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Majid Majzoubi

Three Essays on A Dynamic View of Strategic Positioning and Audience Evaluations

Majid Majzoubi

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Reading Committee:

Suresh Kotha, Chair

Tiona Zuzul

Harvey Steensma

Program Authorized to Offer Degree:

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University of Washington

ABSTRACT

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Majid Majzoubi

Chair of Supervisory Committee

Professor Suresh Kotha

Department of Management and Organization

Foster School of Business

A firm's current strategic position in relation to its past and its peers is a major determinant of how audiences evaluate it. Using three distinctive but related studies, I explore how audience evaluations are influenced by a firm's positioning: (1) vis-à-vis its past (change in firm identity), (2) in relation to multiple categorical benchmarks, and (3) relative to audiences' heterogeneous predispositions and idiosyncratic evaluation schemas. I conduct my empirical analysis in the context of security analysts' coverage decisions and investment recommendations of publicly listed U.S. firms from 1997 to 2018. I apply various text analysis and topic modeling techniques on firms' 10-K filings to measure a firm's positioning over time and in relation to other firms.

In the first study I examine how change to a firm's identity claims may affect its legitimacy. I posit that change in identity claims could render a firm ambiguous and uncertain for its audiences and thus result in a loss of legitimacy. I further hypothesize that the negative effects of change in identity claims are moderated by the direction of change and environmental heterogeneity, such

that the effect on legitimacy is stronger when, as a result of change, firms become less similar to their peers, and in environments with low degree of heterogeneity. I found empirical support for my hypotheses.

In the second study, I explore the effects of similarity to category exemplars for typical and atypical firms. I argue that similarity to a category exemplar enhances a firm's legitimacy and recognizability by signaling association with a well-known category member. Exemplar similarity, however, also increases the chances of being compared against a high performing firm. Drawing upon the mechanisms of association and comparison, I hypothesize an inverted U-shaped relationship between exemplar similarity and firm market value for typical firms, and a U-shaped relationship for atypical firms. This hypothesis was supported by my empirical analysis.

In the third study, I explore optimal positioning strategies in contexts where audiences have heterogeneous predispositions and evaluation schemas. I show that, given the premise of audience heterogeneity, firms can gain an audience composition premium by positioning themselves such that they are evaluated by audiences with a favorable predisposition toward them. I show how a family of machine learning algorithms—i.e., recommender systems—could be utilized for predicting audiences' individualized predispositions toward different firms and gaining higher audience evaluations through more optimal positioning strategies. My empirical analysis provides support for my hypotheses.

This dissertation provides a more dynamic understanding of strategic positioning and its effects on audience evaluations. The first study contributes to research on the intersection of organizational identity and firm legitimacy by incorporating the effects of change in a firm's identity claims on audiences' judgments regarding firm legitimacy. The second study contributes to optimal distinctiveness research by introducing the notion of dual benchmark settings and

investigating some intricate relationships between firm positioning relative to category prototypes and exemplars and firm performance. The third study contributes to management research on audience evaluations by incorporating the premise of audience heterogeneity and introducing the notion of an audience composition premium as a parsimonious construct referring to the gain that accrues to a firm based on the composition of the audience evaluating it.

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CHAPTER ONE

1 A Dynamic View of Strategic Positioning and Audience Evaluations: Introduction to the Research Agenda

1.1 An Overview

External audiences evaluate, rank, and certify firms (Sharkey & Bromley, 2015; Zuckerman, 1999). Such evaluations help reduce uncertainty and information asymmetry about the quality of a firm or product in market transactions (Zhao & Zhou, 2011) and enable a firm to access environmental resources (Pfeffer & Pfeffer, 1981; Pfeffer & Salancik, 1978). For instance, recognition and coverage from security analysts, as key stock market information intermediaries, can impact a firm's access to financial capital and its stock price, while a loss of coverage may lessen shareholder wealth (Zuckerman, 1999). Accounting for the importance of gaining recognition and attention from external audiences, research has explored the effects of a firm's positioning strategy on the external evaluations it receives (Zhao, Fisher, Lounsbury, & Miller, 2017).

A firm's positioning strategies both within and across categories can have an impact on audience evaluations. Organizations need to concurrently navigate the pressure for similarity and the need for differentiation relative to other firms. On one hand, firms need to resemble their peers to gain legitimacy (e.g., Deephouse, 1999; DiMaggio & Powell, 1983; Zhao et al., 2017; Haans, 2019). Such resemblance allows them to avoid the penalties imposed on firms that adopt unique positions (Litov, Moreton, & Zenger, 2012) and those that defy "categorical imperatives," i.e., the pressure to conform to recognized types and established categories (Zuckerman, 1999). On the other hand, firms may gain a competitive advantage by using valuable, rare, and inimitable attributes (Barney, 1991) and by differentiating themselves from their peers (Porter, 1980, 1991).

Differentiation allows firms to avoid getting lost in the crowd (Barlow, Verhaal, & Angus, 2019). Organization scholars have tried to reconcile these two opposing views, traditionally studied in isolation by institutional theory and strategic management scholars (Zhao et al., 2017), by suggesting that firms gain optimal distinctiveness by “being as distinct as legitimately possible” (Deephouse, 1999; Navis & Glynn, 2011).

Despite the growing scholarly attention to research on optimal positioning strategies for gaining favorable audience evaluations (e.g., Barlow et al., 2019; Haans, 2019; Smith, 2011; Smith & Chae, 2017; Zhao, Ishihara, & Jennings, 2018), there is still a need for research that explores the intricacies of strategic positioning through a dynamic lens. As Zhao et al. (2017) put it:

While strategic balance research has significantly enhanced our understanding of how firms cope with the oppositional demands for similarity and difference, the challenges identified suggest the utility of a broader and more dynamic research agenda on optimal distinctiveness. Such research needs to account for the complexity of organizational environments, the processes by which firms strategically differentiate themselves to enhance performance outcomes, and the mediating mechanism of stakeholder perceptions (p. 98).

I specifically identify three key limitations in the extant literature. First, while a large body of research has explicated firms’ need for flexibility and change, the effect of change in a firm’s market positioning on audience evaluations is under-explored. Second, while research suggests there are multiple benchmarks such as category prototypes—i.e., a category’s average and central tendencies—and category exemplars—i.e., a category’s outstanding members—against which audiences can make value judgments, most optimal distinctiveness studies assume the only benchmark against which an organization’s optimal distinctiveness is gauged are category

prototypes. Third, while research has highlighted heterogeneity in audiences' predispositions and evaluation schemas, optimal distinctiveness research assumes that audiences categorize firms uniformly and that they use similar evaluation models to assess firms within a specific category. I aim to address these gaps with three studies that I conducted for this dissertation.

I structure the dissertation as follows. In the next sections of this chapter, I provide an overview of the literature related to the effects of firm positioning on audience evaluations, and explain the key gaps in the literature that have motivated my exploration. In this overview, I provide a review of optimal distinctiveness literature which underlies the theoretical foundation of this dissertation. Next, I highlight the limitations of extant research around three research questions: (1) How does change in a firm's positioning through its identity claims in directions relative to other firms and under different environmental heterogeneity conditions affect its legitimacy? (2) What are the simultaneous effects of a firm's positioning in relation to both category exemplars and category prototypes on the evaluations it receives? and (3) What is an optimal positioning strategy for a firm when audiences hold heterogeneous predispositions and evaluation schemas? At the chapter's end, I provide a brief overview of the three studies presented in this dissertation.

In Chapter 2, I present my study on the effects of firm changes on audience evaluations, addressing the first identified gap. In Chapter 3, I investigate optimal positioning strategy in dual benchmark settings to address the second identified gap. In Chapter 4, I develop theoretical arguments and introduce a novel methodological approach for determining optimal firm positioning in the presence of a heterogeneous audience. Finally, in Chapter 5, I provide a summary of my studies and discuss this dissertation's contributions to the field of optimal distinctiveness, organizational identity change, and management research on audience evaluations.

1.2 Optimal Distinctiveness Research: A Review of the Literature

Optimal distinctiveness research explores how similarity and differentiation vis-à-vis other firms may affect the performance and evaluations a firm receives from audiences. Institutional theorists have argued that when a firm conforms to other firms in terms of its strategic positioning, it garners legitimacy (e.g., Zuckerman, 1999, 2000; Zhao et al., 2018). Firms that are easier to classify and categorize based on an existing schema can obtain easier access to environmental resources (Pfeffer & Salancik, 1978), while those that defy categorical imperatives may incur an illegitimacy discount (Zuckerman, 1999; Litov et al., 2012). Strategic management scholars have emphasized that competitive advantage may be gained by taking a unique market position (Porter, 1980, 1991) based on a firm's valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). Firms may thus benefit from being different compared to their peers, as this allows them to stand out in the crowd (Barlow et al., 2019).

Deephouse (1999) bridged the two contrasting points of view on the need for conformity and the benefits of differentiation. Building upon Brewer's (1991) conceptualization of optimal distinctiveness on the individual level, Deephouse (1999) argued that firms need to strike a balance between the pressures for differentiation and conformity in their strategic attributes. Empirically testing his theories in the context of commercial banks in the Twin Cities (Minneapolis-St. Paul) area of Minnesota, Deephouse found an inverted U-shaped relationship between conformity to the mean of the industry's strategic attributes and firm performance. Based on this finding, firms that adopted an asset strategy that either moderately conformed to industry norms or moderately deviated from them had higher returns on assets than firms either highly deviated or highly conformed to industry norms. Deephouse (1999) proposed that for the highest performance, firms need to be "as different as legitimately possible" (p. 147).

Recent research has expanded optimal distinctiveness theory and explored antecedents to taking distinctive positions, global versus local distinctiveness, and optimal distinctiveness during industry emergence (see Table 1 for a review of key papers on optimal distinctiveness). Park (2007) argued that an antecedent to a firm's direction of change toward similarity to or differentiation from another firm is its performance aspiration and relative performance compared to the target firm. Based on his argument, higher performance, relative to aspiration level and the other firm's performance, increases executive hubris and decreases search efforts outside the firm's internal models. Therefore, firms that are better performing are less likely to conform to other firms and position themselves near them.

Phillips and Zuckerman (2011) posited the middle-status conformity hypothesis, arguing that middle-status actors conform most often because they value their membership in the group, while at the same time they are insecure about whether the audience will consider them members of the group. High-status actors, on the other hand, engage in deviant behavior more often, because they are secure in their legitimacy and group inclusion. Low-status actors engage in deviant behavior because they are excluded from the audience's considerations no matter what they do. Phillips and Zuckerman (2011) found evidence for their arguments in the context of law firms in Silicon Valley. They found that high and low status law firms tended to offer more family law services, a practice that was at the time regarded as deviant and low prestige behavior. Phillips and Zuckerman (2011) also found support for their predictions in the context of security analysts who made "sell" recommendations, a rare behavior in the security analysis domain since it could alienate a financial bank from its potential corporate clients. They found that high-status and low-status analysts made the highest number of sell recommendations.

Prato, Kypraios, Ertug, and Lee (2017) extended Phillips and Zuckerman's (2001) middle-status conformity hypothesis by arguing that while the relationship between status and conformity is an inverted U-shaped for actors with high-ascribed status—i.e., non-malleable status attributes such as race, gender—for low-ascribed status actors the relationship is U-shaped. The reason is that actors at the lowest end of achieved status who also have low-ascribed status become conformist in the fear of becoming even more marginalized. Further, actors with high achieved status but with low-ascribed status will be less secure and willing to take risks since they are under intense scrutiny. Prato et al. (2017) found support for their prepositions in the context of U.S. symphony orchestras between 1918 and 1969.

Several studies have explored the dynamics of adopting similar or differentiated positions during industry or category emergence. Aldrich and Fiol's (1994) seminal work shed light on strategies and activities, such as the use of symbolic language and behavior, that new ventures could adopt to overcome the legitimacy void during industry emergence. Extending that work, Navis and Glynn (2010) studied the emergence of the Satellite Radio industry and found that due to the intensity of the legitimacy imperative during the early stages of industry emergence, firms focused on legitimating their category by emphasizing their collective identity as opposed to individual identities and used linguistic framing techniques to normalize the collective identity of the category. The researchers observed that firms shifted their focus from legitimating their collective identity to establishing a distinct identity, as the industry garnered more legitimacy.

On a similar note, King, Clemens, and Fry (2011) found that during the emergence of Arizona's charter school organizational form, schools were likely to conform to the common practices and identity elements of their peers, and that any differentiation was limited by institutional constraints. Zhao et al. (2018) conducted an empirical study in the context of U.S.

console video games and found that in the initial stages of category emergence, the competitive pressure was low while legitimacy pressure was very high, thus conformity to categorical norms resulted in better performance outcomes. The authors found that as the categories became more established, competitive pressure increased, accentuating the need for taking a differentiated position. In later stages of category development, a moderate level of differentiation resulted in optimal performance outcomes.

Scholars have studied optimal distinctiveness for firms that have both a local and a global presence. Voronov, Clercq, and Hinnings (2013) conducted an inductive study on Ontario's fine wine industry and studied the processes through which firms could conform to global institutional norms while still differentiating themselves locally. They observed that through flexible scripts, firms tried to demonstrate conformance through fidelity to global norms and distinctiveness through making local adaptations, while at the same time and for different audience groups, these firms tried to signal distinctiveness through global fidelity and conformance through local adaptations. In another study, Miller, Indro, Richards, and Chng (2013) incorporated a signaling perspective into the optimal distinctiveness literature and argued that while firms tend to avoid conforming to their local rivals to avoid competitive intensity, they could benefit from such conformance and might be evaluated more positively for doing so. Specifically, in the context of foreign firms raising funds in the U.S., firms could signal higher quality by receiving funds from investment banks that are frequently chosen by their competitors and peers. Garnering funds from these banks signals that a firm is willing to be compared to its competitors and to undergo the tough scrutiny of investment banks.

Research has also explored the processes through which firms could gain optimal distinctiveness. Porac et al. (1989) found a tension between isomorphic and differentiation

pressures in the Scottish knitwear industry. Based on their findings, Scottish knitwear firms were able to navigate these two competing forces by incorporating the core identity attributes of their category, such as targeting classically minded high-income consumers and purchasing yarn from local spinners, in their identity and practices, while differentiating on non-core attributes such as color and subtle technological variations.

Gehman and Grimes (2017) did an inductive study on B-corps and found that firms will forbear from claiming category memberships when such claim would provide them less distinctiveness. Based on their argument, firms promote subordinate category membership to differentiate themselves within basic categories. However, when there is less contextual distinctiveness for a subordinate category such as B-Corps certification, firms might forbear from promoting their membership in that category. Smith and Chae (2016) examined a process through which firms could overcome a lack of legitimacy due to their atypicality. The authors built on Glynn and Azburg's (2002) work and argued that atypical firms are more likely to use deliberate naming strategies (including labels in their names that signal category membership) to partially overcome their lack of legitimacy. They argue that firms resort to deliberating naming strategy more intensely when it is more difficult to objectively assess a firm's quality. In addition, firms that take advantage of a deliberate naming strategy enjoy higher audience evaluations.

Table 1-1 Key papers on optimal distinctiveness

Author	Journal	RQ/Topic	Setting	DV	IVs	Key Arguments and Findings
Chan, Lee 2021	Org. Sci.	Is there a difference between similarity and differentiation to past versus contemporary designs?	Design patents	(1) Stock market reactions in the days after a design patent is granted	(1) Similarity. a Jaccard index capturing the degree of overlap in backward citations (2) Industry product turnover	(1) Design's value is maximized when it is most similar to designs in the past and different from current designs. (2) The market uses two criteria to evaluate a new design: the extent to which it deviates from familiar archetypes established in the past; and the extent to which it competes with contemporaneous designs.
Haans 2019	SMJ	How does the effects of distinctiveness on performance vary in homogeneous versus heterogeneous categories?	Dutch creative industries	(1) Revenue	(1) Distinctiveness. Using topic modeling (2) Distinctiveness heterogeneity: sum of std of topic weights in each industry	(1) There is a U-shaped relationship between distinctiveness and performance in homogeneous categories. (2) The U-shaped relationship flattens out in average categories. (3) There is no effect in categories where everyone is distinct.
Barlow, Verhaal, Angus 2019	SMJ	What are the effects of exemplar similarity?	Google App store	(1) Review Count (ln)	(1) Prototype similarity. Based on text analysis. (2) Exemplar similarity. Similarity to the closest neighbor that is among top 100 in the category.	(1) There is a positive relationship between exemplar similarity and performance for new entrants. (2) The positive baseline effect is stronger with higher distance from prototype.
Tracy, Dalpiaz, Phillips 2018	AMJ	Entrepreneurship through translating an org. form from one institution to another institution with different expectations and norms	H-Farm	-	-	(1) At first, entrepreneurs need to seek legitimacy in the eye of local stakeholders. (2) Next, they need to conform to expectations from category level (global) stakeholders. (3) Finally, they need to make themselves optimally distinctive in both local and global spheres. (4) Navigating dual optimal distinctives hurdles: "what makes a venture legitimate at the local level is what makes it distinct at the category level, and what makes a venture legitimate at the category level is what makes it distinct the local level."
Zhao, Ishihara, Jennings, Lounsbury 2018	Org. Sci.	How does the effects of similarity versus conformance to category reference points change over time?	US console video game industry	(1) Market sales	(1) Differentiation from category exemplar (2) Time since exemplar release (3) Number of prior entrants	(1) In the initial stages of category emergence, the competitive pressure is low while legitimacy pressure is very high, thus conformity to category exemplar results in better performance. (2) As the proto-category develops, competitive pressure heightens while legitimacy pressure still exists, thus a moderate level of differentiation results in better performance . (3) Critics' evaluations mediates the effects of differentiation on performance. (4) Mediating effects of critics evaluations become more prominent as the category matures. (5) In the context of proto-categories (pre-established categories), exemplars rather than the prototype of a category is the reference point for judging differentiation and conformity.
Stigliani, Elsbach 2018	JMS	How can firms simultaneously forge a coherent industry identity and distinctive organizational identity?	Service Design emerging industry	-	-	(1) Firms could navigate simultaneous need for coherence and distinctiveness through iterations of sensemaking and sensegiving mechanisms around work principles, org. identities, and discipline label
Prato, Kypraos, Ertug, Lee 2018	AMJ	What are the boundary conditions for the middle-status conformity hypothesis?	U.S. symphony orchestras	(1) Conductor conformity	(1) Ascribed status. Whether German or Austrian (2) Achieved status. Number of records made	(1) While the relationship between status and conformity is inverted u-shaped for actors with high-ascribed status (non-malleable status attributes such as race, gender), for low-ascribed status actors the relationship is u-shaped.

Cattani, Dunbar, Shapira 2017	Str. Sci.	How can firms gain a unique position by persistence on their local optimal versus moving to a unique, distant optimal location?	Steinway & Sons company	-	-	(1) Firms can benefit from differentiation and uniqueness if they remain at their local positioning while other firms in the field shift their identity/practices and move to a distant competitive position. (2) In the case of Steinway & Sons, when technology enable mass production of pianos, Steinway & Sons differentiated itself by sticking with its traditional method of using craftsmanship for production.
Smith, Chae 2017	Org. Sci.	How does atypicality affect reference group selection by evaluators?	M-Turk Experiment	-	-	(1) Atypicality could enhance audience evaluations by providing the audience, who are willing to make enhancing evaluations, the flexibility to choose from nonconforming referents that deviate from the expected benchmarks. (2) Therefore, atypical firms will be rewarded more for high performance and penalized less for poor performance by their audience, especially if the audience is committed to them.
Askin, Mauskopf 2017	ASR	How does product feature similarity versus differentiation from its peers affect the product's success and cultural popularity?	27,000 songs from Billboard's Hot 100 charts	(1) Chart performance	(1) Song typicality. Determined by computer generated scores on 9 attributes.	(1) Songs that balance similarity to and differentiation from other songs perform best in billboard charts.
Gelman, Grimes 2017	AMJ	Why do some firms forbear from claiming membership in categories that can signal higher quality (B-Corps certification)?	B-Corps companies	(1) B-Corps certificate promotion in company websites	(1) Regional contextual distinctiveness (2) Industry contextual distinctiveness	(1) Firms will forbear from claiming category memberships when such claim would make them less distinctive. (2) There is a distinction between basic categories and subordinate categories. Firms use subordinate category membership to differentiate themselves within the basic categories. (3) When there is less contextual distinctiveness for a subordinate category such as B-Corps certification, firms might forbear from promoting their membership in that category.
Smith, Chae 2016	SMJ	Do atypical firms benefit from using deliberate naming strategies?	Hedge fund industry	(1) Deliberate naming dummy (2) Fund growth (3) Fund survival	(1) Fund atypicality. Investment style as measured by 33 attributes	(1) Atypical firms are more likely to use deliberate naming strategies (including category membership signaling labels in their names) to partially overcome their lack of legitimacy. Name labels serve as signals. (2) Firms resort to deliberating naming strategy more intensely when it is more difficult to objectively assess firm quality. (3) Firms that take advantage of deliberate naming strategy enjoy higher growth rate and better survival chance.
O'kane, Mangematin, Geoghegan, Fitzgerald 2015	Res. Pol.	Identity processes used in university technology transfer offices to gain legitimacy	University technology transfer office	-	-	(1) In the context of TTOs, identity conformance strategies prove inefficient. TTOs establish dual scientific and business identities to gain legitimacy from both academic and management segments of universities, but this dual identity strategy does not provide TTOs the identity they are after. (2) The proposed reason for it is that TTOs solely focus on fitting in and conforming, without creating a unique value proposal through distinctive identity elements.
Giorgi, Weber 2015	ASQ	How do audiences evaluate framing in contexts where there are multiple framings available?	Security analysts and investor judgements	(1) Inclusion in All-America Research Team	(1) Resonance with analyst needs (2) Consistency. Herfindahl index of all reports of the analyst. (3) Novelty	(1) Audiences evaluate framings that resonate with them better. (2) Audiences evaluate framings cumulatively and prefer consistency over time. (3) Audiences evaluate framings comparatively, and prefer moderate distinctiveness from others. (4) Effect of framing on audience evaluations gets attenuated with high status.
Voronov, Clercq, Hinings 2013	JMS	How do firms manage the differentiation and isomorphism pressures at both the local and global institutions?	Ontario wine industry	-	-	(1) Ontario wineries emphasized global conformity and local adaptations to demonstrate both conformity and distinctiveness.

Miller, Indro, Richards, Chng 2013	JOM	What are the signaling effects of conforming to local and non-local rivals?	Foreign firms raising fund in the U.S.	-	-	(1) Firms should conform more to rivals that are non-local. Doing so would increase legitimacy and signal conformance to international standards, while conforming to local rivals would increase competitive and comparison costs. (2) On the other hand, investors would positively evaluate local rival conformance behavior because it is a strong signal of firm quality. Specifically, in this context, firms adopting most frequently adopted practices undergo higher scrutiny, signaling their higher quality.
Tan, Shao, Li 2013	JBV	How can new ventures gain both competitive advantage and legitimacy in highly concentrated locales?	Furniture cluster in Southwestern China	-	-	(1) The pressure to conform is different for firms that are central or peripheral in the network. While peripheral firms in the network need to conform to institutional and competitive isomorphic pressures, central firms can influence and shape the institutional norms and regulations. Central firms also enjoy greater capability to innovate and distinguish themselves, while peripheral firms succumb to competitive isomorphic pressures and imitate the central actors.
Litov, Moreton, Zenger 2012	MS	How does strategy uniqueness affect analyst coverage?	Security analysts	(1) Adjusted coverage	(1) Strategy uniqueness	(1) Firms that have a more unique strategy garner less analyst coverage because they increase the cognitive cost for their analysts.
King, Clemens, Fry 2011	Org. Sci.	How does isomorphic and differentiation mechanism in org. identity influence the emergence of new organizational form (a new collective identity)?	Arizona's Charter Schools	-	-	(1) Identity emergence is path dependent, and the individual identities might converge in more than one clusters of identity elements, creating two or more collective identity categories. (2) Firms adopt distinctive identity elements as long as resources in their institutional environment allows them to. Therefore, in some environments, there will be low levels of distinctiveness.
Navis, Glynn 2011	AMR	How does similarity and differentiation in entrepreneurial identity claims affect investor judgements?	Conceptual	-	-	(1) Investors most highly value claims that are legitimately distinctive. (2) Legitimate distinctiveness of identity claims is dependent on market context—whether the market is established or nascent. (3) The claims influence investor judgements by invoking familiar institutional primes that provide legitimacy and by making equivocal claims that create distinction for new ventures.
Navis, Glynn 2010	ASQ	How new markets emerge through identity claims of new ventures?	Satellite radio 1990-2005	-	-	(1) During category emergence, legitimation of the new category precedes the differentiation of members. This process is evident in identity claims, linguistic frames, announcement of interorganizational ties, as well as media attention and financial audience evaluations.
Park 2007	Org. Sci.	How does firm's performance levels affect direction in change towards getting closer or further from its peers?	Public firms	(1) Dyad Strategic Convergence-Divergence.	(1) Performance Relative to Aspiration Level (2) Target Firm's Performance Relative to Focal Firm's Performance	(1) Firms that perform above their aspiration level tend to diverge more from their competitors. (2) In a dyad, firm that is performing lower will follow the other firm.
McNamee, Deephonse, Luce 2003	SMJ	How does performance differ within and across strategic groups?	Commercial banking industry in the Twin Cities	(1) Firm performance	(1) Core vs peripheral strategic group membership.	(1) Little between difference in performance in strategic groups. (2) Significant within difference in performance in strategic groups. (3) Secondary (peripheral, differentiator) firms in strategic groups had better performance than core members and solo member strategic group firms. Findings support the resource-based view and Porterian views.
Phillips, Zuckerman 2001	AJS	How does an actor's status affect its conforming behavior propensity?	(1) Silicon Valley Law Firms (2) Security analysts	(1) Adoption of family law (deviation behavior in law world) (2) Sell recommendation	(1) Law firm status. Proportion of lawyers from ivy league. (2) Analyst status. Institutional investor magazine ranking.	(1) Middle-status actors conform most, because they value their membership in the group and at the same time are insecure in their inclusion in the group by the audience. (2) High-status actors engage in deviant behavior because they are secure in their legitimacy and group inclusion. (3) Low-status actors engage in deviant behavior because they are excluded from audience's considerations no matter what they do. They have been rendered illegitimate in the screening stage.

Deephause 1999	SMJ	How can firms balance similarity and differentiation?	Commercial banks	(1) Relative ROA	(1) Strategic similarity. Based on 11 strategy variables.	(1) Strategic balance proposition: firms should be as different as legitimately possible. (2) Firms need to take a distinct position from their rivals to have a competitive advantage (3) Based on resource dependence and neo-institutional theories, similarity results in legitimacy
Zuckerman 1999	AJS	How do audiences react to firms that do not have clear category memberships?	Security analysts	(1) Stock market excess value	(1) Coverage mismatch	(1) Categorical imperative and illegitimacy discount theories. When a firm claims membership in a category, but analysts specialized in that category do not cover it, market reacts negatively.
Westphal, Gulati, Shortell 1997	ASQ	What are the interactive effects of institutional pressures and network effects on innovation diffusion?	Surgical hospitals	(1) Conformity. TQM adoption on 20 measures (2) Hospital legitimacy. JCAHO rating. (3) Hospital performance.	(1) Time of adoption. (2) Network ties. The number of alliance partners who adopted TQM prior to the focal firm.	(1) Late adopters of a technology are more likely to conform to institutional norms since early adoptions could have increased the degree of institutionalization. (2) While network ties could increase deviation and customization in the early stages of innovation adoption, in later stages, with increased institutionalization, network ties could facilitate and encourage conformism through conveying information about what are the expected norms. (3) Hospitals that customized TQM practices enjoyed higher performance, while hospitals that conformed to TQM standardized practices gained the most legitimacy.
Brewer 1991	Per. And Psy. Bul.	How could theories of individual identity (focusing on individual distinction) and social identity (focusing on sameness) be reconciled?	Conceptual	-	-	(1) Optimal distinctiveness theory. humans are driven by two opposing forces: need for assimilation and belonging, need for individuation and distinction. Therefore, to the extent that membership in a category increases an individual's sense of sameness, it intensifies the individual's need for differentiation and vice versa. There is an equilibrium state where the differentiation and assimilation needs are met in a balanced manner, that point is called optimal distinctiveness.
Porac, Thomas, Baden-Fuller 1989	JMS	How does cognitive models influence competition?	Scottish Knitwear industry	-	-	(1) Managerial cognition results in the formation of competitive groups. (2) Firms often conform to core category attributes while they differentiate on non-core features to gain optimal distinctiveness.

1.2.1 Positioning vis-à-vis a Firm's Past: Identity Change and Audience Evaluations

A firm's identity claims establish a firm's market position and are a key resource allowing it to influence external audience evaluations and garner legitimacy (Brown, 1997; Sillince & Brown, 2009). Organizational identity claims often serve as a sensemaking device for evaluators (Fisher, Kotha, & Lahiri, 2016; Navis & Glynn, 2011; Weick, 1995), and contribute to firms' legitimacy. Since evaluators have limited information and bounded rationality (Cyert & March, 1963; March & Simon, 1958), organizational self-definitions could expedite and facilitate the judgment formation process for them (Bitektine, 2011; Yamauchi & Yu, 2008). Therefore, identity claims help make a firm "understandable to its external audience" (Fisher et al., 2016).

Albert and Whetten's (1985) definition of organizational identity as organizational elements that are central, enduring, and distinctive has been the departure point for most organizational identity studies. While centrality and distinctiveness are now taken-for-granted, the third element of identity, enduringness, remains controversial (Chreim, 2005; Corley, 2004; Gioia, Patvardhan, Hamilton, & Corley, 2013; Gioia & Thomas, 1996; Ravasi & Schultz, 2006).

Researchers have identified various impetuses to organizational identity change. Beginning with Dutton and Dukerich's (1991) seminal study, researchers have examined how disparity between what insiders think about themselves as an organization, and what they believe outsiders think about their organization (construed external image), often triggers a process of identity change (Gioia, Schultz, & Corley, 2000; Gioia & Thomas, 1996; Ravasi & Schultz, 2006). A second impetus for identity change is a discrepancy between what organizational members think of themselves as an organization, and what they desire to be (the desired future image) (Gioia et al., 2000; Gioia & Thomas, 1996). A third antecedent to identity change is the need for improved

financial performance, and in a few cases, the need to survive (Biggart, 1977; Glynn & Azburg, 2002; Tripsas, 2009).

In addition to research on impetuses to identity change, scholars have examined the processes through which firms attempt identity change. Extant literature has demonstrated that firms could change their identity through discursive strategies for maintaining continuity while affecting change (Chreim, 2005). For example, firms can disentangle between identity labels and meanings associated with them to create change while maintaining some degree of continuity (Corley, 2004; Corley & Gioia, 2004; Gioia et al., 2000). Firms could also differentiate between intangible and tangible identity attributes (Gustafson & Reger, 1995) and core and application attributes (Margolis & Hansen, 2002) to change certain identity attributes while holding others stable.

While this literature informs us about the impetuses of identity change and the processes through which identity change unfolds, there is generally a lack of understanding around how identity change, as reflected in change in identity claims, influences the evaluations that a firm receives from its external audiences. This is while it has been well established that organizational identity claims serve as an important sensemaking device that audiences use to evaluate a firm. It is thus important to examine this relationship and ask how does change in organizational identity claims impact a firm's legitimacy?

1.2.2 Positioning vis-à-vis Category Benchmarks: Exemplar Similarity and Audience Evaluations

Audiences evaluate products and actors by categorizing them into comparison sets (Zuckerman, 1999, 2016). A firm's performance is typically evaluated through comparison against the average performance of all category members: that is, against the category prototype (Glynn & Navis,

2013). A prototype is a set of common features that are seen as differentiating members of a category from non-members (Rosch & Lloyd, 1978; Rosch & Mervis, 1975); these common features are equivalent to the aggregated and averaged tendencies of all category members (Reed, 1972). By eliminating cognitively taxing pairwise comparisons (Bowker & Star, 2000; Smith & Medin 1981) between a firm and all other category members, comparison against a prototype eases the process of judgment formation (Durand & Paoletta, 2013).

Recent studies have tested an alternative to the prototype-based model of evaluation: an exemplar-based model. 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 & Johansen, 2000, p. 375). For example, one might classify a newly met person as Californian, not because she represents the prototypical Californian attributes, but because she looks like a known Californian friend (Medin & Smith, 1981). An exemplar is a member of a category that represents the category’s exceptional and salient features (Smith & Zarate, 1992). For instance, Apple is an exemplar in the smartwatch industry because its product is the best-known and highest performing in the category, while Fitbit is more typical and a better representative of the category’s average and central tendencies.

As the smartwatch example illustrates, in many industries exemplars diverge from category prototypes. Although the pressure to conform to a category prototype constrains variation, categories offer some leeway for firms to differentiate themselves (Anthony, Nelson & Tripsas, 2016; Vergne & Wry, 2014; Wry, Lounsbury, & Glynn, 2011; Zuckerman, 1999). The leeway to deviate is extended for firms that have a record of exceptional performance and are thus given a “legitimacy buffer” (Fisher et al., 2016; Phillips & Zuckerman, 2001). While the average performance of all category members is the default benchmark for comparison (Zuckerman, 1999),

category exemplars also provide a viable point of reference for audiences (Zhao et al., 2018).

In dual benchmark settings, where category prototypes and exemplars diverge, audiences may use either or both as points of comparison in their evaluations (Barsalou, 1985). While research has mostly focused on the impact of firm typicality—the degree of similarity to the category prototype—on audience attention and evaluation, our understanding of whether and how category prototypes and exemplars jointly impact firm evaluations is limited (Barlow et al., 2019).

1.2.3 Positioning vis-à-vis a Heterogeneous Audience: Audience Predispositions and Evaluations

Research has argued that categories are the cognitive schemas that aid audiences in forming evaluations of entities (Vergne & Wry, 2014). These theories rest on a restricting assumption that categories, as the “cognitive infrastructure” of markets (Schneiberg & Berk, 2010), are shared mental models among all members of an audience group. Based on this assumption, a typical audience member has a relatively clear expectation of what a category member should look like. The cognitive perception of a category member could be formed through a prototype view of the category, which entails categorization based on common attributes of all category members (Rosch, 1973), or through an exemplar view of the category, which refers to categorization based on similarity to outstanding category members (Nosofsky & Johansen, 2000). Either way, a common theoretical and empirical assumption is that conceptions of prototypes and exemplars are shared among audience members insofar as category construction “involves gaining agreement within the audience about what it means to carry a label” (Hannan, Hannan, Pólos, & Carroll, 2007, p. 59).

Building upon this assumption, optimal distinctiveness research has examined a firm’s optimal positioning strategy vis-à-vis commonly held category benchmarks, such as prototypes

and exemplars. As a result, researchers often examine audience members within the same category (e.g., analysts specialized in a specific industry) as a homogenous body that reacts uniformly to a firm's within-category positioning strategy. For instance, Litov et al. (2012) examined the negative effects of strategy uniqueness vis-à-vis industry averages on analyst coverage, implicitly assuming a uniform reaction from all analysts in a firm's primary industry. In another study, analysts were shown to uniformly react to firms that changed their market positions by undertaking major spinoffs (Feldman, 2016).

More recently, scholars have questioned the assumption that audiences within the same category evaluate firms uniformly and have started to theorize about important heterogeneities in audiences' evaluations due to idiosyncratic categorization schemas. When audiences embrace different categorization schemas, they tend to evaluate the same firm through different lenses (Beunza & Garud, 2007; Pontikes, 2012) and compare the firm with different reference groups (Bowers, 2015; Goodman & Haisley, 2007; Smith & Chae, 2017).

Multiple mechanisms underlie the heterogeneity in audiences' evaluation schemas. First, audiences may employ different evaluation lenses and categorization schemas based on their prior knowledge and expertise. An audience member's prior knowledge could change his or her world theory (Murphy & Medin, 1985) and influence how he or she prioritizes and ranks various attributes related to a category. For instance, while a layperson might categorize any article published in a scientific journal as a "scientific paper," an expert scholar might first investigate the type of journal, the credibility of the authors, and the accuracy of the method before categorizing the paper as a "scientific paper." Accordingly, Beunza and Garud (2007) showed how analysts from different backgrounds categorized Amazon differently in the early 2000s as either a bookstore or an internet company. Those who categorized Amazon as a bookstore compared it to

Barnes & Nobles, giving it a negative evaluation due to cashflow comparisons, whereas those who categorized Amazon as an internet company compared it to Dell, giving it a high evaluation due to its growth potential. Similarly, Jensen and Kim (2014) showed how variation in audiences' education levels created divergence in how they categorized and evaluated conventional and unconventional operas. Similarly, Kim and Jensen (2011) found that cultural differences in movie audiences resulted in different interpretations of status signals. Further, Theeke, Polidoro, and Fredrickson (2018) demonstrated how brokerage firms reacted differently to firms that adopted innovative practices due to their different exposure to new knowledge and heterogeneous learning processes.

Second, audiences' evaluation schemas could also be affected by their varied goals. Audiences sometimes categorize an entity based on a specific goal (e.g., to find something to stand on to change a light bulb) that they have in mind (Barsalou, 1999; Durand & Paoletta, 2013). As Glaser, Krikorian Atkinson, and Fiss (2020, p. 937) argued, "whereas the traditional prototype and exemplar-based perspectives on categories focus on how audiences or intermediaries evaluate the legitimacy of producers or products, a goal-based category perspective explains how market actors use categorical infrastructure to realize their own idiosyncratic objectives." Consistent with this, Paoletta and Durand (2016) showed that in the context of corporate legal services, consumers who expected more sophisticated services tended to adopt goal-based categorization and evaluate category-spanning law firms more positively.

Finally, audiences' motivations could play a key role in their categorization models and evaluation schemas. For instance, Fleischer (2009) showed that brokerage firms sometimes intentionally created ambiguity in their classification schemas to open their ratings up to different interpretations and avoid the loss of investment banking business with firms they evaluated

negatively. Similarly, Bowers and Prato (2019) showed that audiences were motivated to self-generate changes in their rankings of various actors to make their evaluations seem more legitimate and worthy of attention. Bowers (2020) further showed that analysts were inclined to give negative ratings to some firms after a long streak of positive evaluations in their portfolios to preserve their ratings' credibility.

While optimal distinctiveness research has explored optimal positioning strategies vis-à-vis other firms in a market category, our knowledge regarding optimal strategies given such heterogeneity in audiences' categorization models and evaluation schema, is very limited. Therefore, it is important to explore the optimal positioning strategy that firms could adopt to gain a favorable evaluation considering a heterogeneous audience group.

1.3 This Dissertation

In this dissertation, I draw on the socio-cognitive foundations of social judgments to answer the research gaps identified above. Empirically, I employ natural language processing (NLP) techniques and machine learning algorithms to quantitatively investigate how security analysts respond to firms' various strategic decisions and market positions. Specifically, I apply topic modeling and other textual analysis techniques on the business description section of firms' 10-K filings to measure a firm's positioning over time and in relation to other firms. My empirical setting and analytical approaches enable a dynamic and fine-grained investigation of firms' positioning over time and in relation to other firms. Below, I provide an overview of the three studies in this dissertation.

Study 1: Change in Identity Claims. In my first study, I explore how change in organizational identity claims affects organizational legitimacy. Drawing on the principle of cognitive economy, I posit a negative relationship between the magnitude of change in

organizational identity claims and an audience's ability and willingness to make sense of a given organization and confer legitimacy upon it. I further argue that this relationship is moderated by the level of heterogeneity within an organization's external environment and by the direction of change. Since audiences use classification schemas to make sense of their environment, a change that makes an organization less similar to typical organizations may result in higher legitimacy penalties. In heterogeneous industries that have high levels of identity distinctiveness, changes in identity claims are more tolerated because of the looser institutional norms in such environments. I test my hypotheses by examining security analysts' coverage decisions regarding publicly listed U.S. organizations from 1997 to 2018. I used NLP techniques to develop a new method for measuring change in organizational identity claims.

Study 2: Audience Evaluations in Dual Benchmark Settings. In my second study, I explore the relationship between firm positioning and performance in dual benchmark settings where audiences can evaluate firms against two distinct reference points: category prototypes (category's average and central tendencies) and exemplars (category's outstanding members). I argue that firms benefit from exemplar similarity—positioning near category exemplars—through association with an outstanding firm. However, such benefit comes with the cost of comparison against an exceptionally high-performing firm. I also argue that the impact of exemplar similarity on a firm's market value depends on firm typicality, i.e., its degree of similarity to category prototypes. An analysis of publicly listed U.S. firms from 1997 to 2018 provides strong support for my predictions. My findings suggest that firms need to balance between the association benefits and comparison costs of exemplar similarity.

Study 3: Gaining an Audience Composition Premium Using Machine Learning Algorithms. In my third study, I build on the premise that audiences use different mental models

in their evaluations and propose that firms could increase their evaluations by strategic positioning towards the right audience group. I propose that a firm could influence its audience composition such that it attracts audiences who would evaluate it positively. In other words, firms could strategize to affect which audience determines to evaluate them based on the particular audience's predisposition toward them. In the context of security analysts' evaluations of firms, this could be achieved through two steps: (1) predicting the evaluations that the firm would receive from a given analyst, and (2) positioning in a way to receive attention and maximize the likelihood of being covered and evaluated only by those analysts who have a favorable predisposition toward the firm. For the first step, I propose the use of machine learning algorithms. I develop a predictive model using a machine learning algorithm that was one of the winners of the Netflix Prize competition for predicting users' movie preferences. For the second step, I argue that positioning near the firms previously followed by an analyst increases the chances of receiving attention and gaining coverage from that analyst. I find strong support for my predictions and the proposed methodology.

Together, the three studies expand our understanding of the dynamics of firm positioning strategy and its effects on audience evaluations given certain environmental complexities. Specifically, this dissertation examines audience evaluations (a) when a firm changes its identity claims, (b) by considering the firm's concurrent positioning relative to category prototypes and exemplars, and (c) given the audiences' heterogeneous predispositions and evaluation schema. This dissertation makes contributions to research on optimal distinctiveness, organizational identity change, and management research on audience evaluations. The findings of this dissertation encourage future scholarly work that investigate optimal positioning strategies while

incorporating temporal aspects of firm identity, multiplicity of categorical benchmarks, and idiosyncrasies in audiences' characteristics.

CHAPTER TWO

2 Paying a Price for Change: The Effects of Change in Identity Claims on Firm Legitimacy

2.1 Introduction

“The more you change, the more you might lose analyst coverage because people get tired of trying to adapt with you.”

Top-ranked Security Analyst.

Organizational identity claims describe what is central, distinctive, and relatively enduring about an organization (Albert & Whetten, 1985). Past research suggests that they may change due to (a) external challenges (technological changes) or internal events (spin-offs and M&As) (Clark, Gioia, Ketchen, & Thomas, 2010; Corley & Gioia, 2004; Tripsas, 2009); (b) rare events that provoke organizational learning (Christianson, Farkas, Sutcliffe, & Weick, 2009); (c) an organization’s need for flexibility and adaptability to changing market dynamics (Ravasi & Schultz, 2006); and (d) the organization’s need for improved financial performance and in extreme cases, survival. Organizations can benefit from a change to their identity claims because it enables them to maintain openness and flexibility (Selznik, 1957), adapt to stakeholders’ changing expectations (Dutton & Dukerich, 1991; Fisher, Kotha, & Lahiri, 2016), and maintain distinctiveness vis-à-vis their competitors (Elsbach & Kramer, 1996; Karthikeyan, Jonsson, & Wezel, 2016; Rindova & Kotha, 2001). Through such changes, organizations can maintain the congruence between their identity claims and their actual practices, which can frequently change and evolve (Ravasi & Phillips, 2011).

Externally, organizational identity claims affect how audiences evaluate organizations and confer legitimacy upon them (Zuckerman, 1999). Audiences bestow legitimacy to organizations

when they are comprehensible (Suchman, 1995); identity claims can influence an organization's comprehensibility by serving as a sensemaking device (Fisher et al., 2016; Glynn & Azburg, 2002; Glynn & Marquis, 2007; Navis & Glynn, 2011; Weick 1995). Evidence suggests that identity claims are often strong predictors of organizational conduct and may serve as a lens through which an organization is assessed (Foreman, Whetten, & Mackey, 2012; Smith, 2011).

Most studies that examine the association between identity claims and legitimacy assume that identity claims are relatively stable, a reasonable assumption when studying organizations operating in static industries (e.g., Sillince & Brown, 2009; Smith, 2011; Smith & Chae, 2017; Zuckerman, 1999). Moreover, studies that focus on identity change often highlight antecedents and internal change processes without explicitly addressing the *external* consequences of change (e.g., Gioia et al., 2000; Golant, Sillince, Harvey, & Maclean 2015; Ravasi & Phillips, 2011). To bridge these disparate perspectives, we asked: *How do changes to an organization's identity claims affect its external legitimacy?*

To address this critical research question, we draw on the social-actor conception of organizational identity. From a social-actor perspective, an organization may be perceived and evaluated as an individual entity as opposed to a collective of individuals (Whetten, 2006). As King and Whetten (2008: 195) aptly suggest, "The study of legitimacy and reputation calls for an organization-as-social-actor conception of organizational identity, which can roughly be portrayed as an outside-in, top-down view of organizations and their identifying features." Here, organizational identity is defined as self-referential claims which describe an organization and cement its place in the social sphere.

We posit that organizations that change their identity claims may be penalized in terms of legitimacy. Audiences, seeking to economize on the effort necessary to make sense of an

organization (Bitektine, 2011; Rosch, 1978), are often reluctant to alter previously formed judgments (Tripsas, 2009). Potentially, they may cease trying to comprehend an organization altogether if too much effort is required to understand it (Litov, Moreton, & Zenger, 2012). When an organization alters its identity claims, the external audience's ability to reliably predict its behavior is affected, and the organization may be perceived as ambiguous and unpredictable, and consequently less legitimate (Garud, Schildt, & Lant, 2014; Suchman, 1995). Such ambiguity and unpredictability can be exacerbated given greater magnitudes of changes in identity claims.

The relationship between the magnitude of change in identity claims and organizational legitimacy may be affected by the direction of change and the level of heterogeneity within an organization's external environment. Audiences use cognitive schemas and classifications to make sense of organizations (Weick, 1995; Zuckerman, 1999). During periods of change, and under conditions of heightened uncertainty, audiences may rely more on such cognitive heuristics (Bitektine, 2011; Tversky & Kahneman, 1974). Identity claim changes that result in an increase in distance from peers and industry averages could render a firm less prototypical and make it more difficult to be classified. Hence, we posited that a change in identity claims towards being more different from others would result in higher legitimacy penalties.

We further argued that an audience's response to changes to identity claims can depend on the level of heterogeneity in an organization's external environment (Haans, 2019; Lounsbury & Rao, 2004; Zhao et al., 2017). In industries where organizations are similar and make similar claims about their identities, institutional expectations tend to be more restrictive and patterns of behavior more rigid (Bitektine, 2011; Meyer & Rowan, 1977). In such environments, an audience's tolerance for uncertainty may be lower (Bitektine, 2011; Kruglanski, 2001) and changes to identity claims are likely met with greater legitimacy penalties. Conversely, in

environments where identity claims are heterogeneous, normative and institutional pressures may be weaker (Ruef & Patterson, 2009). Expectations for stability and persistence are thus lower (Pfeffer, 1981), and audiences tend to tolerate a broader range of organizational behavior (Zuckerman, 2017). In such environments, audiences are less likely to penalize organizations that make major identity changes.

To mitigate the challenge of measuring change in organizational identity claims (see Foreman & Whetten, 2016, for a review), we used Natural Language Processing techniques to conduct a textual analysis of organizations' identity claims, using the Item 1 section of 10-K filings with the SEC. We examined the effects of organizational identity claim changes on industry-specialized security analysts' coverage decisions since they represent an ideal audience to explore the consequences of such changes. Security analysts pay careful attention to 10-K filings to the extent that the average number of words per sentence in a document (i.e., the document's readability) significantly impacts their coverage decisions (Lehavy, Li, and Merkley, 2011). Security analysts are further incentivized to cover only those organizations they understand and for which they can provide accurate forecasts for (Litov, Moreton, & Zenger, 2011). Thus, the decision to cover an organization may be interpreted as an acknowledgment of its legitimacy (Zuckerman, 1999). We tested our propositions by examining security analysts' coverage decisions using publicly listed U.S. organizations from 1997 to 2018 and found empirical support for our predictions.

This study contributes to both the fields of organizational identity research and institutional theory. The theoretical arguments we provide may help enrich our understanding of how changes to organizational identity claims can influence an organization's legitimacy. Specifically, we relax the commonly held assumption that the identity claims of established organizations are stable and

enduring. By adopting a dynamic perspective, we highlight the *external* consequences of identity claim changes to show that in addition to internal resistance to change, organizations may face external inertia and experience costs when they make identity claim changes. From a methods perspective, we introduce an NLP technique to the study of identity claim changes. This could enable researchers to examine a large sample of organizations over an extended period of time, a much-needed addition in a domain dominated by conceptual and qualitative case studies that involve few organizations (Foreman & Whetten, 2016).

We also contribute to research on organizational identity by incorporating the potential costs of changing an organization's level of differentiation from others in its industry. We demonstrate that the legitimacy an organization gains by being similar to other organizations (or conversely, the illegitimacy challenges it faces by being too different from others) depends on the path it takes and the degree of change it undertakes to achieve such level of similarity (or distinctiveness). For institutional theory research, we demonstrate that institutions not only demand that organizations conform to their peers and established categories (Zuckerman, 1999) but to their prior selves as well. We also provide empirical support for the assertion that categorical imperative is less restrictive in heterogeneous environments (Bitektine, 2011; Haans, 2019; Zuckerman, 2017).

2.2 Theory and Hypotheses

2.2.1 Organizational Identity and Organizational Legitimacy

Organizational legitimacy is a “generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions” (Suchman, 1995: 574). Institutional theorists suggest that institutions confer legitimacy on organizations that conform to institutional norms and belief systems

(DiMaggio & Powell, 1983; Meyer & Rowan; 1977; Suchman, 1995), thereby putting isomorphic pressure on organizations. Resource dependence theorists, emphasizing managerial agency, argue that legitimacy is a limited and valuable environmental resource for which organizations often compete (Pfeffer & Pfeffer, 1981; Pfeffer & Salancik, 1978).

To confer legitimacy on an organization, audiences must be able to make sense of it (Suchman, 1995). The social world is a complex environment where members resort to schemas and/or sensemaking models to comprehend the activities around them. Here, sensemaking involves selective information processing, interpretation and action-taking aimed at reducing ambiguity, and developing plausible schemas for interpretation and action (Weick, 1979, 1995). When an audience can make sense of an organization, it is seen as more meaningful, more trustworthy, and ultimately more legitimate (Suchman, 1995). Organizations that garner legitimacy may have easier access to critical resources (Pfeffer & Salancik, 1978); those that don't incur an illegitimacy discount (Litov et al., 2012; Zuckerman, 1999).

Organizational identity claims can influence an organization's legitimacy. Organizational identity answers the questions of 'who we are' (Albert & Whetten, 1985) and 'what we do' as an organization (Navis & Glynn, 2011). From a social actor perspective, organizational identity is concerned with self-referential claims that can reveal the central, distinctive, and enduring attributes of an organization to internal and external audiences (Whetten & Mackey, 2002). Importantly, an organization's identity claims serve as a sensemaking device for external evaluators (Fisher et al., 2016; Navis & Glynn, 2011; Weick, 1995). Since evaluators have limited information and exhibit bounded rationality (Cyert & March, 1963; March & Simon, 1958), organizational self-definitions can help expedite and facilitate the judgment formation process (Bitektine, 2011). Therefore, an organization's identity claims serve to make it understandable to

external audiences and help it garner legitimacy (Fisher et al., 2016; Sillince & Brown, 2009).

Researchers have highlighted the link between identity claims and organizational legitimacy. For example, Glynn and Azburg (2002) found that organizations that adopted names in conformance with industry practices and norms tended to increase their understandability in the eyes of their audience and consequently garner greater legitimacy. Sillince and Brown (2009) showed that British constabularies' identity claims on topics such as community membership, effectiveness, and progressiveness significantly affected their legitimacy among their constituents. Similarly, Navis and Glynn (2010) demonstrated that during the emergence of satellite radio, new ventures' identity claims enabled organizations to influence audience perceptions about the legitimacy of their industry and the organizations operating within it.

2.2.2 Change in Organizational Identity Claims

Albert and Whetten's (1985) definition of organizational identity as central, enduring, and distinctive elements often serves as the departure point for scholars interested in the topic. Although centrality and distinctiveness are now taken for granted, the enduringness proposition has been the object of debate (Chreim, 2005; Corley, 2004; Fisher et al., 2016; Gioia et al., 2013; Gioia & Thomas, 1996; Ravasi & Shultz, 2006).

Following Dutton and Dukerich (1991), researchers have examined how the difference between what insiders think about an organization and what they believe outsiders perceive (a construed external image) may trigger identity changes (Gioia et al., 2000; Ravasi & Schultz, 2006). Another impetus for identity change is the disparity between what members think of themselves as an organization and what they wish to become (desired future image) (Gioia et al., 2000; Gioia & Thomas, 1996). Sometimes organizations change their identities to be perceived as desirable and understandable by an audience (Glynn & Azburg, 2002). Other times, an external

technological change (Tripsas, 2009) and events such as M&As and spin-offs can trigger major changes in identity claims (Clark, Gioia, Ketchen, & Thomas, 2010; Corley & Gioia, 2004).

While this rich research stream highlights the antecedents of identity change and the internal processes by which identity changes unfold (Chreim, 2005; Corley, 2004; Corley & Gioia, 2004; Gioia et al., 2000), few studies have examined how identity change influences an external audience's judgment of the organizations undertaking such a change (Bhatt, Van Riel, & Baumann, 2016; for an exception, see Tripsas, 2009). In particular, quantitative studies that directly address this gap have yet to be undertaken. While qualitative studies tend to focus on one or two organizations carrying extreme changes (Foreman & Whetten, 2016), a quantitative approach would enable researchers to examine the effect of identity change at various magnitudes and within different environmental contexts.

2.2.3 Identity Claim Changes and Legitimacy

External audiences use organizational identity claims to make sense of organizations (Fisher et al., 2016; Navis & Glynn, 2011; Weick, 1995). This process is mediated by 'cognitive economy' (Bitektine, 2011; Rosch, 1978), the idea that people try to maximize the information being processed while minimizing the effort required. If the effort required for sensemaking is too great, or the cost of analysis exceeds the benefits, an audience may deny an organization legitimacy (Bitektine, 2011).

Several studies have empirically validated this mechanism. Zuckerman (1999) showed that conglomerates, which are more difficult to classify and analyze, are generally granted less legitimacy, manifested by a reduced degree of specialized security analyst coverage. Similarly, Litov, Moreton, and Zenger (2012) found that adopting a unique strategy that might increase the cognitive effort needed to analyze an organization could result in less security analyst coverage.

Through de-diversification (Zuckerman, 2000) and spin-offs of legacy businesses (Feldman, 2016), organizations can increase their legitimacy by making themselves simpler to analyze and evaluate.

Changes in identity claims increase the cognitive effort needed to make sense of an organization. Evaluators tend to use their previously formed judgments in order to economize on the effort needed to make sense of an organization (Tripsas, 2009). Changes in organizational identity claims, which may demand the reconsideration of existing judgments and evaluation schemas, can increase the cognitive cost of assessing an organization. Tripsas (2009) demonstrated how security analysts covering Linco, a digital photography company, resisted changing their conception long after it had transitioned to become a memory company. Similarly, Benner (2010) found that during industry technological transitions, security analysts prefer organizations that preserve existing technologies as opposed to those who adopt new technologies. Again, the mechanism seems to be the cognitive inertia of analysts and their desire to save the time and effort necessary for assessing and evaluating organizations. Thus, the increased cost of analysis caused by identity claim changes may reduce the audience's willingness to expend the effort needed to make sense of an organization, and increase the cognitive ambiguity surrounding it. Such ambiguity may, in turn, result in a lower level of legitimacy assigned to the organization.

Changes in organizational identity claims also tend to increase uncertainty about an organization's future prospects. In complex and continually changing environments, external audiences rely on the cues that an organization provides (Garud, Schildt, & Lant, 2014). As Foreman, Whetten, and Mackey (2012: 2) have suggested, "The most reliable predictor of an organization's conduct, arguably, is its identity.... An organization generally acts in ways that are consistent with its 'self-view.'" Since identity claims are considered relatively stable and reliable

anchors for predicting an organization's future behavior, changes to such claims can be particularly problematic. In other words, because stable identity claims give structure to patterns of behavior, in their absence prospects are regarded as less predictable (Suchman, 1995). Therefore, any change in an organization's identity claims may lead to increased uncertainty and a decreased level of legitimacy.

Figure 1 illustrates a simplified two-dimensional context where an organization assigns different weights to identity attribute 1 and identity attribute 2 in its claims. For instance, in the context of business schools, identity attributes 1 and 2 could be 'teaching' and 'research,' respectively, where business schools assign different weights to either attribute in their identity claims (all arguments may be extended to a more complex context with a higher number of identity attributes). Figure 1a shows that an organization can make small changes to its claims (see graph on the left) or changes of greater magnitude (see graph on the right). As an example, in 2000 Howtek Company reframed its identity from "a producer of high-end scanners for graphists" to "a producer of scanners for photo-finishing and medical applications." This example exemplifies a relatively small change in an organization's identity claims.¹ A larger

¹ "Howtek develops, manufactures, and markets digitizing systems, or 'scanners,' which convert printed, photographic and other 'hard copy' images to digital form for use in the photo-finishing, medical and graphic arts industries" (Howtek 10-K report, 2000) "Facing diminishing returns in its traditional graphic arts business, Howtek has invested in technology and product development in the medical and photographic imaging markets" (Howtek 10-K filing, 2001).

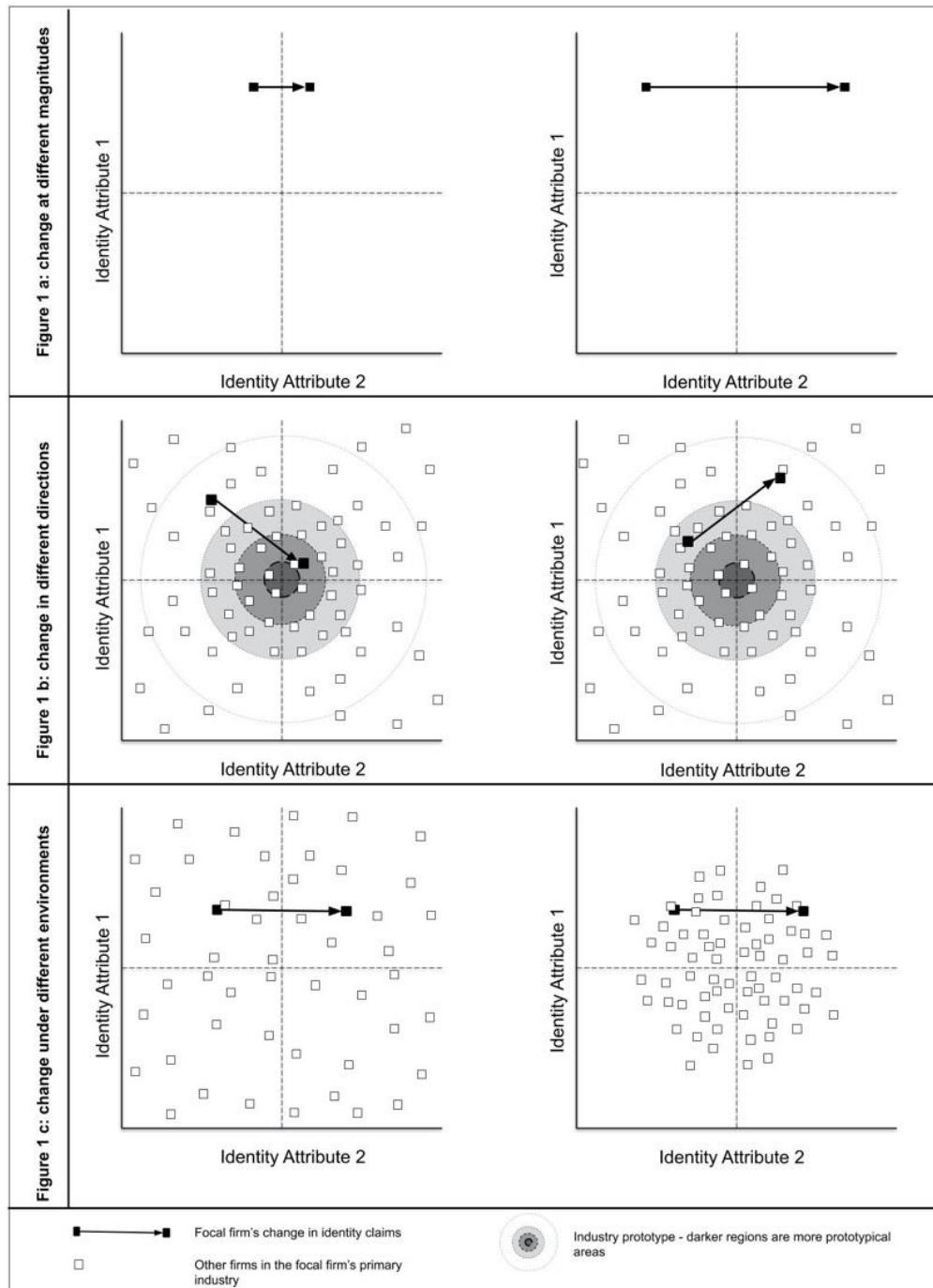


Figure 2-1 Change in identity claims in a simple 2-dimentional context

magnitude of change in a company's identity, studied by Tripsas (2009), was shown in the case of Linco transforming itself from a 'digital photography' to a 'memory' company. The legitimacy penalty incurred by an organization for changes in its identity claims should be proportional to the

magnitude of the changes made, leading to the following hypothesis:

Hypothesis 1. The magnitude of change in organizational identity claims is negatively related to the level of legitimacy an organization garners from its external audience.

Direction of Change

An increase in ambiguity and uncertainty resulting from changes to organizational identity claims may be amplified if the organization moves farther from its industry prototype.² Organizations' audiences resort to cognitive schemas and classifications to make sense of their environment and evaluate the actors within it (Weick, 1995; Zuckerman, 1999). Organizations that are easier to classify and categorize based on existing schemas tend to find it easier to access environmental resources (Pfeffer & Salancik, 1978); conversely, those that defy 'categorical imperatives' (the pressure to conform to recognized types and established categories) may incur an 'illegitimacy discount' (Litov et al., 2012; Zuckerman, 1999).

The institutional pressures to conform, as well as the legitimacy penalties charged due to deviance, are compounded under conditions of heightened uncertainty and ambiguity (Aldrich & Fiol, 1994; Lounsbury & Glynn, 2001). This is because when uncertainty and ambiguity are high, audiences rely on heuristics (Tversky & Kahneman, 1974), such as classification schemas (Bitektine, 2011), to pass judgments. This suggests that during such periods, audiences pay closer attention to an organization's identity claims (Glynn, 2000; Smith & Chae, 2016). Navis and Glynn (2010) have shown that during the emergence of satellite radio, a period of high uncertainty and ambiguity, the legitimacy imperative was so strong that industry actors focused on building a

² Most research in institutional theory and optimal distinctiveness examines differentiation vis-à-vis industry prototypes. In this view, the common features of an industry are equivalent to the central tendencies of all industry members (Reed, 1972). Following this view, we theorize about and test a firm's average differentiation vis-à-vis all other organizations in its industry; in other words, we intend to examine the level of differentiation for an organization as compared to its primary industry's prototype.

collective identity for their nascent industry as opposed to trying to differentiate themselves from each other. Zhao et al. (2018) showed that during the emergence of new categories in the console video gaming industry, a period of heightened uncertainty and ambiguity, the pressure to conform was significantly greater than the pressure to differentiate. On a similar note, King, Clemens, and Fry (2011) demonstrated that during the emergence of charter schools in Arizona, the need for legitimacy resulted in organizations adopting identity elements that resembled those of their peers', thus forming clusters with similar identities.

The above arguments suggest that the negative effects of change in identity claims on legitimacy could be either exacerbated or attenuated based on the direction of such change. On one hand, the negative effects of change in identity claims will be exacerbated if the organization moves further from an industry prototype since doing so will make it more difficult for others to classify and make sense of the organization that pursues this course of action. On the other hand, organizations may partly overcome the negative effects of identity claim changes by maintaining or increasing attributes that signal similarity to established features of their industry. Research has shown that when an organization is perceived as novel and ambiguous by its audience, it can garner legitimacy by adopting identity elements that are familiar and rooted in existing sensemaking schemas in the environment (Aldrich & Fiol, 1994; Rao, 2004). As Bitektine (2011: 165) points out, “Organizations can influence the evaluator's cognitive legitimacy judgment by supplying favorable reference categories and highlighting the relatedness of their new organizational form to well-established legitimate forms” in the environment. In fact, evidence suggests that organizations seen as ambiguous by their audience due to atypicality, increased their legitimacy by adopting organizational names that signaled conformity and similarity to the industry prototype (Smith & Chae, 2016).

Figure 1b illustrates two examples where one organization moves toward greater similarity to others in its industry (the graph on the left), while another organization moves further away from its peers by making a change of a similar magnitude (see the graph on the right). For instance, in the context of business schools, where schools attempt to portray a balance between teaching and research excellence in their identity claims, a school that has traditionally focused on teaching excellence could increase its similarity to others by changing its identity claims to incorporate research elements as well. Conversely, by limiting the emphasis on teaching in its identity claims, a business school that traditionally featured a balance between both research and teaching could render itself less similar to the prototypical business school. Based on our theoretical arguments, audiences perceive these examples of changes quite differently. We thus suggest the following hypothesis:

Hypothesis 2. Direction of change moderates the negative relationship between the magnitude of change in identity claims and an organization's legitimacy such that organizations that move toward becoming more (less) distant from others incur more (less) penalties for changes to their identity claims.

Industry Distinctiveness Heterogeneity

We argue that an audience's judgment of changes to organizational identity claims largely depends on an organization's environment. According to Bitektine (2011), under conditions of bounded rationality (March & Simon, 1958) evaluators base their judgments not only on the characteristics and actions of a focal organization but on the comparison between it and others in its environment. Organizational environments differ significantly in terms of their 'distinctiveness heterogeneity' (Haans, 2019; Lounsbury & Rao, 2004; Zhao et al., 2017), defined as "the degree to which organizations in a category cluster around a single position" (Haans, 2019: 9). Based on this

definition, firms in highly heterogeneous categories display variation in their identity claims, while in homogeneous industries, firms adopt similar identity claims and cluster closely around the industry's typical attributes. Figure 1c depicts these contexts, with the graph on the left representing a heterogeneous industry and the one on the right representing a homogeneous one. Examples of these industries are 'Bolt, Nut, Screw and Rivet' industry (SIC code 3452), where we observe little differentiation in identity claims among firms, and 'Custom Computer Programming' industry (SIC code 7371), where firms tend to adopt identity claims that are highly differentiated. Findings suggest that the effects of differentiation on organizational legitimacy and performance are highly dependent on the level of distinctiveness heterogeneity in the organization's environment (Haans, 2019).

We argue that the effects of changes to an organization's identity claims on audience evaluations will depend on the distinctiveness heterogeneity of the focal organization's primary industry. In more homogenous industries, pressures to conform to institutional norms tend to be intense (Bitektine, 2011; Meyer & Rowan, 1977), audiences hold stronger opinions about the range of acceptable behaviors for an organization (Haans, 2019; Navis & Glynn, 2011; Zuckerman, 1999) and they have a lower psychological tolerance for uncertainty (Bitektine, 2011; Kruglanski, 2001). Homogeneity in such environments may result in the development of restrictive patterns of behavior that call for continuity and persistence (Pfeffer, 1981). Therefore, an organization's deviation from its past can become more apparent and pronounced to external audiences. Hence, when organizations make even the smallest deviations, they face higher legitimacy penalties (Haans, 2019).

In contrast, in industries with greater heterogeneity, classifications are less restrictive and strict patterns of behavior are less developed (Suchman, 1999), and there is less expectation for

stability and persistence (Pfeffer, 1981). In such industries, audiences are less likely to penalize organizations for changes to their identity claims, since they have a greater tolerance for a broader range of behaviors (Zuckerman, 2017). Such heterogeneous industries resemble lenient categories (Haans, 2019; Pontikes & Barnett, 2015), in that audiences hold a looser schematization disposition (Kovács & Hannan, 2010), and normative and institutional pressures are weaker (Ruef & Patterson, 2009). Therefore, we predict that negative effects on an organization's legitimacy from changes to their identity claims will be attenuated when the environment is more heterogeneous. This leads to the following hypothesis:

Hypothesis 3. Industry distinctiveness heterogeneity moderates the negative relationship between the magnitude of change in identity claims and an organization's legitimacy such that organizations in industries with higher (lower) heterogeneity incur less (higher) penalties for changes to their claims.

2.3 Methods

2.3.1 Security Analysts' Coverage Decisions

Our context involves security analysts' coverage decisions of publicly listed U.S. firms. Sell-side security analysts are highly trained and specialized financial professionals, employed by brokerage firms and investment banks.³ Alongside annual and quarterly earnings forecasts and investment recommendations, security analysts provide detailed reports about investment opportunities and risks to a firm. Researchers have documented how such recommendations and forecasts can significantly influence stock prices and investment decisions (for a review of the literature, see Brauer & Wiersema, 2018). Excluding some large investment houses, most investment institutions

³ There are also buy-side security analysts employed by investment banks and funds who do not provide public reports and whose analysis is used internally to inform their employers' investment strategies.

rely on sell-side security analysts' forecasts and recommendations in making investment decisions (Litov et al., 2012).

Analysts are rewarded for the accuracy and novelty of their forecasts and recommendations (Litov et al., 2012). As a result, they cover only those firms that they have a clear grasp of 'what they do' and 'who they are.' In other words, the decision to cover firms is a good proxy for whether an analyst thinks the firm is legitimate. As Zuckerman (1999: 1400) put it, "Encoded in a critical review is an acknowledgment on the part of the reviewer that the product is legitimate". Failure to garner coverage by analysts specialized in a firm's industry results in legitimacy penalties that are manifest in lower demand for a firm's stock and consequently a lower market evaluation (Zuckerman, 1999).

In line with the principle of cognitive economy, analysts try to maximize the predictive accuracy of their forecasts while minimizing the effort required (Benner, 2007; Litov et al. 2012; Zuckerman, 1999). Analysts try to economize on their effort by industry specialization, using the same cognitive schemas for analyzing firms and benchmarking firms against each other (Benner & Ranganathan, 2017; Zuckerman, 1999). Therefore, analysts consider not only the absolute magnitude of change in a firm's identity but also the broader context of the firm's industry and a focal firm's direction of change vis-à-vis other firms. For these reasons, we believe that coverage decisions may provide a particularly useful setting for testing how the impact of change in identity claims can affect a firm's legitimacy and how such relationship is moderated by identity claims of other firms.

2.3.2 Sample and Data

Our sample consists of U.S. public firms that have filed 10-K reports with the SEC between 1997–2018. We chose 1997 as our starting point since that is the year when electronic filing became a

requirement for all public firms. To measure year-to-year identity claim changes, we restricted our sample to those firms that had at least two consecutive years of SEC filings. Our sample is limited to firms within the CRSP/Compustat Merged database. The final sample includes 8,765 firms with an average of 6.7 years of observations for each firm, for a total of 59,149 firm-year observations. In constructing our variables, in addition to the EDGAR system and CRSP/Compustat Merged, we use I/B/E/S Detail History, Recommendations Summary, Compustat Segments, and LexisNexis' Corporate Affiliations databases.

To gain a better contextual understanding of our theoretical arguments, we conducted interviews with security analysts. Specifically, we conducted phone interviews with 5 sell-side analysts, where each interview lasted between 30 to 90 minutes. We also interviewed an investment bank lawyer familiar and experienced in crafting 10-K reports for fortune 500 companies.

2.3.3 Measures

Organizational Legitimacy. To measure the legitimacy of a firm, we examine the proportion of industry specialized analysts who cover a firm, that is, provide annual earnings forecasts for it (Zuckerman, 1999). We regard an analyst covering a firm in a specific fiscal year if that analyst has issued earnings forecast for that firm's fiscal year-end. A firm's primary industry is determined by its 4-digit SIC classification. On average, each firm garners a 12 percent specialized analyst coverage. The standard deviation for this coverage measure is 20 percent.

Magnitude of Change in Organizational Identity Claims. To measure change in organizational identity claims, we used information gathered from 10-K filing for firms in our dataset. We collected 10-K filings from the EDGAR system. We primarily focus on 10-K documents for the following reasons.

First, as our interviews and a large body of the accounting and finance literature confirm, security analysts pay careful attention to 10-K filings. Leheavy, Li, and Merkley (2011) show that 10-K filings that are less readable (have a greater number of words per sentence on average) may increase uncertainty and result in higher dispersion among performance forecasts released by security analysts. Therefore, to study the impact of organizational identity change on security analysts, it is helpful to examine textual changes in 10-K filings. Second, since top management teams represent a company (Hambrick & Mason, 1984), examining annual reports that are authorized and signed by team members is congruent with the social actor conception of organizational identity. Third, since 10-K filings are legally binding documents, they are checked and rechecked for consistency and authenticity. As one industry expert pointed out, “The last thing anyone wants is a shareholder lawsuit or an SEC inquiry.” Fourth, in compiling 10-K filings, year-to-year changes are documented and carefully checked. As an investment bank lawyer experienced in compiling such documents informed us, “We start from the previous year’s filing, then we highlight the parts that need to be changed. Next, we list things that need to be added, and then we make the needed changes.” Finally, 10-K filings have uniform formats and requirements which make them suitable for longitudinal panel studies (Chreim, 2005).

10-K filings consist of four major parts and 16 items in total. Item 1 of a typical 10-K document is usually labeled *Description of Business*.⁴ Here, firms describe who they are and what they do.⁵ As required by law, firms highlight the major developments and changes made during the previous fiscal year. This section serves as an excellent source of major organizational changes and helps us to capture the major year-to-year changes undertaken.

⁴ Other major variations are ‘Business Description’, ‘General’, ‘Business General’ and ‘Business overview’

⁵ More details about the specific requirements of the Item 1 section of 10-K filings may be found at *Item 101 of Regulation S-K (229.101)*.

To prepare information for detailed processing, we split Item 1 of the 10-K filing into words. We measured the weight of each term in relation to an organization's identity by focusing on what is *central*, *distinctive* and relatively *enduring* about a firm (Albert & Whetten, 1985). We started by separately measuring the centrality, distinctiveness, and relative enduringness of each term in a firm's 10-K filing Item 1 section as explained in detail below. We multiply the normalized measures of centrality, distinctiveness and enduringness of each term to determine the final weight of each term in a firm's business description. Next, we measured the similarity between a firm's 10-K filing at t_0 and t_{-1} using the cosine similarity technique. We then transformed this similarity measure into a change measure by subtracting it from one. Below, we outline the steps used to construct our change variable in greater detail.

Step 1: Centrality Measure. To capture the centrality of a word or term used in the Item 1 of a firm's 10-K document, we measured its relative importance with respect to other words or terms used in the same section. In this context, importance is captured as a count measure of how many times a word or term was used to describe the firm's business. We operationalized the count measure using the following formula:

$$Term\ Frequency(t, d) = \frac{F(t, d)}{\sum_{t \in d} F(t, d)} \quad (1)$$

where $F(t, d)$ is the frequency of term t in document d and $Term\ Frequency(t, d)$ is the adjusted frequency of term t in document d .

Step 2: Distinctiveness Measure. To measure the distinctiveness of a word used in the Item 1 section of a 10-K document, we examined how often the specific word appeared in other documents, using the following formula:

$$Inverse\ Document\ Frequency(t) = \log\left(\frac{D}{D_t}\right) \quad (2)$$

where D is the total number of documents included in our analysis, and D_t is the total number of documents containing term t ⁶. Using this formula, the terms or words used by one firm will have the highest coefficient of uniqueness while the terms used by all firms will be given a uniqueness coefficient of zero.

Step 3: Enduringness Measure. To measure the relative enduringness of a term in a firm's business description in t_0 , we count the number of years that the term has been consecutively present in the firm's 10-K filing Item 1 section before and leading up to t_0 . To normalize this number to a variable between 0 and 1, we divide it by the maximum number of continued presences among all words in a firm's business description. Thus, the following formula is used to assign a weight proportional to a term's enduringness within a firm business description.

$$\text{Continued Presence } (t, d) = \frac{P(t, d)}{\max_{t \in d} P(t, d)} \quad (3)$$

Where $P(t, d)$ is the number of consecutive years that a term t has been present before and leading up to document d .

Step 4: Combined Measure. Together, the word frequency count in Item 1 of the 10-K filing (our measure of the centrality of an attribute to a firm), inverse document frequency count (our measure of the uniqueness of an attribute to a firm) and continued presence (our measure of relative enduringness of an attribute in a firm's identity claims) capture a firm's claims about who they are and what they do. To obtain a combined measure, we multiply these three values. Therefore, each term or word used within Item 1 of the 10-K documents was given a weight using the following formula⁷:

⁶ This formula constructs a measure of distinctiveness vis-à-vis all other organizations in our sample. In our robustness checks, we measure distinctiveness using the same formula but vis-à-vis only those organizations within the focal organization's industry. Results remain qualitatively unchanged.

⁷ The combination of the first two elements, Term Frequency and Inverse Document Frequency measures results in the widely used TF-IDF measure. In textual analysis, TF-IDF is the preferred method for locating unique

$$Term\ Weight(t, d) = TF(t, d) * IDF(t) * CP(t, d) \quad (4)$$

Figure 2 is a word cloud representation of four firms' business descriptions where the weight of each word is determined through the formulas discussed above.

Step 5: Cosine Similarity. To operationalize identity change from one year to the next, we used a cosine similarity formula that measures changes from a firm's document in $t-1$ to t_0 . The Cosine Similarity approach is one of the most common methods in textual analysis for capturing similarity between documents (Salton & Buckley, 1988; Teodorescu, 2017). If we assign each document an n -dimensional weight vector, where n is the number of all terms in our corpus,⁸ each given a certain weight in a specific document, then cosine similarity formula measures the similarity between documents by calculating the cosine of the angle between weight vectors of the two documents.

The Cosine Similarity between words found in two documents converted into word vectors $\vec{d_1}$ and $\vec{d_2}$ is calculated using the following formula:

$$Cosine\ Similarity(\vec{d_1}, \vec{d_2}) = \frac{\sum_i d_{1t} * d_{2t}}{\sqrt{\sum_i d_{1t}^2} * \sqrt{\sum_i d_{2t}^2}} \quad (5)$$

where d_{1t} is the weight of term t in document d_1 . We use this measure to determine the magnitude of change in organizational identity claims between consecutive 10-K filings of the same firm. Similarity measures constructed this way take a number between 0 and 1, where a score of 1 means the two documents are identical. In our data, the mean of similarity measure between

and important features in a document (Salton & Buckley, 1988; Teodorescu, 2017). By adding the measure of relative enduringness, we customize the TF-IDF measure to make it suit better to our theoretical definition of organizational identity claims. As a robustness check, we test our models using the TF-IDF measure. The results qualitatively hold.

⁸ We have 131,409 unique terms in our corpus of 612,125,754 words. Unique terms include bigram words such as 'air_freshener,' 'barbeque_sauce,' 'bipolar_transistor,' etc. To reduce the noise in our data, we excluded words that appear less than 30 times in the corpus and words used in more than 80% of our documents.

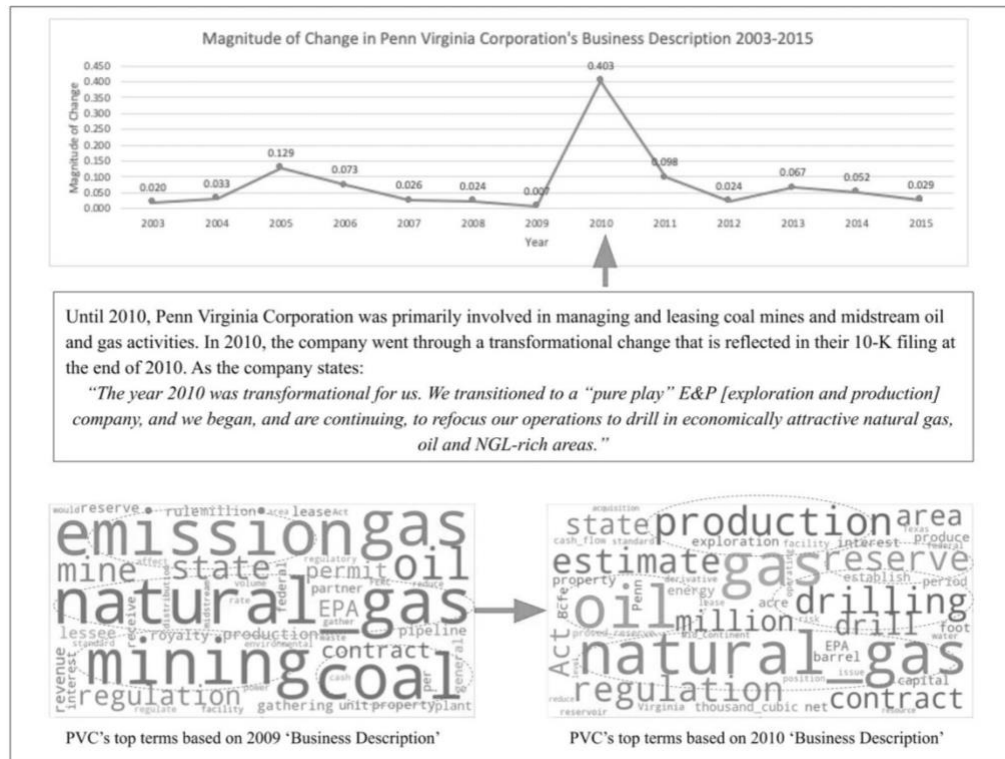


Figure 2-3 PVC's magnitude of change in its central, distinctive and enduring identity attributes (2003-2015)

document with that of other firms in the same year. We determine the direction of change by subtracting the average distance between a focal firm and all others in its industry in year t_0 from the same measure in year $t-1$. The mean average distance between a focal firm and all others in its primary industry is 0.38 with a standard deviation of 0.17. This mean distance measure changes between -0.61 and 0.51 units with a standard deviation of 0.045 year over year. Higher values of this measure demonstrate a firm's getting farther from others in its primary industry.

Industry Heterogeneity. We follow Haans's (2019) methodology in measuring the level of industry heterogeneity. First, we apply Latent Dirichlet Allocation (LDA) to construct a topic model of our corpus of all firms' business descriptions. Topic modeling is a generative statistical method that uncovers latent structures, i.e. topics, within a document (Blei, Ng, & Jordan, 2003).

Specifically, LDA method constructs a specific number of topics within a corpus of text, giving a probability weight to each word in each topic and a probability weight to each topic in each document (for a primer, see Hannigan et al., 2019). Following recent practice, we set the number of topics in our topic modeling to 100 (Haans, 2019; Kaplan & Vakili, 2015)⁹.

We measure the average weight of each topic for each industry. Next, we use the following formula from Haans (2019) to construct a measure for industry heterogeneity.

$$\text{Industry heterogeneity}_I = \sum_{T=1}^{100} \sqrt{\frac{1}{N-1} \sum_{i=1}^N (\theta_{T,i} - \bar{\theta}_{T,I})^2} \quad (6)$$

Where N is the number of firms within a particular industry, $\theta_{T,i}$ is the weight of topic T in firm i 's document and $\bar{\theta}_{T,I}$ is the average weight of topic T in industry I .

Control Variables. We included numerous control variables that were identified through interviews and past research as influencing the decisions to cover or not cover a firm. At the organizational level, size and financial performance have been shown to influence analyst coverage (Bhushan, 1989; McNichols & O'Brien, 1997). To control for size, we used two measures: the log of trade volume and total assets. To control for financial performance, we controlled for ROE and three-year earnings coefficient of variation (Litov et al., 2012).

Next, following Quigley and Hambrick (2012), we controlled for strategic change by investigating “changes in financial resource allocation patterns,” including firm-level R&D intensity, advertising intensity, and changes in intangible resources, and depreciated resources ratios. We also added a dummy variable that demonstrates whether a firm has issued stock in the prior fiscal

⁹ While our approach to topic modeling is completely unsupervised, our qualitative inspection of the constructed topic model confirms a high level of coherence in the topics. For example, our Topic 10's top words are solution, application, software, technology, support and datum, and Topic 19's top terms are design, technology, device, electronic, application, and manufacturing. As another example, Topic 36 demonstrates a firm's international focus by keywords such as global, international, Europe, worldwide, foreign and world.

year (Litov et al., 2012). Additionally, we controlled for potential industry-level variables that could affect our results. Following prior studies, we used the average R&D intensity of firms within an industry as a proxy for the level of dynamism and change within an industry (e.g., Tatarynowicz, Sytch, & Gulati, 2015). We control for the number of firms and the number of specialized industry analysts for a firm's primary industry. To verify that our results were not driven by outliers, we winsorized all accounting variables on the firm-level at the 2.5th percentile in each tail (Litov et al., 2012).

Prior research has established a strong link between top management teams and security analysts' behavior (e.g., Gomuly & Boeker, 2014; Westphal & Clement, 2008). Therefore, we control for top management team turnover. Zuckerman (2000) demonstrated that firms could increase their analyst coverage by de-diversifying and having a more focused identity. We construct a measure for a firm's identity focus using the topic models constructed previously. To measure identity focus, we sum the squares of the weight of each topic in a firm's business description. This approach is similar to the Herfindahl-Hirschman Index of concentration (Rhoades, 1993). As a robustness check, we also run our models replacing this measure with the number of segments that a firm has posted sales in. Furthermore, Litov et al. (2012) demonstrated that a firm's uniqueness could decrease its analyst coverage. We create a measure of a firm's identity uniqueness using an approach similar to Litov et al.'s (2012), with the following difference. Instead of using the proportion of sales in an industry, we use the weight of various topics in a firm's business description. We use the following measure:

$$\text{Firm identity uniqueness}_i = \sum_{T=1}^{100} (\theta_{T,i} - \bar{\theta}_{T,I})^2 \quad (7)$$

Where $\theta_{T,i}$ is the weight of topic T in firm i document and $\bar{\theta}_{T,I}$ is the average weight of topic T in industry I .

Table 2-1 Summary statistics

	Mean	S.D.	Min	Max	Count
Analyst coverage	12.07	20.60	0.00	100.00	59149
Number of analysts	4.65	6.63	0.00	55.00	59149
ROE	0.31	1.16	-2.93	3.40	59149
Earning Coef. Variation	0.47	2.22	-5.70	5.27	59149
Total assets (log)	6.30	1.99	2.50	10.48	59149
Trade volume (log)	17.31	2.00	13.04	21.04	59149
R&D intensity	0.05	0.10	0.00	0.45	59149
Advertising intensity	0.01	0.02	0.00	0.09	59149
Intangibles ratio	0.13	0.18	0.00	0.64	59149
Depreciation ratio	0.03	0.03	0.00	0.13	59149
Debt ratio	1.76	2.47	-2.37	5.96	59149
M&A expenditure	0.68	2.71	0.00	15.00	59149
Equity issuance dummy	0.63	0.48	0.00	1.00	59149
TMT turnover	0.22	0.16	0.00	1.00	59149
Firm identity focus (LDA)	0.23	0.13	0.04	0.92	59149
Firm identity uniqueness (LDA)	-2.78	0.75	-4.61	-0.23	59149
No. analysts in industry	81.05	124.38	0.00	736.00	59149
No. firm in industry	77.35	99.40	1.00	420.00	57302
Industry dynamism	0.05	0.08	0.00	0.45	59149
Magnitude of change (log)	-3.21	0.85	-4.61	0.01	50798
Change in average distance	0.01	0.05	-0.62	0.52	48707
Industry heterogeneity (LDA)	0.07	0.03	0.00	0.24	59149
Observations	59149				

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1) Analyst coverage	1.00																					
(2) Number of analysts	0.49	1.00																				
(3) ROE	0.31	0.33	1.00																			
(4) Earning Coef. Variation	0.04	0.04	0.17	1.00																		
(5) Total assets (log)	0.38	0.52	0.47	0.09	1.00																	
(6) Trade volume (log)	0.36	0.55	0.24	0.01	0.56	1.00																
(7) R&D intensity	-0.18	-0.07	-0.29	-0.09	-0.42	0.08	1.00															
(8) Advertising intensity	0.08	0.04	0.00	-0.01	-0.05	0.07	-0.01	1.00														
(9) Intangibles ratio	0.17	0.15	0.06	-0.01	0.10	0.20	-0.06	0.10	1.00													
(10) Depreciation ratio	0.02	-0.01	-0.19	-0.08	-0.22	0.08	0.13	0.10	0.15	1.00												
(11) Debt ratio	-0.07	-0.04	0.04	0.01	0.27	-0.19	-0.22	-0.11	-0.17	-0.23	1.00											
(12) M&A expenditure	0.13	0.22	0.12	0.02	0.26	0.22	-0.06	-0.01	0.26	-0.00	0.02	1.00										
(13) Equity issuance dummy	0.08	0.09	0.41	0.11	0.17	0.03	-0.19	-0.03	0.02	-0.16	0.06	0.04	1.00									
(14) TMT turnover	0.01	0.02	-0.00	-0.02	0.05	0.06	0.01	0.02	0.05	0.01	0.03	0.02	-0.02	1.00								
(15) Firm identity focus (LDA)	-0.08	0.05	0.04	0.02	0.16	-0.05	-0.01	-0.13	-0.21	-0.19	0.24	-0.04	0.06	-0.02	1.00							
(16) Firm identity uniqueness (LDA)	-0.19	-0.08	-0.07	-0.02	-0.14	-0.04	0.13	0.02	0.01	-0.01	-0.05	-0.05	-0.04	0.01	-0.01	1.00						
(17) No. analysts in industry	-0.15	0.30	-0.03	-0.01	0.05	0.18	0.23	0.01	0.08	0.00	-0.02	0.06	0.04	-0.00	0.09	0.10	1.00					
(18) No. firm in industry	-0.33	-0.02	-0.10	-0.02	0.05	-0.09	0.17	-0.09	-0.20	-0.23	0.36	-0.02	0.02	0.03	0.33	0.10	0.49	1.00				
(19) Industry dynamism	-0.21	-0.02	-0.24	-0.07	-0.38	0.13	0.75	0.00	0.04	0.08	-0.26	-0.00	-0.12	0.00	-0.07	0.18	0.34	0.21	1.00			
(20) Magnitude of change	-0.07	-0.07	-0.12	-0.02	-0.12	0.07	0.14	0.03	0.07	0.11	-0.08	0.01	-0.06	0.09	-0.15	0.06	0.01	-0.01	0.16	1.00		
(21) Change in average distance	0.00	-0.01	-0.01	0.00	0.01	-0.00	0.01	0.00	0.00	-0.01	0.01	0.01	0.01	0.02	0.01	-0.11	-0.00	0.03	0.01	0.07	1.00	
(22) Industry heterogeneity (LDA)	-0.31	-0.06	-0.10	-0.03	-0.10	-0.04	0.18	-0.03	-0.02	-0.11	0.06	-0.05	-0.04	0.02	0.03	0.55	0.24	0.35	0.23	0.08	-0.08	1.00

Table 2-2 Bivariate correlations

2.3.4 Models

Our models estimate the relationship between the magnitude of identity claim changes and the proportion of industry specialized analysts that cover an organization. We use an OLS model with clustered robust variance estimator. We include firm fixed effects to control for unobserved between-firm differences that might affect analyst coverage. Additionally, we include year fixed effects to control for unobserved periodic effects that might cause variation in coverage across our sample. In our robustness checks, we use the number of analysts as dependent variable and test our models using a conditional fixed-effects Poisson quasi-maximum likelihood model with Huber-White robust standard errors. Further, we check the consistency of our results by using a random effects Tobit model.

2.4 Results

Table 1 provides descriptive statistics for our sample and Table 2 demonstrates the bivariate correlations among the variables. As shown, the mean of the proportion of analysts covering a firm each year is 12.07 percent. While the bivariate correlation between variables are small to medium, we checked for multicollinearity using the variance inflation factor (VIF) method. The VIF index for each variable was well below the problematic threshold of 10, with an average of 1.7 for all the variables.

Model 1 in Table 3 is our control variables-only model. Model 2 highlights the impact of the ‘*magnitude of change*’ in organizational identity claims on our dependent variable, after controlling for other factors. Model 3 shows the moderating role of the direction of change on the base relationship. Model 4 highlights the impact of industry heterogeneity on the base hypothesis. Finally, Model 5 represents the full model.

Model 1 results are consistent with prior findings. Better performing firms (i.e., those with

a higher ROE), garnered more coverage ($\beta = 0.24$), a result which is line with analysts' incentives to increase trading volume and have a coverage portfolio that attracts more investment banking opportunities for their respective employers (Litov et al., 2012). Also, firm size is positively correlated with analyst coverage. Larger firms delineated by higher trade volume and larger total assets attracted greater analyst coverage ($\beta = 1.13$ and $\beta = 1.73$, respectively). In line with Litov et al.'s (2012) finding, an organization's identity uniqueness results in lower analyst coverage ($\beta = -1.13$, $p < 0.01$). Furthermore, a firm's R&D intensity and industry dynamism both result in higher analyst coverage ($\beta = 5.28$ and $\beta = 8.76$, respectively). M&A expenditure is shown to increase coverage ($\beta = 0.07$). The coefficient for TMT turnover is negative but statistically insignificant.

Hypothesis 1 posited a negative relationship between the magnitude of change in organizational identity claims and the level of specialized analyst coverage, our dependent variable. In Model 2, the coefficient for this variable is negative ($\beta = -0.21$) and significant ($p < 0.05$). Therefore, hypothesis 1 is supported. Results are graphed in Figure 4.

Hypothesis 2 posited that the direction of change moderates the negative relationship between the magnitude of change in organizational identity claims and the proportion of industry specialized analysts that cover a firm. In Model 3, the interaction term between the magnitude of change and the direction of change is negative ($\beta = -3.11$) and statistically significant ($p < 0.01$). This suggests that when a firm changes its identity towards becoming more different from other firms in its industry, the negative effect of the magnitude of change on coverage will be more severe. Hence, we claim support for Hypothesis 2. A one standard deviation change that is combined with one standard deviation increase in distance to other firms results in a loss of 3.6 percent of specialized industry coverage (see Figure 5).

Hypothesis 3 suggested that industry heterogeneity moderates the relationship between the

magnitude of change in identity claims and analyst coverage. We tested this hypothesis by adding the industry heterogeneity variable and its interaction term to our model. In Model 4, the coefficient for the interaction term is positive ($\beta = 17.39$) and statistically significant ($p < 0.01$). Hence, we claim support for Hypothesis 3. The model shows that the effect of identity claim changes is more severe in homogenous industries. A one standard deviation of change in a homogeneous industry (two standard deviations below the mean) results in a loss of 9.3 percent of specialized industry analyst coverage. This compares to a loss of 5.5 percent in analyst coverage by one standard deviation in uniqueness measure found by Litov et al. (2012). The same amount of change in an industry with an average heterogeneity level results in only a 2 percent loss of coverage. Figure 6 illustrates this relationship further.

Finally, in Model 5, the full model, the coefficients for the key independent variables remain consistent and statistically significant.

Table 2-3 Main regression models

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
ROE	0.24*** (0.09)	0.21** (0.09)	0.18** (0.08)	0.20** (0.09)	0.17** (0.08)
Earning Coef. Variation	0.01 (0.03)	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	0.01 (0.03)
Total assets (log)	1.73*** (0.24)	1.89*** (0.27)	1.62*** (0.25)	1.91*** (0.26)	1.63*** (0.24)
Trade volume (log)	1.13*** (0.11)	1.04*** (0.12)	0.98*** (0.11)	1.03*** (0.12)	0.97*** (0.11)
R&D intensity	5.28*** (1.12)	4.65*** (1.19)	3.70*** (1.14)	4.76*** (1.18)	3.77*** (1.13)
Advertising intensity	11.15 (11.03)	13.40 (11.74)	16.57 (10.08)	14.03 (11.68)	17.05* (10.07)
Intangibles ratio	1.76* (1.00)	0.98 (1.07)	1.16 (0.98)	1.11 (1.06)	1.28 (0.97)
Depreciation ratio	-5.49 (4.85)	-2.39 (5.27)	-4.39 (4.79)	-2.69 (5.26)	-4.63 (4.78)
Debt ratio	-0.06 (0.07)	-0.09 (0.07)	-0.05 (0.07)	-0.09 (0.07)	-0.05 (0.07)
M&A expenditure	0.07** (0.03)	0.05 (0.03)	0.05 (0.03)	0.06 (0.03)	0.05 (0.03)
Equity issuance dummy	-0.19 (0.13)	-0.20 (0.14)	-0.21* (0.13)	-0.20 (0.14)	-0.21* (0.13)
TMT turnover	-0.26 (0.33)	-0.07 (0.35)	-0.22 (0.32)	-0.03 (0.34)	-0.20 (0.32)
Firm identity focus (LDA)	1.85 (2.08)	2.15 (2.19)	0.30 (1.79)	1.58 (2.20)	-0.10 (1.80)
Firm identity uniqueness (LDA)	-1.13*** (0.29)	-1.33*** (0.31)	-0.56** (0.27)	-1.02*** (0.30)	-0.35 (0.26)
No. analysts in industry	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
No. firm in industry	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)
Industry dynamism	8.76** (4.45)	9.99** (4.95)	7.50 (4.70)	10.35** (4.92)	7.82* (4.67)
Magnitude of change		-0.21** (0.09)	-0.17** (0.09)	-1.49*** (0.32)	-1.18*** (0.33)
Change in average distance (log)			-7.82*** (2.68)		-5.92** (2.65)
Mag. of change* Change in average distance			-3.11*** (1.09)		-2.40** (1.08)
Industry heterogeneity (LDA)				41.54*** (13.66)	31.45** (14.36)
Mag. of change* Industry heterogeneity (LDA)				17.39*** (3.69)	13.12*** (3.79)
Constant	-22.57*** (2.21)	-23.61*** (2.46)	-18.54*** (2.14)	-25.59*** (2.87)	-20.15*** (2.62)
Observations	57,302	49,479	46,770	49,479	46,770
Number of firms	8,486	7,331	6,920	7,331	6,920
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table uses OLS regression to test our hypotheses. Dependent variable in all models is the proportion of industry specialized analysts that cover a firm (0-100). In all models, accounting variables are winsorized at 2.5 percent in each tail.

Table 2-4 Robustness checks for the main results

VARIABLES	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
ROE	0.17** (0.08)	0.17** (0.08)	0.17** (0.08)	0.12 (0.09)	0.13 (0.09)	0.19** (0.08)
Earning Coef. Variation	0.00 (0.03)	0.00 (0.03)	0.00 (0.03)	-0.01 (0.03)	-0.01 (0.03)	0.00 (0.03)
Total assets (log)	1.60*** (0.25)	1.63*** (0.24)	1.63*** (0.24)	1.79*** (0.29)	1.81*** (0.29)	1.61*** (0.24)
Trade volume (log)	0.99*** (0.11)	0.97*** (0.11)	0.97*** (0.11)	0.82*** (0.12)	0.82*** (0.12)	0.97*** (0.11)
R&D intensity	3.65*** (1.14)	3.77*** (1.14)	3.77*** (1.14)	3.37** (1.33)	3.42** (1.33)	3.63*** (1.13)
Advertising intensity	16.62 (10.22)	17.06* (10.08)	17.01* (10.08)	12.29 (12.82)	12.04 (12.84)	17.24* (10.14)
Intangibles ratio	1.31 (0.98)	1.25 (0.97)	1.26 (0.97)	1.37 (1.12)	1.20 (1.12)	1.30 (0.97)
Depreciation ratio	-4.32 (4.82)	-4.58 (4.77)	-4.58 (4.77)	-2.06 (6.60)	-1.77 (6.61)	-4.20 (4.74)
Debt ratio	-0.06 (0.07)	-0.05 (0.07)	-0.05 (0.07)	-0.08 (0.09)	-0.08 (0.09)	-0.05 (0.07)
M&A expenditure	0.05 (0.03)	0.05 (0.03)	0.05 (0.03)	0.03 (0.03)	0.03 (0.03)	0.05 (0.03)
Equity issuance dummy	-0.21 (0.13)	-0.21* (0.13)	-0.21* (0.13)	-0.23* (0.14)	-0.23 (0.14)	-0.21* (0.12)
TMT turnover	-0.21 (0.32)	-0.20 (0.32)	-0.20 (0.32)	-0.37 (0.35)	-0.40 (0.35)	-0.24 (0.32)
Firm identity focus (LDA)	-0.39 (1.81)	-0.16 (1.80)	-0.18 (1.80)	0.03 (2.10)	0.19 (2.11)	0.00 (1.78)
Firm identity uniqueness (LDA)	-0.32 (0.26)	-0.36 (0.26)	-0.36 (0.26)	-0.39 (0.29)	-0.42 (0.29)	-0.36 (0.26)
No. analysts in industry	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)
No. firm in industry	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)
Industry dynamism	7.96* (4.72)	7.81* (4.67)	7.83* (4.67)	6.21 (5.88)	6.20 (5.88)	8.15* (4.73)
Magnitude of change (log)	-1.19*** (0.34)	-0.98*** (0.34)	-1.00*** (0.33)	-1.86*** (0.62)	-1.12** (0.52)	-0.99*** (0.28)
Change in average distance	-6.81** (2.68)	-5.79** (2.57)	-5.51** (2.48)	-2.45 (4.59)	-0.58 (1.65)	-6.63** (2.76)
Mag. of change* Change in average distance	-2.60** (1.10)	-2.44** (1.10)	-2.43** (1.10)	-0.55 (1.42)	-1.26 (1.51)	-2.58** (1.13)
Industry heterogeneity (LDA)	32.30** (14.63)	20.87 (14.03)	20.69 (13.42)	67.17** (29.62)	33.46 (22.72)	24.61** (12.44)
Mag. of change*Industry heterogeneity (LDA)	13.41*** (3.89)	10.61*** (3.93)	10.79*** (3.80)	22.37*** (7.50)	14.83** (6.19)	11.22*** (3.19)
Constant	-20.34*** (2.65)	-19.35*** (2.58)	-19.32*** (2.56)	-13.03*** (2.81)	-13.11*** (2.80)	-19.51*** (2.53)
Observations	45,802	46,770	46,770	35,565	35,565	47,432
Number of firms	6,614	6,920	6,920	5,323	5,323	6,931
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: this table tests for the robustness of the findings in table 3. In Model 6, we measure distinctiveness vis-à-vis other firms in a firm's primary industry. In Model 7, we estimate our change variable using only the frequency of words in a document, excluding measures for distinctiveness and enduringness. In Model 8, we measure change in organizationally identity claims by measuring frequency and distinctiveness and excluding the effect of enduringness of a term. In Model 9, we estimate change by measuring a firm's change identity claims compared to the average of previous three years. In Model 10, we only keep the top 25 words that have the highest centrality and distinctiveness in a firm's business description, as well as that they have been present in at least three consecutive years prior to the focal year. In Model 11, we winsorize the change variable at 1 percentile in each tail. In all models, accounting variables are winsorized at 2.5 percent in each tail.

Table 2-5 Robustness checks for the main results

VARIABLES	Model 12	Model 13	Model 14	Model 15	Model 16
ROE	0.11 (0.09)	0.16* (0.09)	0.12 (0.09)	0.17** (0.09)	0.19** (0.08)
Earning Coef. Variation	-0.03 (0.04)	-0.01 (0.04)	0.02 (0.03)	-0.01 (0.03)	0.00 (0.03)
Total assets (log)	2.43*** (0.37)	2.02*** (0.36)	1.64*** (0.28)	1.77*** (0.27)	1.62*** (0.24)
Trade volume (log)	2.11*** (0.17)	1.52*** (0.18)	0.95*** (0.12)	0.70*** (0.11)	0.96*** (0.11)
R&D intensity	7.98*** (1.97)	7.86** (3.90)	3.57*** (1.28)	3.36*** (1.22)	3.83*** (1.14)
Advertising intensity	14.25 (16.42)	16.89 (17.15)	16.06 (11.53)	8.97 (10.70)	19.92** (10.00)
Intangibles ratio	-0.15 (1.36)	1.57 (1.54)	1.57 (1.08)	0.53 (1.04)	1.39 (0.98)
Depreciation ratio	-4.60 (7.75)	-2.14 (9.78)	-2.63 (5.63)	-2.04 (5.70)	-5.95 (4.59)
Debt ratio	-0.05 (0.10)	-0.07 (0.10)	-0.09 (0.08)	-0.06 (0.09)	-0.04 (0.07)
M&A expenditure	-0.01 (0.03)	0.03 (0.03)	0.04 (0.03)	0.04 (0.03)	0.05 (0.03)
Equity issuance dummy	-0.11 (0.16)	-0.15 (0.18)	-0.16 (0.13)	-0.16 (0.13)	-0.21* (0.12)
TMT turnover	-0.36 (0.41)	-0.50 (0.43)	-0.22 (0.34)	-0.24 (0.33)	-0.26 (0.33)
Firm identity focus (LDA)	-0.10 (1.93)	-0.50 (2.57)	0.27 (1.95)	-0.63 (1.92)	0.39 (1.83)
Firm identity uniqueness (LDA)	-0.23 (0.29)	-0.55 (0.38)	-0.44 (0.28)	-0.38 (0.27)	-0.34 (0.27)
No. analysts in industry	-0.04*** (0.00)	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)	0.00** (0.00)
No. firm in industry	-0.01*** (0.00)	-0.03*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)	-0.02*** (0.00)
Industry dynamism	16.51** (8.33)	8.97 (7.46)	7.44 (5.21)	6.37 (5.97)	8.30* (4.74)
Magnitude of change	-0.93** (0.36)	-1.16*** (0.38)	-1.07*** (0.35)	-0.85** (0.37)	-1.18*** (0.34)
Change in average distance (log)	-9.90** (4.05)	-7.90** (3.90)	-7.64*** (2.86)	-6.63** (2.77)	-5.86** (2.98)
Mag. of change*Change in average distance	-4.11*** (1.49)	-2.89* (1.49)	-3.14*** (1.16)	-2.75** (1.14)	-2.36** (1.17)
Industry heterogeneity (LDA)	18.10 (16.86)	26.92 (16.93)	28.04* (15.47)	25.54 (17.13)	31.84** (14.62)
Mag. of change*Industry heterogeneity (LDA)	9.97** (4.18)	13.87*** (4.27)	11.94*** (4.07)	10.07** (4.38)	13.18*** (3.84)
Constant	-33.28*** (4.11)	-30.03*** (4.00)	-19.48*** (2.87)	-14.14*** (2.85)	-20.23*** (2.69)
Observations	27,594	31,234	42,043	40,344	45,835
Number of firms	5,152	4,677	6,304	6,132	6,855
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In Model 12, we limit our sample to firms that have at least one analyst covering them. In Model 13, we restrict our sample to firms that have above \$ 100 million of sales. In Model 14, we restrict our sample to firms that have been listed publicly for at least 5 years. In Model 15 we restricted our sample to observations after 2001. In Model 16, we limit our sample to firms that have at least 500 words in their business description. In all models, accounting variables are winsorized at 2.5 percent in each tail.

Table 2-6 Robustness check for the main results

VARIABLES	Model 17	Model 18	Model 19	Model 20
ROE	0.17** (0.08)	0.24** (0.10)	0.00 (0.00)	0.40*** (0.05)
Earning Coef. Variation	0.00 (0.03)	0.03 (0.03)	0.00* (0.00)	-0.01 (0.02)
Total assets (log)	1.66*** (0.24)	1.65*** (0.24)	0.20*** (0.02)	2.34*** (0.08)
Trade volume (log)	0.97*** (0.11)	1.10*** (0.11)	0.17*** (0.01)	1.18*** (0.06)
R&D intensity	3.82*** (1.12)	4.48*** (1.17)	0.43*** (0.16)	5.32*** (1.14)
Advertising intensity	17.08* (10.05)	13.19 (9.33)	2.45*** (0.87)	27.76*** (5.08)
Intangibles ratio	1.32 (0.97)	0.43 (0.93)	0.16** (0.08)	1.63*** (0.48)
Depreciation ratio	-4.52 (4.78)	-6.52 (4.21)	-1.41*** (0.47)	4.14 (2.77)
Debt ratio	-0.05 (0.07)	-0.04 (0.07)	0.00 (0.00)	-0.12*** (0.04)
M&A expenditure	0.05 (0.03)	0.08** (0.04)	0.00* (0.00)	0.05*** (0.02)
Equity issuance dummy	-0.21* (0.13)	-0.27* (0.14)	0.00 (0.01)	-0.30*** (0.11)
TMT turnover	-0.20 (0.32)	-0.28 (0.37)	0.02 (0.02)	-0.12 (0.29)
Firm identity focus (LDA)		0.73 (1.91)	0.15 (0.13)	-3.00*** (0.87)
Number of segments	-0.27 (0.23)			
Firm identity uniqueness (LDA)	-0.36 (0.26)		-0.02 (0.02)	-0.46*** (0.14)
Firm uniqueness (Litov 2012)		-1.57** (0.71)		
No. analysts in industry	0.00** (0.00)	0.00 (0.00)	0.00*** (0.00)	0.00*** (0.00)
No. firm in industry	-0.02*** (0.00)	-0.03*** (0.00)	0.00*** (0.00)	-0.03*** (0.00)
Industry dynamism	7.84* (4.66)	8.72* (4.83)	-1.33*** (0.36)	-7.66*** (2.11)
Magnitude of change	-1.18*** (0.33)	-1.45*** (0.37)	-0.05*** (0.01)	-1.22*** (0.15)
Change in average distance	-5.93** (2.64)	-5.13* (2.88)	-0.10 (0.17)	-5.64** (2.29)
Mag. of change*Change in average distance	-2.41** (1.08)	-1.93* (1.17)	-0.01 (0.06)	-1.78** (0.83)
Industry heterogeneity (LDA)	31.43** (14.35)	34.10** (16.32)	-0.12 (0.68)	0.72 (6.71)
Mag. of change*Industry heterogeneity (LDA)	13.14*** (3.79)	17.31*** (4.35)	0.47*** (0.17)	13.09*** (1.85)
Constant	-19.95*** (2.61)	-20.64*** (2.73)		-23.27*** (1.24)
Observations	46,770	38,415	37,164	46,770
Number of firms	6,920	6,000	4,451	6,920
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In Model 17, we estimated the model number of segments to measure a firm's focus. In Model 18, we replace our measurement of a firm's identity uniqueness built using LDA techniques with Litov et al.'s (2012) measurement of uniqueness. In Model 19, we use a simple count of the number of analysts that follow a firm as the dependent variable and use a Poisson specification. In Model 20, we estimate the effects using a random effects Tobit specification. In all models, accounting variables are winsorized at 2.5 percent in each tail.

2.4.1 Robustness Checks

We performed additional robustness checks for change variable operationalization, sampling decisions, and model specifications.

The Change Variable. In our main models, we measured the distinctiveness of each term by counting the number of all other documents in our corpus that contained that term. Thus, we constructed a measure of distinctiveness vis-à-vis every other firm in our sample. To change the comparison set, in Model 6, we measured the distinctiveness of each term vis-à-vis other firms in the same industry. We did this by counting only the number of other documents within the same industry that contained that term. Model 6 in Table 4 demonstrates the results using this operationalization of term distinctiveness. In Model 7, we use a count of word frequency in each document and build our change variable based on only the centrality of a term in a document, thus excluding the role of distinctiveness and enduringness. The results still hold while the effect size is smaller. In Model 8, we measure identity claim changes by measuring frequency and distinctiveness and excluding the effect of enduringness of terms. Thus, this measure is identical to TF-IDF measure widely used in NLP techniques (Teodorescu, 2017). The results still obtain, with a slightly larger effect size compared to the previous step, where we only used the frequency measure. In Model 9, we use our main change variable with one adjustment: instead of examining the magnitude of change over the previous year's business description, we measured the magnitude of change over the average of the past three years. While the coefficient for the baseline hypothesis gets stronger, the moderation effect of the direction of change becomes insignificant. In Model 10, we build upon the previous step, but this time we only keep the top 25 highly weighted words that have been present in at least three consecutive years prior to the focal year. We measure change using only such top 25 words. The results still hold with the exception that the effects of change's

direction become statistically insignificant. Finally, in Model 11, we winsorize the change variable at 1 percentile in each tail to make sure our results are not driven solely by extreme cases. The results obtain.

Sampling Decisions. In Model 12 in Table 5, we limit our sample to firms that have at least one analyst covering them. In Model 13, we restrict our sample to firms that have above \$100 million of sales to control for smaller firms that tend to be more volatile. In Model 14, we restrict our sample to firms that have been listed publicly for at least 5 years, therefore excluding younger firms that may still not have an established identity. In Model 15, we restrict our sample to observations after 2001. Although electronic filing of 10-K reports became a requirement in 1997, over the first few years there were some inconsistencies in electronic filings due to the newness of the practice. Excluding observations from the first five years of electronic filing, our results are consistent as shown in Table 5. In Model 16, we limit our sample to firms that have at least 500 words in their business description. The results are consistent with prior findings and demonstrate that our main findings are robust to these sampling decisions.

Variable Operationalizations. We estimated our main models with slightly different operationalizations for some of the variables. In Model 17, we used a slightly different measurement for a firm's identity focus. Instead of using topic modeling on business description texts to measure the level of focus in a firm's identity, we used a count variable of the number of segments that an organization reports sales in. This measure is a widely used measure of firm diversification (Zuckerman, 2000). In Model 18, we replace our measurement of a firm's identity uniqueness that we built using LDA technique with Litov et al.'s (2012) measurement of uniqueness that is built using segment sales data. Consistent with the prior findings, uniqueness

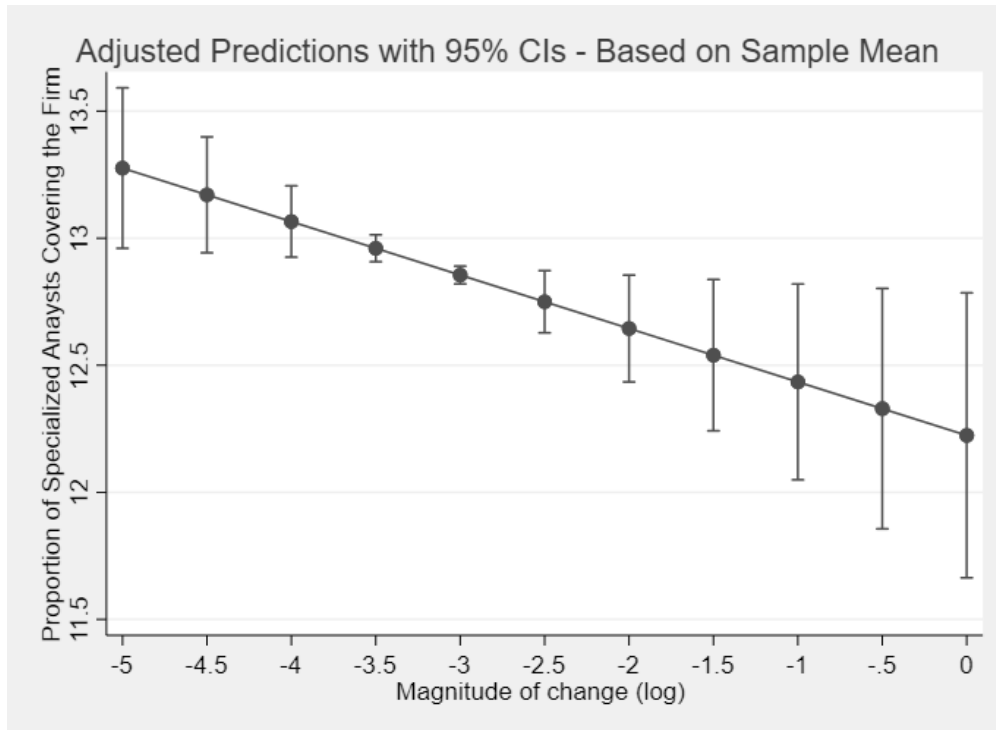


Figure 2-4 Effects of the magnitude of change in identity claims on analyst

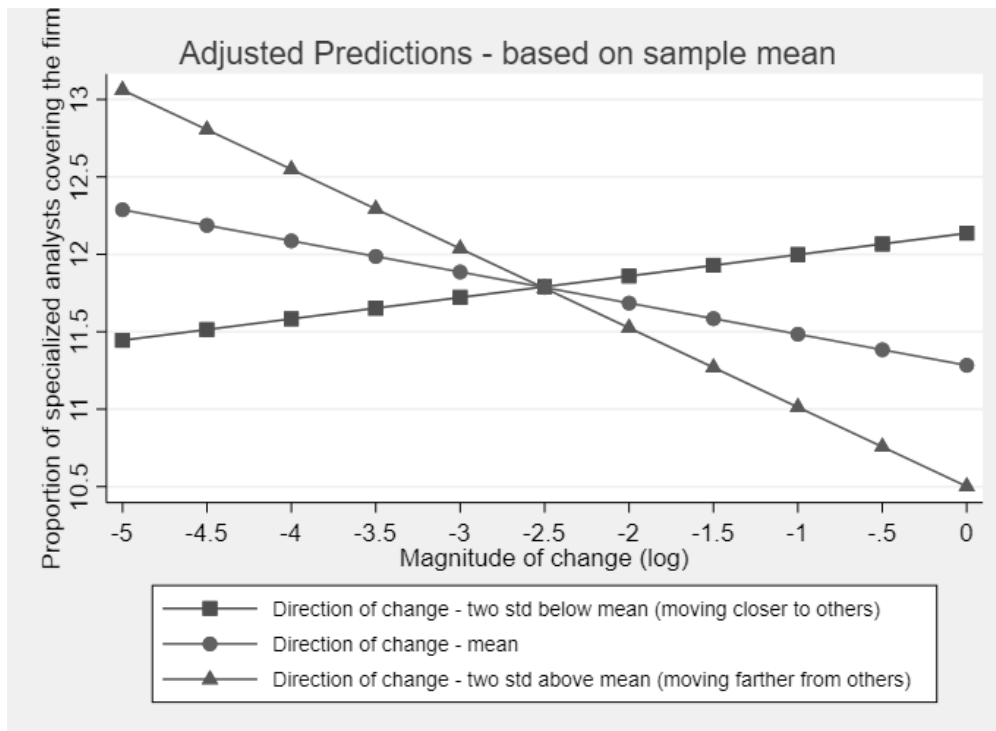


Figure 2-5 Direction of change moderating the effects of the magnitude of change on analyst coverage

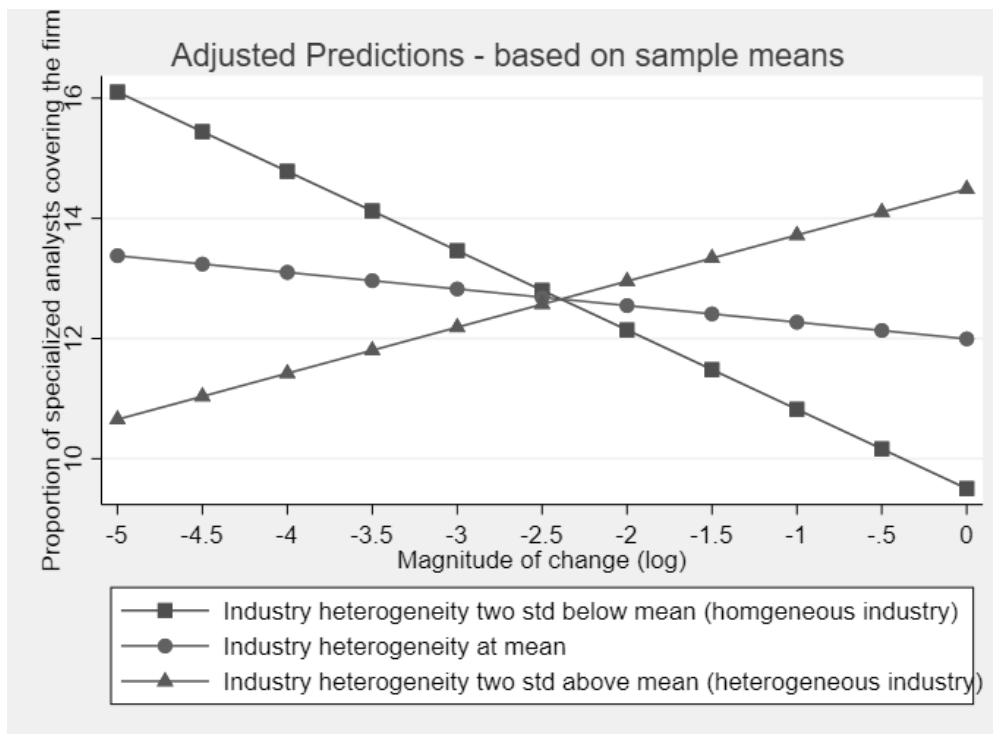


Figure 2-6 Industry heterogeneity moderating the effects of the magnitude of change on analyst coverage

has a significant negative effect on a firm's analyst coverage. Including this variable, our results generally obtain with the exception that the moderation effect of the direction of change becomes only weakly significant ($p < 0.1$).

Model Specifications. The robustness of our findings was checked against different model specifications. In Model 19, we use a simple count of the number of analysts that follow a firm as the dependent variable. Since our dependent variable is a non-negative count variable, a quasi-Poisson or negative binomial would be the most appropriate specification (Hausman, Hall, & Griliches, 1984). We chose a quasi-Poisson specification which is robust to overdispersion (Cameron & Trivedi, 1990; Woolridge, 1990). The results generally obtain. The interaction effect of the direction of change becomes statistically insignificant in the full model.

Since approximately 27% of our observations had a coverage value of zero, we were concerned about any issues that might result from the left censoring of the data. Model 20 shows the results using the Tobit method with random effects specifications to control for any incidental parameter issues (Lancaster, 2000). Again, results were generally consistent with the findings shown in Table 3.

2.5 Discussion, Contributions, and Limitations

2.5.1 Discussion

Organizational identity claims—information about what is central, distinctive and enduring about an organization—serve as sensemaking devices that enable audiences to comprehend an organization and endow it with legitimacy. Since research into the *external consequences* of identity claims is limited, we examined how changes to an organization's identity impact its legitimacy among one important external audience, security analysts. We posited that identity claim changes negatively impact an organization's legitimacy because such changes, when significant, force audiences to alter their judgments and cognitive schemas (Benner, 2007, 2010; Tripsas, 2009) and increase the cognitive effort needed for assessing the organization. Because of the extra effort required, an audience may choose to deny legitimacy to an organization (Litov et al., 2012; Zuckerman, 1999).

Additionally, we predicted that the legitimacy loss that can result because of identity claim changes is amplified when the change also results in the organization getting farther from the prototypical claims made by other organizations in its industry. We further argued that in homogeneous environments, where patterns of behavior are more solidified and expectations are more restrictive, organizations that make significant changes to their identity claims will face greater legitimacy penalties (Haans, 2019; Lounsbury & Rao, 2004).

We tested these propositions by examining security analysts' coverage decisions regarding publicly listed U.S. organizations from 1997 to 2018. Applying NLP techniques on a large sample of business descriptions included in 10-K filings, we found empirical support for our predictions. Our key findings are robust in terms of sampling decisions and model specifications.

2.5.2 Contributions

Organizational Identity Contributions. We contribute to the research at the intersection of organizational identity and organizational legitimacy (Fisher, Kotha, & Lahiri, 2016; Glynn & Azburg, 2002; Glynn & Marquis, 2007; Navis & Glynn, 2010, 2011; Smith, 2011; Zuckerman, 1999). Research on organizational identity and legitimacy has generally examined the effects of conformity versus deviance of identity claims on audience evaluations, assuming relative stability in organizational identity (Smith, 2011; Zuckerman, 1999). In contrast, we focused on how *changes* in identity claims impact audience evaluations of the organization. Drawing on the role of cognitive economy (Rosch, 1989) and cognitive inertia (Benner, 2007; Tripsas, 2009) in audience evaluations, we extend previous scholarship to show that an organization may incur legitimacy penalties (loss of legitimacy) for deviating from its formerly espoused claims of identity. Our findings suggest that when an organization makes identity claim changes, it is vulnerable to losing some of its legitimacy.

Our theoretical arguments extend research on organizational identity change (e.g., Clark, Gioia, Ketchen, & Thomas, 2010; Gioia et al., 2000; Golant, Sillince, Harvey, & Maclean 2015; Ravasi & Nelson, 2011; Ravasi & Schultz, 2006). While past research has focused on the antecedents and processes organizations employ to navigate identity change, little research has examined how external audiences respond to changes in identity claims. In addition to the *internal* need for continuity recognized in the literature (e.g., Chreim, 2005), our findings show there may

be an *external* resistance to change stemming from how audiences evaluate such changes. These novel findings indicate that during periods of identity change, in addition to addressing internal organizational members' reactions to the change, managers should also consider how external audiences might perceive the change. Our findings suggest the need for further research around signals organizations may employ to garner or maintain their legitimacy with external audiences, especially those that follow the organization closely, when making changes to identity claims.

We also make a methodological contribution to organizational identity research. Using the Item 1 sections of 10-K filings, we examined a large sample of organizations over an extended time period. As Foreman and Whetten (2016) point out, one serious concern about studies of organizational identity change is that they are mostly small-sample qualitative case studies which, although highly informative, are mainly focused on generating rather than testing theories. Also, since such studies have mainly examined 'revelatory' cases of organizational identity change, it is difficult to generalize their findings. Using a large sample over time addresses this critical limitation and helps open up avenues for further quantitative studies on organizational identity research. By measuring centrality, distinctiveness, and continuity longitudinally, we address organizational identity scholars' concerns that "few [organizational identity studies] are explicit in declaring the criteria they employ to measure identity" (Gioia et al., 2013: 177). Our approach paves the path for greater theory testing; the techniques we use may enable researchers to quantitatively examine the antecedents and consequences of organizational identity changes.

Relatedly, research on optimal distinctiveness suggests that organizations navigate the concurrent pressures to conform and differentiate by claiming an identity that is as distinct as legitimately possible (Deephouse, 1999; Navis & Glynn, 2011). Although studies have examined the contextual factors affecting the optimal distinctiveness assertions, most assume either a static

external environment or examine organizations with relatively stable identities or both. Recognizing this Zhao et al. (2017: 99) have suggested that optimal distinctiveness “...research needs to account for the complexity of organizational environments, the processes by which organizations strategically differentiate themselves to enhance performance outcomes, and the mediating mechanism of stakeholder perceptions.” In other words, among other things, research on organizations’ identity needs to simultaneously explore the dynamics of identity temporality and an organization’s position vis-à-vis its peers. We partially address this need by demonstrating that when an organization changes its identity claims, it will incur higher legitimacy penalties if its claims position it farther away from its peers. Our approach also shows that the point of optimal distinctiveness is not the same for all organizations in an industry, but it is determined by an organization’s past and its previous claims. Such path dependency dynamics suggest that while a differentiated position might be within the legitimacy restrictions of an industry for most organizations, it could be outside the boundaries of a focal organization’s audience expectations. This is because such an organization would need to make significant changes to claim such a position.

Further, with the exception of Haans’ (2019) recent work, research on optimal distinctiveness dynamics under varying environmental conditions is nonexistent (Zhao et al., 2017). Haans (2019) argued that the categorical imperative is looser in heterogeneous industries and audiences in such environments are tolerant of higher degrees of differentiation. Recognizing that his study was cross-sectional with the underlying assumption of static identities, Haans (2019: 24) suggested “further work taking a longitudinal empirical approach could [...] investigate within-firm developments in distinctiveness and performance over time—in turn also allowing for a much more fine-grained set of theoretical mechanisms that may be investigated using such an

approach” Our longitudinal study extends Haans’ work by incorporating the role of temporality in firm identities, demonstrating that not only claims of differentiation are better accepted by evaluating audiences in industries where organizational identities are distinct, but also changes in identity claims are more tolerated in such contexts.

Institutional Theory Contributions. Institutional theory suggests that isomorphic processes within an organization’s environment may pressure it to act in a certain manner to garner legitimacy (DiMaggio & Powell, 1983; Meyer & Rowan, 1977). Organizations that defy the so-called ‘categorical imperatives’—the pressure to conform to recognized types and established categories—may incur legitimacy penalties (Litov et al., 2012; Zuckerman, 1999). Our findings suggest that organizations are pressured to conform not only to the established categories but to their own established identities. In other words, an organization’s past may, in a sense, become a schema for audience evaluation and as a result, any deviation may invite a penalty in the form of legitimacy loss. Although the role of categorization and classification in social evaluations has been widely explored (e.g., Zuckerman, 1999, 2016), our findings shed light on the important role played by cognitive inertia and cognitive economy mechanisms in audience judgments and the consequent institutional pressures that influence organizational behavior.

Additionally, our findings provide empirical support for the theoretical assertions that institutional pressures and norms are more restrictive in environmental contexts where organizations make similar identity claims (Bitektine, 2011; Meyer & Rowan, 1977). We found that in environments where organizations make distinctive identity claims (i.e., displaying greater heterogeneity in identity claims) changes in such claims do not result in legitimacy penalties. Our findings suggest that audiences in such environments may have a greater tolerance for uncertainty and ambiguity.

2.5.3 Limitations and Future Research

Our study is subject to several limitations. First, we examined the effects of organizational identity claim changes on a select audience, namely security analysts. This makes our study specific to a high-stakes environment (Bitektine, 2011) and potentially restricts its generalizability. It is possible that the mechanisms highlighted apply differently to other audiences. Future studies could examine how different audiences such as customers, media, and investors choose to expend cognitive resources to assess organizational identity claim changes they confront. Drawing on Pontikes's (2012) study which demonstrates how market-makers compared to market-takers are more open to complex and ambiguous organizational identities, researchers could examine how audiences that are more risk-tolerant confer legitimacy to organizations that undertake substantive identity claim changes. Second, although we tried to account for endogeneity concerns via a fixed-effects model with robust standard errors and controls for numerous organizational- and environmental-level variables, lacking a suitable instrumental variable for identification purposes, we do not claim causation based on our findings. While a fully identified study design is difficult, if not impossible, using archival data, future studies could use experimental methods to examine a causal relationship between identity claim changes and audience evaluations.

Third, we examined only the short-term effects of identity claim changes. Future studies could examine the long-term consequences of such changes and incorporate the antecedents to change as well as how the change process was managed by the organizations. Fourth, we limited our study to organizations with established organizational identities. Future studies could investigate the external consequences of identity claim changes and its impact on legitimacy among younger organizations, especially for those whose identities are evolving and for whom attaining legitimacy is paramount for resource acquisition (Fisher et al., 2016; Rindova & Kotha,

2001). It would be interesting to explore how audiences' cognitive inertia and their perceptions of organizations may reinforce path dependency in organizational identity formation (King, Clemens, & Fry, 2011).

2.5.4 Conclusion

Our study explores the impact of changes to identity claims on an organization's legitimacy. Although past findings suggest a strong relationship between organizational identity and legitimacy, researchers have primarily assumed that an established organization's identity is enduring. We shed light on the cognitive inertia and disinclination of audiences to expend the effort to understand an organization's changing claims and found a negative relationship between the magnitude of change in an organization's identity claims and its legitimacy. We showed that the negative effect of identity claim changes on organizational legitimacy is moderated by the direction of identity claim changes such that an organization incurs higher penalties if it becomes less similar to its peers as a result of such changes. Additionally, we showed that audiences tolerate identity claim changes in industries where identity claims by organizations are more heterogeneous, while such change is met with greater legitimacy penalties in industries where organizations are more homogenous in their respective identity claims.

CHAPTER THREE

3 Optimal Distinctiveness in Dual Benchmark Settings: Effects of Exemplar Similarity and Firm Typicality on Audience Evaluation¹⁰

3.1 Introduction

Firms are multidimensional, dynamic entities; assessing them relative to one another is a challenging task (Semadeni, 2006). A growing body of research has assumed category prototypes—the features that are viewed as average or central in a category (Rosch & Mervis, 1975; Rosch & Lloyd, 1978)—function as baseline benchmarks for audience evaluation (Deephouse, 1999; Durand & Paoletta, 2013; Haans, 2019). Recent research has also highlighted category exemplars—a category’s outstanding, high performing organizations (Nosofsky & Johansen, 2000; Smith & Zarate 1992)—as an alternative benchmark for audience evaluation (Barlow, Verhaal, & Angus, 2019; Zhao, Ishihara, Jennings, & Lounsbury, 2018). Assessing a firm against category prototypes or exemplars eliminates the need for cognitively taxing pairwise comparisons with all the other firms in its category (Glynn & Navis, 2013).

Research on optimal distinctiveness has examined the effects of both a firm’s typicality (its degree of deviation from category prototypes) and exemplar similarity (its degree of similarity to category exemplars) on audience attention and firm legitimacy and performance (Negro, Kocak, & Hsu, 2010; Smith, 2011; Zhao, Fisher, Lounsbury, & Miller, 2017). However, recent research has highlighted the need for studies that examine how the co-existence of both benchmarks—category prototypes and exemplars—influences audience attention and evaluation (Barlow et al.,

¹⁰ Eric Zhao, Tiona Zuzul, and Greg Fisher contributed to this chapter.

2019). We conceptualize contexts where category exemplars diverge from the category prototype as *dual benchmark* settings. Studying how audiences evaluate firms in dual benchmark settings is necessary to understand both how firms are evaluated by audiences, and how firms should position to gain audience attention and a favorable evaluation (Zhao et al., 2017).

In this study, we examine how security analysts' coverage and investment recommendations, as well as a firm's market valuation, are influenced by the firm's exemplar similarity and its typicality. Because analysts are incentivized to cover firms that are familiar and thus easier to analyze (Litov, Moreton, & Zenger, 2012; Zuckerman, 1999), a firm's *association* with an exemplar generates recognizability that likely increases analysts' breadth of coverage. At the same time, exemplar similarity increases the probability that a firm's performance will be *compared* against the performance of the exemplar (Festinger, 1954; Smith, 2011; Smith & Chae, 2017). Comparison with an exceptionally well-performing firm could result in lower evaluations (Audio, Brion, & Greve, 2015; Goodman & Haisley 2007; Meitner, 2006)

We argue that the relative strength of these countervailing mechanisms—*benefits from association* and *costs due to comparison*—varies depending on a firm's typicality. For a typical firm with low to moderate degrees of exemplar similarity, the benefits of association are likely higher than the costs of comparison. A firm in this market position benefits from the attention and legitimacy conferred through some similarity to the exemplar. At the same time, because the firm is similar to many other firms, audiences benchmark its performance against the average performance of all category members. However, at higher degrees of exemplar similarity, audiences likely benchmark a typical firm's performance against that of the exemplar, resulting in comparison costs that outweigh the benefits of association. This implies an inverted U-shaped relationship between the degree of exemplar similarity and a typical firm's market value.

The interplay of these two mechanisms is likely different for *atypical* firms, resulting in a U-shaped relationship. Audiences are less likely to benchmark an atypical firm against the category averages (Smith & Chae, 2017). Even a marginal increase in similarity of an atypical firm to an exemplar can prompt audiences to compare the focal firm's performance against that of the exemplar, resulting in a stronger negative effect caused by the comparison mechanism.

We test these predictions using a sample of 8,943 U.S. public firms from 1997 to 2018. To construct a measure of similarity between firms, we applied Natural Language Processing techniques to the 'Description of Business' section of firms' 10-K reports. We used Term Frequency-Inverse Document Frequency (TF-IDF) and cosine similarity techniques (Salton & Buckley, 1988) to measure a firm's typicality and exemplar similarity. We analyze the effects of exemplar similarity on audience attention to and evaluations of a firm, as well as its effects on a firm's market value. We further examine how these effects vary depending on the firm's typicality. Our findings provide strong and robust evidence supporting our key predictions.

Our study makes several contributions to research on optimal distinctiveness. First, we theorize and examine the dynamics of audience evaluation in dual benchmark settings where firms can be compared to both category exemplars and prototypes. Second, by bringing social comparison theory to the study of optimal distinctiveness, we illuminate association and comparison as two unique and countervailing mechanisms that underpin a firm's evaluation. Our findings also have practical implications for understanding the complexity of audience evaluation and how firms can optimally position in dual benchmark settings.

3.2 Theory and Hypotheses

3.2.1 Prototypes and Exemplars: Two Distinct Models of Audience Evaluation

Audiences evaluate products and actors by categorizing them into comparison sets (Zuckerman, 1999, 2016). A firm's performance is typically evaluated through comparison against the average performance of all category members: that is, against the category prototype (Glynn & Navis, 2013). A prototype is a set of common features that are seen as differentiating members of a category from non-members (Rosch & Mervis, 1975; Rosch & Lloyd, 1978); these common features are equivalent to the aggregated and averaged tendencies of all category members (Reed, 1972). By eliminating cognitively taxing pairwise comparisons (Bowker & Star, 2000; Smith & Medin 1981) between a firm and all other category members, comparison against a prototype eases the process of judgment formation (Durand & Paoletta, 2013).

Recent studies have tested an alternative to the prototype-based model of evaluation: an exemplar-based model. 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 & Johansen, 2000: 375). For example, one might classify a newly met person as Californian, not because she represents the prototypical Californian attributes, but because she looks like a known Californian friend (Medin & Smith, 1981). An exemplar is a member of a category that represents the category's exceptional and salient features (Smith & Zarate, 1992). For instance, Apple is an exemplar in the smartwatch industry because its product is the best-known and highest-performing in the category, while Fitbit is more typical and a better representative of the category's average and central tendencies.

As the smartwatch example illustrates, in many industries exemplars diverge from category prototypes. Although the pressure to conform to a category prototype constrains variation,

categories offer some leeway for firms to differentiate themselves (Anthony, Nelson & Tripsas, 2016; Vergne & Wry, 2014; Wry, Lounsbury, & Glynn, 2011; Zuckerman, 1999). The leeway to deviate is extended for firms that have a record of exceptional performance and are thus given a ‘legitimacy buffer’ (Fisher, Kotha, & Lahiri, 2016; Phillips & Zuckerman, 2001). While the average performance of all category members is the default benchmark for comparison (Zuckerman, 1999), category exemplars also provide a viable point of reference for audiences (Zhao et al., 2018). Table 1 summarizes the key distinctions between the prototype and exemplar models of categorization and evaluation.

In dual benchmark settings, where category prototypes and exemplars diverge, audiences may use either or both as points of comparison in their evaluations (Barsalou, 1985). While research has mostly focused on the impact of firm typicality—the degree of similarity to the category prototype—on audience attention and evaluation, our understanding of whether and how category prototypes and exemplars jointly impact firm evaluations is limited (Barlow et al., 2019). We draw on theories of optimal distinctiveness and social comparison to fill this gap.

3.2.2 Exemplar Similarity and Audience Attention

Category exemplars typically produce a ‘halo effect,’ enhancing the visibility and legitimacy of category members that imitate them (Barlow et al., 2019). This phenomenon is well-established in cognitive psychology (Smith & Zarate, 1992). For example, Gilovich (1981) gave subjects descriptions of fictitious football players and one highly successful real football player. The subjects tended to rate the success potential of fictitious players that shared linkages with the exemplar player higher, even though there was no logical link between those similarities (e.g., coming from the same hometown) and the potential for professional success.

Table 3-1 A summary of prototype and exemplar models

	Prototype Model	Exemplar Model
Cognitive psychology premise	People define categories by a set of common features and attributes and determine membership into a category by assessing an object's attributes against the common features of the category (Rosch & Mervis, 1975).	"People represent categories by storing individual exemplars in memory and classify objects on the basis of their similarity to these stored exemplars" (Nosofsky & Johansen, 2000).
Example (non-organizational)	A fruit is an edible and sweet product of a plant. A pear is a fruit because it is edible and sweet, and it is a product of a tree.	Apples exemplify what a fruit is. A pear is a fruit because it resembles apples.
Example (Organizational)	A media streaming firm is an online platform for streaming movies and shows where audiences can gain access by paying a subscription fee. Hulu is a member of this category because it has these attributes.	Netflix exemplifies the media streaming category. Hulu is a member of this category because it resembles Netflix.
Select studies in management literature	Deephouse (1999) Zuckerman (1999) Navis & Glynn (2011) Haans (2019)	Zhao et al. (2018) Barlow et al. (2019)
Identification of the prototype/exemplar	Central and average tendencies of the category. Features that are most common among all category members. In our study, we average across all firms' business descriptions.	Best performing members of the category. In our study, we used security analysts' coverage and recommendations to identify the exemplars.
Similarity vis-à-vis prototype/exemplar	Measurement: Firm typicality is calculated by comparing a firm's business description with the aggregated and averaged business description of all firms in its industry. Firms whose business description is closer to the averaged business description of all category members are more typical firms. Effect: Firms gain legitimacy by conforming to prototypes since it makes them more familiar.	Measurement: Exemplar similarity is calculated by comparing a firm's business description with the business description of its closest exemplar firm. Effect: Firms gain increased attention and legitimacy by exemplar similarity since it makes them more recognizable and familiar.
Reference group selection using a prototype/exemplar model	The focal firm's performance is compared to the average performance of all firms in the category. Effect: Neutral effect by comparison with averages; depends mostly on the focal firm's performance.	The focal firm's performance is compared to the performance of the exemplar firm. Effect: Negative effect since the exemplar is exceptionally high performing.

Organizational scholars have recently demonstrated the advantages that firms can gain through exemplar similarity. Zhao et al. (2018) studied the console video game industry and found that, during the early stages of a category's emergence and before a category prototype was

established, video games that entered the market with similar features to a recent hit game were more favorably evaluated by critics and achieved higher market performance. Barlow et al. (2019) demonstrated that similarity to the best-performing apps in each category on Google Play platform resulted in a higher number of app downloads for new entrants.¹¹ In both studies, association with a high-performing product generated attention and recognizability.

Exemplar similarity could have a significant impact on security analysts' coverage decisions. Analysts are rewarded for the accuracy of their forecasts (Litov et al., 2012). This induces them to specialize by industry (Zuckerman, 1999, 2000) and to cover only firms that are familiar and recognizable (Bhushan, 1989). Similarity to an exemplar—by definition a well-known member of a category—is likely to increase a firm's familiarity in the eyes of analysts. Following this argument, we expect that similarity to an exemplar increases a firm's recognizability, contributing to a higher analyst coverage. Therefore, we hypothesize:

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

In markets where audiences face significant valuation challenges, intermediaries play an important role in filtering information and providing recommendations (Zhao et al., 2018; Zuckerman, 1999). The importance of information intermediaries is compounded in stock markets because stock prices are in part determined by the markets' consensus as opposed to explicit calculations of the stocks' intrinsic values (Zuckerman, 1999, 2000). Security analysts are the salient intermediaries in stock exchange markets (Chung & Jo, 1996; Jensen, 2004; Litov et al., 2012; Zuckerman, 1999). Through their analysis and reporting and due to their specialized skills,

¹¹ Barlow et al. (2019) went further to suggest that the positive effect of exemplar similarity on performance is compounded when it is combined with distancing from category prototypes. They argue this effect is specific to platform markets where the platforms act as gatekeepers that bestow legitimacy to firms and products, thus reducing the benefits of similarity with a prototype.

security analysts provide value-adding information to investors (Healy & Palepu, 2001); by doing so, they increase market efficiency. Analysts, therefore, play a critical role in determining investment decisions and hence a firm's market value (Litov et al., 2012).

Security analysts' coverage of a firm signals the firm's legitimacy as a member of its category (Jensen, 2004; Zuckerman, 1999). Failure to garner industry specialized analyst coverage signals confusion over a firm's identity and can result in lower demand for the firm's stock (Zuckerman, 1999). Security analysts' coverage could also contribute to a firm's market value by serving as a monitoring device, publicizing and disciplining corporate managers' behaviors (Chung & Jo, 1996). Therefore, analyst coverage increases awareness of a firm among the investment and business community and reduces agency costs caused by a separation between ownership and control (Jensen & Meckling, 1976), both of which contribute to a firm's market value. Accordingly, we hypothesize:

Hypothesis 1b. A firm's market value (proxied by Tobin's Q) is positively related to the breadth of analyst coverage.

3.2.3 Exemplar Similarity and Audience Evaluation

Social evaluation does not occur in isolation but is shaped by comparison to a reference group (e.g., Festinger, 1954; Goodman, 1974; Goodman & Haisley, 2007). The same outcome can be evaluated positively or negatively depending on the reference group (for a review, see Goodman & Haisley, 2007). For example, Chen, Choi, and Chi (2002) showed that Chinese workers viewed their pay as fair when compared to local workers, and unfair when compared to expatriates with higher salaries. At the organizational level, scholars have shown that between-firm comparisons shape evaluations by managers and audiences (e.g., Baum, Rowley, Shipilov, & Chuang, 2005; Hu, He, Blettner, & Bettis, 2017; Smith & Chae, 2017).

When covering a firm, analysts assess the firm's performance and publish recommendations about whether to buy, hold, or sell the stock based on whether it appears under- or over-valued (e.g., Feldman, 2016; Westphal & Clement, 2008). There are two major valuation methods: (1) absolute valuation based on comprehensive net present value calculations using discounted future cash flows; (2) relative market valuation based on a firm's performance metrics relative to a comparison set (e.g., Alford, 1992; Liu, Nissim, & Thomas 2002; for a review, see Meitner, 2006). Security analysts often use the relative valuation method¹² (Bhojraj & Lee, 2002; Meitner, 2006). The first step in conducting the relative market valuation method is choosing a firm or a group of firms to benchmark the focal firm against. The choice of comparison firms thus shapes analysts' recommendations (Bowers, 2015). Such selection in practice is mainly done by comparing the similarity between firms (Meitner, 2006).

Firms with high exemplar similarity are likely to increase their chances of being benchmarked against the category exemplar. Since there are often only a few exemplars in each category, such pairwise comparison would not be cognitively overwhelming for analysts. When compared against an exceptionally well-performing exemplar, the focal firm's value could be discounted. As Meitner (2006: 44) wrote, "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." Based on these arguments, we propose the following:

Hypothesis 2a. There is a negative relationship between exemplar similarity and analyst recommendations.

¹² The relative method is commonly referred to as "the market approach to comparable company valuation." Other alternatives are "market multiple valuation," "guide-line-company valuation," "relative valuation analysis," "direct comparison valuation," and "twin company approach" (Holthausen & Zmijewski, 2012). The firm being valued is usually referred to as the "target" and the firms in the comparison set (peer-group) are referred to as "comparables" or simply "comps."

While an analyst's coverage of a firm signals that the firm has some legitimacy and meets the basic requirements for membership into its primary category (Zuckerman, 1999), the analyst's investment recommendations provide further information about whether a firm's stock is under- or over-valued. Buy or sell investment recommendations have a significant impact on firms' stock prices (Womack, 1996). Womack (1996) documented stock reactions to analyst recommendations in the 1989-1991 period, showing that sell recommendations were followed by a drift of -9.1% in the stock price over six months. Similarly, Barber, Lehavy, McNichols, and Truman (2001) showed that within the 1985-1996 period, a portfolio of most highly recommended stocks yielded an average annual abnormal gross return of 4.13% while a portfolio of least recommended stocks yielded an abnormal return of -4.91%. Hence, we predict:

Hypothesis 2b. A firm's market value (proxied by Tobin's Q) is positively related to analysts' recommendations.

3.2.4 Exemplar Similarity and Firm Market Value: A Curvilinear Relationship

Building on research in optimal distinctiveness, we assume that the two mechanisms—benefits of association and costs of comparison—have an additive effect on a firm's market value (Haans, Pieters, & He, 2016; Zhao et al., 2018). We propose that the relative strength of these mechanisms depends on a firm's typicality. First, a firm's legitimacy stems from similarity to a category prototype (Zuckerman, 1999). Thus, the benefits of association with an exemplar are likely different for a typical firm (that already enjoys a certain level of legitimacy due to its similarity to the prototype) versus an atypical firm (that suffers from a lack of legitimacy and recognizability). Second, audience members' choice of a reference group for firm performance depends on the firm's position within its category (Smith, 2011; Smith & Chae, 2017). A typical firm's performance will likely be compared to the average performance of all category members, while

an atypical firm's performance will be evaluated against other benchmarks including the exemplar. Next, we expand on these ideas to argue that the effect of exemplar similarity on a firm's market value is moderated by the degree of its typicality.

3.2.4.1 The Effects of Exemplar Similarity for Typical Firms

Typical firms, being near the populated centers of the category, are at risk of 'being lost in the crowd' (Barlow et al., 2019). Thus, a typical firm gains some benefit from a low to moderate degree of similarity to the exemplar (Figure 1 depicts a typical firm at low and high degrees of exemplar similarity). By incorporating some exemplar attributes, a typical firm can stand out and benefit from the increased attention (Barlow et al., 2019; Zhao et al., 2018)

At the same time, for a typical firm, the costs of being compared against an exemplar are weak. Audiences' choice of a reference group is influenced by the amount of information about available comparable firms and the perceived similarity among firms (Goodman & Haisley, 2007). Since a typical firm is close to the center of an industry, it is often similar to many other typical firms. Audiences are therefore likely to benchmark the firm's performance against them, instead of a specific exemplar company. This line of reasoning is observed in the context of security analysts' decisions for selecting comparable firms. By default, security analysts benchmark a firm's performance against the median performance of all other firms in its industry (Meitner, 2006). As Alford (1992: 95) wrote, "comparable firms are generally selected on the basis of industry since firms in the same industry are expected to be similar in terms of risk and earnings growth." Based on these arguments, we expect that for a typical firm, at lower degrees of exemplar similarity, the benefits of association outweigh the costs of comparison.

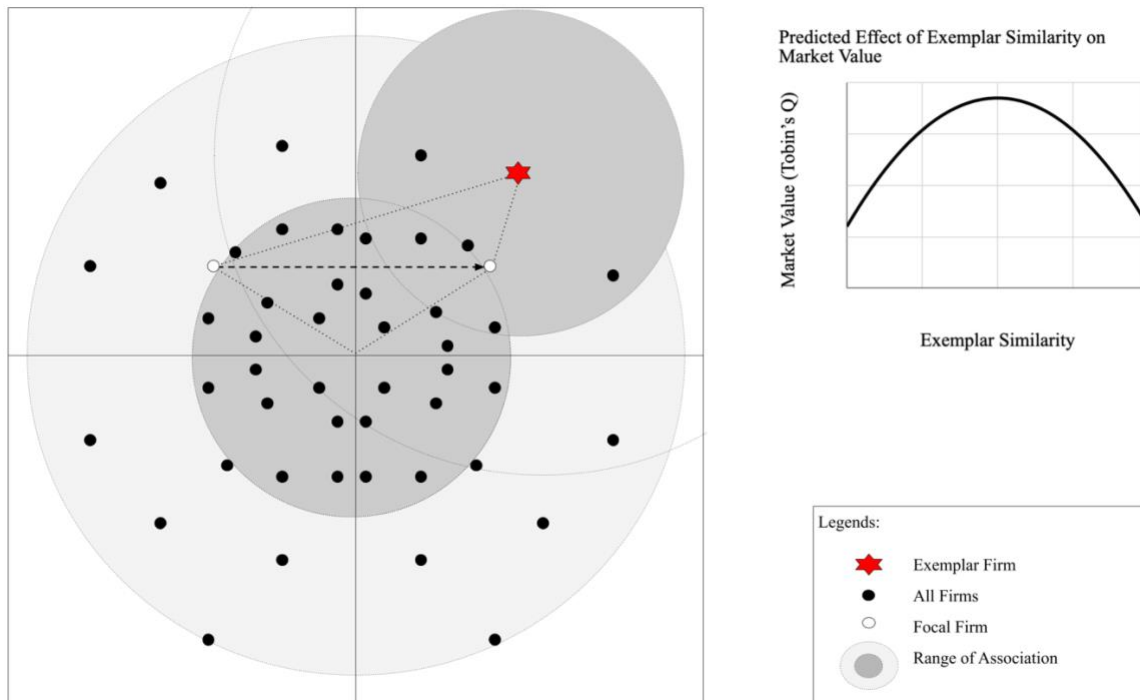


Figure 3-1 The Effects of Similarity to an Exemplar - The Case of a Typical Firm

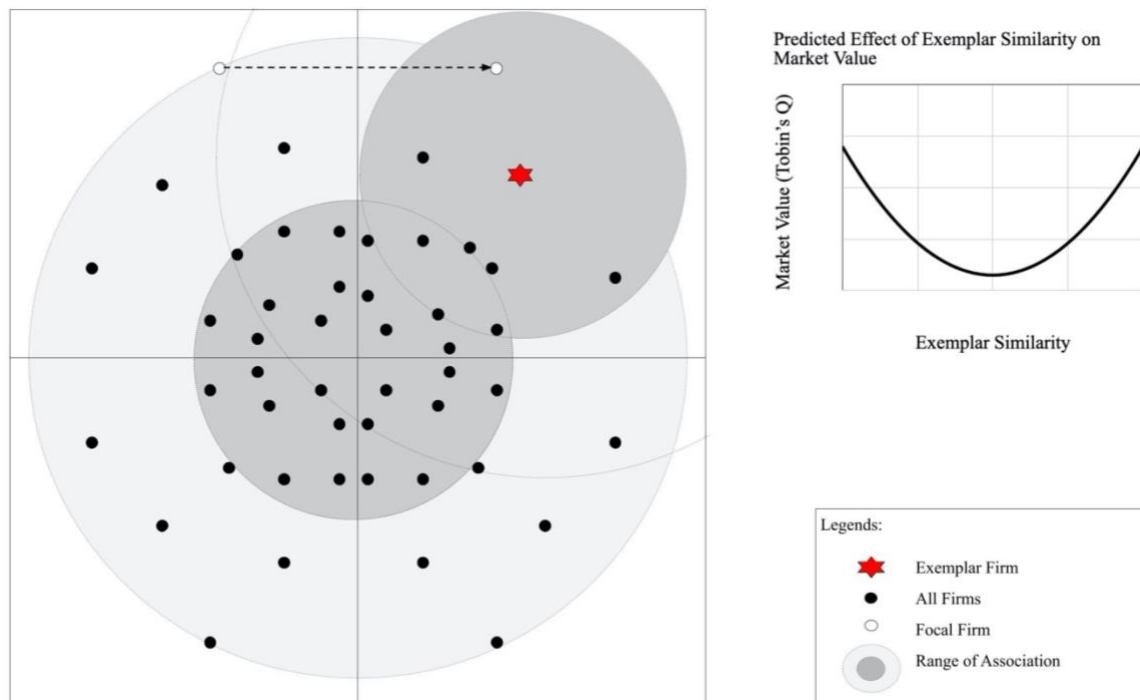


Figure 3-2 The Effects of Similarity to an Exemplar - The Case of an Atypical Firm

However, at higher degrees of exemplar similarity, audiences are more likely to benchmark the firm's performance against the exemplar. Once the firm is more similar to the exemplar than the prototype (as shown in Figure 1), it is more likely to be compared to the exemplar and receive a lower evaluation. In the context of security analysts, once there is a highly similar firm to compare a focal firm against, analysts tend to benchmark the focal firm against that similar firm as opposed to benchmarking it against aggregate and average measures. As Meitner (2006: 69) wrote, "it is even sufficient to apply only one comparable company in case this comparable company perfectly matches with the target company." Therefore, at high degrees of exemplar similarity, the comparison mechanism intensifies, and the negative effects of being compared against an exemplar outweigh the benefits of being associated with it.

Overall, we predict that, while a typical firm benefits from increasing similarity to an exemplar up to a certain point, at higher levels of exemplar similarity the firm would be at a disadvantage. In line with the dominant view in optimal distinctiveness theory, we expect that a typical firm could maximize its benefits by maintaining a middle ground when it comes to the level of similarity vis-à-vis a category exemplar. Accordingly, we propose the following:

Hypothesis 3. For a typical firm, there is an inverted U-shaped relationship between exemplar similarity and the firm's market value.

3.2.4.2 The Effects of Exemplar Similarity for Atypical Firms

Atypical firms—firms that diverge from their category's prototype—are likely to face different outcomes by positioning close to an exemplar (Figure 1 illustrates an atypical firm at low and high degrees of exemplar similarity). For these firms, even at low degrees of exemplar similarity, the comparison mechanism is likely to play a significant role in determining market value. For an

atypical firm, audiences are less likely to choose industry averages as a benchmark in assessing performance. As Smith and Chae (2017: 1136) wrote, “evaluators may perceive that expected, or otherwise conforming reference groups, benchmarks, or indexes are simply less relevant for atypical organizations.” Similarly, Meitner (2006: 41) argued that “companies can only be put into the peer group if they do not deviate too much from the target company.” In such a situation, when audiences cannot use the aggregated performance of an industry’s typical firms as a benchmark, even a marginal increase in similarity to an exemplar can increase the probability of being compared against the exemplar.

In addition, for an atypical firm, a relatively high level of similarity is required to activate the benefits of association. An atypical firm is difficult for audiences to assess and classify, and is prone to being overlooked and discounted (Litov et al., 2012; Zuckerman, 1999). A low degree of similarity to an exemplar is not enough for analysts to overcome their tendency to favor typical and familiar firms. Thus, while the costs of being compared against an exemplar are high, the benefits of association are likely low. Therefore, at lower levels of exemplar similarity, the overall effect of exemplar similarity on an atypical firm’s market value is likely negative.

At higher degrees of exemplar similarity, audiences are likely to choose the exemplar as the reference point. However, the likelihood of being compared against an exemplar does not increase beyond a certain degree of exemplar similarity, and therefore the negative effects of comparison increase at a diminishing rate. At the same time, the benefits of association play a more prominent role if the focal firm is highly similar to an exemplar (inside the range of association with the exemplar as shown in Figure 2). The main reason is that an atypical firm, compared to a typical firm, is in strong need of legitimacy that could be gained through such association. Therefore, for

an atypical firm, the highest market valuation benefits are gained through either high differentiation from or high similarity to an exemplar. Overall, we predict:

Hypothesis 4. For an atypical firm, there is a U-shaped relationship between exemplar similarity and the firm's market value.

3.3 Methods

3.3.1 Data and Sample

We test our theoretical arguments in the context of security analysts' coverage and investment recommendations as well as the stock market's valuation of publicly listed U.S. firms. Our initial sample consists of all firms that have filed 10-K reports with the Securities and Exchange Commission (SEC) between 1997 and 2018.¹³ We collected firms' 10-K reports from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. Firms' financial and accounting data were collected from CRSP/Compustat Merged database, limiting our sample to U.S. firms traded on NYSE, AMEX, or NASDAQ. We collected security analysts' data from IBES Detail History and Recommendations Summary databases. We also used Compustat's Segments database in constructing some of our control variables. After merging all these data sources, our final sample is a panel of 8,943 firms with a total number of 59,412 observations.

3.3.2 Measures

Dependent variables. We have three primary dependent variables in our models: (1) analyst coverage, (2) analyst recommendations, and (3) Tobin's Q. *Analyst coverage* was measured by the proportion of industry specialized analysts that followed a firm (Litov et al., 2012; Zuckerman, 1999). We indicated an analyst as following a firm if that analyst released earnings

¹³ We choose 1997 as the starting point since that is the year when all public firms became required to file 10-K reports electronically.

forecast for the firm's fiscal year-end in a specific year. For firms that had no analysts following them and firms that operated in industries that garnered zero analysts in total, we assumed the coverage to be zero. To measure *analyst recommendations*, we relied on the consensus recommendation data provided by IBES's Recommendations Summary database. IBES standardizes analyst recommendations into five discrete categories ranging from 'strong buy' to 'strong sell,' assigning a number between 1 to 5 to each category. We reverse coded these numerical assignments so that a higher numerical recommendation value corresponded to a more positive investment recommendation; an investment recommendation of 5, therefore, indicated a 'strong buy' recommendation in our coding.

Tobin's Q, i.e., a firm's market value to book value, is one of the preferred ways for measuring a firm's valuation by the stock market (Lindenberg, 1981; Litov et al., 2012).¹⁴ Following the formula suggested by Chen, Harford, and Lin (2015),

$$\text{Tobin's } Q = \frac{(AT - CEQ) + (CSHO * PRCC_F)}{AT}, \quad (1)$$

where *AT* is the size of total booked assets, *CEQ* is the size of common shareholder equity (net of assets and liabilities), *CSHO* is the number of common shares outstanding, and *PRCC_F* is the closing price of stocks in fiscal year-end.

Independent variables. We have two primary independent variables: *exemplar similarity* captures a firm's degree of similarity to exemplars in its industry, and *firm typicality* captures a firm's degree of similarity to the industry prototype. To measure the similarity between firms, we

¹⁴ Tobin's Q ratios are highly affected by the degree of asset intensity of an industry (Meitner, 2006). While firms in industries such as banking and utilities heavily rely on their assets, resulting in high book value of assets and low Tobin's Q ratio, firms in services industries enjoy a high Tobin's Q ratio due to their low book value of assets. Since our analysis is a longitudinal study that controlled for firm fixed effects and our sample consists of large public firms that predominantly operate in the same sector over time, Tobin's Q ratio's sensitivity to industry structure does not bias our results.

used data provided in the ‘Description of Business’ section of their annual 10-K filings. In this section of 10-K filings, firms are required to provide a narrative description of who they are and what they do.¹⁵ These self-descriptions are highly reliable sources for our study. First, since 10-K filings are legally binding documents, they are crafted with care and consistency. Second, research has demonstrated that security analysts pay close attention to these documents in forming their forecasts (Lehavy, Li, & Merkley, 2011). Third, since 10-K filings have had a uniform format over a long period, they are well suited for longitudinal panel studies (Chreim, 2005). Finally, the use of 10-K filings for measuring the similarity between firms has been validated in previous works (Hoberg & Philips, 2010, 2016).

We prepared the business description sections extracted from 10-K filings by conducting preliminary data processing techniques. These included tokenizing the documents (splitting each document into a bag of words), lemmatizing words, and removing stop words (such as ‘is’, ‘that’, and ‘the’). To reduce noise, we dropped terms that were present in more than ninety percent of the document and the terms that had a total frequency of less than 50 in the corpus. Our final sample included 131,409 unique terms. Next, we transformed our corpus into a vector space model, where each row represented one of the documents and each column one of the 131,409 unique terms in our corpus. The weight of each term in each document was determined using the TF-IDF technique. TF-IDF is one of the preferred methods for determining unique and important terms in a document (for a review, see Salton & Buckley, 1988). Accordingly, we used the following formula to measure the weight of each term in each document:

$$\text{TF-IDF}(t, d) = \frac{\text{Freq}(t, d)}{\sum_{t \in d} \text{Freq}(t, d)} * \log\left(\frac{D}{D_t}\right), \quad (2)$$

¹⁵ For a detailed description of the requirement for this section, see *Item 101 of Regulation S-K (229.101)*.

where $\text{Freq}(t, d)$ is the frequency of term t in document d , D is the total number of documents in the corpus, and D_t is the total number of documents containing term t . Using this formula, we determined the relative importance of each term in a document.

We used the vector representation of our documents to construct a measure of similarity. Specifically, we used the cosine similarity method to calculate the similarity between two documents. When fed a pair of word vectors, cosine similarity formula returns the cosine of the angle between the two vectors. Cosine similarity is the most common similarity measure in textual analysis (Salton & Buckley, 1988). The formula for calculating the similarity between a pair of word vectors $\vec{d_1}$ and $\vec{d_2}$ is as follows:

$$\text{Cosine Similarity } (\vec{d_1}, \vec{d_2}) = \frac{\sum_i d_{1t} * d_{2t}}{\sqrt{\sum_i d_{1t}^2} * \sqrt{\sum_i d_{2t}^2}} \quad (3)$$

where d_{1t} and d_{2t} are the weights of term t in corresponding documents d_1 and d_2 .

To measure *exemplar similarity*, we calculated cosine similarity between the vector representations of a focal firm's and its closest exemplar firm's documents. We indicated a firm as an exemplar if it garnered both a large breadth of analyst coverage and positive evaluations. Specifically, we first summed the normalized measures of analyst coverage and analyst recommendations for each firm. We indicated a firm as an exemplar if the resulting number was one standard deviation above all other firms in the firm's primary industry as determined by its 4-digit SIC classification. Following this approach, in 2014, Delta Airlines, Southwest Airlines, and United Airlines were exemplars in 'Air Transportation' (SIC = 4512); Tiffany & Co. was the exemplar in 'Jewelry Stores' (SIC = 5944); and Aetna Inc. the exemplar in 'Hospital and Medical Service Plans' (SIC = 6324).

To measure *firm typicality*, we examined the similarity between the word vector constructed from a firm's document and the industry's word vector. An industry's word vector is constructed using the formula below:

$$\text{Industry TF-IDF}(t, I) = \frac{\sum_{d \in I} \text{TF-IDF}(t, d)}{N_I}, \quad (4)$$

where the weight of term t in industry I is determined by the sum of the weight of term t in all documents in the industry in a specific year, divided by the total number of firms (N_I) in the industry in that year. Once we created the industry's word vector using the above formula, we then calculated the cosine similarity between a focal firm's word vector and the industry's word vector. Firms with a higher similarity with the industry's aggregate word vector were considered more typical. For example, in 2014, in 'Management Consulting Services' industry (SIC = 8742), ICF International, which described itself as a company that "provide[s] management, technology, and policy consulting and implementation services to government and commercial clients," had a typicality measure of 0.640 (about one standard deviation above the mean of typicality). In contrast, Interpace Bioscience, which described itself as a "provider of outsourced commercial services to established and emerging pharmaceutical, biotechnology and healthcare companies in the United States," had a typicality measure of 0.333 (about one standard deviation below the mean of typicality).

Control variables. We controlled for several firm-level and industry-level factors in our analysis. At the firm level, we controlled for firm size, performance, and market share, because these can all affect analyst behavior (Bhushan, 1989; Litov et al., 2012). Following Litov et al. (2012), we controlled for firm size using the log of its annual trading volume and the log of the total number of shareholders. We controlled for firm performance using return on equity (ROE), available slack, and debt ratio. We also controlled for firms' strategic change by examining the

change in resource allocation patterns (Quigley & Hambrick, 2012), as reflected in R&D, advertising intensity, and the size of intangible assets and depreciation as a share of total assets (Barth, Kaznyck, & McNichols, 2001). Because firm diversification could create an extra cognitive burden on analysts, resulting in lowered analyst coverage and market valuations (Zuckerman, 1999, 2000), we controlled for the number of segments that a firm reported sales in. Research has also shown that mergers can result in identity changes (Clark, Gioia, Ketchen & Thomas, 2010) and thus affect analysts' coverage decisions. We thus controlled for the size of M&A activity during the firm's fiscal year using the log of total pretax acquisition/merger expenditure reported in firms' annual reports (item AQP in Compustat).

At the industry level, we controlled for industry dynamism using the industry's R&D intensity measure (e.g., Tatarynowicz, Sytch, & Gulati, 2015). We further controlled for industry munificence measured by industry growth rate (Dess & Beard, 1984), and industry concentration using Herfindahl-Hirschman Index (Rhoades, 1993). These variables affect the stock market's reactions to firm actions (Park & Mezias, 2005). We controlled for the number of firms in the industry because in more populated industries firms would on average garner a lower proportion of industry specialized analysts. Furthermore, we controlled for industry heterogeneity, i.e., the degree to which firms take differentiated positions within the industry, since it affects how audiences respond to a firm's level of differentiation from industry prototype (Haans, 2019). Finally, following previous research (Litov et al., 2012), we winsorized all accounting variables at one percentile in each tail to make sure our results are not driven by outliers.

3.3.3 Empirical Strategy

In our models, we first estimated the effects of exemplar similarity on analyst coverage and analyst recommendations. Next, we examined the relationship between exemplar similarity and Tobin's

Q moderated by firm typicality. Since our dependent variables are all continuous variables, we used OLS regressions with clustered robust standard errors. A benefit of using OLS regressions is that it facilitates the interpretation of moderation effects on quadratic relationships (Haans et al., 2016). We included firm fixed effects in our models to control for unobserved and time-invariant firm-level factors that may bias our results. We also created a one-year lag between our dependent and independent variables to further alleviate reverse causality concerns.

3.4 Results

Tables 2 and 3 present descriptive statistics and bivariate correlations. We conducted a variance inflation factor (VIF) test to check for multicollinearity issues. The results show that the VIF values are well below the problematic threshold of 5-10 (Sheather, 2009), with an average of 1.44 for all variables. We do, however, find a relatively high bivariate correlation between exemplar similarity and firm typicality (correlation=0.70). This correlation demonstrates some similarities between our context and the context of the Google Play app store studied by Barlow et al. (2019), where the correlation between exemplar similarity and prototype similarity was 0.57. To make sure our results are not biased due to such collinearity, in the robustness checks we re-run our models after limiting the sample to reduce the bivariate correlation to below 0.40.

Table 3-2 Descriptive Statistics

	Mean	S.D.	Min	Max	Count
Tobin's Q	0.98	1.69	-0.81	9.70	59294
Analyst coverage	8.21	12.79	0.00	100.00	59412
Analyst recommendations	3.75	0.55	1.00	5.00	33768
Exemplar similarity	0.28	0.20	0.00	1.00	59412
Firm typicality	0.48	0.17	0.01	0.96	59412
Trade volume (log)	17.44	1.97	12.45	21.74	59394
No. of common shareholders (log)	-0.11	2.17	-4.83	5.22	53207
ROE	0.24	1.35	-5.39	4.77	59322
Firm slack	0.06	0.38	0.00	2.79	59412

Debt ratio	0.62	2.21	-8.81	14.36	47097
R&D intensity	0.09	0.18	0.00	0.82	59412
Advertising intensity	0.01	0.03	0.00	0.18	59412
Intangibles/Assets	0.13	0.18	0.00	0.74	59412
Depreciation/Assets	0.04	0.04	0.00	0.19	59412
Number of segments	1.37	0.77	1.00	5.00	59412
M&A expense (log)	-1.33	7.04	-56.52	3.62	59412
Market share	0.03	0.08	0.00	1.00	59362
Industry dynamism	0.03	0.02	0.00	0.13	53685
Industry munificence	0.03	0.08	-0.21	0.29	53685
Industry concentration (HHI)	1041.25	1272.47	14.04	6763.30	53685
No. firms in industry	93.29	102.63	3.00	403.00	59412
Industry heterogeneity	0.07	0.03	0.00	0.14	59412

Table 3-3 Bivariate Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
(1) Tobin's Q	1.00																					
(2) Analyst coverage	0.01	1.00																				
(3) Analyst recommendations	0.19	-0.13	1.00																			
(4) Exemplar similarity	-0.12	-0.01	-0.06	1.00																		
(5) Firm typicality	-0.14	0.19	-0.06	0.70	1.00																	
(6) Trade volume (log)	0.18	0.41	-0.11	-0.06	-0.09	1.00																
(7) No. of common shareholders (log)	-0.06	0.21	-0.15	-0.06	-0.04	0.26	1.00															
(8) ROE	0.05	0.30	-0.01	0.00	0.02	0.18	0.25	1.00														
(9) Firm slack	-0.06	0.09	-0.08	-0.09	-0.04	0.03	0.19	0.13	1.00													
(10) Debt ratio	-0.10	0.04	-0.04	0.04	0.04	0.03	0.02	0.02	0.01	1.00												
(11) R&D intensity	0.32	-0.17	0.17	-0.01	-0.11	0.13	-0.16	-0.25	-0.08	-0.11	1.00											
(12) Advertising intensity	0.07	0.03	-0.04	0.02	0.01	0.06	-0.01	0.01	-0.06	-0.01	-0.08	1.00										
(13) Intangibles/Assets	-0.02	0.13	0.06	-0.18	-0.10	0.19	-0.01	0.02	-0.08	0.04	-0.04	0.11	1.00									
(14) Depreciation/Assets	0.01	0.02	0.00	-0.18	-0.09	0.10	0.00	-0.21	-0.02	-0.03	0.00	0.03	0.14	1.00								
(15) Number of segments	-0.08	0.15	-0.02	-0.18	-0.06	0.08	0.16	0.12	0.17	0.03	-0.15	-0.04	0.12	0.06	1.00							
(16) M&A expense (log)	0.02	-0.14	-0.01	-0.02	-0.01	-0.21	-0.11	-0.11	-0.01	-0.06	0.02	-0.02	-0.22	0.01	-0.05	1.00						
(17) Market share	-0.02	0.52	-0.07	-0.11	0.08	0.31	0.25	0.25	0.01	0.05	-0.14	0.03	0.18	0.02	0.24	-0.16	1.00					
(18) Industry dynamism	-0.10	0.06	-0.05	0.06	0.12	-0.09	0.03	0.01	0.01	0.01	-0.14	-0.09	-0.11	-0.08	0.04	0.03	0.03	1.00				
(19) Industry munificence	0.14	-0.04	0.14	-0.13	-0.15	0.04	-0.02	0.01	-0.02	0.00	0.17	-0.03	0.00	0.02	-0.01	0.04	-0.02	-0.10	1.00			
(20) Industry concentration (HHI)	0.04	0.12	0.05	-0.27	-0.06	0.01	-0.05	-0.02	-0.01	-0.04	-0.01	-0.02	0.12	0.07	0.07	0.01	0.14	0.04	0.00	1.00		
(21) No. firms in industry	0.03	-0.33	-0.02	0.39	0.02	-0.10	-0.06	-0.09	-0.10	-0.02	0.22	0.04	-0.18	-0.21	-0.24	0.02	-0.28	-0.11	0.09	-0.37	1.00	
(22) Industry heterogeneity	0.09	-0.30	0.04	-0.12	-0.34	-0.02	-0.05	-0.08	-0.15	0.03	0.19	0.03	0.04	-0.11	-0.12	0.03	-0.15	-0.11	0.10	-0.12	0.27	1.00

Table 3-4 Models Estimating Analyst Coverage, Recommendations, and Tobin's Q

Model	Dependent variable:					
	Analyst coverage t	Analyst coverage t	Tobin's Q $_{t+1}$	Analyst Recoms. t	Analyst Recoms. t	Tobin's Q $_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
Exemplar similarity $t-1$		3.883*** (0.607)			-0.148*** (0.039)	
Analyst coverage t			0.002** (0.001)			
Analyst recommendations t						0.199*** (0.022)
Trade volume (log)	1.386*** (0.079)	1.080*** (0.071)	-0.078*** (0.011)	-0.051*** (0.006)	-0.032*** (0.008)	-0.067*** (0.016)
No. of common shareholders (log)	-0.219** (0.096)	-0.165** (0.082)	-0.012 (0.011)	0.003 (0.005)	0.006 (0.006)	-0.016 (0.016)
ROE	0.263*** (0.056)	0.251*** (0.051)	0.042*** (0.006)	0.045*** (0.003)	0.044*** (0.003)	0.027*** (0.007)
Firm slack	-2.050 (3.596)	1.301 (4.471)	0.110 (0.067)	-0.045 (0.127)	-0.202 (0.169)	0.154 (0.094)
Debt ratio	-0.025 (0.031)	0.022 (0.022)	-0.012*** (0.003)	-0.005*** (0.002)	-0.005*** (0.002)	-0.011** (0.004)
R&D intensity	0.578 (0.494)	0.294 (0.484)	0.054 (0.287)	0.034 (0.085)	0.018 (0.092)	-0.477 (0.486)
Advertising intensity	9.103* (4.736)	9.411** (4.561)	-1.037 (0.807)	-0.120 (0.378)	-0.400 (0.42)	-1.042 (1.231)
Intangibles/Assets	4.162*** (0.656)	3.188*** (0.564)	-1.333*** (0.098)	-0.051 (0.045)	0.007 (0.049)	-1.410*** (0.129)
Depreciation/Assets	-4.135* (2.200)	-5.532*** (1.854)	1.558** (0.606)	-2.342*** (0.258)	-2.201*** (0.277)	0.496 (0.788)
Number of segments	-0.321 (0.196)	-0.299 (0.193)	-0.048*** (0.014)	0.024*** (0.009)	0.036*** (0.011)	-0.060*** (0.020)
M&A Expense (log)	-0.041*** (0.013)	-0.045*** (0.013)	0.001 (0.001)	-0.002*** (0.000)	-0.002*** (0.000)	0.001* (0.001)
Market share	39.984*** (3.417)	30.061*** (3.801)	-0.173 (0.126)	0.062 (0.072)	0.002 (0.111)	-0.221 (0.166)
Industry dynamism	8.525** (4.299)	4.052 (3.622)	0.522 (0.418)	1.244** (0.227)	1.494*** (0.265)	1.090** (0.477)
Industry munificence	-3.924*** (1.031)	-3.181*** (0.899)	0.349*** (0.104)	0.492*** (0.062)	0.508*** (0.071)	0.068 (0.124)
Industry concentration (HHI)	0.001*** (0.000)	0.001*** (0.000)	-0.000 (0.000)	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)
No. firms in industry	-0.014*** (0.002)	-0.014*** (0.002)	-0.001** (0.001)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)
Industry heterogeneity	-47.907***	-33.964***	0.218	-0.102	-0.12	-1.463**

	(6.453)	(5.599)	(0.564)	(0.329)	(0.406)	(0.654)	
Intercept	-12.288***	-9.574***	2.644***	4.700***	4.353***	2.003***	
	(1.458)	(1.332)	(0.206)	(0.116)	(0.143)	(0.314)	
Observations	52793	40354	46054	29990	23499	27357	
R2 (FE included)	0.843	0.860	0.637	0.510	0.533	0.669	
Residual Std. Error	6.740(df = 45836)	4.984(df = 34202)	0.995(df = 39932)	0.378(df = 24796)	0.366(df = 18917)	0.892(df = 22699)	=
F Statistic	14.964***(df = 6956; 45836)	16.035***(df = 6151; 34202)	9.595***(df = 6121; 39932)	4.348***(df = 5193; 24796)	4.163***(df = 4581; 18917)	7.704***(df = 4657; 22699)	=

Note: *p<0.1; **p<0.05; ***p<0.01. All controls at time t . All accounting variables winsorized at one percentile in each tail.

Table 3-5 Main and Robustness Analysis of the Effects of Exemplar Similarity on Tobin's Q, Moderated by Firm Typicality

Model	<i>Dependent variable:</i>					
	Tobin's Q _t	Tobin's Q _t	Tobin's Q _t	Tobin's Q _t	Tobin's Q _t	Tobin's Q _t
	(7)	(8)	(9)	(10)	(11)	(12)
Exemplar similarity _{t-1}	-2.878*** (0.642)	-3.415*** (0.778)	-5.592*** (1.278)	-3.919*** (0.82)	-7.740*** (1.605)	-2.836*** (0.525)
Exemplar Similarity Squared _{t-1}	2.896*** (0.801)	4.065*** (1.014)	7.673*** (1.987)	4.410*** (1.29)	14.530*** (3.998)	2.670*** (0.649)
Firm Typicality _{t-1}	-0.858*** (0.226)	-0.782*** (0.276)	-0.971** (0.421)	-0.822*** (0.220)	-0.595 (0.375)	-0.819*** (0.195)
Exemplar similarity _{t-1} * Typicality _{t-1}	4.441*** (1.204)	3.559** (1.499)	5.872** (2.64)	6.011*** (1.423)	8.293*** (2.707)	4.147*** (1.030)
Exemplar Similarity Squared _{t-1} * Typicality _{t-1}	-4.600*** (1.440)	-4.164** (1.833)	-7.798** (3.897)	-7.106*** (2.056)	-16.892*** (5.798)	-4.124*** (1.227)
Trade volume (log)	0.154*** (0.013)	0.164*** (0.016)	0.167*** (0.021)	0.153*** (0.013)	0.168*** (0.020)	0.147*** (0.012)
No. of common shareholders (log)	-0.019 (0.014)	-0.022 (0.018)	-0.006 (0.023)	-0.019 (0.014)	-0.009 (0.020)	-0.015 (0.013)
ROE	0.142*** (0.007)	0.164*** (0.010)	0.170*** (0.015)	0.141*** (0.007)	0.161*** (0.013)	0.143*** (0.006)
Firm slack	0.078 (0.131)	0.039 (0.170)	-0.059 (0.211)	0.084 (0.133)	0.281 (0.316)	0.100 (0.115)
Debt ratio	-0.015*** (0.003)	-0.014*** (0.005)	-0.013* (0.007)	-0.015*** (0.003)	-0.018*** (0.006)	-0.014*** (0.003)
R&D intensity	-0.235 (0.279)	-0.165 (0.302)	-0.433 (0.34)	-0.237 (0.279)	-0.364 (0.319)	-0.168 (0.272)
Advertising intensity	-0.490 (0.992)	-0.052 (1.101)	0.576 (1.471)	-0.481 (0.991)	0.575 (1.375)	-0.558 (0.897)
Intangibles/Assets	-1.803*** (0.109)	-2.013*** (0.131)	-2.047*** (0.174)	-1.805*** (0.109)	-2.047*** (0.164)	-1.806*** (0.106)
Depreciation/Assets	-4.048*** (0.599)	-3.299*** (0.698)	-3.628*** (0.836)	-4.048*** (0.598)	-3.608*** (0.792)	-4.280*** (0.558)
Number of segments	-0.033* (0.017)	-0.015 (0.024)	-0.015 (0.038)	-0.032* (0.017)	-0.038 (0.034)	-0.041*** (0.015)
M&A Expense (log)	0.002*** (0.001)	0.002** (0.001)	0.004** (0.002)	0.002*** (0.001)	0.002 (0.001)	0.002*** (0.001)
Market share	-0.433* (0.231)	-0.580* (0.321)	-0.775 (0.594)	-0.430* (0.230)	-2.093** (0.826)	-0.549** (0.249)
Industry dynamism	0.630 (0.483)	1.882*** (0.686)	1.935* (1.082)	0.648 (0.483)	1.490 (1.064)	-0.291 (0.471)
Industry munificence	1.177***	1.776***	2.300***	1.181***	2.072***	1.017***

	(0.135)	(0.196)	(0.315)	(0.135)	(0.310)	(0.134)	
Industry concentration (HHI)	-0.000	-0.000	-0.000**	-0.000	-0.000	-0.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
No. firms in industry	0.000	0.000	-0.000	0.000	-0.000	0.001***	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	
Industry heterogeneity	-0.205	-1.475	-3.043*	-0.321	-4.926***	-1.042*	
	(0.699)	(0.998)	(1.671)	(0.702)	(1.777)	(0.626)	
Intercept	-0.742***	-0.724**	-0.228	-0.727***	-0.203	-0.584**	
	(0.271)	(0.335)	(0.460)	(0.271)	(0.445)	(0.238)	
Observations	40331	27668	17568	40331	19820	46401	
R2 (FE included)	0.618	0.612	0.628	0.618	0.617	0.643	
Residual Std. Error	1.036(df = 34178)	1.120(df = 21982)	1.189(df = 13145)	1.036(df = 34178)	1.180(df = 15935)	1.016(df = 39711)	=
F Statistic	6.836***(df = 6152; 34178)	4.454***(df = 5685; 21982)	3.468***(df = 4422; 13145)	6.871***(df = 6152; 34178)	4.613***(df = 3884; 15935)	8.117***(df = 6689; 39711)	=

Note: *p<0.1; **p<0.05; ***p<0.01. All controls at time *t*. All accounting variables winsorized at one percentile in each tail.

Table 3-6 Robustness Checks (continued)

	<i>Dependent variable:</i>			
	Tobin's Q _t (13)	Tobin's Q _{t+1} (14)	Tobin's Q _t (15)	Tobin's Q _t (16)
Exemplar similarity _{t-1}	-3.083*** (0.839)	-1.975*** (0.670)	-2.920*** (0.696)	-3.201*** (0.699)
Exemplar Similarity Squared _{t-1}	3.116*** (1.026)	2.220*** (0.830)	3.039*** (0.921)	3.459*** (0.891)
Firm Typicality _{t-1}	-1.241*** (0.298)	-0.596** (0.244)	-0.852*** (0.233)	-0.963*** (0.253)
Exemplar similarity _{t-1} * Typicality _{t-1}	5.234*** (1.773)	4.168*** (1.311)	4.432*** (1.314)	4.955*** (1.290)
Exemplar Similarity Squared _{t-1} * Typicality _{t-1}	-5.356** (2.133)	-4.663*** (1.594)	-4.712*** (1.653)	-5.467*** (1.569)
Trade Volume (log)	0.159*** (0.016)	-0.060*** (0.013)	0.154*** (0.013)	0.154*** (0.013)
Number of Common Shareholders	-0.039** (0.018)	-0.010 (0.014)	-0.019 (0.014)	-0.019 (0.014)
ROE	0.173*** (0.01)	0.037*** (0.006)	0.142*** (0.007)	0.143*** (0.007)
Firm Slack	0.485*** (0.133)	0.125 (0.101)	0.079 (0.131)	0.057 (0.128)
Debt ratio	-0.020*** (0.005)	-0.017*** (0.004)	-0.015*** (0.003)	-0.014*** (0.003)
R&D intensity	-0.255 (0.384)	-0.061 (0.300)	-0.235 (0.279)	-0.240 (0.280)
Advertising intensity	-0.705 (1.312)	-0.763 (1.044)	-0.495 (0.992)	-0.471 (1.004)
Intangibles/Assets	-1.852*** (0.144)	-1.312*** (0.107)	-1.803*** (0.109)	-1.813*** (0.109)
Depreciation/Assets	-5.022*** (0.781)	1.731*** (0.654)	-4.050*** (0.599)	-4.021*** (0.603)
Number of segments	-0.027 (0.025)	-0.047*** (0.017)	-0.033* (0.017)	-0.035** (0.017)
Mergers (expenditure)	0.001 (0.001)	0.001 (0.001)	0.002*** (0.001)	0.002*** (0.001)
Market share	-0.988** (0.444)	-0.448** (0.187)	-0.433* (0.231)	-0.409* (0.235)
Industry dynamism	0.510 (0.738)	0.383 (0.489)	0.630 (0.483)	0.650 (0.489)
Industry munificence	1.035*** (0.191)	0.253** (0.124)	1.176*** (0.135)	1.189*** (0.137)
Industry concentration (HHI)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)

No. firms in industry	0.001*	-0.001*	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Industry heterogeneity	-2.280**	-0.413	-0.209	-0.341
	(1.078)	(0.712)	(0.700)	(0.717)
Intercept	-0.550	2.652***	-0.738***	-0.677**
	(0.335)	(0.270)	(0.272)	(0.282)
Observations	20666	34949	40331	39789
R2 (FE included)	0.650	0.628	0.618	0.617
Residual Std. Error	0.978(df = 16483)	0.977(df = 29561)	1.036(df = 34178)	1.039(df = 33670)
F Statistic	5.752***(df = 4182; 16483)	7.399***(df = 5387; 29561)	6.834***(df = 6152; 34178)	6.707***(df = 6118; 33670)

Note: *p<0.1; **p<0.05; ***p<0.01. All controls at time t . All accounting variables winsorized at one percentile in each tail.

Table 4 reports the results for testing Hypotheses 1a-2b. Model 1 includes control variables only. As shown, trade volume (log), ROE, advertising intensity, intangibles/assets, and market share variables positively relate to analyst coverage. In contrast, number of common shareholders (log), depreciation/assets, and M&A expense (log) are negatively related to analyst coverage. At the industry level, industry dynamism and industry concentration (HHI) positively relate to analyst coverage, while industry munificence, the number of firms in the industry, and industry heterogeneity are negatively associated with analyst coverage.

Hypothesis 1a predicted a positive relationship between exemplar similarity and analyst coverage. The coefficient for exemplar similarity in Model 2 is positive and significant ($\beta = 3.883$, $p < 0.01$), providing support for Hypothesis 1a. The results suggest that one standard deviation increase in exemplar similarity results in a 9.5% increase in a firm's analyst coverage¹⁶. Model 3 tests the relationship between analyst coverage and Tobin's Q. The coefficient for analyst coverage on Tobin's Q_{t+1} is positive and statistically significant ($\beta = 0.002$, $p < 0.05$), providing support for

¹⁶ In other words, a firm gains 0.77% industry specialized analyst coverage. Since firms on average receive 8.2% industry specialized analyst coverage, the 0.77% would translate into a 9.5% increase in coverage for an average firm.

Hypothesis 1b. The results suggest that a one standard deviation increase in analyst coverage leads to a 2.5% increase in the market value of a firm.

Model 4 shows the effects of our control variables on analyst recommendations. ROE, number of segments, and industry dynamism and industry munificence positively relate to analyst recommendations. In comparison, there is a negative relationship between trade volume (log), debt ratio, depreciation/asset, M&A expense (log), and industry concentration, and the analyst recommendation garnered by firms.

Hypothesis 2a posited a negative relationship between exemplar similarity and analyst recommendations. In Model 5, the coefficient for exemplar similarity is negative ($\beta = -0.148$) and significant ($p < 0.01$), supporting Hypothesis 2a. The results suggest that the negative effect of a one standard deviation increase in exemplar similarity on analyst recommendation equals the negative effect of a sharp decline in firm performance (a half standard deviation decline in ROE). Hypothesis 2b predicted a positive relationship between analyst recommendations and Tobin's Q. In Model 6, the coefficient for analyst recommendation on Tobin's Q is positive and statistically significant ($\beta = 0.199$, $p < 0.01$), offering support for Hypothesis 2b.

Hypotheses 3 and 4 predicted the effect of exemplar similarity on Tobin's Q moderated by firm typicality. Specifically, Hypothesis 3 posited an inverted U-shaped relationship between exemplar similarity and Tobin's Q for typical firms, while Hypothesis 4 posited a U-shaped relationship between the same variables for atypical firms. To test these hypotheses, in Model 7 of Table 5, we included exemplar similarity and its squared term, as well as the interaction between these two and firm typicality, while controlling for other covariates. As shown, the coefficients for exemplar similarity and exemplar similarity squared are -2.878 and 2.896, and they are statistically significant ($p < 0.01$). Also, the coefficients for the interaction terms between exemplar similarity,

its squared term, and firm typicality are significant at $p < 0.01$ level ($\beta = 4.441$ and $\beta = -4.600$, respectively). Since the coefficient of exemplar similarity squared and that of its interaction with firm typicality are both significant and in opposite directions, we observe a curve flattening/flipping moderation effect (Haans et al., 2016). Specifically, the curve flipping occurs at a typicality degree of 0.63, which is well within the observed range of the firm typicality variable (less than one standard deviation above the mean).

To facilitate the interpretation of the results, we illustrated the predicted outcomes of exemplar similarity for typical (one and two standard deviations above the mean of firm typicality) and atypical firms (one and two standard deviations below the mean of firm typicality) in Figure 3. As shown in the graph, while there is an inverted U-shaped relationship between exemplar similarity and Tobin's Q for typical firms, the relationship is U-shaped for atypical firms. These results suggest that a typical firm enjoys the highest benefits in terms of market valuation by taking a middle ground when it comes to positioning vis-à-vis category exemplars (at the curve's turning point of 0.45). From that point, by moving a standard deviation closer to or farther from the exemplar, the typical firm could lose 5% of its market valuation. The effects are stronger for atypical firms. A highly atypical firm (two standard deviations below the mean in terms of prototype similarity) received the lowest market valuation by pursuing moderate differentiation from the exemplar (at the curve's turning point of 0.5). From that point, the atypical firm would generate a 9% increase in its market value if it moves a standard deviation closer to or farther from the exemplar.

3.4.1 Robustness of Main Results

We conducted multiple robustness checks to further verify the validity of the main findings in Model 7. The results of these robustness analyses are presented in Tables 5 and 6.

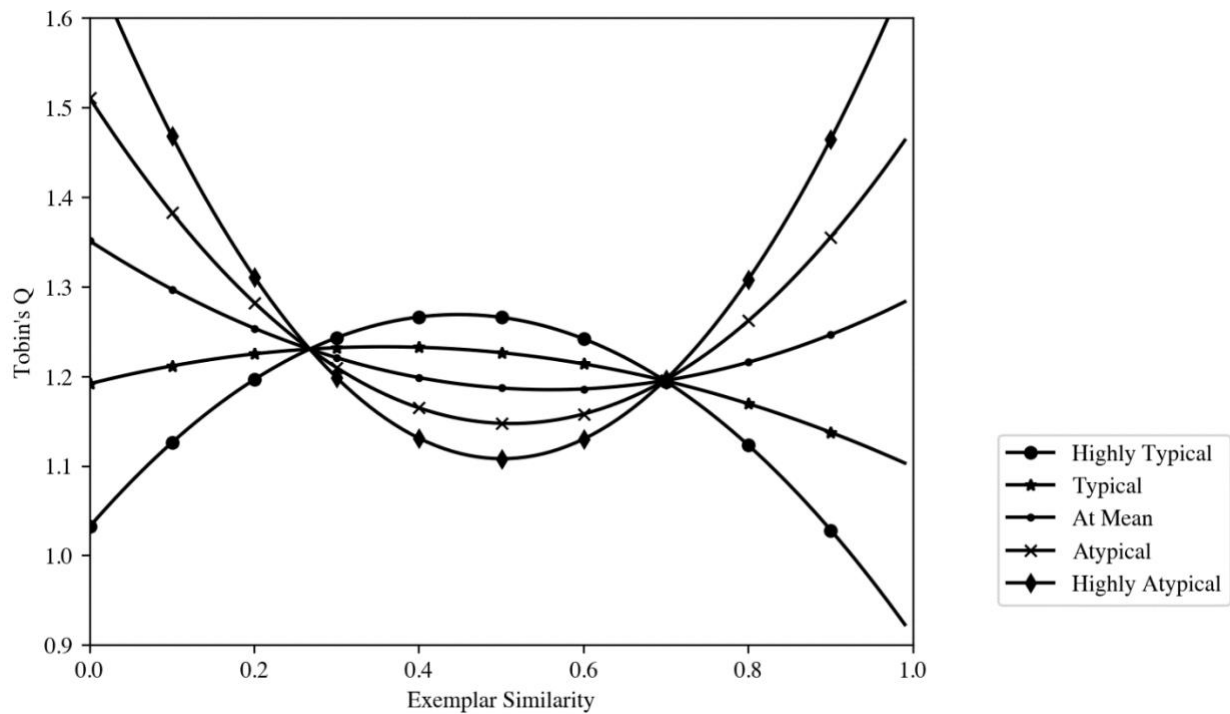


Figure 3-3 Effects of Exemplar Similarity on Tobin's Q for Typical versus Atypical Firms

First, we tried alternative ways for identifying the exemplar and measuring exemplar similarity. In our main models, we identified exemplars based on analyst coverage and analyst recommendations. We indicated a firm as an exemplar if its combined normalized measure of coverage and recommendations was one standard deviation above the mean of the industry in a specific year. In Model 8, we indicated a firm as an exemplar if the amount of analyst coverage it received was one standard deviation above the industry average and if the consensus recommendation for it was 4 or above ('buy' or 'strong buy'). In Model 9, we used a similar approach as in Model 8 but used a two standard deviation cutoff point instead. The results remain robust regardless of the particular approach for identifying exemplars. In Model 10, instead of measuring exemplar similarity by examining the distance between a firm and its closest exemplar, we measured it by averaging a firm's similarity with all exemplars in its primary industry. In Model

11, we followed a similar approach as in Model 10 but used two-standard deviation as threshold instead. The results remain consistent. In Model 12, we checked the consistency of our results by changing the industry classification from 4-digit SIC codes to 3-digit SIC codes. The results remain qualitatively unchanged.

Second, as mentioned earlier, there might be a concern regarding the high correlation between exemplar similarity and firm typicality. To alleviate this concern, we removed observations in industry-years where the correlation between exemplar similarity and firm typicality is extremely high (above 0.8). The correlation between the two variables in the remaining sample is below 0.4, which could be regarded as unproblematic, given that the VIF test also reveals a score of well below 5 for our main variables. In Model 13 of Table 6, we run our models using this limited sample. The results remain robust.

In Model 14, we changed the lag period between our main independent variable, exemplar similarity, and dependent variable, Tobin's Q, to two years. The results remain consistent, although the effect size gets smaller when using the longer lag period. In Model 15, we winsorized the exemplar similarity measure at one percentile in each tail to make sure our results are not driven by outliers, and again generated consistent results. Finally, In Model 16, we limited our sample to firms that had a business description section longer than 500 words to reduce noise in our data. The results remain qualitatively unchanged. Taken together, these robustness checks significantly enhanced our confidence in the main findings.

3.5 Discussion, Contributions, and Limitations

Research on optimal distinctiveness has explored the performance consequences of a firm's similarity to either category prototypes (Deepphouse, 1999; Haans, 2019; Navis & Glynn, 2011) or category exemplars (Barlow et al., 2019; Zhao et al., 2017; Zhao et al., 2018). One important

underexplored topic in this area is how audiences evaluate an organization in dual benchmark settings when both prototypes and exemplars serve as relevant, yet distinct, reference points. In this paper, we addressed this gap by examining how exemplar similarity affects analysts' coverage, investment recommendations, and the market's valuation of firms with different degrees of typicality. We began with a baseline hypothesis in line with research showing that firms can garner audience attention and legitimacy by positioning near a well-known exemplar firm. We predicted an increase in analyst coverage as a result of exemplar similarity. Next, drawing upon social comparison theory (Goodman & Haisley, 2007; Smith & Chae, 2017), we argued that similarity to an exemplar firm could increase a firm's chances of being compared against an exceptionally well-performing firm, resulting in a relatively lower evaluation of the focal firm's performance. We predicted that such a discount would manifest as lower investment recommendations by analysts following the firm.

These contrasting mechanisms prompted an examination of the overall effect of exemplar similarity on the stock market's valuation of a firm. We theorized a 'curve-flipping' moderation effect of firm typicality on the relationship between exemplar similarity and a firm's market value. We predicted that, for a typical firm, the relationship is an inverted U-shape. Based on our assertions, to maximize market valuations, a typical firm should position neither too close nor too far from an exemplar. In the case of atypical firms, however, we posited that the relationship is U-shaped. Atypical firms are thus better off either highly conforming to or differentiating from exemplars. We provided robust evidence in support of our theoretical arguments by conducting a longitudinal study of U.S. public firms from 1997 to 2018.

3.5.1 Contributions

Contributions to optimal distinctiveness research. This study makes four contributions to optimal distinctiveness research. First, most studies to date have either explicitly or implicitly assumed there is a single benchmark against which an organization's optimal distinctiveness is gauged. Such benchmarks can be either externally derived based on category prototypes or exemplars (Zhao et al., 2018) or substitutes (McDonald & Eisenhardt, 2020), or internally driven by founder identity or aspirations (Grimes, 2018; Zuzul & Tripsas, 2020). Regardless of the origin of the benchmarks, most studies have focused on examining how conforming to or differentiating from one particular type of benchmark shapes organizational actions and performance outcomes. This approach, while conceptually and empirically parsimonious, defies the reality where multiple benchmarks may co-exist and simultaneously serve as important reference points as audiences evaluate an organization's optimal distinctiveness. To address this, we introduced the notion of dual benchmark settings, and revealed some intricate relationships between firm positioning and performance when category prototype and exemplar are both considered relevant, yet distinct, benchmarks in audience evaluation.

Second, in theorizing and modeling the joint effects of exemplar similarity and firm typicality on audience evaluation and firm performance, we pinpoint association and comparison as two important, yet underexplored, mechanisms. Optimal distinctiveness research has mainly focused on studying the effects of firm positioning on performance outcomes such as sales revenue (Haans, 2019) through legitimacy and competition mechanisms (e.g., Barlow et al., 2019; Deephouse, 1999; Zhao et al., 2018). While highly informative, such investigation prevents a more fine-grained theorization about the underlying socio-cognitive mechanisms affecting audiences' attention and evaluations. Drawing on social comparison research (Audio, Brion & Greve, 2015;

Goodman & Haisley, 2007; Smith & Chae, 2017), we provide a set of theoretical arguments to explain the potential negative consequences of similarity with category's highest performing members due to comparison mechanism. By examining the effects of exemplar similarity on analysts' investment recommendations through the comparison mechanism, we address the call for more research on the mediating role of audiences such as critics and analysts (Zhao et al., 2018).

Third, our findings extend research on optimal distinctiveness by focusing on publicly-traded firms. Previously, Zhao et al. (2018) explored the effects of exemplar similarity in the context of video games and Barlow et al. (2019) examined such dynamics in the context of mobile applications. While these studies significantly advanced our understanding of the role of a category exemplar as an important benchmark for gauging optimal distinctiveness, both focused on the product level (as opposed to the firm level) in entrepreneurial settings. Our study extends this research by examining the effects of exemplar similarity on a large sample of firms in a mature setting. Our findings bolster 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" by showing that their effects persist even in established industries. Furthermore, by introducing a new natural language processing method to this stream of research, our study opens new avenues for future large-scale quantitative studies using significant amounts of textual data produced by firms (Haans, 2019; Hannigan et al., 2019).

Fourth, our study complements previous research that explores the boundary conditions for the commonly theorized inverted U-shaped relationship in optimal distinctiveness literature. Previous research has provided evidence showing that the shape of the curve is affected by category heterogeneity (Haans, 2019) and market evolution (Zhao et al., 2018). Our study proposes

a new curve-flipping moderator for the relationship between exemplar similarity and market valuations of firms. Specifically, we introduce firm typicality as a moderator in the curvilinear relationship between exemplar similarity and firms' market value.

Contributions to social comparison theory. We make two contributions to research on social comparison and performance evaluations. First, we extend previous research that typically assumes category averages as the primary external reference point (e.g., Audia & Greve, 2006; Kacperczyk, Beckman, & Moliterno, 2015; Miller & Chen, 2004). Our study extends previous work by showing that category exemplars can also serve as key reference points. By doing this, we address the suggestion by Blettner, He, Hu, and Bettis (2015: 1003) that “a rich direction for future research is to experiment with less aggregate measures, such as using best in groups or better quartiles as the reference groups.”

Second, we extend the literature on social comparison by examining reference group selection dynamics from the perspective of external audiences evaluating firms. As Goodman and Haisley (2007) described, “Most of the social comparison literature focuses on how the individual makes sense of attitudes, opinions, abilities, and performance. The question is how we can extend our understanding of social comparison to other levels of analysis.” Furthermore, within the social comparison literature, the locus of comparison and evaluations has often been internal managers. Our study joins recent research by Smith (2011) and Smith and Chae (2017) that examined the effects of firms' positioning within a category on external audiences' reference group selection and performance evaluations. We demonstrate that, through strategic positioning, firms can play an active role to influence the reference groups used by their evaluators.

Practical implications. Our findings have two practical implications. First, we show that the way a firm positions itself within its category has a significant impact on how audiences

compare and evaluate its performance. To illustrate this, consider the case of Ford company, which, in 2018, reframed itself from an automaker to a mobility company. Our findings suggest that such a move could result in the company being compared against another mobility company such as Uber, instead of being compared against an automaker such as GM. There could be positive or negative implications of doing this depending on how Ford performs relative to its new comparison set.

Second, our study brings to light an important trade-off firms face when associating with an exceptional firm. For example, in the context of media streaming services, many firms may be tempted to associate themselves with Netflix. As our findings suggest, such association, while perhaps generating some attention and legitimacy, could backfire by prompting analysts and customers to directly compare the firm's performance with that of Netflix, which is a high benchmark to beat. We recommend that a firm situate and manage this trade-off in light of its broader differentiation strategy (i.e., being a typical or an atypical firm). For a firm such as Quibi¹⁷, which has framed itself as an innovator and disruptor, our findings suggest they should either position their services as completely different from Netflix or highly similar to it. Conversely, for typical media streaming firms such as Hulu, they would do best to assume a middle ground when it comes to positioning vis-à-vis Netflix.

3.5.2 Future Research

Our study opens several productive avenues for future research. First, our study is limited to studying the impact of firm positioning vis-à-vis category exemplars and prototypes on the evaluations of a specific set of actors: security analysts. While security analysts provide an ideal context for testing our theoretical arguments because of their influence on the stock market, this

¹⁷ The firm offers services similar to Netflix, except for its contents of 5-10 minute durations which are designed specifically for consumption on mobile devices.

choice of context limits our study to high-stake environments and evaluations done by industry experts. Different stakeholder groups may use different cognitive styles (Murnieks, Haynie, Wiltbank, & Harting, 2011) and evaluating lenses (Fisher et al., 2016; Pontikes, 2012) in conducting firm evaluations. Future work could explore the effects of similarity to category exemplars and prototypes on the evaluations made by various stakeholder groups.

Second, we assumed a relatively unbiased evaluation on the side of security analysts, which is a fair assumption given the analysts' incentive to maximize the accuracy of their reports and investment recommendations (Litov et al., 2012). While a large body of research has documented how self-enhancement motivations influence managers' choice of reference groups (e.g. Blettner et al., 2015; Sensoy, 2009), there is limited research exploring how audiences' motivations and their incentives influence their choice of reference group selection and performance evaluations of firms (for exceptions, see Bowers & Prato, 2019; Smith & Chae, 2017). We see ample opportunities for scholars to further explore how such audience-side dynamics shape firm evaluations and how firms can account for these motivations and self-interests of audiences in their positioning strategies.

Third, we measured conformity and differentiation along with a single measure: similarity based on business description texts. While the business description in firms' 10-K filings is a reliable source for measuring a firm's positioning within a market (Hoberg & Phillips, 2010, 2016), an aggregated measure based on these texts limits our study to a single dimension. Future studies that break apart firms' conformity to and differentiation from various category benchmarks on multiple dimensions would be valuable. Specifically, future works could build on the notion that firms can manage and orchestrate various organizational dimensions for achieving optimal distinctiveness (Philippe & Durand, 2011; Zhao et al., 2017), and examine whether firms could

selectively conform to exemplars in ways that could generate the benefits of association without incurring the costs of comparison.

Fourth, future work can examine the dynamics of optimal distinctiveness for firms that operate across multiple categories. Such inquiry would be of great importance especially when considering the simultaneous roles of dual benchmarks. For example, future research could explore whether a firm that operates in multiple market categories could gain legitimacy by conforming to the prototype in one category while garnering the benefits of association by positioning itself near exemplars in other categories.

Fifth, while we included firm fixed effects in our study and controlled for multiple firm-level and industry-level variables in our analytical models, our study lacks a suitable instrumental variable and we refrain from claiming strong causality based on our results. We believe this limitation could be best addressed through an experimental research design. Smith and Chae's (2017) experimental design provides a useful starting point for conducting such research. An experimental design would allow scholars to directly observe audiences' choices of reference groups when provided with multiple different benchmarks and could thus provide further empirical evidence in this line of inquiry.

Sixth, although we controlled for firm performance in our models, we did not theoretically investigate how a focal firm's capabilities influence the decision and outcomes related to exemplar similarity. As Semadeni and Anderson (2010) show, the appropriateness of the decision to follow another firm is dependent on the focal firm's internal capabilities to implement the necessary changes. Future studies could build on this insight to investigate how audiences respond to exemplar similarity based on the focal firm's perceived capability to successfully imitate the exemplar. It would be particularly interesting to unravel the apparent paradox that firms with

perceived lower capabilities benefit more by being associated with an exemplar and lose more by being compared against one.

3.5.3 Conclusion

Drawing on optimal distinctiveness and social comparison theories, we explored the effects of similarity to category exemplars on analysts' coverage and investment recommendations, as well as the stock market valuations of typical versus atypical firms. We argued that the implications of exemplar similarity are twofold: on the one hand, a firm may gain benefits through increased attention and legitimacy; on the other, the firm may be compared against an exceptionally high performing firm. The outcome of these two opposing mechanisms is different for typical and atypical firms. While the relationship between exemplar similarity and market valuation of a firm is inverted U-shaped for typical firms, the relationship is U-shaped for atypical firms. We encourage scholars to further explore the performance implications of various strategies in dual benchmark settings.

CHAPTER FOUR

4 Strategic Positioning and Audience Composition: A Machine Learning Approach to Predicting Audience Evaluations¹⁸

4.1 Introduction

With the rising popularity of artificial intelligence and machine learning, researchers from various social science domains have started to add new and sophisticated machine learning algorithms to their arsenals of empirical methods (e.g., Belloni, Chernozhukov, & Hansen, 2014; Mullainthan & Spiess, 2017). In management research, two important frontiers regarding the use of machine learning techniques have emerged. In the first frontier, scholars have used machine learning techniques to reveal and measure theoretical constructs that are then used for hypothesis testing with traditional econometrics models (Choudhury, Allen, & Endres, 2018; Hannigan et al., 2019; Giorgi & Weber, 2015; Kaplan & Vakili, 2015; Choudhury, Wang, Carlson, & Khanna, 2019). In the second frontier, scholars have highlighted machine learning algorithms as exploratory data-analysis tools for inductive theory building (Puranam, Shrestha, He, & von Krogh, 2020; Choudhury et al., 2018; Tidhar & Eisenhardt, 2020). We believe there is a largely underexplored area related to machine learning and management research. Machine learning algorithms enable cheap, accurate, and generalizable predictions that can significantly influence firm strategy (Agrawal, Gans, & Goldfarb, 2017). Management researchers could engage machine learning as

¹⁸ Eric Zhao contributed to this chapter.

prediction tools to make theoretical and practical advancements. In this paper, we explore the use of machine learning to predict audiences' heterogeneous predispositions toward firms.

Garnering audience attention is a critical precursor to firm success (Lounsbury & Glynn, 2001; Zhao, Ishihara, & Lounsbury, 2013; Zuckerman, 1999). As cognitive infrastructures of markets that simplify thoughts and evaluations (Rosch & Lloyd, 1978; Schneiberg & Berk, 2010), categories direct audience attention and shape the lens through which audiences evaluate firms (Pontikes, 2018). Firms that defy categorical norms and expectations, for example, through deviation from prototypes or categorical straddling, are typically less successful in garnering audience attention or positive evaluations (Hsu, 2006; Hsu, Hannan, & Koçak, 2009; Zuckerman, 1999). Categorical imperative research has implicitly assumed that categories are shared and commonly held mental models. This reasoning implies that audiences categorize firms uniformly and that all audience members within a category use the same categorical benchmarks to evaluate a firm's positioning strategy.

More recently, scholars have challenged this assumption by exploring heterogeneities and idiosyncrasies within audiences (e.g., Beunza & Garud, 2007; Kovács & Sharkey, 2014; Paoletta & Durand, 2016; Pontikes, 2012). For example, Beunza and Garud (2007) showed that in the early 2000s, some security analysts categorized Amazon as a bookstore, whereas others categorized it as an internet company, resulting in contrasting evaluations. When a firm is categorized differently, audience members evaluate it using different criteria and against different reference groups (Bowers, 2015; Goodman & Haisley 2007; Smith & Chae, 2017). Audiences categorize the same firm differently based on their prior knowledge and preferences (Beunza & Garud, 2007; Durand & Paoletta, 2013; Jensen & Kim, 2014; Kim & Jensen, 2011; Theeke, Polidoro, & Fredrickson, 2018) as well as their different goals and motivations (Bowers & Prato, 2019;

Bowers, 2020; Durand & Paoletta, 2013; Glaser, Krikorian Atkinson, & Fiss, 2020; Paoletta & Durand, 2016).

We propose taking advantage of the strong pattern recognition and predictive power of machine learning algorithms (Agrawal, Gans, & Goldfarb, 2018) for predicting audiences' heterogeneous predispositions and evaluation schema, which in turn informs firms' positioning strategies. Specifically, we develop a predictive model using a machine learning algorithm that was one of the winners of the Netflix Prize competition for predicting users' ratings of movies and shows (Bennet & Lanning, 2007). To showcase an application of our proposed method in management research, we demonstrate how optimal positioning could be achieved above and beyond what extant optimal distinctiveness research has suggested. Indeed, our knowledge regarding firms' optimal positioning strategies in light of the heterogeneity of audience evaluations remains limited. Past studies at the intersection of categories and optimal distinctiveness have generally proposed that enhancing familiarity among audiences and gaining their attention are universally beneficial to firms (e.g., Barlow, Verhaal, & Angus, 2019; Haans, 2019; Zhao, Ishihara, & Jennings, 2018). The premise of audience heterogeneity suggests instead that gaining an audience's attention could benefit or harm a firm depending on audiences' categorization schemas and predispositions toward the firm. For instance, a restaurant that offers high-quality authentic Asian food might do itself harm by attracting audiences who are accustomed to unauthentic Americanized Asian food and might accordingly give the restaurant low ratings on Yelp. As such, we need to examine firms' optimal positioning strategies while taking into account the heterogeneity of audiences' evaluation criteria. In other words, we must go beyond simply examining how firms can gain legitimacy and audience attention to exploring whose attention firms should aim to gain. Therefore, the central research question guiding our study is: *How can*

firms strategically position themselves to increase their positive evaluations given audiences' heterogeneous predispositions toward them?

Our core contention is that when audiences have varying predispositions toward a firm, strategic positioning entails a selective approach to gaining audience attention (as opposed to broadly conforming to categorical norms to maximize audience attention). To gain attention from the right audience, a firm could influence its audience composition such that it is evaluated mostly by audiences who have a favorable predisposition toward it (and less by those with an unfavorable predisposition). By doing so, firms can gain more positive aggregate evaluations. We term this gain an *audience composition premium*. Essentially, this concept captures the increase in positive evaluations that is due to the composition of audiences evaluating an entity. For instance, an average restaurant might receive an above-average rating on Yelp, not because of the quality of its food or services, but due to attracting the right customers and being rated only by audiences with a favorable predisposition toward it.

We empirically show how such positioning can be achieved in the context of security analysts' investment recommendations. In this case, a firm can increase the chances of receiving attention and gaining coverage from a particular analyst by strategically positioning near other firms covered by that analyst. This is based on the premise that an analyst's portfolio of coverage is a good proxy for his or her idiosyncratic approach to categorization and evaluation (Bowers, 2015; Zuckerman, 2004). We develop a measure of audience composition premium based on firms' positioning and audiences' predispositions. We test the predictive significance of this variable as an explanatory variable for the aggregate evaluations that firms receive. We find strong support for our predictions and show that audience composition premium, constructed using our

proposed methodology, is a significant predictor of firms' aggregate evaluations, above and beyond its typicality.

Our contributions are twofold. First, by integrating the role of audience heterogeneity and firms' strategic agency in influencing audience categorization processes and evaluations, we extend previous literature which suggests that firms need to conform to categorical norms to garner audience attention. We theorize instead that firms need to strategically position themselves to garner attention selectively from audiences with a positive predisposition toward them. Second, by introducing and showcasing the application of a family of machine learning models to management scholarship, we advance the methodological frontiers of our field. Specifically, we show how recommender systems could be used for making individualized predictions in the presence of heterogeneities within a group of actors. Finally, we make a prescriptive contribution that could be practically utilized to enhance firms' agency in influencing their audience composition and categorical expectations.

4.2 Heterogeneity In Audiences' Categorization Schemas

Firms are increasingly being evaluated, ranked, and certified by external audiences (Sharkey & Bromley, 2015; Zuckerman, 1999). Audience evaluations help reduce uncertainty and information asymmetry about the quality of a firm or product in market transactions (Zhao & Zhou, 2011). Previous research has shown that audiences use categorization schemas in a two-stage process when evaluating firms. First, audiences screen candidates using established categories to limit their consideration set to a manageable sample of comparable actors. Second, they sort through the selected sample to evaluate and rank the actors (Zuckerman, 1999, 2017). Categories are thus cognitive schemas that aid audiences in forming evaluations of entities (Vergne & Wry, 2014).

Early studies in this domain demonstrated that firms need to conform to their categories' established norms and prototypes to be perceived as familiar and easy to classify and analyze (e.g., Hsu, 2006; Zuckerman, 1999, 2000). According to this research, firms that defy such “categorical imperatives” receive less attention from audiences and thus face an “illegitimacy discount” (Litov, Moreton, & Zenger, 2012; Zuckerman, 1999). Later studies went beyond the categorical imperative hypothesis, suggesting that in some contexts, categorical boundaries could be blurry and ambiguous (Durand, Rao, & Monin, 2007; Rao, Monin, & Durand, 2005), thus enabling—and sometimes rewarding—firms that adopt an atypical market position (Negro, Koçak, & Hsu, 2010; Smith, 2011; Smith & Chae, 2017). More recent studies in this area have explored the effects of conformity and differentiation vis-à-vis category exemplars. Via similarity to exemplars—namely, outstanding category members—firms can garner legitimacy and audience attention (Barlow et al., 2019; Zhao et al., 2018) while risking lower performance evaluations due to comparisons with outstanding firms.

These theories rest on a restricting assumption that categories, as the “cognitive infrastructure” of markets (Schneiberg & Berk, 2010), are shared mental models among all members of an audience group. Based on this assumption, a typical audience member has a relatively clear expectation of what a category member should look like. This cognitive perception of a category member could be formed through a prototype view of the category, which entails categorization based on common attributes of all category members (Rosch, 1973), or through an exemplar view of the category, which refers to categorization based on similarity to outstanding category members (Nosofsky & Johansen, 2000). Either way, a common theoretical and empirical assumption is that conceptions of prototypes and exemplars are shared among audience members

insofar as “category construction ... involves gaining agreement within the audience about what it means to carry a label” (Hannan, Hannan, Pólos, & Carroll, 2007: 59).

Building upon the aforementioned assumption, optimal distinctiveness research has examined a firm’s optimal positioning strategy vis-à-vis commonly held category benchmarks, such as prototypes and exemplars. As a result, researchers often examine audience members within the same category (e.g., analysts specialized in a specific industry) as a homogenous body that reacts uniformly to a firm’s within-category positioning strategy. For instance, Litov et al. (2012) examined the negative effects of strategy uniqueness vis-à-vis industry averages on analyst coverage, implicitly assuming a uniform reaction from all analysts in a firm’s primary industry. In another study, analysts were shown to uniformly react to firms that change their market positions by undertaking major spinoffs (Feldman, 2016).

More recently, scholars have questioned the assumption that audiences within the same category evaluate firms uniformly and have started to theorize about important heterogeneities in audiences’ evaluations due to idiosyncratic categorization schemas (Beunza & Garud, 2007; Kim & Jensen, 2011; Kovács & Sharkey, 2014; Pontikes, 2012). These studies have highlighted that audiences adopt different categorization schemas (Paolella & Durand, 2016) due to their idiosyncratic knowledge and expertise (Beunza & Garud, 2007; Theeke et al., 2018) and their different goals and motivations (Bowers & Prato, 2019; Durand & Paolella, 2013; Fleischer, 2009; Glaser et al., 2020). When audiences embrace different categorization schemas, they tend to evaluate the same firm through different lenses (Beunza & Garud, 2007; Pontikes, 2012) and compare the firm with different reference groups (Bowers, 2015; Goodman & Haisley, 2007; Smith & Chae, 2017).

To illustrate, consider how a book is categorized and evaluated by audiences. A book is typically categorized and shelved in a public library based on one (or sometimes a few) of the widely accepted book genres. For instance, the book *Thinking, Fast and Slow* belongs to the category of “psychology; cognition and memory” (Code 153 in the Melvil Decimal System). However, we know intuitively that there is a significant degree of heterogeneity in how individuals would categorize and shelve this book in their personal libraries. In fact, as of the time of this writing, the book was categorized (shelved) in 22,399 distinct ways by users on Goodreads.com. The categories created and used by audiences on this platform include both more commonly used categories such as “psychology,” “economics,” and “self-development,” and less commonly used categories such as “brains-stuff,” “armchair-science,” and “bedside-tables.”

4.3 Use Of Machine Learning as a Prediction Tool

4.3.1 Machine Learning in Management Research

Our goal in this paper is to leverage the increasingly popular machine learning techniques (e.g., Belloni et al., 2014; Mullainthan & Spiess, 2017) to predict the heterogeneous evaluation schemas of audiences and based on that to inform firms’ positioning strategies. In management research, machine learning techniques have been employed to advance research on two fronts. In the first frontier, machine learning techniques have been used to reveal and measure theoretical constructs that are then used for hypothesis testing with traditional econometrics models (Choudhury et al., 2018). An example following this approach includes the use of topic modeling techniques, such as latent Dirichlet allocation (LDA) (Hannigan et al., 2019) to measure framing repertoires (Giorgi & Weber, 2015), knowledge-recombination characteristics (Kaplan & Vakili, 2015), and strategic differentiation (Haans, 2019). More recently, Choudhury et al. (2019) applied topic modeling and sentiment analysis algorithms to textual data and combined this method with deep learning models

on image data to measure CEO communication styles. They then used traditional regression models to showcase the effects of CEO communication styles on firms' merger and acquisition activities.

In the second frontier, machine learning algorithms have been utilized as exploratory data-analysis tools for inductive theory building (Puranam et al., 2020). Machine learning techniques can aid theory building by discovering patterns in quantitative data that might otherwise go unnoticed by researchers (Choudhury et al., 2018). Discoveries made using machine learning can also serve as robust and novel observations in inductive or abductive theory building (Choudhury et al., 2018; Croidieu & Kim, 2018; Puranam et al., 2020). In this regard, machine learning algorithms could become powerful tools for augmenting and aiding grounded theory building. In a recent study, Tidhar and Eisenhardt (2020) combined machine learning and multi-case methods to build theory about the optimum revenue model in the App Store. The use of machine learning corroborated and enriched the case studies with non-linear findings and accurate predictions and effect sizes.

We believe there is a third largely underexplored area related to machine learning and management research. While the two previous streams focus on the impact of machine learning in research, less attention has been paid to the prescriptive power of machine learning for firm strategy.¹⁹ We believe there is opportunity to explore ways firms can use machine learning to make strategic decisions. In addition to having theoretical importance, research in this area could have a significant prescriptive value that most contemporary management research lacks (Bazerman,

¹⁹ There is an emerging body of research in both economics and management disciplines that focuses on the future of work and explores the potential of artificial intelligence to substitute or complement traditional human jobs (e.g., Acemoglu and Restrepo 2017, Autor 2015, Choudhury et al. 2020, Frank et al. 2019, Nordhaus 2015). Our focus in this paper is different in that we explore how machine learning could be used for specific strategic problems that companies face.

2005; Pfeffer & Fong, 2002). Indeed, recent studies have suggested that artificial intelligence and, more specifically, machine learning algorithms enable cheap, accurate, and generalizable predictions that can significantly influence firm strategy (Agrawal et al., 2017). Agrawal et al. (2018) illustrated the potential effect of accurate prediction on firm strategy through the following example. Amazon currently uses a shopping-then-shipping strategy. If at some point it could accurately predict what customers want to buy, it could transition to a shipping-then-shopping strategy, delivering products to customers before they make an order online. Machine learning algorithms could also impact innovation processes by facilitating the discovery of useful combinations in complex discovery spaces (Agrawal et al., 2018; Cockburn, Henderson, & Stern, 2018). In addition, Goldfarb, Gans, and Agrawal (2019) explored how machine learning can facilitate firms' ability to distinguish reliable partners, thus reshaping theories built on search inefficiencies and partner frictions in traditional economics. In this paper, we explore the use of machine learning to predict audiences' predispositions toward firms.

4.3.2 A Machine Learning Approach to Predicting Audience Evaluations

A tremendous amount of research in the computer science domain focuses on using machine learning algorithms to predict the fit between a product and an audience. Generally known as recommender systems, these models are widely used to help firms better serve their customers by recommending products to them based on their individual preferences and needs. With the exponential growth of the internet and e-commerce and the immense variety of product offerings, a pressing need emerged to filter which products were recommended to different customers (Ricci, Rokach, & Shapira, 2011). A specific event that further popularized recommender systems was the Netflix Prize competition (Bennet & Lanning, 2007). Netflix traditionally used its subscribers' ratings of movies they had previously watched to recommend new movies to them. The

competition offered \$1,000,000 to any team that could develop an algorithm to increase the accuracy of Netflix's previous model by 10% (in terms of predicted ratings of movies by users). Some of the methods developed by the teams participating in this competition became cornerstones for further developments in recommender system research and application (Ricci et al., 2011). Today, companies like Amazon, Netflix, Spotify, and (Alphabet's) YouTube use sophisticated recommender system algorithms to predict customers' evaluations of merchandise, movies, music, and videos, respectively. Based on these predictions, they choose which products to recommend to a particular user (Lu, Wu, Mao, Wang, & Zhang, 2015), often to a satisfactory result. For instance, in the mid-2010s, more than 80% of the shows people watched on Netflix were attributed to the platform's recommender system (Wired, 2017).

A recommender system's job is to use users' previous ratings of items (in sample) to predict ratings for user-item pairs for which data is not available (out of sample). There are two basic approaches to developing a recommender system: content-based and collaborative filtering approaches (Aggarwal, 2016). A content-based approach utilizes users' previous ratings of items with specific features to predict their rating of items with given combinations of features. For example, assume movies are coded based on various features such as genre, date of production, number of celebrity actors, budget, etc. (see Figure 1). The problem here is to find patterns that would predict a user's rating of a movie with certain features (e.g., User 1's rating of Movie 1) given the user's previous ratings of other movies. There are two major limitations to this approach: first, it requires coding each item's features, which is often an unreliable, daunting, or even impossible task; second, it does not take advantage of how users with similar preferences have previously rated a specific item. A collaborative filtering approach addresses these two limitations.

Collaborative filtering requires no data regarding the features or content of items. Instead, an algorithm predicts a user's rating of a focal item by examining how other users with similar preferences (i.e., those who have given similar ratings to the same items) previously rated the item. For instance, a collaborative filtering algorithm might predict a user's rating of a movie based on how users with similar preferences rated the movie before (in Figure 2, User 2's rating of Movie 3 could be predicted based on User 1's and User M's previous ratings of the movie). The advantage of a collaborative filtering algorithm is that it does not require explicit codification of each item's features. A major limitation of these algorithms is the “cold start” problem—namely, making predictions for new users (or items) that have not rated (or been rated) by a large enough sample. In practice, companies often address this issue by using another algorithm, such as a content-based recommender system, for newer users and items.

Multiple algorithms are available for developing a recommender system using a collaborative filtering approach. One of the most popular and efficient of these is FunkSVD (Funk, 2006). This algorithm tied for third place in the aforementioned Netflix Prize competition and gained significant traction due to its simplicity and relative low cost of implementation. Intuitively, this algorithm takes the high-dimensional user-item space into a latent lower-dimensional space. For instance, in the case of predicting movie ratings, the FunkSVD algorithm could be used to estimate each user's preferences and item's attributes along 15–20 latent features. Thus, each user and each item would be assigned a vector of corresponding weights for the latent features. In the example illustrated in Figure 3, to predict User 2's rating of Movie 3, we would measure the similarity between User 2's and Movie 3's weight vectors corresponding to the latent features. While the estimated features could correspond to interpretable variables, such as genre, budget, production year, etc., they are mathematical constructs built to optimize

	Features					Users	
	Genre	Production Date	Celebrity Actors		Budget (\$M)	User 1	...
Movie 1	Horror	2001	0	...	24	?	...
Movie 2	Comedy	2020	1	...	120	5	...
Movie 3	Drama	1973	4	...	210	2	...
...	...	...	...	...	...	...	...
Movie N	Action	2012	2	...	950	1	...

Notes: In a content-based recommender system, a user's rating of an item is predicted by examining how the user previously rated items with similar features. For example, in the table above, User 1's rating of Movie 1 is calculated using User 1's ratings of movies with similar characteristics as Movie 1: horror movies in early 2000s with few celebrity actors.

Figure 4-1 A Content-Based Recommender System

	User 1	User 2	User 3	...	User M
Movie 1	2	1	4	...	2
Movie 2	5	5	2	...	4
Movie 3	4	?	1	...	5
...	...	...	...	...	...
Movie N	1	1	3		2

Notes: In a collaborative filtering recommender system, a user's rating of an item is predicted by examining how other users with similar previous ratings rated the item. For example, in the table above, User 2's rating of Movie 3 could be estimated using similar users' ratings of Movie 3. In this case, User 1 and User M (compared with User 3) seem to have preferences that are more aligned with those of User 2.

					Latent Feature 20	?				
					...	?				
					Latent Feature 3	?				
					Latent Feature 2	?				
					Latent Feature 1	?				
Latent Feature 20	...	Latent Feature 3	Latent Feature 2	Latent Feature 1		User 1	User 2	User 3	...	User M
					Movie 1	2	1	4	...	2
					Movie 2	5	5	2	...	4
?	?	?	?	?	Movie 3	4	?	1	...	5
					...	...	...	...	...	...
					Movie N	1	1	3		2

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

prediction accuracy and are not necessarily open to interpretation. There are various computational methods for estimating latent feature weights such that the errors between predicted ratings and observed ratings are minimized. Most of these methods, such as gradient descent or stochastic descent, start from some predefined initial parameters (e.g., all feature weights initiated randomly) before updating the parameters through rounds of iterations that aim at reducing some cost function (e.g., sum of squared errors). The algorithm stops once the parameters yield an error term below a prespecified value.

4.3.3 Predicting Analysts' Investment Recommendations

We develop a model that predicts security analysts' investment recommendations for US public firms using the Institutional Broker Estimate System's (IBES) Recommendations Detail dataset. We considered an analyst's latest investment recommendation in a calendar year as his or her recommendation for the firm for that year. We inverse coded IBES' standardized recommendations so that a higher score corresponds with a more favorable investment recommendation (5 being the most favorable and 1 the least). We limited the sample to firms that had at least 10 analysts covering them in a given year and analysts who had covered at least 10 firms in their portfolio historically. In addition, we dropped unnamed analysts from our dataset. To construct a variable regarding firms' strategic positioning (as discussed later), we used firms' business descriptions in their 10-K filings. Therefore, we limited our sample to firms whose 10-K filings were available on the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. Furthermore, to create control variables, we limited our dataset to firms with accounting data available on Compustat. In our final sample, we have 71,518 firm-analyst-year observations.

Model Estimation. We developed a FunkSVD model to predict security analysts' investment recommendations regarding specific firms. We determined the number of factors by testing the predictive accuracy of different models on the validation set. In Figure 4, we plot Mean Squared Error (the average squared difference between the predicted recommendations and the actual recommendations) for different number of factors (from 50 to 1000, at 50 increments.) Based on this plot, we determine the number of factors to be 400. We used a similar approach for determining the algorithm's learning rate and regularization term. We trained a FunkSVD model with 400 factors with a learning rate of 0.005 and a regularization term of 0.2^{20} .

²⁰ As robustness check for our regression models, we train the FunkSVD model using different numbers of factors (200, 300, 500). Our results remain qualitatively unchanged.

The trained model had high accuracy in predicting analysts' recommendations. We used the model trained using the training set to test how accurately it predicted recommendations for our sample in the test set (the test set was not used for training or tuning the model). The Mean Squared Error between the predicted and actual recommendations was 0.782. Regressing the actual recommendations (y) against the predicted recommendations (x), the coefficient for predicted recommendations is 0.776 with a p-value of .000 (Table 1). The result shows that the predicted recommendations are a statistically significant predictor of the actual recommendations. We graphed the predicted ratings against actual ratings in Figure 5. The graph further illustrates the strong correlation between predicted recommendations and actual recommendations.

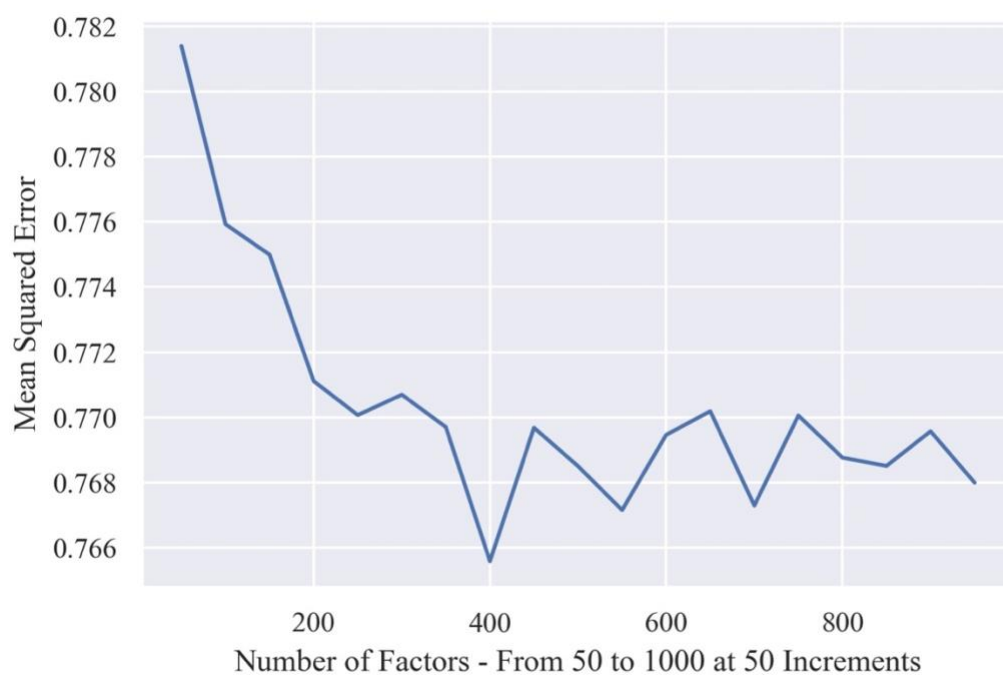


Figure 4-4 Mean Squared Error between predicted and actual recommendations for models with different number of factors (from 50 to 1000, at 50 increments)

Table 4-1 Regressing Security Analysts' Actual Recommendations on Predicted Recommendations of US Public Firms

Dependent Variable: Actual Recommendations

	β	p	Conf. 0.025	Int.	Conf. 0.975	Int.
Predicted Recommendations	0.776	0.000	0.726		0.827	
Intercept	0.797	0.000	0.618		0.977	
N. Observations	7152					
R-Squared	0.113					
F-Statistic	908.5					
Prob (F-Statistic)	0.000					

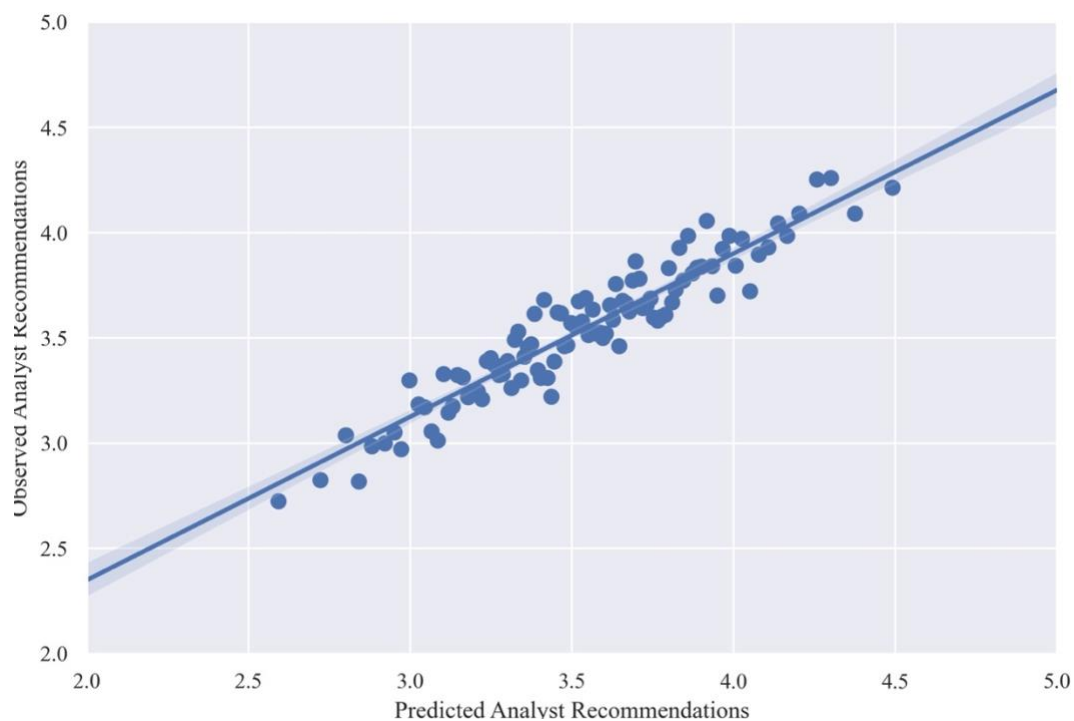


Figure 4-5 Analysts' Recommendations for Public Firms: Predicted Recommendations versus Actual Recommendations.

4.4 Proof of Concept: Strategic Positioning in Light of Audience Heterogeneity

One of the key strategic decisions a firm must make is how to position itself (Porter, 1996; Rumelt, Schendel, & Teece, 1995). A firm's positioning strategies both within and across categories impact the audience evaluations it receives (Pontikes, 2018; Smith, 2011; Smith & Chae, 2017; Wry, Lounsbury, & Jennings, 2014, Zhao et al., 2018). The premise of audience heterogeneity begets a deeper examination of positioning strategies that could maximize firm benefits. The two-stage

model of evaluation indicates that audiences first screen through firms to determine for each firm if it is worthy of evaluation, and only then, if the firm passes through the initial screening, evaluate and confer a rating to it. Given the premise that audiences have varying predispositions when evaluating a firm, it is of crucial importance to consider the interdependence between the two stages: what evaluation will an audience member give a firm (second stage) once he or she decides to evaluate it (first stage)? Depending on the predicted outcome of the second stage, a firm should strategize to influence the first stage. In other words, a firm should strategically influence its audience composition to gain favorable evaluations. We develop this contention in more detail below.

In virtually every important evaluation context, not every audience member evaluates every firm or product. Instead, each firm or product is evaluated by a limited number of audience members. As argued before, audiences hold different categorization schemas due to differences in their knowledge, goals, and motivations. Such heterogeneity translates into different evaluations of the same firm by different audience members. Consequently, any aggregate evaluation that a firm receives depends on the specific group of audiences that decides to evaluate it. In other words, the make-up of the group of audiences that evaluates a firm—namely, its audience composition—is an important determinant of the overall evaluation it receives. Kovács and Sharkey (2014) examined the evaluations given to books on Goodreads and observed that once a book received a prestigious award, the average rating it received went down. They found the cause to be a change in audience composition: as a result of receiving an award and gaining popularity, a book's audience composition changed such that more people whose preferences did not inherently match the book were more likely to read and rate it. In other words, by gaining an award, books attracted the wrong readers, resulting in lower evaluations (Kovács & Sharkey, 2014).

Firms can adopt strategies to influence their audience composition to receive a higher aggregate evaluation. We term this gain in evaluations an *audience composition premium*.²¹ To illustrate, reconsider the example of Amazon being evaluated differently by security analysts (Beunza & Garud, 2007). Back in the early 2000s, Amazon could have gained an audience composition premium by positioning itself strategically so that it was evaluated more often by analysts who viewed it as an internet company and less often by those who categorized it as a bookstore.

We propose that firms can strive to achieve a favorable audience composition through two major steps: (1) predict the evaluations they would receive from given audience members and (2) strategically position themselves to maximize the likelihood of receiving attention from and being evaluated by only those audience members who have a favorable predisposition toward them. Let us illustrate this idea through the familiar example of the peer-review process, in which a manuscript functions as a candidate being evaluated by a specific audience group—namely, reviewers. A manuscript needs favorable evaluations from reviewers to be published. Reviewers, being scholars themselves, often come from different backgrounds, have distinctive theories of value, and will therefore ascribe different evaluations to a given manuscript (second stage of the evaluation process). Moreover, reviewers are likely to evaluate a manuscript only if it is positioned in or near their areas of expertise and research (first stage of the evaluation process). A manuscript's chance of publication thus depends on both stages of the evaluation process: it will be evaluated positively to the extent that it is positioned to attract the right reviewers.

²¹ Similarly, we could think of an *audience composition penalty*, which refers to a firm's loss in evaluations due to a suboptimal audience composition. We will use the term audience composition premium to parsimoniously refer to this loss as well.

Our assertions stand in contrast with suggestions from prior research. Category research has often suggested that firms need to conform to categorical benchmarks to garner attention and pass through the first stage of the evaluation process and then differentiate to stand out and garner a high evaluation in the second stage (Zuckerman, 1999, 2017). Based on this logic, optimal distinctiveness researchers have considered an increase in attention and coverage by audiences as a positive organizational outcome. We suggest a contrasting point of view. Specifically, we argue that the benefit of garnering attention from an audience member is dependent on his or her predisposition toward the focal firm. Accordingly, we propose that:

Proposition. *firms can increase the evaluations they receive by strategically positioning themselves to attract audiences that have a positive predisposition toward them (i.e., by generating an audience composition premium).*

4.4.1 Audience Composition Premium and Security Analysts' Investment Recommendations

In the context of security analysts' investment recommendations, a firm's audience composition premium could be proxied by taking into account two factors: (1) the probability of the firm receiving coverage from each specific analyst based on the firm's strategic positioning and (2) the predisposition of each specific analyst toward the firm. To estimate our measure of audience composition premium for each firm-year in our sample (4,883 observations), we calculated the two values mentioned above for all possible firm-analyst-year combinations. There were 6,918,413 such combinations in our sample.²² We used our previously constructed FunkSVD

²² It is worth mentioning again that we had only 71,518 firm-analyst-year combinations in our dataset with actual investment recommendations. That is because in any given year, each analyst only covers a few firms, and each firm is covered by only a few analysts. In other words, the matrix containing actual firm-analyst-year data is a sparse matrix. A recommender system, however, is capable of generating predictions for all possible firm-analyst pairs in a given year. In other words, the matrix containing predicted firm-analyst-year data is a dense matrix. Thus, there is the observed difference between 71,518 actual recommendations and 6,918,413 predicted recommendations.

model to estimate the predisposition of each specific analyst toward a firm for all the firm-analyst-year combinations.

To estimate the probability of a firm receiving coverage from each analyst based on its strategic positioning, we examined how close (similar) the firm is positioned to other firms in the specific analyst's portfolio. The assumption here is that a firm is more likely to receive coverage from an analyst who covers similar and comparable other firms (Bowers, 2015). To measure the similarity between firms in an analyst's coverage portfolio, we applied a topic modeling algorithm to firms' business description sections in their 10-K reports. Topic modeling uses the statistical co-occurrence of words in

documents to identify latent topics within a corpus (for a review, see Hannigan et al., 2019). We used a latent Dirichlet allocation (LDA) (Blei, Ng, & Jordan, 2003) algorithm to discover the latent topics in our corpus of firms' business descriptions. The LDA algorithm assumes that each document includes a mixture of topics and that each topic itself includes a mixture of different words. Therefore, the algorithm finds an optimal solution for a two-layer distribution of topics over documents and terms over topics. Following common practice, we set the number of topics at 100 (Haans, 2019; Kaplan & Vakili, 2015).²³ We used the cosine similarity method to measure the similarity between firms based on their topic weight vectors. Our method for measuring the similarity between firms is a close replication of Haans' (2019) approach. We averaged the topic weight vectors of all firms covered by an analyst and measured each firm's distance to this averaged vector.

An exploratory analysis confirmed that there is a high degree of correlation between the

²³ As a robustness check, we tried setting the number of topics at 75, 125, and 150, and the results did not qualitatively change.

probability of a firm being covered by an analyst and that firm's similarity to other firms in the analyst's coverage portfolio. The mean similarity score between a firm and its covering analyst's portfolio is .858, while that number is .076 for the similarity score between a firm and all analysts' portfolios regardless of whether they followed it or not. Figures 6a and 6b show the distribution of similarity scores between firms and analysts' portfolios for all possible firm-analyst combinations and for firm-analyst combinations in which the analyst actually followed the firm. This analysis corroborates our assumption that a firm's probability of being covered by an analyst is proportional to the similarity between that firm and all the firms in the analyst's coverage portfolio:

$$Pr_{ij} \propto Similarity_{ij}$$

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

We conceptualize audience composition premium as the gain in evaluations due to the specific composition of audiences opting to evaluate a firm, relative to the average evaluation that it would have received had everyone in the audience evaluated it. For example, assume that in a small town of 1000 restaurant customers, a restaurant would have received an average star rating of 3.5 if it was rated by everyone. However, if the restaurant positions itself such that it receives only 100 ratings with an average of 4.0, based on our conceptualization, it has an audience composition premium of 0.5.

In our context, we operationalize this variable by subtracting the average predicted rating of all analysts from the average predicted rating of analysts that are likely to cover a firm based on its position. As argued before, the likelihood of coverage is proportional to the similarity between a firm and an analysts' portfolio of firms. Therefore, the average predicted rating of analysts based on the likelihood of coverage is the sum of all analysts' predicted evaluations of a firm multiplied

by the probability of them covering the firm, normalized by the sum of all probabilities. We use the formula below to calculate a firm's audience composition premium in each given year:

$$Audience\ Composition\ Premium_i = \frac{\sum_j Pr_{ij} * Rating_{ij}}{\sum_i Pr_{ij}} - \frac{\sum_j Rating_{ij}}{N}$$

where Pr_{ij} is the similarity between firm i and analyst j 's portfolio, $Rating_{ij}$ is the predicted rating of analyst j of firm i , and N is the total number of predicted ratings for firm i . The constructed variable has a mean of 0.002 with a standard deviation of 0.032. Figure 7 shows the distribution of this variable. As shown, while some firms enjoy a positive audience composition premium, some experience a negative audience composition premium.

(a) Based on all possible firm-analyst combinations (including analyst-firm pairs with no actual coverage) **(b) Based on firm-analyst pairs in which the analyst has actually followed the firm**

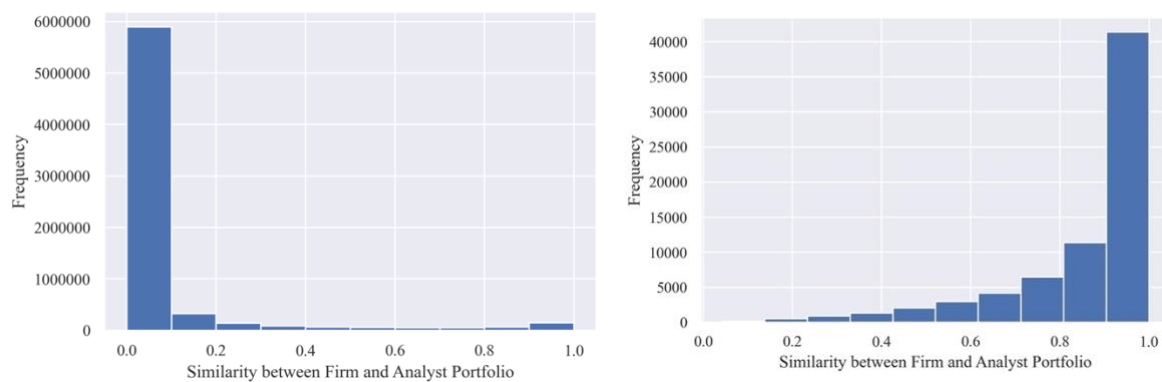


Figure 4-6 Distribution of Similarity Scores between Firms in an Analyst's Coverage Portfolio

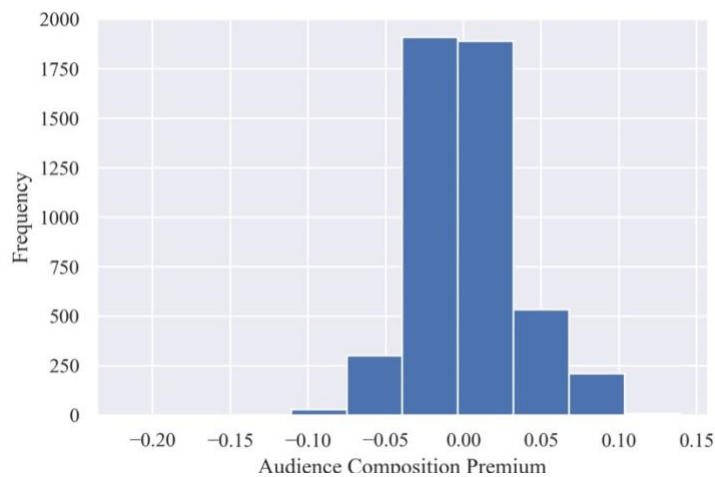


Figure 4-7 Distribution of the Audience Composition Premium

We tested the effect of audience composition premium on the aggregate investment recommendation a firm receives from the analysts who follow it while controlling for other covariates established in prior research. In particular, we controlled for firm size using trade volume (log); for firm performance using return on equity (ROE) and market share; and for firm strategic resource allocation using research and development (R&D) intensity, advertising intensity, and intangibles and depreciation as shares of total assets (Litov et al., 2012). We also controlled for merger and acquisition (M&A) activity using a mergers expenditure (log) variable, since M&As have been shown to affect analyst coverage (Sibilkov, Straska, & Waller, 2013). We also controlled for the number of segments in which a firm reports sales (4-digit SIC) and each firm's average similarity to other firms in its industry (firm typicality) as these factors have been shown to affect audience evaluations (Smith, 2011; Zuckerman, 1999). Similarity to other firms was measured using the same LDA model previously implemented for measuring similarity between firms and analysts' portfolios. At the industry level, we controlled for the number of firms in the industry, industry concentration, and industry heterogeneity (Haans, 2019). We included a detailed description of how each control variable was constructed in Table 2.

Table 4-2 Descriptive Statistics and Measurement of Variables

Variable	Mean	SD	Description
Aggregate Investment Recommendations	3.67	0.35	The average of recommendations given to a firm in a given fiscal year by all analysts covering it. Only the latest recommendation kept for each analyst.
Audience Composition Premium	0.00	0.03	Developed a FunkSVD model using the training set. Used the model to predict ratings for all possible firm-analyst pairs in each year. Used the formula below to calculate the audience composition premium: $\frac{\sum_j Pr_{ij} * Rating_{ij}}{\sum_i Pr_{ij}} - \frac{\sum_j Rating_{ij}}{N}$
Trade Volume (Log)	20.24	1.17	Log of total annual trade volume.
ROE	1.19	2.55	Return on equity.
Market Share	0.15	0.22	Firm sales divided by total sales in a firm's primary industry (SIC 4-digit).
R&D Intensity	0.09	0.15	R&D expenditure divided by total operating expenditure.
Advertising Intensity	0.02	0.04	Advertising expenditure divided by total operating expenditure.
Intangibles (share of total assets)	0.16	0.19	Intangibles as part of fixed assets divided by total assets.
Depreciation (share of total assets)	0.04	0.04	Total depreciation and amortization divided by total assets.
Mergers Expenditure (Log)	-14.57	191.04	Log of pre-tax merger or acquisition expenditure.
Number of Segments	1.53	1.06	Number of segments in which a firm reports sales (4-digit SIC)
Firm Typicality	0.50	0.17	Developed a TF-IDF representation of firms' business descriptions. Measured the similarity between a firm's TF-IDF weight vector and that of its industry's average.
No. of Firms in Industry	77.00	88.31	Number of firms in a firm's industry (4-digit SIC).
Industry Concentration	1113.54	1299.17	Industry concentration measured by the Herfindahl-Hirschman index.
Industry Heterogeneity	0.07	0.03	Industry heterogeneity measured using Haans's (2019) methodology: developed a topic model on firms' business descriptions; measured the distance between a firm's topic model weight vector and that of its industry's average; summed the squared distances and divided by the total number of firms.

4.4.2 Results

In our models, we examined the relationship between audience composition premium and firms' aggregate recommendations. Since our dependent variable is a continuous variable, we used OLS

regressions. We included firm fixed effects to control for unobserved between-firm differences that might affect analyst recommendations. Table 3 demonstrates the results of our tests. Model 1 shows the effect of the audience composition premium variable on aggregate recommendations. Model 2 is similar to Model 1 except it controls for other covariates. The coefficient for analyst composition premium in Model 2 supports our core prediction that a firm that positions itself toward audiences with a positive predisposition toward it will garner higher aggregate recommendations ($\beta = 2.64$; $p = .000$). This suggests that a better positioning strategy resulting in an increase of one standard deviation in audience composition premium could yield an increase of 0.25 standard deviation in analyst recommendations.

Table 4-3 Effects of Audience Composition Premium on Aggregate Investment Recommendations for US Public Firms

	Dependent Variable: Aggregate Investment Recommendations			
	Model 1		Model 2	
	β	p	β	p
Audience Composition Premium	2.864	0.000	2.641	0.000
Trade Volume (Log)			-0.076	0.000
ROE			0.013	0.001
Market Share			0.297	0.143
R&D Intensity			0.088	0.446
Advertising Intensity			0.329	0.618
Intangibles (share of total assets)			0.013	0.894
Depreciation (share of total assets)			-0.016	0.968
Mergers Expenditure (Log)			0.000	0.091
Number of Segments			0.004	0.792
Firm Typicality			-0.143	0.179
No. of Firms in Industry			0.001	0.027
Industry Concentration			0.000	0.017
Industry Heterogeneity			-0.537	0.390
Constant	3.668	0.000	5.233	0.000

N. Observations	3793	3519
R-Squared	0.558	0.582
F-Statistic	109.20	15.248
Prob (F-Statistic)	0.000	0.000

4.5 Discussion and Conclusion

Audiences evaluate organizations through a two-stage process: first, they screen for firms that are worthy of attention and evaluation, and second, they evaluate and rank the ones that pass the first stage (Zuckerman, 1999, 2017). Research has shown that firms need to adopt strategies, such as conforming to category prototypes (Deephouse, 1999; Haans, 2019) or category exemplars (Barlow et al., 2019; Zhao et al., 2018), to garner audience attention, increase their legitimacy in the eyes of audiences, and pass through the first stage of audience evaluations. Most of these studies are built on the assumption of audience homogeneity, presuming that audiences react uniformly to specific firm strategies. More recently, studies have departed from this assumption and have examined the heterogeneity in audience evaluations (Beunza & Garud, 2007; Kim & Jensen, 2011; Kovács & Sharkey, 2014; Pontikes, 2012). These studies have highlighted that audiences adopt different categorization schemas (Paolella & Durand, 2016) due to their idiosyncratic knowledge and expertise (Beunza & Garud, 2007; Theeke et al., 2018) and their different goals and motivations (Bowers & Prato, 2019; Durand & Paolella, 2013; Fleischer, 2009; Glaser et al., 2020).

The premise of audience heterogeneity motivated us to revisit the theories built around the two-stage model. While previous research has suggested that firms benefit from gaining attention and legitimacy in the eyes of audiences, we argue instead that firms can do themselves a disservice by attracting attention from audiences that have a negative predisposition toward them (Kovács &

Sharkey, 2014). Firms only gain an audience composition premium when they influence the composition of audiences evaluating them such that a larger proportion of evaluations are from audiences with a favorable predisposition. Therefore, firms should strategize to influence a specific audience's attention (the first stage in the evaluation process) based on the evaluations they expect to receive from that audience (the second stage in the evaluation process).

In addition to our theoretical arguments, we provide a prescriptive method using machine learning algorithms and test our proposed method empirically in the context of investment recommendations that US public firms receive from security analysts. We show how firms can use the power of machine learning and the availability of big data to develop accurate and reliable models that help them identify and measure audiences' predispositions toward them. We show that firms can increase the probability of being covered by an analyst by positioning themselves near firms in the analyst's coverage portfolio. Firms can thus strategically position themselves such that they receive attention from analysts with a more favorable predisposition toward them (and conversely, become unfamiliar to analysts with a less favorable predisposition). The results of our empirical test demonstrate that the audience composition premium variable operationalized based on the above logic had a significant impact on the aggregate evaluations firms received.

4.5.1 Contributions

Contributions to audience evaluations research. Our study contributes to management research on audience evaluations of firms. First, we extend prior theories building upon the two-stage evaluation model (Zuckerman, 1999, 2017) and research exploring strategies firms could adopt to garner legitimacy and audience attention (e.g., Barlow et al., 2019; Deephouse, 1999; Navis & Glynn, 2011; Zhao et al., 2018). By incorporating the premise of audience heterogeneity, we show the importance of studying the interdependent effects of a firm's positioning strategy on

both stages in the evaluation process. Specifically, we show that firms need to strategically influence a specific audience's attention (stage one) based on how the audience would evaluate them (stage two). Moreover, we argue that not all attention is (equally) positive; receiving attention from an audience member who has a negative predisposition toward a firm could actually harm the firm's total evaluations.

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

Third, we highlight the strategic agency of firms in influencing their audiences' evaluation criteria and categorical expectations. While the extant literature has emphasized the conformity pressure imposed on firms due to the categorical imperative, we highlight firms' ability to strategically target audiences that have a specific categorization and evaluation predisposition toward them. By doing so, we bolster recent work proposing "a move towards a more agency-oriented approach, aiming to redirect scholarly emphasis away from thinking of categories largely

as a constraint or as being ascribed ex ante and homogeneously to whole portions of the market, that is, producers, audiences, and intermediaries” (Durand & Khaire, 2017: 3). To this end, our study puts forward the idea that firms can influence the categorical lens through which they are evaluated by shaping the composition of their audiences.

Contributions to machine learning in strategy research. We contribute to research at the intersection of artificial intelligence and firm strategy. Our study advocates for and advances a new research agenda exploring how machine learning techniques could address specific strategic challenges firms face (Agrawal et al., 2018). As proposed in a series of papers and an influential book by Agrawal and colleagues, machine learning is a predictive machine that could significantly change firms’ strategies (Agrawal et al., 2018, 2019). When prediction is available and reliable, even problems that were not already prediction problems can be reformulated and reframed as prediction challenges (Agrawal et al., 2017). Our study builds upon this insight and suggests that the “what is the optimal positioning strategy” problem could be reformulated as a “how will the market and its key stakeholders react to a specific market position” problem. Given the availability of data and the sophistication of machine learning techniques, firms could predict how specific audience members would react to a given positioning strategy. Through the empirical investigation of security analysts’ evaluations of US public firms, we demonstrate how a specific family of machine learning techniques—namely, recommender systems—could prove particularly useful for this purpose.

Our study is designed to have strong prescriptive value (Bazerman, 2005). As Agrawal and colleagues mentioned (2018: 17), “The most common question board members ask us is: ‘How will AI affect our strategy?’” The question of how machine learning influences strategy is of great concern to managers. Our study provides a practical solution that firms and managers could use to

drive tangible performance outcomes. Our study's message is straightforward and clear, and our proposed methods are implementable within a reasonable resource budget. For instance, a restaurant that is planning to open a new branch in its city could use the insights from our paper to increase its success prospects. Specifically, the restaurant would need to apply our proposed machine learning methodology to Yelp data to identify locations where it could attract audiences with a positive predisposition toward it and gain the highest audience composition premium.

4.5.2 Limitations and Future Research Directions

Our study has limitations that provide grounds for future research. First, our study was conducted using archival data, so our inferences lack the causal strength of a randomized experiment. Today, firms test their machine learning models using the A/B testing methodology, which is based on a randomized controlled experiment logic except it is done in a real-time environment and usually on a large scale. A/B testing experimentation would be ideal for testing our proposed arguments for strategic positioning.

Second, our proposed methodology of using machine learning for predicting audience evaluations limits our study to contexts where big data on audiences' previous evaluations are available and accessible. A consequence of this notion is that data could be regarded as a source of competitive advantage (Ng, 2016). Future studies should therefore investigate the competitive dynamics that arise due to firms' varying degrees of access to audience evaluation data and explore how such competitive advantages could translate into more optimal positioning strategies.

Third, our methodology is applicable when firms or products can have a dynamic positioning strategy. While some firms are relatively flexible in changing their positioning strategies, some products are not. For instance, while a restaurant could change its position based on the evaluations it receives (either through a change in operations or location), the market

positioning of a book or movie could hardly be changed after it has been produced and delivered to the market. As such, future studies may advance our methodology by suggesting strategies for products that have a static market position.

Fourth, due to computational requirements, we limited our sample to firms and analysts for which we had a certain minimum amount of data available. In the recommender systems domain, the problem of dealing with users and items with few previous ratings is known as the “cold start” problem (Aggarwal, 2016) and is usually addressed through more sophisticated algorithms, such as combinations of content-based and collaborative filtering methodologies. Future studies could explore such methodologies, including ensemble methods, and compare the accuracy of these methods against each other for different types of firms and audiences.

4.5.3 Conclusion

In this study, we integrated the premise of audience heterogeneity and firms’ strategic agency into audience evaluations research. We argued that the value of gaining a specific audience’s attention depends on its categorical schema and evaluation predispositions toward the focal firm. Moreover, we conceptualized audience composition premium as the gain in evaluations that a firm could garner by having a favorable audience composition. Building on this insight, we developed a prescriptive method enabling firms to use machine learning to predict audience evaluations and to help them choose optimal strategies based on such predictions. We empirically tested our proposed methodology and showed that firms positioned in a way that attracts attention from customers/analysts with a more favorable predisposition toward them received higher aggregate evaluations. We believe there are immense opportunities to further study how artificial intelligence and machine learning techniques could help address and/or reformulate specific strategic challenges firms face.

CHAPTER FIVE

5 Conclusion and Contributions

External evaluations have an important impact on firm success. Evaluations reduce information asymmetry in markets (Zhao & Zhou, 2011) and give firms access to environmental resources (Pfeffer & Pfeffer, 1981; Pfeffer & Salancik, 1978). Recognition and favorable evaluations from credible external audiences increase a firm's legitimacy and its market value, while the lack of such recognition is shown to lower its valuation (Zuckerman, 1999).

Research has explored strategies that firms should adopt to gain recognition and muster favorable evaluations (Zhao et al., 2017). Optimal distinctiveness research, for instance, suggests that to garner an "optimum" evaluation, firms should balance between the need for similarity and with that of differentiation (Deephhouse, 1999; Navis & Glynn, 2010). On the one hand, by conforming to categorical norms and expectations, firms become recognizable to their audiences and gain legitimacy (Haans, 2019; Zhao et al., 2018). On the other hand, firms need to differentiate themselves from rivals to garner attention and avoid being lost in the crowd (Barlow et al., 2019).

There are three gaps in optimal distinctiveness research that are addressed in the studies featured in this dissertation. First, in the majority of empirical studies on this topic, firms' identities and market positions are assumed to be stable. To address this limitation, in the first study of this paper, I explored the following research question: *How do changes in a firm's identity claims affect its external legitimacy?* I posited that change in identity claims should negatively impact a firm's legitimacy. When a firm undergoes change, there might be an increase in ambiguity and uncertainty surrounding the firm, increasing the cognitive effort needed to evaluate it. Audiences, seeking to economize on their sensemaking efforts, might be reluctant to to expend the extra cognitive effort needed to make sense of the firm and might thus view the firm as less

comprehensible, and consequently, less legitimate. Furthermore, I hypothesized that the negative effect of change on legitimacy is stronger when a firm becomes less prototypical as a result of change and in homogeneous contexts where most firms make similar identity claims. Empirical analysis in the context of security analysts coverage decisions provided support for my hypotheses.

Second, most of optimal distinctiveness research assesses the effects of firms' similarity and differentiation vis-à-vis a single categorical benchmark, usually the category prototype (Deephouse, 1999; Durand & Paoletta, 2013; Haans, 2019). However, recent research has highlighted the importance of other categorical benchmarks, such as category exemplars (Barlow et al., 2019; Zhao et al., 2018). In my second study, I explored the concurrent effects of similarity to both categorical benchmarks, namely, category prototypes and exemplars. I argued that, on the one hand, similarity to a category exemplar, by definition an outstanding and high-performing firm, increases a firm's recognizability and legitimacy, due to the firm being associated with the exemplar. On the other, exemplar similarity could result in a loss in firm evaluations, due to the firm's performance being compared against that of an exemplary high performing firm.

I posited that the outcome of the interplay between these two mechanisms—benefit of association and cost of comparison—depends on a firm's typicality—i.e., its degree of similarity to the category prototype. Typical firms with moderate degrees of exemplar similarity can balance association and comparison mechanisms to gain an optimal evaluation outcome. Therefore, the interplay between the two mechanisms results in an inverted U-shaped relationship between the degree of exemplar similarity and a typical firm's market value. But atypical firms achieve sharp gains either at low levels of exemplar similarity, where the cost of comparison is weak, or at high levels of exemplar similarity, where the benefit of association outweighs the cost of comparison. This implies a U-shaped relationship between the degree of exemplar similarity and an atypical

firm's market value. I found support for my predictions using a longitudinal study of public firms' market values and investment recommendations they received.

Third, optimal distinctiveness research, in general, assumes that categorical schema and evaluation models are commonly held mental models among audiences. As a result, research has assumed that audiences categorize firms uniformly and that similar evaluation models are used for assessing firms within a specific category. Recent research, however, has demonstrated that there is heterogeneity in how audiences categorize and evaluate firms (Beunza & Garud, 2007; Kovács & Sharkey, 2014; Paoletta & Durand, 2016; Pontikes, 2012). So, in my third study, I explored firms' optimal positioning strategy in light of such heterogeneity in audiences' evaluation models. Using ML algorithms' predictive power for deriving predictions regarding audiences' individualized predispositions toward a firm, I suggested that firms can position themselves in markets such that they attract mostly audiences that have a favorable predisposition toward them. I conceptualized the term "audience composition premium," i.e., the increase in positive evaluations that is due to the composition of audiences evaluating an entity. I developed a recommender system for predicting security analysts' investment recommendations and found support for my core suggestions by conducting empirical assessment pertaining to investment recommendations that public firms received.

5.1 Contributions

My dissertation makes several key contributions. First, by incorporating the role of cognitive economy into the study of audiences' reactions to firm changes, it extends prior studies on firm identity changes that only focus on antecedents and internal processes of change. My first study highlighted the external costs for firms undergoing changes. Specifically, I showed that even though change is sometimes a necessary measure for adapting with the times, it could come at the

cost of a firm becoming unrecognizable and less legitimate in the eye of external audiences. Furthermore, I extended prior literature on firm identity change by studying the differential effects of change when accounting for the direction of change relative to peer firms. Specifically, I showed that a change resulting in greater differentiation from peers is associated with greater legitimacy loss.

Second, it contributes to optimal distinctiveness research by examining audiences' evaluations in settings where category prototypes and exemplars both serve as viable benchmarks for evaluations. By pinpointing association and comparison as two key mechanisms determining the effects of exemplar similarity on audience evaluations, I provided a more fine-grained understanding of the socio-cognitive mechanisms underlying audience evaluations in dual benchmark settings where both prototypes and exemplars serve as relevant, yet distinct, category benchmarks. In contrast to prior research, I showed that similarity to a category exemplar is not necessarily related to an increase in audience evaluations. I demonstrated that the interplay between the benefit of being associated with an exemplar and the cost of being compared against one results in a U-curved relationship between exemplar similarity and evaluations that a firm receives. My findings thus advanced research on the consequences of similarity to category exemplars.

Third, it extends research on the two-stage evaluation model by studying the interdependent effects of the two stages on the eventual evaluations that a firm receives. Specifically, I argued that firms need to position themselves such that they receive a specific audience's attention (stage one) based on how the specific audience would evaluate the firm (stage two). I showed that the aggregate evaluation that a firm receives depends on not only the quality and unbiased impression that it makes on audiences, but on the specific group of audiences that

opt to evaluate it. In other words, I showed that firms can gain an “audience composition premium” by strategically positioning such that they receive evaluations mostly from audiences with a positive predisposition toward them. My theoretical arguments and findings extend prior research on optimal positioning strategies by suggesting that, to gain an optimal evaluation, firms should be strategic not only in relation to positioning relative to categorical benchmarks, such as prototypes and exemplars, but also relative to their audiences’ idiosyncratic and heterogeneous evaluation schema.

Fourth, it makes empirical and methodological contributions. I conducted my studies in the context of security analysts’ coverage and evaluations of public US firms from 1997 to 2018. I thus validated my theoretical assertions on a key audience group—i.e., security analysts—using a large sample of firms. By applying NLP techniques and machine learning algorithms on the Item 1 section of 10-K filings, I was able to measure a firm’s positioning over time and in relation to other firms, with an enhanced accuracy compared to previous management research on this topic. Furthermore, by introducing a new family of machine learning algorithms, i.e., recommender systems, to management research, my work advances the methodological frontier of management research. Specifically, my third study showcases how, in contexts where big data is available, management research could utilize the pattern recognition power of machine learning algorithms to theorize about firm strategies based on idiosyncrasies within firms and audiences.

Through these three essays I sheds light on some underexplored areas regarding how a firm’s positioning within a market affects the external audience evaluations that it receives. I provided a fine-grained theoretical and empirical investigation of the effects of firm positioning vis-à-vis its past, in relation to multiple categorical benchmarks, and relative to audiences with heterogeneous predispositions. I hope that this work encourages future empirical studies that take

advantage of the availability of big data and sophisticated modeling algorithms to delve into a more nuanced examination of firm positioning strategies, given idiosyncratic and individualized characteristics of firms and audience.

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