuance in our argument.

value may be discounted (Du and Shen 2018). As argued by Meitner (2006), "If a company performs principally worse than the rest of the peer group or has a weaker strategic and competitive position, then the application of a discount would probably be appropriate." Bowers (2015) found evidence for this argument by showing that, regardless of a firm's raw performance, if its relative performance was worse than other firms within an analyst's consideration set, it received lower evaluations. Other research has shown that when peers' relative performance is high, the market's pressure on firms to deliver and report better performance is amplified (Du and Shen 2018). Conversely, firms outperforming comparable firms on tangible or intangible dimensions are rewarded by the market by receiving higher valuation ratios (Yin et al. 2018). Firms that are compared with category exemplars are likely to be perceived unfavorably due to their relative performance gaps. This is because exemplars tend to set a benchmark that is challenging for most firms to meet or exceed. Consequently, when firms are evaluated against such high-performing exemplars, their performance, even if objectively good, may be discounted due to the heightened expectations set by the exemplar.[4] Based on these arguments, we propose:

Hypothesis 1b. *Among firms that pass the screening stage and proceed to the assessment stage, there is a negative relationship between exemplar similarity and analyst recommendations.*

2.3. Category Coherence and Distinctiveness

We argue that the impact of exemplar similarity on analyst evaluations is moderated by two key characteristics of the categories they represent: coherence and distinctiveness (Lo et al. 2020, Soublière et al. 2022). At a high level, coherence accounts for the *internal* alignment of category members whereas distinctiveness accounts for the *external* alignment of the category relative to other categories.

Category coherence refers to the degree of resemblance and relational patterns among members within a category (Porac et al. 1995, Haans 2019). Intra-category resemblance makes a category

[4] Even in cases where a firm surpasses the performance of the exemplar, the comparison premium garnered may be subdued. This is because the benchmark set by the exemplar might be so high that the relative outperformance may not be as pronounced as it would be against a more moderate benchmark. In essence, while outperforming an exemplar can lead to a positive evaluation, the extent of this positive gain in evaluation is likely to be more modest compared to a scenario where the firm's performance is juxtaposed with that of an average-performing firm, where the performance differential could appear more striking.

understandable (Rosch 1978, Mervis and Rosch 1981), discernible, and viable for audiences (Lo et al. 2020). That is, because highly coherent categories are comprised of clearly similar members, audiences can easily evaluate what potential members would or would not fit. Coherent categories therefore simplify information processing and enable efficient decision-making (Porac et al. 1995). Audiences are more likely to employ coherent categories in evaluating entities (Durand and Paolella 2013), influencing both stages of firm evaluation.

Category distinctiveness pertains to a category's relative position within the broader classification and meaning system, emphasizing its uniqueness and separation from other categories (Lo et al. 2020). When a category is distinct, it exhibits less overlap with other categories in the system, enhancing its classificatory utility. Category distinctiveness thus influences the utility of a category for audiences and thereby also impacts both stages of firm evaluation.

2.3.1. The Moderating Role of Category Coherence and Distinctiveness on Analyst Coverage

When a category exhibits strong coherence, the entities within it share connections and similarities, facilitating audience recognition and evaluation of firms based on their similarity to the exemplar. Within this context, a firm's similarity to the exemplar serves as a signal of quality and legitimacy, indicating its adherence to clear and established norms and standards within the category. This can lead to increased analyst coverage, as analysts are more inclined to consider firms that conform to the category's expectations and are easily recognizable and understandable. For instance, in the highly coherent category of "Jewelry stores" (NAICS code of 448310), Tiffany & Co. serves as a clear exemplar, and similarity to it offers the benefits of familiarity and enhanced legitimacy in the eye of analysts. Conversely, in a highly heterogeneous category, where categorical norms and expectations are less pronounced, audiences are generally more accepting of and even expect deviations from categorical benchmarks (Haans 2019). For example, the category of "Computer systems design services" (NAICS code of 541512) encompasses a diverse range of firms, such as tech consulting firms (e.g., Cognizant Technology Solutions), cloud computing firms (e.g., VMware), and healthcare IT solutions (e.g., Allscript Healthcare Solutions), and hence is it is not a very coherent category. While Netsuite Inc. is an exemplar in this category, it does not represent clear categorical definitions, norms or standards, and thus, similarity to this exemplar offers fewer benefits in terms of generating analyst coverage.

Category distinctiveness also enhances a category's viability and relevance for sensemaking and evaluation (Lo et al. 2020, Janisch and Vossen 2022, Soublière et al. 2022, Taeuscher et al. 2022). A distinct category occupies a unique and recognizable position within the broader classification system, offering clear boundaries between other categories with minimal categorical overlap. In such categories, the exemplar becomes a more valuable reference point for audiences assessing firms, because the exemplar is representative of something that is recognizable and clear. Hence, exemplar similarity serves as a stronger signal of category membership and legitimacy within a distinct category. This leads to increased analyst coverage. In contrast, in an indistinct category, an exemplar provides less valuable information about the salient features of firms in that category, because the category boundaries are less clear. Therefore, being similar to an exemplar does not confer the same benefits in terms of garnering analyst coverage. For example, the category of "Couriers and express delivery services" (NAICS code of 492110) is a highly distinctive category with clear categorical boundaries. By exhibiting similarity to the exemplar of this category, FedEx, firms can enhance their familiarity and legitimacy as a courier in the eyes of analysts. Conversely, the category of "Family clothing stores" (NAICS code of 448140) is less distinctive and has more overlap with adjacent categories like shoe retailers, sporting goods retailers, general merchandise stores. In this scenario, similarity to the exemplar, Urban Outfitters, may yield fewer legitimacy benefits. Therefore, category distinctiveness strengthens the positive effect of exemplar similarity on the breadth of analyst coverage. Summarizing preceding arguments, we propose:

Hypothesis 2a. *Category coherence strengthens the positive effect of exemplar similarity on the breadth of analyst coverage.*

Hypothesis 2b. *Category distinctiveness strengthens the positive effect of exemplar similarity on the breadth of analyst coverage.*

2.3.2. The Moderating Role of Category Coherence and Distinctiveness on Analyst Recommendations

We also propose that category coherence and distinctiveness moderate the baseline relationship between exemplar similarity and analyst recommendations. We propose that category coherence amplifies the negative effect of exemplar similarity on analyst recommendations. Category coherence solidifies the exemplar firm as a primary benchmark within its category, increasing its salience and perceived legitimacy (Rosch and Mervis 1975). Analysts are more inclined to apply the relative evaluation method in coherent categories, as these categories exhibit reduced heterogeneity and therefore offer increased comparability among their constituent firms. Category coherence also enhances the perception of substitutability among firms in a category. High substitutability can diminish a firm's market position and erode a firm's bargaining power, profit potential, and growth prospects (Porter 1980, Barney 1991). Analysts, primarily concerned with future earnings and cash flows, often give lower recommendations to firms with higher substitutability and reduced profitability prospects within their categories (Bradshaw 2011). In coherent categories, where offerings are more standardized and interchangeable, firms similar to the exemplar may face heightened substitutability from the exemplar and/or from other firms in the category; this heightened substitutability reduces profitability projections, leading to lower analyst recommendations.

Category distinctiveness can also intensify the negative effect of exemplar similarity on analyst recommendations. While analysts typically utilize firms from the same industry in their peer evaluations, they may also select firms from similar industries that share certain characteristics with the focal firm (Taeuscher et al. 2022). De Franco et al. (2015), in their analysis of a sample of analyst reports, found that 92% of the peers used for evaluating a focal firm belonged to the same two-digit GIC industry classification, and 52% belonged to the same five-digit GIC industry classification for single-segment firms. In less distinct categories, analysts may more readily find suitable comparables in neighboring or even overlapping categories, providing alternative benchmarks, and diluting the impact of the exemplar in the focal category.[5] However, distinct categories, characterized by minimal overlap with adjacent

[5] This is not to say that indistinct categories do not contain enough firms within themselves for analysts' comparisons. The number of firms used for comparison can differ, ranging from 1 (1st percentile) to 30 (99th

categories, limit the availability of comparable firms for benchmarking. In this case, the exemplar becomes a more prominent reference point, increasing the scrutiny and comparison intensity for firms close to it. This heightened comparison can result in lower investment recommendations, as the performance of these firms is more rigorously contrasted against that of the high performing exemplar.

Thus, category coherence makes comparative evaluation more likely and amplifies the impact of exemplar similarity on perceived substitutability with the exemplar, while category distinctiveness intensifies the comparative scrutiny against the exemplar due to limited alternative benchmarks. For these reasons, both category coherence and distinctiveness exacerbate the negative implications of exemplar similarity on analyst recommendations. Accordingly, we propose:

Hypothesis 3a. *Category coherence strengthens the negative effect of exemplar similarity on analyst recommendations.*

Hypothesis 3b. *Category distinctiveness strengthens the negative effect of exemplar similarity on analyst recommendations.*

2.4. The Moderating Role of Exemplar Typicality

Finally, we propose that the typicality of exemplars within their categories influences the impact of exemplar similarity on audience evaluations. In many industries, exemplars differ from category prototypes: that is, the prototypical attributes of most firms within that category (Durand and Paolella 2013, Glynn and Navis 2013). While categories impose certain constraints on firms' behavior and differentiation, they also allow for a certain degree of variation (Zuckerman 1999, Wry et al. 2011, Vergne and Wry 2014, Anthony et al. 2016). This possibility to deviate is often granted to firms that have established a reputation for exceptional performance, affording them a "legitimacy buffer" (Phillips and Zuckerman 2001, Fisher et al. 2016). For instance, Tesla's exemplar status enables it to occupy a

percentile), and averaging around 6 (De Franco et al. 2015). Cooper and Lambertides (2023) indicate that a group of 10 firms is usually sufficient for a reliable comparison. Thus, most categories should have enough firms for a standard comparison set, whether they are distinct or indistinct. However, analysts often look for highly similar firms to the focal one. In less distinct categories, such firms may be found in adjacent categories, offering alternative benchmarks. This availability can reduce the likelihood of choosing an exemplar from the focal category or lessen its influence by expanding the comparison set.

distinctive, atypical position within the automobile industry. Similarly, Firefox held a distinct position compared to the prototype in Google Play's "Communication" category (Barlow et al. 2019). These examples demonstrate how exemplars can position themselves apart from the category prototype while maintaining recognizability as a category exemplar. In our context, Delta Airlines represents a typical exemplar within the scheduled passenger air transportation category (NAICS code of 481111), Boeing is a typical exemplar in the aircraft manufacturing category (NAICS code of 336411), while Electronic Arts, a video game development and publishing company, is an atypical exemplar in the software publisher category (NAICS code of 511210).

In cases where the exemplar is atypical, its effectiveness as a category representative is reduced, thereby diminishing the positive impact of exemplar similarity on coverage. When an exemplar significantly deviates from the category prototype, analysts may question its reliability as a benchmark for categorizing firms. This is because an atypical exemplar may not embody the core features and norms that define the category, complicating the assessment of a firm's legitimacy and performance based on its similarity to the exemplar. As a result, the positive relationship between exemplar similarity and analyst coverage may be weaker if the exemplar is atypical[6]. Therefore, we propose:

Hypothesis 4a. *Exemplar typicality amplifies the positive relationship between exemplar similarity and the breadth of analyst coverage.*

Furthermore, exemplar typicality also affects the relationship between exemplar similarity and analyst recommendations. When an exemplar firm is considered atypical within the category, analysts may not view it as a reliable reference point for categorizing and evaluating other firms within the same category. In contrast, when an exemplar firm is typical of the category, analysts are more likely to perceive it as a valid and relevant referent point for comparison, as it embodies the average or ideal characteristics of the category. Bowers (2015) suggested that typical firms, which neatly fit into a category, facilitate comparison and evaluation using performance metrics reflective of key category

[6] As described in our empirical analysis section, we are referring specifically to the exemplar that the focal firm most closely resembles. A category might have more than one exemplar with varying degrees of typicality.

attributes. Therefore, when a firm resembles a typical exemplar, analysts can easily assess its performance in relation to the exemplar, leading to more precise and reliable recommendations. In contrast, when a firm resembles an atypical exemplar, the evaluation process becomes more complex and uncertain. As Bowers (2015: 574) argued, "Incoherent objects may possess some critical attributes defining category membership, but they also exhibit other differing attributes. Consequently, they are not as easily comparable, regardless of their performance." Therefore, the negative association between exemplar similarity and analyst recommendations may be less pronounced when the exemplar is atypical, and vice versa. This leads us to propose the following hypothesis:

> **Hypothesis 4b**. *Exemplar typicality strengthens the negative relationship between exemplar similarity and analyst recommendations.*

3. Methods

3.1. Data and Sample

We conducted our empirical analysis using a sample of publicly listed US firms. We included all firms that had electronically filed 10-K reports with the Securities and Exchange Commission (SEC) through the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system between 1997 and 2022.[7] For our analysis, we obtained financial and accounting data from the CRSP/Compustat Merged database, which contains data for US firms traded on NYSE, AMEX, or NASDAQ. Additionally, we collected security analysts' data from the IBES Detail History and Recommendations Summary databases. After merging these databases, our final sample comprised a panel of 7,603 firms, yielding 46,786 observations.

3.2. Dependent Variables

We have two primary dependent variables in our models: analyst coverage and analyst recommendations. *Analyst coverage* refers to the number of analysts who actively follow a specific firm in a given year. To determine whether an analyst follows a firm, we identified analysts who issued fiscal year-end earnings forecasts for the firm. On average, the firms in our sample had four analysts providing coverage. In cases

[7] We selected 1997 as the starting point because it marks the year when a requirement was enforced for all public firms to electronically file their 10-K reports.

where no analysts issued an earnings forecast for a particular firm in a given year, we assumed the coverage to be zero. To measure *analyst recommendations*, we relied on the consensus recommendation data available in IBES's Recommendations Summary database. IBES standardized analyst recommendations into five discrete categories, ranging from 'strong buy' to 'strong sell,' with each category assigned a numerical value between 1 and 5. We reverse-coded these numerical assignments, associating higher numerical recommendation values with more positive investment recommendations. For instance, a recommendation value of 5 indicated a 'strong buy' in our coding scheme.[8] The average investment recommendation across the firms in our sample was 3.72.

3.3. Independent Variables

Our main independent variable is *exemplar similarity*, which quantifies the degree to which a firm resembles exemplars in its industry. To measure the similarity between firms, we used data from the 'Description of Business' section (Item 1) of their 10-K filings. This section mandates firms to provide a narrative description of who they are and what they do.[9] The textual business descriptions extracted from the 10-K filings serve as reliable sources for our study. First, as legally binding documents, 10-K filings undergo careful preparation and exhibit consistency. Second, previous research has demonstrated that security analysts closely scrutinize these filings when formulating their forecasts (Lehavy et al. 2011). Third, since the format of 10-K filings has remained consistent over a significant period, they are well-suited for longitudinal panel studies (Chreim 2005). Our method of measuring similarity between firms, utilizing the textual business description from the 10-K Item 1 section, aligns with the approach developed by Hoberg and Phillips (2010, 2016, 2018).

To evaluate the similarity between firms, we first compiled a corpus of business descriptions for the firms under study. Next, we employed a pre-trained Sentence Transformer model[10], all-mpnet-base-

[8] While the individual analyst recommendations are categorical, averaging them all recommendations that a firm receives in a given year produces a continuous numerical variable between 1 and 5.
[9] For a thorough understanding of the specific guidelines that govern this section, please refer to *Item 101 of Regulation S-K (229.101).*
[10] A more detailed description of the transformer model and our analytical steps are provided in Appendix A.

v2, to convert these textual documents into 768-dimension numerical vector representations. Finally, we utilized cosine similarity to quantify the degree of similarity between each pair of vectorized business descriptions.[11]

To measure *exemplar similarity*, we calculated cosine similarity between the vectorized business description of a focal firm and that of all exemplar firms in its industry. Following Barlow et al. (2019), we used the highest cosine similarity (i.e., similarity with the nearest exemplar) as our measure of exemplar similarity. For a firm to be classified as an exemplar, it needed to exhibit substantial analyst coverage and positive evaluations. To capture this, we first normalized the measures of analyst coverage and analyst recommendations to have a mean of 0 and a standard deviation of 1[12]. Subsequently, we created a composite variable by summing the normalized values of analyst coverage and analyst recommendations for each firm in each year. To identify exemplars within each industry, we classified a firm as an exemplar if the resulting composite score exceeded one standard deviation above the average of all other firms within the same primary industry. The primary industry was determined using the firm's North American Industry Classification System (NAICS) code, a standard classification system used by federal statistical agencies to categorize business establishments.[13] Applying this approach, in 2020, Constellation Brands was identified as an exemplar in "Breweries" industry (NAICS code of 312120), Caterpillar was an exemplar in the "Construction machinery manufacturing" industry (NAICS code of 333120), Hilton Worldwide Holding and Marriot International were exemplars in the "Hotels and motels" industry (NAICS code of 721110), and JPMorgan Chase & Co was an exemplar in the "Commercial

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[11] All codes for data collection, cleaning, and analysis could be found on https://anonymous.4open.science/r/exemplar_similarity-89D8/ [This link is to be replaced with the original and non-anonymized GitHub link after the review process.]

[12] We normalized the measures of analyst coverage and analyst recommendations to ensure that our composite variable would not be unduly influenced by the different scales of the two variables.

[13] In our paper, we have opted to use the NAICS classifications instead of the older SIC codes. This decision is based on the fact that NAICS is a more contemporary, comprehensive, and consistent system. Introduced in 1997 and built upon the SIC system established in 1937, NAICS has gradually replaced SIC over time due to the latter's inconsistencies resulting from numerous modifications and additions. Moreover, NAICS codes have demonstrated their applicability to emerging sectors and industries, particularly in the technology field, as they offer a more detailed and specific structure. As a result, NAICS proves to be a more suitable and reliable choice for the classification used in our paper.

banking" industry (NAICS code of 522110). Appendix B contains a full list of exemplars for each industry in 2015.

We theorized three key moderators in our hypotheses: category coherence, category distinctiveness, and exemplar typicality. To calculate *category coherence,* we first computed the average document vector for each industry by year. This involved taking the average of the vectorized business descriptions of all firms within the industry for that specific year. The resulting industry average vector served as a numerical representation of the shared characteristics within the industry. Next, we calculated the similarity between the document vector of each firm and the industry average vector of its primary industry for the same year, using cosine similarity as the metric. These similarity values reflect the firm's typicality within its industry. We referred to this measure as *firm typicality*, which was utilized both as a control variable in our models and as a means of evaluating exemplar typicality.[14] Finally, we calculated the average typicality of all firms within an industry, which we referred to as "category coherence." This was accomplished by computing the mean firm typicality measures within the industry for the specific year. Our rationale for adopting this approach was to assess the level of coherence within an industry by measuring the degree of similarity between individual firms and the industry's typical characteristics. High category coherence indicated a greater similarity among firms within the industry, while low category coherence suggested a higher level of diversity and deviation from the industry average.

To measure *category distinctiveness*, we utilized the average vector for each industry per year and assessed the similarities between each focal industry and all other industries within the same broader sector (2-digit NAICS code)[15] and year, using cosine similarity as the metric. The resulting similarity

[14] As a supplementary analysis, we explored the impact of exemplar similarity on a firm's performance (earnings per share) and examined firm typicality's moderating effect on this relationship. Consistent with Barlow et al. (2019), we found short-term positive effect of exemplar similarity on earnings, negatively moderated by firm typicality. See Appendix C for further details.

[15] The two-digit NIACS codes cover broad sectors, including educational services (61), health care and social assistance (62), and utilities (22). By focusing the comparison on industries within the same sector, we not only ensure that our calculations are computationally feasible but also obtain a more meaningful measure of industry distinctiveness when compared to related and neighboring industries. Soublière et al. (2022) adopted a similar approach and measured a category's distinctiveness relative to other categories within the same superordinate set of categories.

measure for each industry and year were averaged to calculate the category distinctiveness. To improve data and results interpretation, we multiplied the resulting variable from the previous step by -1. As a result, higher values of this variable indicate greater category distinctiveness and reduced similarity with neighboring categories within the sector.

To assess *exemplar typicality*, we utilized the above-mentioned firm typicality variable and identified the typicality value for the most similar exemplar to the focal firm each year. Exploratory analysis revealed that on average, exemplars tend to exhibit higher typicality compared to other firms (0.919 versus 0.915), although the difference is not large. There is notable variation in the level of typicality among exemplars. For example, in 2020, Phillip Morris International stood out as an exemplar within the "Tobacco manufacturing" industry (NAICS code of 312230) with a significantly high degree of typicality (0.97). In contrast, Peloton Interactive stood out as an exemplar with a relatively low degree of typicality (0.86) within the "Sporting and athletic goods manufacturing" industry (NAICS code of 339920). We also observed exemplars such as Under Armour, Walmart, and Salesforce.com with a moderate degree of typicality (0.93, 0.91, 0.93) in 2020. We have depicted the distribution of our key variables using histograms in Figure A1 in Appendix A.

3.4. Control Variables

In our analysis, we included a variety of control variables across firm, industry, and exemplar levels. At the firm level, we controlled for firm scale by including total sales, firm size (measured by the log of the number of employees), and the firm's market share within its primary industry (indicated by Compustat's NAICSH variable). To account for firm performance, we included earnings per share (EPS) and available slack (current assets to current liabilities ratio). To capture firms' strategic change, we examined resource allocation patterns (Litov et al. 2012, Quigley and Hambrick 2012), focusing specifically on R&D expenditure (R&D expense to total operating expense), advertising expenditure (advertising expense to total operating expense), intangible assets ratio (intangible assets to total assets), and depreciation ratio (depreciation to total assets) (Barth et al. 2001). Additionally, we controlled for firm typicality as it has been shown to impact analyst coverage and evaluations (Zuckerman 1999, Litov et al. 2012). Firm diversification, which may impose a cognitive burden on analysts leading to reduced coverage and market valuations (Zuckerman 1999, 2000), was addressed by including the number of sales segments reported by the firm. We accounted for mergers, which can influence identity changes (Clark et al. 2010) and subsequently affect analysts' coverage decisions, by controlling for the size of M&A activity using the logarithm of total pretax acquisition/merger expenditure reported in firms' annual reports (item AQP in Compustat). Furthermore, we considered a firm's financial leverage (total long-term and current debt to stockholder equity). Lastly, we included a dummy variable that takes a value of 1 if the firm is included in the S&P500 Index by the S&P Dow Jones Indices in the given year.

At the industry level, we accounted for the number of analysts and the number of firms in the industry, along with the average coverage and average recommendations received by firms in the industry in the given year. We also included a measure of category instability, capturing the degree of change in an industry in terms of its shared characteristics across all member firms.[16] To measure category instability, we calculated the cosine similarity between the average vectors of an industry at two consecutive time points, t_{-1} and t_0. We then transformed this similarity measure into a change measure by subtracting it from 1. Furthermore, we incorporated a control variable for the industry's Herfindahl-Hirschman Index (HHI), a widely used measure of industry concentration and a proxy for industry competitive intensity. The HHI measure was constructed using firms' sales data.

For the exemplar, we controlled for its typicality and performance (EPS). To ensure the robustness of our results, we winsorized all accounting variables at the 1st and 99th percentiles to mitigate the influence of outliers, following established research practices (Litov et al. 2012).

3.5. Empirical Strategy

Our empirical strategy was designed to examine the relationship between exemplar similarity and analyst coverage and recommendations, while also considering the moderating effects of category coherence, category distinctiveness, and exemplar typicality. We employed Ordinary Least Squares (OLS)

[16] As an additional analysis, we also explore and assess the moderating effect of category instability on the baseline relationship between exemplar similarity and analyst coverage. Details and results can be found in Appendix C.

regressions with cluster-robust standard errors, which allowed us to address the potential correlation of errors within clusters and heteroskedasticity across clusters. To mitigate the potential bias arising from unobserved, time-invariant firm-level factors, we included firm fixed effects in our models. Additionally, we accounted for seasonal patterns specific to each industry by incorporating the average of the dependent variable for each industry-year in our models. This adjustment was crucial in isolating the effects of our variables of interest from the impacts of time-varying industry-specific factors, such as regulatory changes, technological advancements, or economic fluctuations. Furthermore, to address reverse causality concerns, our models used the dependent variables at time $t+1$ while holding the independent variables and controls at time t, thereby introducing a one-year lag between our explanatory variables and dependent variables.

4. Results

In Tables 1 and 2, we present the descriptive statistics and bivariate correlations. Table 3 displays the regression results. In Model 1, the coefficient estimate for exemplar similarity is positive and highly significant ($\beta = 2.453$, $p = 0.000$), supporting Hypothesis 1a, which suggests a positive relationship between exemplar similarity and the breadth of analyst coverage. In Model 2, the coefficient estimate for exemplar similarity is negative and significant ($\beta = -0.282$, $p = 0.014$), supporting Hypothesis 1b, which proposes a negative relationship between exemplar similarity and analyst recommendations. These findings indicate that a one standard deviation (SD) increase in exemplar similarity corresponds to a 0.213 increase in analyst coverage. For a firm with median analyst coverage, this translates to approximately a one percentile increase in coverage, indicating a shift from the 50th percentile to roughly the 51st percentile. However, the same increase in exemplar similarity leads to a 0.022 decrease in analyst recommendations. For a firm with median analyst recommendations, this corresponds to a reduction of approximately 1.5 percentiles in the firm's analyst recommendations. Figure 1 visually presents these results.

In Models 3 and 4, we examine how exemplar similarity interacts with category coherence and category distinctiveness to influence the breadth of analyst coverage. In Model 3, the coefficient estimate for the interaction between exemplar similarity and category coherence is positive and highly significant ($\beta = 61.741$, $p = 0.000$), supporting Hypothesis 2a, which posits that category coherence amplifies the positive effect of exemplar similarity on the breadth of analyst coverage. The findings indicate that a one SD increase in exemplar similarity leads to a 0.0748 increase in analyst coverage when category coherence is low (2 SD below the mean). However, in categories with high coherence (2 SD above the mean), a one SD increase in exemplar similarity corresponds to a 0.773 increase in analyst coverage. For a firm with median analyst coverage, this translates to approximately 3.4 percentile changes. In Model 4, the coefficient estimate for the interaction between exemplar similarity and category distinctiveness is positive and highly significant ($\beta = 39.915$, $p = 0.000$), supporting Hypothesis 2b, which posits that category distinctiveness strengthens the positive effect of exemplar similarity on the breadth of analyst coverage. When category distinctiveness is low (2 SD below the mean), a one SD increase in exemplar similarity leads to a 0.218 decrease in analyst coverage. However, this effect becomes positive and significant when category distinctiveness is high (2 SD above the mean), where a one SD increase in exemplar similarity results in a 0.779 increase in analyst coverage. This corresponds to a 3.43 percentile increase for a firm with median level of analyst coverage.

Models 5 and 6 test how exemplar similarity interacts with category coherence and category distinctiveness to influence the breadth of analyst recommendations. In Model 5, the coefficient estimate for the interaction term is negative ($\beta = -3.400$, $p = 0.048$), providing support to Hypothesis 3a, which proposes that category coherence strengthens the negative effect of exemplar similarity on analyst recommendations. The results indicate that a one SD increase in exemplar similarity leads to a 0.015 decrease in analyst recommendations when category coherence is low (2 SD below the mean). However, in categories with high coherence (2 SD above the mean), a one SD increase in exemplar similarity results in a 0.053 drop in analyst recommendations. This corresponds to approximately 3.35 percentile changes for a firm with median analyst recommendations. In Model 6, the coefficient estimate for the interaction term is negative and significant ($\beta = -3.092$, $p = 0.017$), supporting Hypothesis 3b, which posits that category distinctiveness strengthens the negative effect of exemplar similarity on analyst recommendations. Under high category distinctiveness (2 SD above the mean), a one SD increase in exemplar similarity leads to a -0.068 change in analyst recommendations, corresponding to a percentile change of -4.2. In contrast, for categories with low distinctiveness (2 SD below the mean), the respective numbers are 0.009 and 0.46.

Models 7 and 8 examine the interaction effect of exemplar similarity and exemplar typicality on the breadth of analyst coverage and analyst recommendations. In Model 7, the coefficient estimate for the interaction term is positive and significant ($\beta = 19.996$, $p = 0.000$), supporting Hypothesis 4a, which posits that exemplar typicality strengthens the positive relationship between exemplar similarity and the breadth of analyst coverage. When exemplar typicality is low (2 SD below the mean), a one SD increase in exemplar similarity leads to a 0.19 increase in analyst coverage, which corresponds to a 0.7 percentile change for a firm with median analyst coverage. This effect becomes more pronounced when exemplar typicality is high (2 SD above the mean), where a one SD increase in exemplar similarity results in a 0.5 increase in analyst coverage, corresponding to a 1.9 percentile increase. In Model 8, the coefficient estimate for the interaction term is negative and significant ($\beta = -2.744$, $p = 0.001$), supporting Hypothesis 4b, which proposes that exemplar typicality weakens the negative relationship between exemplar similarity and analyst recommendations. With low exemplar typicality (2 SD below the mean), a one SD increase in exemplar similarity leads to a decrease of 0.02 in analyst recommendations, representing a percentile change of -1.21. However, under conditions of high exemplar typicality (2 SD above the mean), a one SD increase in exemplar similarity leads to a larger decrease of 0.063 in analyst recommendations, corresponding to a percentile change of -3.76. To facilitate the interpretation of these results, we have graphed the moderation results in Figure 2.

Insert Tables 1-3 and Figures 1 and 2 about here
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5. Supplementary Analysis

5.1. Validating the Method for Identifying Exemplars

Exemplars consistently emerge as pivotal category references in various contexts. In media articles that focus on a particular firm and discuss its category and key players, exemplars are often frequently mentioned as reference points. For example, in a WSJ article that highlighted Volkswagen's (VW) transition towards electric vehicles (EVs), Tesla, an exemplar in the EV category, was cited as a benchmark:

> *"The management shake-up has worried investors though. They look to VW's new boss, Oliver Blume, to accelerate Mr. Diess's plan to beat Tesla Inc. in the electric-vehicle space, reboot VW's lagging software unit, and guide it through an increasingly tumultuous macroeconomic environment"* (Kantchev 2022).

If our identification of category exemplars, based on their positive coverage from security analysts, is accurate, we would expect to observe that companies with higher levels of positive analyst coverage are more likely to be mentioned in media articles that discuss a focal firm within their category. To test this prediction, we used the RavenPack database which covers media articles from various sources. One valuable feature of this database is the Relevance score assigned to each firm mentioned in an article. A Relevance score of 100 indicates that the article revolves around the focal firm, while a score below 100 indicates that a firm is merely mentioned in the article. For instance, in the aforementioned article, VW would receive a Relevance score of 100, while Tesla might receive a score of approximately 20. We retrieved all the articles from the year 2015, totaling 1.5 million articles[17], and identified firms mentioned in these articles with a relevance score below 100. From a total of 4,457 unique firms[18] in our 2015 database, we identified 219 firms mentioned in media articles using this approach. We found analyst coverage and recommendation data for 170 of these 219 firms (See Appendix B for a full list).

[17] The RavenPack database also categorizes articles using a classification schema that includes categories like 'patent-filing,' 'executive-firing,' 'market-entry'. This schema consists of 2065 categorical codes. To prevent designating acquired firms or partner firms as exemplars, we excluded articles that fell under categories with any of these terms: 'acquisition,' 'merger,' 'alliance,' and 'partner.'
[18] These are the companies for which we could find CRSP-Compustat data.

We ran a logistic regression between our composite exemplar variable of analyst coverage and recommendation and the likelihood of a firm appearing among the 170 RavenPack exemplars (See Table D1 of Appendix D). The composite variable coefficient was 0.61 (p=0.000), indicating that a one-unit increase in this measure substantially enhances the odds (by a factor of 1.84) of a firm being highlighted as an exemplar in media articles. This finding corroborates the validity of our exemplar identification approach.

5.2. The Impact of Exemplar Performance on Analyst Recommendations

We proposed that firms with higher exemplar similarity would receive lower analyst recommendations due to the typically high performance of exemplars. To identify exemplar firms, we relied on the perspective of our target audience, security analysts, and considered firms that received significant positive coverage from analysts within their respective industries as exemplars. Our data confirm that these identified exemplars significantly outperform other firms in their categories in terms of EPS: the average EPS was 0.58 for non-exemplar firms and 1.57 for exemplars. A t-test confirmed the statistical significance of this difference (t-stat = -44.52, p-value = 0.000).

Despite including controls for exemplar performance and firm performance in our models, a considerable degree of variation in the performance of exemplars remains. Consistent with our theoretical framework, we expect that a greater performance gap between the exemplar and the focal firm would negatively impact the investment recommendations received by a firm exhibiting similarity to the exemplar. To further validate this proposed mechanism, we divided the sample into four quadrants based on the EPS difference variable, using 25^{th}, 50^{th}, and 75^{th} percentiles as cutoffs. We then conducted regressions with analyst recommendations as the dependent variable.[19] Figure 3 graphically presents the coefficients of exemplar similarity on analyst recommendations for different levels of EPS difference. The results reveal that higher performance difference between the exemplar and the focal firm amplifies

[19] We categorize the firms into quartiles based on the annual difference in EPS between the exemplar and the focal firm. As a result, the same firm may belong to different quartiles in different years. This leads to highly unbalanced panel data for the split samples. Therefore, for this analysis, we removed the firm fixed effects from the models.

the negative influence of exemplar similarity on analyst recommendations. Additional regression results are detailed in Table D2 of Appendix D.

Insert Figure 3 about here

5.3. Interaction Between Category Coherence and Distinctiveness

Our theoretical model treats category coherence and distinctiveness as distinct constructs, each with its own theoretical underpinnings from sociocognitive (Rosch 1978) and relational views of categorization (Peirce 1992), respectively. While we explore them separately, their interactive effects are also worthy of examination (Lo et al. 2020), which may be particularly relevant when considering the impact of exemplar similarity on analyst coverage.[20]

The effectiveness of exemplar similarity in offering firms a beneficial positioning hinges on the exemplar's recognizability and its ability to set a clear standard for the category. In categories where coherence and distinctiveness are both pronounced, firms aligning with a prominent exemplar are likely to gain substantial benefits, especially in terms of analyst recognition. In contrast, when both coherence and distinctiveness are low, the exemplar offers limited insight into the category's norms and boundaries. In this case, exemplar similarity may neither bolster a firm's legitimacy nor attract analyst coverage.

To empirically investigate this interaction, we conducted regression analyses examining the interplay between exemplar similarity, category coherence, and category distinctiveness. Our findings, detailed in Table D3 (see Appendix D), reveal a significant and positive coefficient for the three-way interaction ($\beta = 777.25$, $p = 0.001$). This result supports that notion that coherence and distinctiveness can jointly shape the influence of exemplar similarity on analyst coverage, aligning with Lo et al.'s (2020) proposition on the joint impact of coherence and distinctiveness on category viability.

[20] In our theoretical arguments for hypotheses with analyst recommendations as outcome, we partially leaned on mechanisms not directly related to category viability, such as the availability of alternative peers and substitutability. Therefore, in this section, we focus on models with analyst coverage as the outcome. As an exploratory analysis, we did test the interactive effect of category coherence and distinctiveness as moderators on the effect of exemplar similarity on analyst recommendations, and found no significant results.

5.4. Further Robustness Tests

In our main models, we used a panel OLS regression to estimate analyst coverage, a count outcome variable. While panel OLS can handle count data under certain conditions and has the benefit of simplicity for interpretation, it might result in heteroskedasticity and non-normality of errors. To ensure our results are not driven by model misspecification, we re-estimated our models with analyst coverage as DV using a Poisson regression with fixed effects and robust standard errors. The Poisson model is better suited for count DVs as it explicitly models the discrete, non-negative nature of the data. Our findings were qualitatively consistent across both the OLS and Poisson specifications (see Table D4 in Appendix D). Additionally, our analyst coverage variable was right-skewed. Therefore, we conducted a log transformation of the analyst coverage variable, adding a constant of one to all observation of zero counts before the transformation. Our main findings persisted after this adjustment (see Table D5 in Appendix D).

To further validate our results, we conducted additional analyses using Generalized Estimating Equations (GEE). GEE provides an appropriate framework for longitudinal data with repeated measures, as it accounts for potential correlations between observations on the same unit over time (Zeger and Liang 1986). An advantage of GEE is that it estimates population-averaged effects, emphasizing the generalized impact of predictors on the entire population. This enhances interpretability and generalizability of the findings (Diggle 2002). Moreover, GEE allows flexibility in modeling different outcome distributions tailored to the variable type. For analyst coverage, a count variable, we utilized a negative binomial distribution to accommodate overdispersion (Cameron and Trivedi 2013). Across all GEE models, we used robust standard errors to ensure reliability against any misspecification of the working correlation structure. Except for the interaction between category distinctiveness and exemplar similarity on analyst recommendations which loses statistically significance, the GEE results (see Table D6 in Appendix D) are qualitatively consistent with our main findings, providing further support for our hypotheses.

In models estimating analyst recommendations, firms with zero analyst coverage (and thus no recommendations) were excluded, which may have caused concerns of potential selection bias. We addressed this concern by implementing a two-stage Heckman selection model (Heckman 1979). In the first stage, we estimated a probit model to predict the likelihood of a firm gaining analyst coverage based on all our explanatory variables. We also included an instrumental variable, proximity to a financial services hub, that influences the probability of coverage but does not directly affect analyst recommendations (Angrist and Krueger 2001, Loughran and Schultz 2005). In the second stage, we re-estimated our analyst recommendation models while controlling for the inverse Mills ratio obtained from the first stage probit model. The inverse Mills ratio captures the probability of sample selection and helps adjust for the missing data from firms without analyst coverage. The results remain robust (see Table D7 in Appendix D).

It is important to note the high correlation between category coherence, firm typicality, and exemplar typicality. Such a high correlation is theoretically expected, since more heterogeneous categories are likely to contain more atypical member firms and exemplars. Due to this correlation, full models including interactions between both category coherence and exemplar typicality with exemplar similarity demonstrate unstable coefficient estimates. To ensure our main findings are not driven by highly correlated variables, we re-ran models each time omitting the other highly correlated variable. These analyses yielded results that were qualitatively consistent with our initial findings, suggesting our conclusions are robust to the inclusion/exclusion of the correlated variables (see Table D8 in Appendix D).

Further robustness tests are presented in Appendix D. Specifically, we tested the sensitivity of our results to different industry classification systems, alternative measurements of key variables, the inclusion of additional control variables, and changes in sampling criteria. For industry classifications, we examined the 5-digit, 4-digit, and 3-digit NAICS codes as well as the 4-digit and 3-digit SIC codes. While most findings remained robust, the moderating effect of category distinctiveness on the relationship between exemplar similarity and analyst recommendations exhibited some sensitivity to the choice of industry code. We also replaced firm typicality with alternative measures like strategy uniqueness and firm complexity. The results generally persisted except for occasional loss in significance of one of the interactions. Additionally, we controlled for textual attributes of 10-K reports related to tone, sentiment, and readability. Again, the overall pattern of findings remained mostly unchanged. Finally, we varied the minimum number of firms per industry criteria for sample inclusion. With cutoffs of 20 firms per industry or 5 firms per industry, the results continued to support our hypotheses. Collectively, these additional analyses increase the reliability of our main findings.

6. Discussion

In this paper, we theorized and tested how a firm's similarity to category exemplars influences analyst evaluations, with a particular focus on the sequential nature of the evaluation process. We proposed that the effects of exemplar similarity differ across the two evaluation stages: screening and assessment. In the screening stage, we argued that a firm's similarity to an exemplar enhances its recognizability and legitimacy, leading to broader analyst coverage. However, in the assessment stage, this similarity may invite unfavorable comparisons with the exemplar, resulting in lower investment recommendations. Furthermore, we theorized that the impact of exemplar similarity on firm evaluations is contingent upon category coherence, distinctiveness, and exemplar typicality. Our findings revealed that the effects of exemplar similarity on both evaluation stages are more pronounced in categories characterized by higher coherence and distinctiveness. Additionally, we theorized and found that typical exemplars amplify the positive impact of exemplar similarity on analyst coverage, while intensifying its negative effect on analyst recommendations. These findings have important implications for research on category exemplars, category viability, optimal distinctiveness, as well as security analysts.

6.1. Contributions to Category Exemplars Research

Our study delves into the implications of positioning vis-à-vis categorical benchmarks, thereby contributing to a deeper understanding of how such positioning shapes organizational outcomes. While past research has examined category prototypes as important benchmarks for positioning (Deephouse 1999, Navis and Glynn 2011, Haans 2019), category exemplars have only recently gained scholarly attention in management research as alternative benchmarks (Zhao et al. 2018, Barlow et al. 2019, Younger and Fisher 2020, Gouvard and Dourand 2023). The primary focus for these studies has been on on the overall impact of exemplar similarity on firm performance, overlooking the sequential nature of firm evaluation and the contextual factors that moderate the effects of exemplar similarity on evaluation outcomes. In this study, we address these gaps by examining the role of exemplar similarity across two distinct stages of evaluation: screening and assessment. Additionally, we account for key contextual factors such as category characteristics (coherence and distinctiveness) and exemplar typicality. In doing so, we offer a more holistic understanding of how a firm's positioning against an exemplar influences analysts' evaluations of the firm.

Our study also enriches our understanding of category exemplars by investigating them within established categories. Recent studies on the effects of exemplar similarity (Zhao et al. 2018, Barlow et al. 2019) have primarily focused on the product level, often within entrepreneurial contexts. In contrast, our study expands this line of inquiry by investigating the effects of exemplar similarity on a large sample of established firms. Our research has one key implication: as categories become more established and prominent, exemplars become more salient and are used more frequently by audiences. This proposition extends Zhao et al.'s (2018: 589) assertion that "in the absence of a clear prototype, exemplars serve as tangible manifestations of information cues and focus market participants' attention." Our findings demonstrate that even in established categories with increased coherence and distinctiveness, audiences appear to place significant weight on exemplars in their evaluations.

Furthermore, our research addresses a crucial aspect often overlooked in studies of exemplar similarity: variations in exemplar typicality. We demonstrate that exemplar typicality significantly influences how exemplar similarity affects firm evaluation. Our theoretical framework suggests that similarity to typical exemplars amplifies both the positive and negative consequences of positioning near an exemplar. Therefore, positioning relative to a highly typical exemplar like Netflix may have more pronounced implications than to an atypical exemplar like Peloton. By introducing the concept of exemplar typicality into the research on category exemplars, we offer a more nuanced understanding of strategic positioning choices around different exemplar types.

Additionally, while previous studies have used various qualitative (e.g., Santos and Eisenhardt 2009) and quantitative (e.g., Zhao et al. 2018) methods for identifying exemplars in nascent categories, often customized to a specific context, our study introduces a more generalizable approach. We identified exemplars by examining two key dimensions: the amount of attention received (measured through analyst coverage) and the valence of evaluations (captured through analyst recommendations). Firms receiving significantly above-average coverage and recommendations were classified as exemplars. Our approach was further validated by examining media mentions for the identified exemplars. The key insight is that exemplars tend to stand out not just in terms of attention received, but also in terms of the positivity of evaluations. This methodology, which combines attention and evaluation metrics, has potential for broader application. For instance, to identify exemplar books within Goodreads genres, one could measure both the number of reviews and the average ratings for books. Those receiving exceptionally high review volumes combined with above-average ratings could be considered exemplars.

6.2. Contributions to Research on Category Viability and Optimal Distinctiveness

Our study enriches recent discussions on category viability (Kennedy et al. 2010, Kennedy and Fiss 2013, Haans 2019, Lo et al. 2020, Soublière et al. 2022). Category viability refers to the degree to which a category is actively used by audiences for evaluation (Lo et al. 2020) and is influenced by category coherence and distinctiveness (Lo et al. 2020, Soublière et al. 2022). We join this conversation by examining how category coherence and distinctiveness moderate the effects of exemplar similarity on firm evaluation. We argued that in a well-defined, coherent category, deviation from an exemplar could lead to significant losses in the first stage of evaluation, whereas similarity to exemplars might not offer significant benefits in heterogeneous categories. This aligns with prior research suggesting that in heterogeneous categories "experimentation and variations may not just be tolerated but even encouraged (Lounsbury and Crumley 2007, Pontikes 2012, Haans 2019)" (Soublière et al. 2022: 21). Additionally, our work explores the impact of between-category boundaries on the effects of firms' within-category positioning (Lo et al. 2020, Soublière et al. 2022, Taeuscher et al. 2022). We advance this discussion by demonstrating how category distinctiveness affects the second stage of evaluation, where audiences assess a firm against its peers. We showed that in more distinct categories, if a firm positions close to another category member, it is more likely to be directly compared against it. Thus, our study highlights the influence of category distinctiveness on the dual-stage evaluation process for firms.

Our study highlights the pivotal role of category coherence and distinctiveness in shaping firms' strategies of imitation and differentiation relative to prominent category exemplars. While research on category viability has traditionally emphasized how these variables influence audience's perceptions of a category, we demonstrate their importance for firms' positioning within a category. Our findings show that the implications of emulating an exemplar are amplified in highly coherent and distinct categories, suggesting that these factors strongly influence firms' choices to pursue similarity or differentiate themselves from prominent exemplars. Consider a nascent firm seeking attention: our research indicates greater benefits from emulating an exemplar within a coherent category. This phenomenon could trigger clustering around exemplars within an already coherent category, instigating an interesting cycle of imitation and differentiation. This pattern may not only influence individual firm positioning but also progressively shape the category's trajectory, molding its development and evolution in the long run. Our study thus offers insights into firm-level strategic positioning decisions while also suggesting a broader opportunity for investigating category dynamics, exploring the interplay between coherence, distinctiveness, and the role of exemplars in shaping firms' strategic positioning (and vice versa) throughout a category's life cycle.

Our study also diverges from the current conversation on category viability in an important way. Lo et al. (2020) argued that optimal viability requires a balance of category coherence and distinctiveness. They assert that too much of either creates detrimental effects: excessive coherence leads to rigidity, while excessive distinctiveness pushes a category beyond established systems. Soublière et al. (2022) provided further nuance to this relationship by proposing a non-linear effect where the impact of coherence on viability depends on distinctiveness. In contrast, we examine the linear moderating role of category coherence and distinctiveness on the exemplar similarity effects. We attribute these different conceptualizations of category coherence and distinctiveness to two factors. First, a crucial distinction exists between bottom-up, socially constructed categories (e.g., music genres, fashion trends) and top-down, expert-defined categories (e.g., medical diagnoses codes, industry classifications). The former have greater potential for becoming overly distinct, while the latter are meticulously designed to integrate with broader systems. Given our context of NAICS-defined categories, the likelihood of "too much distinctiveness" is significantly reduced. Second, audience expertise matters. Our focus on security analysts – who meticulously analyze firms' strategies and are perceptive to their distinctions – means a highly coherent category doesn't obscure nuanced distinctions. Expert audiences are more likely to "recognize fine-grained categories" (Tanaka & Taylor, 1991; Lo et al. 2020: 102). Thus, while a category might seem overly coherent for a general audience, experts likely perceive sufficient nuance. This makes Soublière et al.'s (2022:17) argument about audiences seeking out heterogeneity less applicable to expert security analysts. Overall, we call for future research integrating audience expertise and the nature of classification systems (top-down vs. bottom-up) into the study of category viability and its core dimensions.

Our central proposition – that exemplar similarity positively influences the initial stage of evaluation but negatively impacts the subsequent assessment phase – has important implications for optimal distinctiveness research. While traditional perspectives in this domain (e.g., Deephouse 1999) advocate for a balance between similarity and differentiation, our findings reveal a more complex picture. We demonstrate the dual, counteractive effect of exemplar similarity on two key firm outcomes: garnering attention and receiving positive evaluations. Consequently, a firm's optimal positioning may hinge on which outcome it prioritizes. For instance, a high-performing but less legitimate firm might benefit from increased similarity to an exemplar to boost its recognition. Conversely, a well-established firm with average performance may seek to differentiate itself from high-performing exemplars to avoid unfavorable comparisons. This leads to another key implication: the dynamism of optimal positioning strategies (Zhao 2022, Zhao et al. 2018). Firms may initially pursue legitimacy by aligning with high-performing exemplars. However, upon achieving recognition, they might shift towards greater differentiation. Therefore, our arguments underscore the evolving nature of strategic positioning as firms respond to changing needs and competitive landscapes.

6.3. Contributions to Research on Security Analysts

Management scholars have shown growing interest in understanding the mutual relationships between firm strategies and analysts' evaluations. Firm strategies, such as downsizing, CSR practices, and technological changes, have been found to influence analysts' recommendations and evaluations (Brauer and Wiersema 2018, Qian et al. 2019). Analysts' recommendations and evaluations have also been found to impact firms' strategic decisions and outcomes, including internal capital allocation and CEO dismissal (Wiersema and Zhang 2011, Park et al. 2021, Busenbark et al. 2022). Existing research in management has predominantly focused on either analyst coverage (e.g., Zuckerman 1999, Litov et al. 2012, Feldman 2016, Brauer and Wiersema 2018, Durand et al. 2019, Qian et al. 2019) or analyst recommendations (Westphal and Clement 2008, Wiersema and Zhang 2011, Luo et al. 2015, Kim and Youm 2017) as the key dependent or independent variable. While these studies provide valuable insights into the different aspects of the relationship between firm strategy and analyst evaluations, there is a lack of research that examines the distinct and sometimes opposing relationship between analyst coverage and recommendations (for an exception, see Zhang et al. 2020). To address this gap, our research contributes to the field of analyst research by investigating how a crucial firm strategy, namely conformity versus differentiation relative to prominent firms in its category, influences these two significant analyst outcomes in distinct ways. By employing a two-stage model and associating each stage with one of the main analyst evaluation outcomes, we present a concise and straightforward theoretical framework for future studies that simultaneously consider the effects of firm strategies on analyst coverage and recommendations through this two-stage model.

Furthermore, our study connects to research in accounting and finance that has examined the analysts' selection process of peer firms and its impact on their evaluations of firms (Bhojraj and Lee 2002, De Franco et al. 2015, Young and Zeng 2015). By documenting how similarity to an outstanding firm could result in lower analyst recommendations, our study contributes to the literature on peer selection and the comparative evaluation method. Notably, prior research in finance and accounting has not extensively explored the contextual factors that influence peer selection. We integrate management research on categories and combine it with accounting and finance research, which allows us to develop a comprehensive theory that explains the influence of contextual and categorical factors, specifically coherence and distinctiveness, on the fundamental relationship under examination.

6.4. Opportunities for Future Research

Heterogeneities within audiences. Our study focuses on the impact of firm positioning on the evaluations of a specific set of actors: security analysts. While security analysts serve as an ideal context for testing our theoretical arguments due to their influence on the stock market, it is worth noting that our study's scope is limited to high-stakes environments and evaluations conducted by industry experts. Different stakeholder groups bring different theories of value (Paolella and Durand 2016), evaluating lenses (Pontikes 2012, Fisher et al. 2016), and logic and expectations (Benner and Ranganathan 2012, Durand and Jourdan 2012) to their firm evaluations. Even within a specific audience group, such as security analysts, there is a spectrum of evaluative schemas and preferences (Hsu et al. 2012, Benner and Ranganathan 2017, Falchetti et al. 2022, Majzoubi and Zhao 2023). It is plausible to speculate that certain analysts, particularly those with a track record of accurate forecasts for a firm, might rely less on comparisons with an exemplar and instead develop more firm-specific evaluation models.

Another promising direction for future research is to examine the role of analyst status in driving imitation effects among analysts. Investment banks often assign their higher status analysts to cover prominent exemplar firms. It would be interesting to investigate if these analysts are more likely to initiate coverage of non-exemplars that exhibit similarities to the exemplars they cover. Coverage by high status analysts can stimulate bandwagon effects among other analysts (Rao et al. 2001). Therefore, coverage by elite analysts of firms mimicking exemplars may amplify the benefits of exemplar similarity even further. Furthermore, we assumed relatively unbiased evaluations on the part of security analysts, which is reasonable considering their incentive to maximize the accuracy of their reports and investment recommendations (Litov et al. 2012). However, it is worth noting that a large body of research has demonstrated how self-enhancement motivations influence managers' choice of reference groups (e.g., Sensoy 2009, Blettner et al. 2015). Further research is needed to explore how the motivations and incentives of audiences influence their choice of reference groups and the subsequent evaluations of firm performance (Crilly et al. 2016, Smith and Chae 2017, Bowers and Prato 2019).

Multi-dimensional and between-category exemplar similarity. We recognize that our study's measurement of exemplar similarity, relying solely on business description texts, limits its scope to a single dimension. Future research can explore firms' conformity to and differentiation from various category benchmarks across multiple dimensions (Bu et al. 2022). Specifically, it would be valuable to explore whether firms can orchestrate and coordinate various organizational dimensions to achieve optimal distinctiveness (Philippe and Durand 2011, Durand 2012, Zhao et al. 2017, Zhao 2022). This would involve investigating whether firms can selectively conform to exemplars in ways that generate the benefits of exemplar similarity without incurring the cost of unfavorable comparisons. A configurational modeling approach could be particularly useful for this purpose (Fiss 2007).

In this study, we focused on within-category exemplar similarity consequences. Future studies could examine the impact of between-category associations, a prominent example of which is firms describing themselves as "the Uber" of their industry. Research could investigate if firms can gain legitimacy benefits from distant-category exemplar associations while mitigating comparison costs due to distinct performance expectations. For multi-category firms, studies could explore the effect of positioning near exemplars in one category while differentiating from exemplars in other categories. This strategic positioning could be based on contextual factors such as the coherence and distinctiveness of the categories and the typicality of the exemplars within them. By examining these dynamics, future studies can shed light on how multi-category firms leverage exemplar similarity strategically to achieve favorable associations in specific categories while maintaining distinctiveness in others.

Temporal dynamics of imitation and similarity. In this study, we refrain from drawing conclusions regarding the final outcome resulting from gains in coverage and losses in recommendations as a result of exemplar similarity. The ultimate result might vary based on the relative importance of these outcomes, differing by firm-specific characteristics and the life-cycle stage of a category or industry. For example, a nascent firm in a nascent category or industry may place greater value on gaining legitimacy and attention (Santos and Eisenhardt 2009, Zuzul and Edmondson 2017, Zuzul and Tripsas 2020), prioritizing the gains in legitimacy during the initial stage over the subsequent losses in recommendations. More broadly, there is a need to incorporate temporal dynamics into the study of optimal distinctiveness in the presence of different benchmarks. This becomes particularly important when considering the agency of exemplar firms and their ability to modify their positioning when imitated by other category members. While firms within a category may be inclined to imitate and follow the exemplar, the exemplar itself may need to constantly innovate and differentiate to maintain uniqueness and occupy a less contested space in the market. It would be important to investigate the consequences of closely following the exemplar in a dynamic environment.

6.5. Conclusion

Our study contributes to a comprehensive and nuanced understanding of the impact of a firm's similarity to category exemplars on analyst evaluations. By considering the staged nature of firm evaluation and the contextual factors that shape these effects, we provide valuable insights. Our findings reveal the dual nature of exemplar similarity: it can enhance a firm's recognizability and legitimacy in the screening stage but lead to unfavorable comparisons in the assessment stage. Moreover, we emphasize the importance of considering category characteristics and exemplar typicality in understanding these effects. By integrating insights from category exemplars research, category viability research, and security analyst research, our study enriches the understanding exemplars as benchmarks in complex decision-making scenarios and opens up new avenues for exploring the multifaceted nature of audience evaluations and the strategic implications of exemplar similarity for firms. Importantly, our findings hold practical implications for firms and managers, underscoring the need for careful consideration of the benefits and drawbacks of following exemplars in various contexts.

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Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Analyst Coverage	3.592	5.029	0.000	50.000
Analyst Recoms	3.721	0.585	1.000	5.000
Exemplar Similarity	0.866	0.087	0.156	1.000
Category Coherence	0.907	0.033	0.755	1.000
Category Distinctiveness	-0.797	0.072	-0.933	-0.542
Exemplar Typicality	0.931	0.045	0.615	0.992
Total Sales	1907.656	6534.649	0.000	51245.617
Firm Size	6.816	34.282	0.000	2545.209
Market Share	0.023	0.065	-0.073	1.000
EPS	0.577	2.144	-7.035	9.956
Available Slack	2.423	3.616	0.000	21.031
R&D Expenditure	0.093	0.185	0.000	0.805
Advertising Expenditure	0.010	0.025	0.000	0.176
Intangible Assets Ratio	0.096	0.166	0.000	0.724
Depreciation Ratio	0.032	0.037	0.000	0.192
Firm Typicality	0.906	0.061	0.092	1.000
No. Segments	2.007	1.663	1.000	20.000
Mergers (expenditure)	-0.889	5.291	-48.000	2.291
Financial Leverage	0.880	2.152	-6.991	14.656
S&P500 Dummy	0.051	0.221	0.000	1.000
No. Analysts in Industry	142.183	129.511	1.000	751.000
No. Firms in Industry	137.981	150.979	10.000	609.000
Average Coverage (Year-Ind)	7.304	3.427	1.000	29.429
Average Recoms (Year-Ind)	3.766	0.314	2.000	5.000
Category Instability	0.006	0.012	0.000	0.163
Industry HHI	0.185	0.200	0.000	1.000
Exemplar EPS	1.573	2.686	-7.035	9.956

Table 2. Bivariate Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
(1) Analyst Coverage	1.00																										
(2) Analyst Recoms	-0.09	1.00																									
(3) Exemplar Similarity	0.07	-0.08	1.00																								
(4) Category Coherence	0.01	-0.12	0.57	1.00																							
(5) Category Distinctiveness	-0.04	0.16	0.14	0.04	1.00																						
(6) Exemplar Typicality	0.02	-0.06	0.62	0.60	0.16	1.00																					
(7) Total Sales	0.18	-0.06	0.01	0.09	-0.04	0.01	1.00																				
(8) Firm Size	0.11	-0.04	-0.01	0.05	-0.04	-0.01	0.56	1.00																			
(9) Market Share	0.15	-0.04	-0.11	0.00	-0.10	-0.10	0.46	0.36	1.00																		
(10) EPS	0.16	-0.09	0.03	0.12	-0.19	0.03	0.24	0.13	0.16	1.00																	
(11) Available Slack	-0.01	0.19	-0.16	-0.22	0.34	-0.09	-0.12	-0.07	-0.09	-0.20	1.00																
(12) R&D Expenditure	0.01	0.20	0.00	-0.22	0.63	0.02	-0.11	-0.08	-0.13	-0.29	0.50	1.00															
(13) Advertising Expenditure	0.05	-0.03	-0.02	-0.04	-0.01	-0.04	-0.01	0.01	0.01	0.00	-0.02	-0.06	1.00														
(14) Intangible Assets Ratio	0.13	0.07	-0.15	-0.20	0.04	-0.15	0.04	0.04	0.12	-0.04	-0.02	0.02	0.11	1.00													
(15) Depreciation Ratio	0.04	0.03	-0.17	-0.15	-0.08	-0.14	0.05	0.07	0.05	-0.20	0.00	0.02	0.03	0.20	1.00												
(16) Firm Typicality	0.06	-0.07	0.75	0.53	0.00	0.42	0.05	0.02	0.01	0.05	-0.17	-0.10	-0.04	-0.08	-0.09	1.00											
(17) No. Segments	0.17	-0.09	-0.06	0.05	-0.16	-0.02	0.37	0.20	0.28	0.19	-0.14	-0.20	-0.01	0.11	0.07	0.02	1.00										
(18) Mergers (expenditure)	-0.17	0.00	-0.03	-0.01	0.00	-0.01	-0.15	-0.08	-0.10	-0.06	0.04	0.02	-0.02	-0.21	-0.01	-0.03	-0.10	1.00									
(19) Financial Leverage	0.00	-0.07	0.07	0.11	-0.09	0.04	0.09	0.04	0.07	0.04	-0.19	-0.16	-0.02	-0.03	-0.08	0.06	0.07	-0.03	1.00								
(20) S&P500 Dummy	0.31	-0.09	-0.02	0.01	-0.08	-0.01	0.32	0.20	0.31	0.19	-0.07	-0.07	0.02	0.08	0.02	0.00	0.21	-0.17	0.04	1.00							
(21) No. Analysts in Industry	0.08	0.08	0.14	-0.19	0.27	0.05	-0.10	-0.07	-0.23	-0.15	0.16	0.36	0.15	0.13	0.08	-0.09	-0.15	-0.03	-0.11	-0.06	1.00						
(22) No. Firms in Industry	-0.14	-0.05	0.40	0.17	0.25	0.27	-0.10	-0.07	-0.23	-0.02	-0.12	0.09	0.01	-0.21	-0.32	0.14	-0.23	0.04	0.05	-0.11	0.42	1.00					
(23) Average Coverage (Year-Ind)	0.34	-0.02	-0.01	0.00	-0.09	0.01	0.14	0.08	-0.01	0.04	0.02	-0.01	0.05	0.18	0.24	0.00	0.17	-0.11	-0.02	0.16	0.20	-0.33	1.00				
(24) Average Recoms (Year-Ind)	-0.03	0.34	-0.11	-0.10	0.26	-0.09	-0.11	-0.06	0.00	-0.14	0.24	0.28	0.00	0.07	0.10	-0.12	-0.11	0.01	-0.10	-0.05	0.11	-0.13	-0.07	1.00			
(25) Category Instability	-0.11	0.02	-0.26	0.02	-0.10	-0.22	0.01	0.02	0.17	-0.01	-0.04	-0.13	-0.04	-0.05	-0.02	-0.07	-0.02	0.05	0.02	-0.01	-0.29	0.04	-0.25	0.20	1.00		
(26) Industry HHI	-0.12	0.05	-0.34	-0.03	-0.06	-0.25	0.01	0.05	0.19	-0.06	0.00	-0.06	-0.06	0.03	-0.06	-0.09	-0.06	0.02	-0.07	-0.03	-0.35	0.11	-0.29	0.03	0.42	1.00	
(27) Exemplar EPS	0.08	-0.08	-0.01	0.12	-0.21	0.01	0.14	0.06	0.05	0.27	-0.18	-0.25	-0.01	0.01	-0.09	0.04	0.16	-0.07	0.04	0.09	-0.20	-0.14	0.15	-0.12	-0.03	0.03	1.00

Table 3. Main Results

VARIABLES	(1) Analyst Coverage t+1	(2) Analyst Recom t+1	(3) Analyst Coverage t+1	(4) Analyst Coverage t+1	(5) Analyst Recom t+1	(6) Analyst Recom t+1	(7) Analyst Coverage t+1	(8) Analyst Recom t+1
Exemplar Similarity (1)	2.453	-0.282	-51.091	35.021	2.688	-2.807	-14.657	2.081
	(0.000)	(0.014)	(0.000)	(0.000)	(0.076)	(0.008)	(0.000)	(0.003)
Category Coherence (2)	21.515	-1.795	-30.309	21.287	1.121	-1.780	21.448	-1.783
	(0.000)	(0.000)	(0.000)	(0.000)	(0.459)	(0.000)	(0.000)	(0.000)
Category Distinctiveness (3)	-2.607	-0.234	-2.777	-36.982	-0.242	2.456	-2.790	-0.216
	(0.182)	(0.386)	(0.151)	(0.000)	(0.369)	(0.031)	(0.151)	(0.426)
Exemplar Typicality (4)	-1.368	-0.051	-1.638	-0.971	-0.042	-0.075	-17.471	2.194
	(0.048)	(0.720)	(0.016)	(0.162)	(0.769)	(0.601)	(0.000)	(0.001)
(1) x (2)			61.741		-3.400			
			(0.000)		(0.048)			
(1) x (3)				39.915		-3.092		
				(0.000)		(0.017)		
(1) x (4)							19.996	-2.744
							(0.000)	(0.001)
Total Sales	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.010)	(0.347)	(0.011)	(0.011)	(0.360)	(0.362)	(0.010)	(0.362)
Firm Size	0.005	-0.001	0.006	0.006	-0.001	-0.001	0.005	-0.001
	(0.464)	(0.320)	(0.446)	(0.454)	(0.319)	(0.317)	(0.460)	(0.319)
Market Share	2.997	-0.307	2.942	2.993	-0.304	-0.303	3.004	-0.302
	(0.192)	(0.143)	(0.198)	(0.191)	(0.146)	(0.144)	(0.190)	(0.150)
EPS	0.068	0.014	0.068	0.068	0.014	0.014	0.068	0.014
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Available Slack	0.005	-0.002	0.006	0.009	-0.003	-0.003	0.006	-0.003
	(0.540)	(0.187)	(0.498)	(0.285)	(0.173)	(0.116)	(0.495)	(0.165)
R&D Expenditure	-1.084	0.063	-1.050	-1.015	0.065	0.052	-1.069	0.064
	(0.003)	(0.405)	(0.003)	(0.005)	(0.393)	(0.489)	(0.003)	(0.399)
Advertising Expenditure	7.778	-0.288	7.687	7.698	-0.276	-0.288	7.765	-0.275
	(0.000)	(0.478)	(0.000)	(0.000)	(0.496)	(0.478)	(0.000)	(0.497)
Intangible Assets Ratio	2.314	-0.142	2.325	2.283	-0.142	-0.141	2.295	-0.140
	(0.000)	(0.005)	(0.000)	(0.000)	(0.005)	(0.005)	(0.000)	(0.006)
Depreciation Ratio	-8.470	-1.515	-8.528	-8.254	-1.514	-1.532	-8.507	-1.510
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Typicality	0.343	-0.030	-1.322	-0.710	0.040	0.035	-1.056	0.147
	(0.688)	(0.867)	(0.137)	(0.420)	(0.824)	(0.847)	(0.255)	(0.432)
No. Segments	0.089	-0.008	0.083	0.088	-0.007	-0.007	0.086	-0.007
	(0.025)	(0.107)	(0.037)	(0.026)	(0.124)	(0.112)	(0.029)	(0.120)
Mergers (expenditure)	-0.034	-0.002	-0.033	-0.034	-0.002	-0.002	-0.034	-0.002
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Financial Leverage	-0.012	-0.006	-0.010	-0.012	-0.006	-0.006	-0.011	-0.006
	(0.298)	(0.002)	(0.397)	(0.281)	(0.001)	(0.002)	(0.333)	(0.001)
S&P500 Dummy	1.579	-0.090	1.573	1.579	-0.089	-0.089	1.574	-0.090
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
No. Analysts in Industry	0.006	-0.001	0.006	0.006	-0.001	-0.001	0.006	-0.001

	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. Firms in Industry	-0.002	0.000	-0.002	-0.003	0.000	0.000	-0.002	0.000
	(0.004)	(0.255)	(0.007)	(0.000)	(0.281)	(0.169)	(0.003)	(0.232)
Average Coverage (Year-Ind)	0.220	0.001	0.221	0.220	0.001	0.001	0.220	0.001
	(0.000)	(0.685)	(0.000)	(0.000)	(0.691)	(0.671)	(0.000)	(0.656)
Average Recoms (Year-Ind)	0.218	0.358	0.238	0.214	0.358	0.358	0.231	0.356
	(0.006)	(0.000)	(0.002)	(0.006)	(0.000)	(0.000)	(0.003)	(0.000)
Category Instability	-33.947	1.241	-31.907	-33.434	1.193	1.232	-32.675	1.175
	(0.000)	(0.145)	(0.000)	(0.000)	(0.161)	(0.148)	(0.000)	(0.169)
Industry HHI	1.768	-0.094	1.898	1.744	-0.100	-0.090	1.807	-0.099
	(0.000)	(0.209)	(0.000)	(0.000)	(0.183)	(0.228)	(0.000)	(0.189)
Exemplar EPS	0.011	-0.001	0.013	0.014	-0.001	-0.001	0.012	-0.001
	(0.219)	(0.469)	(0.155)	(0.121)	(0.430)	(0.395)	(0.190)	(0.445)
Constant	-22.152	4.312	24.154	-49.389	1.690	6.459	-7.370	2.238
	(0.000)	(0.000)	(0.000)	(0.000)	(0.223)	(0.000)	(0.065)	(0.003)
Observations	46786	30688	46786	46786	30688	30688	46786	30688
R-squared	0.118	0.053	0.122	0.121	0.053	0.053	0.119	0.053
Entities	7603	5975	7603	7603	5975	5975	7603	5975

P-values in parentheses. Firm fixed effects are included in all models.

Figure 1. Effects of Exemplar Similarity on Analyst Coverage and Recommendations

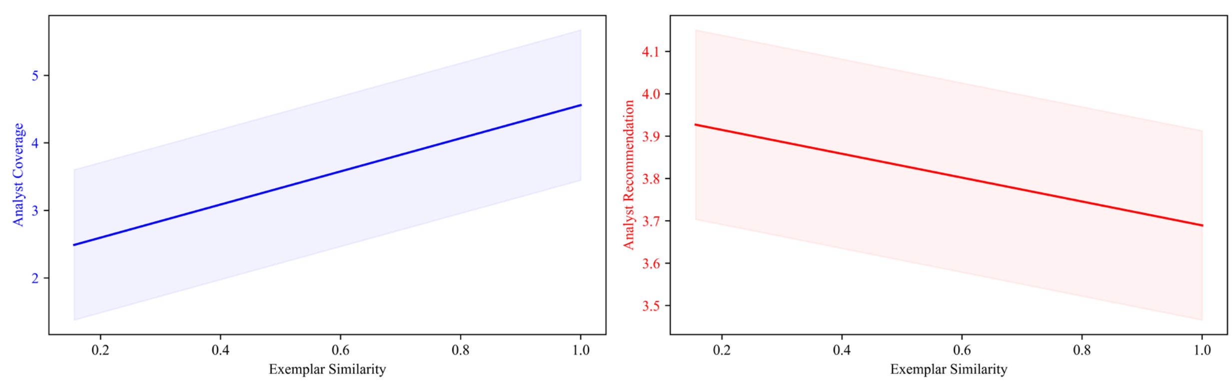
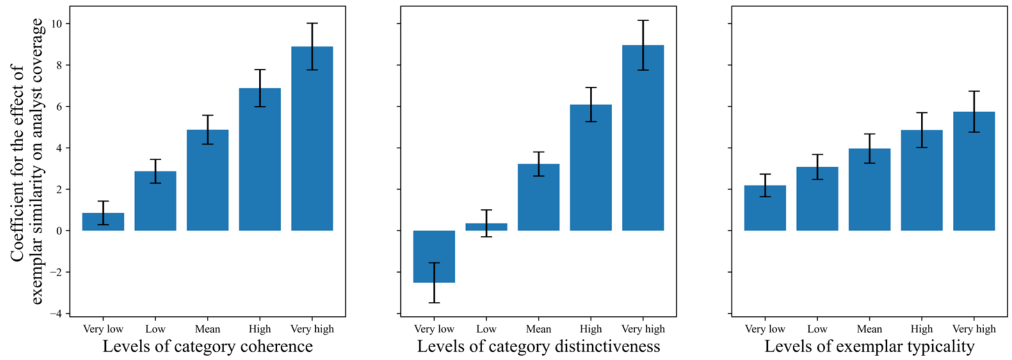


Figure 2. Moderation Effects of Category Coherence, Category Distinctiveness and Exemplar Typicality

Panel A. Moderators' effects on the relationship between exemplar similarity and analyst coverage



Panel B. Moderators' effects on the relationship between exemplar similarity and analyst Recommendations

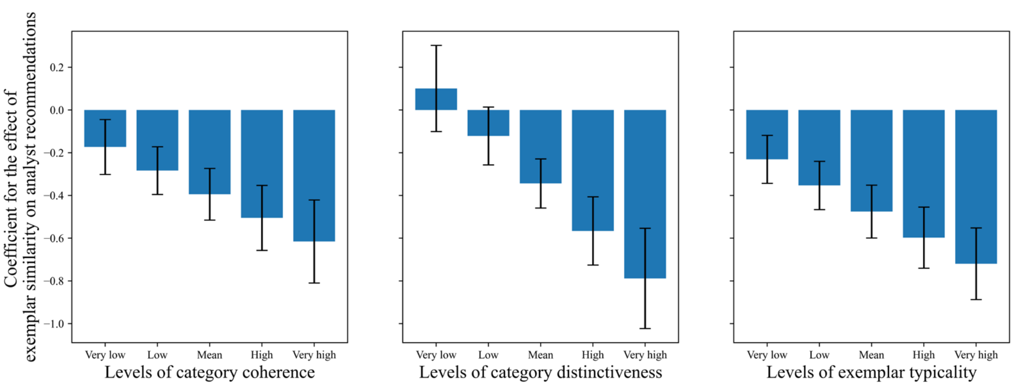


Figure 3. The Moderation Effect of the Performance Differences between the Exemplar and the Focal Firm