DOES IMITATION HELP OR HARM PERFORMANCE? BOUNDARY CONDITIONS AND LONGITUDINAL EVIDENCE FROM S&P 500 FIRMS

Abstract. Strategy research is divided on whether imitation erodes or builds competitive advantage, with contradictory theoretical assumptions and sparse empirical evidence. We address this impasse using text-based measures that capture latent information on imitation as strategic convergence around innovation topics. Analyzing nearly ten thousand annual reports from S&P500 firms across fifteen years, we provide novel large-scale empirical evidence reconciling static and dynamic imitation theories. Imitation benefits shareholder returns and short-term operational performance via capability building but erodes long-term profitability. Critically, we establish boundary conditions: sectoral uncertainty enables learning and amplifies imitation benefits, whereas global uncertainty creates strategic paralysis. Firm strength shows minimal moderation, rendering imitation as a democratic strategy. Our findings integrate temporal, environmental, and organizational contingencies governing when imitation builds versus erodes competitive advantage.

Keywords: *Imitation; innovation; firm performance; topic modelling, S&P500*

INTRODUCTION

Strategic imitation - the 'attempt to reproduce [...] another firm's product, processes, capabilities, technologies or [strategic] decision [...]' (Posen et al. 2023, p. 76), occupies a central yet paradoxical position in strategy research. On one hand, imitation is described as the primary mechanism through which competitive advantages erode: When firms reproduce valuable resources, they destroy the rareness that creates rents (Barney 1991; Peteraf 1993). On the other hand, imitation also enables competitive advantage: when firms learn from competitors and recombine knowledge, they build capabilities that drive innovation and performance (Teece et al. 1997; Posen et al. 2013; Posen & Martignoni 2018). This tension manifests in a fundamental theoretical question: Does strategic imitation enhance or erode firm performance?

Despite imitation's theoretical centrality, this question remains empirically ambiguous and underexplored. Posen et al. (2023) comprehensively reviewed 338 publications on imitation and found management scholars divided between two contradictory models. The *static model* assumes imitation is easy, weak firms imitate, uncertainty fosters imitation, and knowledge transfer erodes advantages. The *dynamic model* assumes imitation is difficult, strong firms imitate, uncertainty hinders imitation, and knowledge recombination fosters innovation. Critically, the literature seldom tests the imitation-performance relationship empirically and when they do, studies rely on small samples from narrow contexts with data from decades past, yielding contradictory findings (Banker et al. 2013; Barreto & Baden-Fuller 2006; Deephouse 1999; Giachetti et al. 2017; Giachetti & Pira 2022). This empirical void perpetuates the theoretical stalemate: without robust evidence on whether imitation helps or harms performance, the field cannot adjudicate between competing models or specify the boundary conditions under which each mechanism operates. In this paper, we provide the first large-scale, longitudinal empirical evidence from S&P500 firms on the imitation-performance relationship. We uncover the temporal dynamics of imitation and identify the boundary conditions under which imitation is beneficial for the firm. Specifically, we reveal how the magnitude and type of uncertainty and the relative strength of the imitating firm, alter outcomes across various performance measures. In doing so, we address the diagnosed long-standing theoretical impasse and join the most recent efforts, for example Sharapov & Ross (2023), who study the question of whom a leader should imitate in the context of sailboat racing. We directly respond to Posen et al.'s call for robust empirical insights on the imitation dichotomy and provide systematic evidence on how imitation relates to performance, when it does, and for whom. To provide this evidence, we leverage established machine learning techniques (Blei et al. 2003; Bellstam et al. 2021; Hutto & Gilbert 2014) and unveil hidden patterns in nearly 10,000 annual reports from S&P 500 firms. We construct firm-year measures of imitation behavior as correlated communication patterns around innovation topics (Hwang & Salmon 2004; Nofsinger & Sias 1999) over a period of 15 years. To perform deep empirical analysis, we measure whether firms discuss similar topics as peers and whether they adopt similar evaluative stances toward those innovation topics. We then test how these imitation measures predict stock returns, revenue growth, and profitability growth across multiple time horizons. Simultaneously, we systematically examine the boundary conditions to adjudicate between the static and dynamic models of imitation. Our empirical findings reconcile the theoretical divide of the literature by demonstrating that both models hold under different conditions. In the short to medium term, imitation positively predicts shareholder returns and firm performance, supporting the dynamic model's capability-building logic. However, in the long-term, operational performance (sales, profitability) decrease, thus revealing the static model's rent-erosion mechanism. Boundary condition tests further sharpen theoretical understanding: sectoral uncertainty *enhances* imitation benefits by enabling interpretable vicarious learning, while global uncertainty creates strategic paralysis where imitation provides minimal differentiation. Surprisingly, imitation appears to be remarkably democratic: firm strength shows negligible moderating effects, as both strong and weak firms experience similar outcomes. Complementary tests of early-mover behavior provide mirror-image validation: pioneers experience negative performance outcomes from e.g., bearing costs that imitators avoid.

This study makes three contributions. First, we clarify and extend imitation theory (Makadok et al. 2018) by providing the first systematic, large-scale evidence contributing to the imitation-performance debate. We advance the discussion from whether imitation helps or harms performance to specifying *when*, *where*, and for *whom* each mechanism operates (Posen et al. 2023). Specifically, we demonstrate that dynamic mechanisms dominate short-term and under sectoral uncertainty, while static mechanisms emerge long-term and under global uncertainty. Second, we reconcile static and dynamic models by establishing these temporal and environmental boundary conditions, revealing an integrated framework where both mechanisms may operate sequentially and contingently rather than in opposition. Third, methodologically, we address a long-standing research gap by transforming imitation from a challenging-to-measure, often contested construct into an empirically tractable phenomenon. By employing established text-based measures that capture hidden imitation patterns across thousands of annual reports, we reveal latent strategic information on imitation at an unprecedented S&P500 scale.

THEORY AND HYPOTHESES

Human beings, by their very nature, are social creatures, and this inherent sociality has played a crucial role in our evolutionary history. From the earliest days of hunter-gatherer societies to the complex world of the global economy, the tendency to align our actions and decisions with those of others - a phenomenon also known as herding - has been a constant presence. This instinct, deeply embedded in the human psyche, drives us to look to our peers for cues on how to behave, which can help us in situations of uncertainty or ambiguity (Keynes 1937), but can also lead to inefficient decisions (Banerjee 1992). Transposed to the firm level, where companies can make similar strategic decisions and follow competitors' behaviors (Simon & Lieberman 2010; Haunschild & Miner 1997; Keister 2004), the theoretical idea of imitation has developed in central, yet paradoxical, pillar in strategy research (Posen et al. 2023). On the one hand, imitation is traditionally described as the primary mechanism through which firm heterogeneity and competitive advantages erode (Lippman & Rumelt 1982; Peteraf 1993; Barney 1991). Here, imitation reduces the rareness and value of resources, dissipating rents, and dissolving the very advantage firms seek to protect (Levinthal 1997, 2011; Rivkin 2000). On the other hand, firms also benefit by learning from others (Levitt & March 1988; Terlaak and Gong 2008), and absorbing knowledge (Cohen & Levinthal 1990) from their environment (Strang & Soule 1998; Jaffe et al. 2000). As such, imitation becomes essential to the firm's ability to integrate, build, and reconfigure internal and external resources to address rapidly changing environments (Posen & Martignoni 2018; Posen et al. 2023) and thus improve and sustain their own competitive advantages (Teece et al. 1997; Eisenhardt & Martin 2000). However, this paradoxical tension on the nature of imitation-performance relationship manifested in a severe theoretical divergence in the strategy and management literature: Posen et al. (2023) distils the underlying assumptions of imitation theorizing from hundreds of peer-reviewed articles into dichotomous static and dynamic understanding of imitation. The static model assumes imitation is easy, weak firms imitate, and uncertainty fosters imitation, resulting in erosion of competitive advantages. Contradictory, the dynamic model assumes imitation is difficult, strong firms imitate, uncertainty hinders imitation, and firms recombine target knowledge where imitation drives innovation and performance (Posen et al. 2013; Posen & Martignoni 2018; Wang et al. 2023). Imitation is no longer a mere dyadic process between leaders and followers, but also an ongoing market-level phenomenon in which firms are simultaneously targeted by multiple others while also imitating many in return (Posen et al., 2023). The fundamental divergence in the underlying assumptions between the static and dynamic model of imitation however hinders theoretical progress and results in a myriad of frictions (Posen et al. 2023). One key reason for this persistent dichotomy is the lack of robust and general empirical evidence on the very nature of the imitation-performance relationship. While the imitation-performance relationship is already rarely tested, and when so, rather via simulation approaches (Posen et al. 2023; Ethiraj & Zhu 2008), the few existing empirical studies lack generalizability, are often outdated, and yield inconsistent findings regarding the performance outcomes of imitation. For example, Deephouse (1999), Barreto & Baden-Fuller (2006), Sirmon & Hitt (2009), and Wu & Salomon (2016) use data from the banking sector on their lending practices or decisions to open subsidiary offices; the data is predominantly from the 1980s and 1990s with small sample sizes. A second line of empirical evidence uses data from mobile phone vendors and the telecommunications sector, again with small sample sizes and data from the early 2000s (Banker et al. 2013; Giachetti et al. 2017; Giachetti & Pira 2022). The most recent study, by Sharapov & Ross (2023), reports a positive imitation-performance relationship, yet its context, sailboat racing, raises questions about generalizability of these findings for managerial decision-making and whether such evidence alone is sufficient to reconcile the deep theoretical divide between static and dynamic models of imitation. To empirically address this paradox, we draw on Posen et al. (2023)'s dynamic model linking imitation to improved firm performance, while additionally grounding our hypotheses in the economic foundations of imitation and extending them with a complementary deduction about the inverse relationship between imitation benefits and pioneering efforts.

Hypothesis (H1). *Imitation behavior has a positive effect on firm performance.*

We argue that the dynamic view of imitation provides a compelling theoretical foundation for understanding the imitation-performance relationship. Among the assumptions that managers and stakeholders intend to take conscious and reinforced decisions to improve firm performance, imitation directly supports a firm's dynamic capabilities by strengthening its abilities to sense, seize and transform. Specifically, imitation enhances sensing through improved access to external intelligence about market opportunities and technological developments. Next, it facilitates seizing by reducing the risks and costs associated with entirely novel approaches while leveraging firms' absorptive capacity (Cohen & Levinthal 1990; Davis & Aggarwal 2020). Finally, it enables transformation by fostering resource reconfiguration, and the development of new competencies (Eisenhardt & Martin 2000). As such, imitation behavior should improve firm performance. Importantly, imitation thus can be more than mere copying but a strategic learning mechanism. The outcomes of such behavior are expected to be associated with improve performance, aligning with broader views on strategic learning processes such as vicarious learning, where firms learn from others' experiences without bearing the full costs of exploration and experimentation (Levitt & March 1988; Terlaak & Gong 2008). In summary, the dynamic perspective views imitation as the driver of performance by enabling competitive advantage when firms learn, reproduce, and combine resources (Teece et al. 1997; Posen et al. 2013; Posen & Martignoni 2018; Wang et al. 2023). The theoretical foundations of imitation in the form of economic herding - aligning one's own actions with the ones of others - provide additional theoretical support for a positive imitation-performance relationship. Although herding can carry negative connotations due to its association with irrational conformity, it can represent rational behavior under, for example, uncertainty (Banerjee 1992; Bikhchandani et al. 1992; Ross 1973; Scharfstein & Stein 1990). As firms are rather expected to combine private and public information than completely disregarding their own knowledge, the outcomes of such should also contrast from pure herding where actors abandon all private information and can experience negative performance outcomes (Devenow & Welch 1996; Haunschild & Miner 1997; Keister 2004; Simon & Lieberman 2010). Imitation should fundamentally differ from mindless copying where only weak firms imitate without strategic intent (DiMaggio et al. 1983; Vasudeva 2013; Korn & Baum 1999) or seek legitimacy for potential mistakes (Dye et al. 2014). As corporate growth is furthermore not necessarily constrained by market liquidity, what distinguishes it from financial herding (Komalasari et al. 2022; BenMabrouk 2018; Jiang & Verardo 2013), multiple firms should be able to benefit simultaneously from successful innovations (Argyres et al. 2015) and avoid adverse outcomes that occurs when incumbents fail to recognize and adopt superior knowledge from competitors (Christensen & Bower 1996). Unlike scenarios where herding can lead to suboptimal equilibria, imitation enables firms to build upon successful practices while adding their own capabilities and innovations (Argyres et al. 2015; Sharapov & Ross 2023). In summary, from economic and strategic perspectives, firms are assumed to discern patterns, leverage collective insights, and make informed choices that enhance their performance.

Critically, a positive imitation-performance relationship carries important theoretical implications. If imitators systematically avoid the costs and risks borne by early movers while capturing similar benefits, early movers should experience disadvantages. Conversely, if imitation should have a negative effect, early movers should benefit from first-mover advantages and unique resources. Consistent with Hypothesis 1, which suggests a positive imitation-performance relationship, we expect negative early-mover-outcomes.

Hypothesis (H2). *Being an early-mover has a negative effect on firm performance.*

Early-movers face substantial burdens when pioneering new markets or technologies (Lieberman & Montgomery 1988). This means they bear expenses of market education, technology refinement, and overcoming initial resistance, costs that imitators would systematically avoid by observing others' experiences. Simultaneously, knowledge spillovers play a critical role in diminishing early-mover benefits (Jaffe et al. 1993; Hoppe 2000), as later entrants leverage early-movers' trials and errors to sidestep pitfalls and enhance their strategic positioning (Eisenhardt & Martin 2000; Suarez & Lanzolla 2005). This aligns with evidence that failing to learn from others may be a main cause of incumbent failure (Christensen & Bower 1996). Importantly, both perspectives on imitation and early-mover behavior should not be treated as mutually exclusive. The relative strength of imitation versus early-mover advantages determines which effect predominates; yet, under certain boundary conditions, both mechanisms may operate simultaneously, be attenuated, or amplified. Given the sparse empirical evidence (e.g., Banker et al. (2013); Barreto & Baden-Fuller (2006); Deephouse (1999); Giachetti et al. (2017); Giachetti & Pira (2022)), clarifying the underlying assumptions of imitation would allow to reconcile the competing theoretical camps. Thus, aligned with Sharapov & Ross (2023), we extend the testing of boundary conditions to who the imitator is and under what conditions the imitation is happening. For example, previous research showed, that imitation should yield superior outcomes particularly in complex or changing environments (Rivkin 2000). We test how uncertainty and firm strength moderate imitation outcomes (Posen et al. 2023).

Hypothesis (H3A). *The imitation-performance relationship is moderated by firm strength and the degree of uncertainty.*

Similarly, and considering auxiliary Hypothesis H2, we also test whether early-mover outcomes are moderated by the firm strength, and conditions of high or low uncertainty.

Hypothesis (H3B). *The early-mover–performance relationship is moderated by firm strength and the degree of uncertainty.*

Together, testing H3A and H3B serves to provide a more nuanced understanding of the imitation-performance and early-mover-performance relationships. Specifically, they aim to reconcile the static and dynamic theoretical perspectives by refining the theoretical understanding of the assumptions and boundary conditions of imitation theory.

EMPIRICAL STUDY

To measure imitation behavior at scale, we employ established machine learning techniques, including topic-modeling (Blei et al. 2003; Bellstam et al. 2021) and sentiment analysis Hutto & Gilbert (2014); Choudhury et al. (2019), on large textual datasets. Our novel approach systematically transforms the previously difficult-to-observe phenomena of imitation into measurable constructs by analyzing hidden patterns in official firm communications of S&P 500 companies as expressed in their annual 10-K reports. The advantage of using these reports lies in their nature as long-panel data: they are updated annually, represent a reliable and standardized information source, and are legally required to disclose accurate formulations regarding firms’ risks, strategic plans, major projects, dependencies, and legal proceedings. Because 10-K filings capture both favorable outcomes and inconvenient details, they provide an exceptionally rich and objective dataset that has not previously been employed in the literature to empirically investigate the imitation-performance relationship.

When studying imitation, it is furthermore important to note that the imitation-behavior does not happen vacuum and that the context matters. We take on the challenge of measuring imitation not only at a novel scale but also within one of the theoretically most interwoven and practically relevant contexts: *innovation* (Posen et al. 2023). Innovation provides a particularly suitable context for two reasons: First, it is theoretically central to imitation research, as seminal works have established innovation as the primary domain in which firms face the strategic tension between conformity and differentiation (Barney 1991; Peteraf 1993; Teece et al. 1997; Posen et al. 2023). Second, innovation contexts are typically characterized by the adoption of technologies and practices that enable new products, services, processes, or business models to improve performance (Nguyen & Agrawal 2023; Christensen 1997; Zhou et al. 2005), thus suitable to understand imitation behavior and competitive dynamics (Christensen 1997).

Lastly, and aligned with Posen et al.'s (2023) findings, we view imitation as an ongoing market-level process, where each actor can imitate all other actors at the same time, while possibly also being target by multiple actors simultaneously.

Research Design

Our empirical strategy builds on a simple yet compelling idea: if firms are imitating each other, this should be observable in how they communicate about certain topics (e.g., innovation, business models, products, challenges, and opportunities). Thus, when they follow similar paths, their language, emphasis, and sentiment around key topics should exhibit correlated patterns.

To execute on this empirical strategy, the study follows a four-stage process. First, we systematically identify patterns in the language companies use to discuss innovation-related topics and capture how these elements evolve dynamically over time. Here, we apply a well-established machine-learning topic modelling technique to a corpus of annual reports to extract the innovation topics (Bellstam et al., 2021). Second, we observe how individual firms communicate around and about these innovation topics through intensity of discussion and sentiment towards the topic. Third, we calculate imitation behavior as the degree to which individual firm communication patterns correlate with the ones of their peers. Here, we overcome major empirical issues by not attempting to directly observe whether firms copy each other's actions but rather build on the economic foundations of imitation, and measure imitation as the 'observable correlated behavior of a group of organizations, occurring consciously or unconsciously, as they pursue similar opportunities or evaluate topics and trends in similar manners at the same time (Hwang & Salmon 2004; Nofsinger & Sias 1999). Thus, we can capture both conscious imitation (where firms deliberately follow others) and unconscious imitation (e.g., similar response to environmental pressures). In essence, we observe the outcome of their actions via their communication patterns. Simultaneously, and considering our auxiliary hypotheses we also observe whether firms address innovation topics early, or more positively before others. Fourth, we test whether firms exhibiting higher imitation (or early-mover behavior) achieve heterogenous performance outcomes. We employ robust panel regression techniques with multiple performance measures across varying time horizons.

In summary, our approach yields three methodological contributions. First, we develop dynamic innovation contexts using topic modeling, and as such overcome the limitation of pre-defined keyword lists (Miric et al. 2023). Second, we measure imitation as correlation patterns of communication around innovation topics, and as such overcome the diagnosed previous empirical narrowness. Third, we combine different communication indicators to capture nuances of imitation, and ultimately regress imitation (and early-mover) behavior against various dimensions of firm performance. Our conceptual framework is summarized in Figure 1.

INSERT FIGURE 1 HERE

Variables

We employ indicators capturing how firms communicate about innovation topics. We use these communication indicators as the basis for calculating imitation and early-mover variables.

Lastly, we define firm strength and uncertainty variables for boundary condition testing. Our operationalized framework is depicted in Figure 2, and a summary of all variables in Table 1.

INSERT TABLE 1 HERE

INSERT FIGURE 2 HERE

Innovation context and topic modelling. Our approach requires addressing a fundamental challenge: What constitutes 'innovation language' in corporate communications? We tackle this challenge using an established machine learning technique - topic modelling - which identifies words that constitute topics (Blei et al. 2003). Topic-modelling was seminally employed by Bellstam et al. (2021) to measure innovation. Furthermore, our approach is dynamic and longitudinal: we track emerging innovation topics year by year. By doing so, we overcome the limitations of static, expert-defined topics that quickly become outdated (Miric et al. 2023). Next, we use those innovation topics to understand how firms communicate around them.

Communication indicators. In this study, we extract nuanced understandings on how firms communicate about innovation topics. We capture not only the intensity but also the tone around the innovation topics. The first communication indicator, *Mentions*, measures the frequency with which firms discuss innovation topics. It is defined as the raw count of topic-words appearing in each report. This indicator reflects the timing and intensity of topic discussion, a key variable in prior empirical work on imitation (Giachetti et al. 2017; Giachetti & Pira 2022). The second indicator, *Sentiment*, captures the emotional tone or evaluative stance that firms adopt toward the innovation topic. Measuring sentiment is important because merely identifying whether firms discuss, for instance, cloud computing may not reveal whether they support or oppose it. Consider the difference between 'Cloud computing will help us with [..]' and 'Cloud computing is risky because [...] .' Thus, these represent different positions. Accordingly, the sentiment indicator identifies whether firms perceive certain innovation topics as, e.g., beneficial, or undesirable (Davis 1989; Devaraj et al. 2008; Schepman & Rodway 2023). Incorporating sentiment adds an important dimension to our analysis by showing not only whether firms engage with innovation topics but how they position themselves toward them. In the next step, we relate these firm-level communication indicators to those of other firms. Comparing patterns across firms allows us to construct imitation and early-mover variables.

Imitation variables. To test Hypothesis 1, we use each communication indicator to construct independent variables that capture the degree to which a firm's communication correlates with the ones of their peers. Concretely, we measure the imitation variable as observable correlated behavior of firms, occurring consciously or unconsciously, as they pursue similar opportunities or evaluate topics and trends in similar manners at the same time (Hwang & Salmon 2004; Nofsinger & Sias 1999). Building on this definition, we develop a text-based imitation variable that views imitation as an ongoing process in which all actors could simultaneously imitate and be imitated by multiple others (Posen et al. 2023), avoiding limitations of dyadic approaches (Haveman 1993). Concretely, the imitation variable is computed as Spearman rank correlation between each firm's communication indicator and the market average over a five-year period.

$$Imitation_{ObservationPeriod} = \rho(FirmIndicator, MarketAverage), \tag{1}$$

where ρ represents Spearman's rank correlation coefficient. High positive correlations indicate that a firm's communication patterns closely align with the ones of others. High negative correlations suggest contrarian behavior, while correlations near zero indicate independent paths. We use Spearman rank correlation rather than Pearson's *r*, as it better captures relative co-movement patterns consistent with the theoretical views of imitation among peers. To compute these correlations, we employ 5-year observation period to ensure statistical reliability while maintaining sufficient data points for performance analysis. This period is arguably sufficient to ensure that imitation patterns reflect meaningful and stable behavioral trends, rather than short-term fluctuations, yet also shifts in firms' communication over time. Shorter observation windows would make the measure more sensitive to temporary noise and isolated events, while substantially longer windows would blur meaningful temporal dynamics. The 5-year horizon therefore provides a balanced perspective, capturing medium-term imitation behavior while maintaining sufficient variation for subsequent performance testing. Figure 3 visualizes the mechanics of the imitation variable. We use the imitation variable logic from Equation 1 on both communication indicators, thus yielding the (i) *Imitation mentions variable*, measuring the correlation between a firm's frequency of innovation discussions and market-wide patterns, and (ii) for *Imitation sentiment variable*, capturing correlation in sentiment.

Early-mover variables. To test the auxiliary Hypothesis 2, we construct independent variables that capture whether firms address innovation topics ahead of their peers (Lieberman & Montgomery 1988; Giachetti et al. 2017; Giachetti & Pira 2022). Early-mover variables are calculated as the sum of differences between firm indicators and market averages across the 5-year observation period for each new dynamic innovation topic:

$$\sum_{year} EarlyMover = FirmIndicator_{year} - MarketAverage_{year} \ , \qquad (2)$$

where *year* moves from the first to last year of the observation period. Positive values indicate above-average emphasis on the newest innovation topic, suggesting early-mover behavior. Figure 3 illustrates the logic of Equation 2, used to calculate two variables: (i) *Early-mover mentions*, which measure a firm's above-average frequency of innovation discussions compared to the market, and (ii) *Early-mover sentiment*, which captures a firm's above-average positive sentiment toward innovation topics relative to the market.

INSERT FIGURE 3 HERE

Performance variables. Following Posen et al.'s (2023) call for robust and diverse performance measures in imitation research, we examine three key dimensions across 1-, 2-, and 5-year horizons: stock returns, sales change, and EBIT (earnings before interest and taxes) change. Stock returns measure annualized percentage changes in stock prices, reflecting shareholder value and forward-looking market expectations. Sales change captures percentage changes in revenue, indicating whether strategic choices translate into market success. EBIT changes reflect operational profitability beyond revenue expansion. The multiple time horizons enable us to examine whether imitation effects are temporary, dynamic, or persistent.

Boundary condition variables. To test Hypothesis 3 and the boundary conditions of imitation, we employ uncertainty and firm strength at global and sectoral levels. Following the seminal approach of Baker et al. (2016), we measure uncertainty as the frequency with which firms use 'uncertainty' or 'uncertain' in their communications. Critically, uncertainty can vary in scope: sectoral uncertainty may enable interpretable learning, whereas global uncertainty affects all firms uniformly, potentially limiting the information value of imitation (Sutcliffe & Zaheer, 1998). We therefore distinguish global uncertainty (based on all S&P 500 firms) from sectoral uncertainty (based on within-industry firms, classified by GICS (Global Industry Classification Standard)). We measure firm strength as each firm's stock performance percentile over 5 years (Sirmon et al. 2010), computed globally (relative to all firms) and sectoral (relative within sector). This two-level design provides granularity to test whether the static model (uncertainty facilitates imitation) or the dynamic model (uncertainty hinders imitation) prevails.

Data

We populate the variables defined above with data from S&P 500 firms, including annual 10-K reports and financial performance indicators from 2009–2023.

Company sample. Our sample includes all firms listed in the S&P 500 index during 2009-2022. The S&P 500 represents roughly 80% of U.S. market capitalization (S&P Global 2024), and its constituents typically operate globally, developing dynamic capabilities required to achieve and sustain their index positions (Uotila et al. 2009). To mitigate survivorship bias, we track persistent and transitory members throughout the observation period (Fung & Hsieh 1997). We impose the following data requirements: Firms must have (i) at least five consecutive years of annual reports to enable imitation measurement; (ii) at least one subsequent year of performance data, and (iii) normal operations. The latter condition excludes episodes the episodes of extreme performance (e.g., returns in the thousands of percentage points from extraordinary events such as SPAC listings or accounting adjustments rather than operational outcomes). We implement this safeguard using a standard inter-quartile range (IQR) filter to detect and remove such error observations. The final sample size varies across regressions depending on data availability, the performance variable, the corresponding time horizon.

Corporate communications data. We collect 9,552 annual 10-K reports filed by sample companies during 2009-2022, sourced from the University of Notre Dame SEC/EDGAR database. The 10-K report is an SEC-mandated annual disclosure providing comprehensive strategic and operational information (Nguyen & Agrawal 2023). Analyzing corporate sentiment and strategy through 10-K reports, including topic modeling to measure innovation, is well-established in management research, and serve as a valuable source for three reasons (Bellstam et al. 2021; Li et al. 2013; Bayer et al. 2017; Nousiainen et al. 2022; Nguyen & Agrawal 2023): First, SEC regulations and legal liability for misstatements ensure reliable disclosure of strategic initiatives, including innovation investments. Second, the standardized format and annual frequency enable systematic comparison across firms and time periods. Third, the substantial length and detail provide rich textual data for innovation measurement.

Performance data. We obtain financial performance data from 2009-2023 from WRDS's Center for Research in Security Prices/Compustat Merged databases. Performance data includes: (i) stock returns, computed from monthly prices adjusted for dividends and splits and compounded to annual returns;(ii) sales growth, calculated as year-over-year percentage changes in net sales; and (iii) EBIT growth, calculated as year-to-year percentage changes in EBIT.

Methodology

This section describes the analytical procedures applied to operationalize our framework and test our hypotheses. We follow a systematic four-stage approach that transforms raw data into testable variables and empirical results. First, we apply topic modeling to extract dynamic innovation topics from the corpus of annual reports. Second, we measure firm-level communication indicators using these topics. Third, we construct our key independent variables and assemble the panel dataset with the dependent performance variables (see Figure 4 for panel data structure). Fourth, we estimate panel regressions to test the imitation-performance relationship. Throughout these stages, we employ established analytical tools and diagnostic procedures to ensure validity and reliability. Figure 5 provides an overview of the process.

Text processing and feature extraction. First, we transform unstructured textual data from the 10-K annual reports into structured communication indicators. This stage comprises three sequential steps: (i) identifying innovation language through topic modelling; (ii) extracting frequency-based mentions; and (iii) measuring sentiment orientation.

For the topic-modelling, we apply Latent Dirichlet Allocation (LDA) to identify innovation-related language for each year in our sample period (2009-2022). LDA is a probabilistic machine learning technique that detects patterns of word co-occurrence (Blei et al. 2003), robust for measuring innovation from text data (Bellstam et al. 2021). For each year, we aggregate the annual reports and extract topics from this yearly corpus. This yields innovation dictionaries with the top hundred innovation-related words for each year. LDA produces coherent and distinct topics, enabling confident identification of the innovation context (Bellstam et al. 2021).

For the mentions extraction: we use the year-appropriate innovation dictionary. We measure the frequency with which each firm discusses innovation topics in their annual 10-K report. Specifically, we count the raw occurrences of the topic words appearing in each document. We employ raw counts rather than document-length-normalized frequencies to preserve information about the absolute emphasis firms place on innovation topics (Li et al. 2013; Giachetti et al. 2017). This yields the *Mentions* communication indicator for each firm-year observation.

For the sentiment extraction: we capture the evaluative stance firms adopt toward innovation topics. For each sentence in the annual report containing innovation topics, we perform sentiment analysis using VADER (Valence Aware Dictionary for Sentiment Reasoning), a deterministic, lexicon-based tool designed for text analysis (Hutto & Gilbert 2014). We use the sentiment model to produces a score ranging from -1 (negative) to +1 (positive) for each sentence. We compute the average innovation sentiment score for all annual reports, yielding the *Sentiment* communication indicator for each firm and year.

Variable population and panel assembly. We now use Equations 1 and 2 to calculate the imitation and early mover variable values based on the communication indicators we just extracted. This involves: (i) calculating market-level aggregates, (ii) computing firm-specific imitation and early-mover scores and structuring the panel with appropriate temporal alignment.

For each year and communication indicator, we first calculate market-wide averages by taking the mean across S&P 500 firms with available data in that year. These averages serve as benchmark against which individual firm behavior is compared. We implement rolling 5-year observation windows to populate the imitation and early-mover variables. This rolling-window approach generates multiple observations per firm. For instance, a firm present from 2009-2022 contributes observations for windows ending in 2013, 2014, 2015, through 2022 (ten distinct measurement periods). Each window produces one set of imitation and early-mover scores. Crucially, we enforce strict temporal separation between independent and dependent variables. For each measurement window ending in year t (e.g., 2009-2013 ending in 2013), we link the calculated imitation and early-mover scores to forward-looking performance outcomes measured over subsequent periods: 1-year performance covers year $t + 1$ (e.g., 2014), 2-year performance covers years $t + 1$ to $t + 2$ (e.g., 2014-2015), and 5-year performance covers years $t + 1$ to $t + 5$ (e.g., 2014-2018). This structure ensures that all independent variables are calculated using only information available at time t, while all dependent variables reflect outcomes materializing after time t. The resulting panel contains multiple overlapping observations per firm across different measurement windows (see Figure 4 for an example of the panel data assembly).

INSERT FIGURE 4 HERE

Descriptive statistics. Before estimating regression models, we examine the distributional properties and relationships of the variables. These are presented in the results section.

Econometric specification and estimation. We follow standard econometric procedures (Berry 1993; Wolf & Best 2013) and estimate panel regressions with firm and year fixed effects to control for time-invariant firm characteristics as specified in the following Equation 3:

$$Performance_{i,t+k} = \alpha + \beta_1 ImitationMentions_{i,t} + \beta_2 ImitationSentiment_{i,t} + \beta_3 EarlyMoverMentions_{i,t} + \beta_4 EarlyMoverSentiment_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t}, \tag{3}$$

where $Performance_{i,t+k}$ is firm i's performance in period $t + k$; γ_i and δ_t represent firm and year fixed effects, respectively; and ε_{it} is the idiosyncratic error term.

We estimate this model for each combination of performance (stock returns, sales change, EBIT change) and time horizon *k* (1-, 2-, 5-year). Our significance thresholds, while ultimately arbitrary, corresponds to 10%, 5%, and 1%, as used in sentiment-based contexts (e.g., Nauhaus et al., 2021). We report robust standard errors, observing alignment with the thresholds.

Robustness and validation. We conduct several robustness checks to ensure findings are not methodological artifacts. First, we verify robustness to dictionary construction by repeating analyses using the static Disruptive Innovation Score (DIS) dictionary (Nguyen and Agrawal 2023; Bloom et al. 2021) instead of our dynamic LDA topics. Consistent results across both approaches validate our findings, while differences in significant factors illuminate the value of dynamic context adaptation over static dictionaries (Miric et al. 2023). Second, and alternative to firm fixed effects, we repeat the estimations with random effects specifications.

Figure 5 summarizes the entire empirical study from raw text data to regression results.

INSERT FIGURE 5 HERE

RESULTS

We now present results from testing the three hypotheses. We begin with descriptive statistics and model-free evidence, followed by regression results. The descriptives (see Table 2) show imitation variables means near zero with substantial variation, indicating heterogeneous imitation behavior. Early-mover variables display higher average mention counts but sentiment measures center near zero, indicating that while some firms actively discuss innovation topics early, their evaluative stances vary widely. Together, the substantial variation in both imitation and early-mover variables reflects heterogeneous strategic positioning relative to innovation topics.

INSERT TABLE 2 HERE

Pairwise correlations between variables (Table 3) provide initial support for our expectations. Imitation variables show positive performance correlations, while early-mover variables show negative correlations across time horizons. These patterns align with our hypotheses: imitation is associated with better performance (H1), whereas early-movers incurring disadvantages (H2).

INSERT TABLE 3 HERE

We proceed with the systematic regression analysis. Table 4 reports the main results on relationships between imitation, early-mover behavior, and performance across the time horizons and outcomes. All models include firm and year fixed effects and are estimated using OLS with heteroskedasticity-robust standard errors. Results are robust to alternative specifications with consistent coefficient signs and minor differences in magnitude and significance (see Appendix A, Table A1). Tables 5 and Table 6 present the boundary condition tests covering global and sectoral uncertainty and firm strength for the most relevant five-year performance horizon (see Appendix A, Table A3-A6 for full results over other horizons). We organize results around our hypotheses, examining: (i) the temporal dynamics of imitation and performance, (ii) early-mover behavior and performance, and (iii) the boundary conditions moderating these relationships.

INSERT TABLE 4 HERE

Imitation and Firm Performance

Hypothesis 1 predicts that imitation positively affects firm performance through capability building. Results provide nuanced support. We examine the two imitation dimensions: imitation-mentions (topic convergence) and imitation-sentiment (evaluative alignment). For stock returns, imitation mentions show positive coefficients across horizons (1-year: $\beta = 1.75$, $p < 0.05$; 5-year: $\beta = 3.36$). Strikingly, imitation sentiment reveals progressively strengthening coefficients over time: non-significant at 1 year ($\beta = 0.37$), significant at 2 years ($\beta = 2.36$, $p < 0.05$), and highly significant at 5 years ($\beta = 8.25$, $p < 0.01$), suggesting substantial long-term shareholder benefits. This pattern aligns with the dynamic model where imitators integrate competitors' knowledge with their own capabilities, creating value through recombination (Posen et al. 2023; Wang et al. 2023), noticed by the financial markets. Operational performance, however, reveals a temporal reversal. For sales, imitation mentions show positive short-term coefficients (1-year: $\beta = 0.66$, $p < 0.05$; 2-year: $\beta = 0.91$, $p < 0.1$) that sharply reverse at 5 years ($\beta = -1.56$). Imitation sentiment mirrors this pattern, with a significant negative 5-year coefficient ($\beta = -2.14$, $p < 0.05$). EBIT results demonstrate this striking inversion even more: imitation sentiment shows significant positive coefficients at 1-2 years ($\beta = 1.31$ and 1.92, both $p < 0.05$) but reverses to negative at 5 years (β = -3.25, p < 0.1). This divergence between positive market returns and eventually negative operational performance offers reconciliation of the static and dynamic models.

We evaluate two competing interpretations. First, the pattern reflects the fundamental tension between capability development and rent erosion. Short-term, imitation enables dynamic capabilities, enhancing abilities to sense, seize, and transform through absorptive capacity and vicarious learning (Cohen & Levinthal 1990; Levitt & March 1988; Teece et al. 1997), thus generating positive returns. However, in the long-term, the static model's predictions manifest: continued imitation increases strategic similarity, eroding performance differentiation and rents (Barney 1991; Peteraf 1993). Thus, when sales decline, EBIT follows. The alternative explanation recognizes that EBIT can decline through not only through reduced revenues but also increased costs or spending. The long-term EBIT inversion could reflect rising investment costs rather than falling sales: successful imitators might engage in additional exploratory R&D (March 1991), that then depresses profitability. Critically, however, we can rule out this investment-driven explanation: additional regressions show imitation does not predict meaningful R&D spending changes across all time horizon (see Appendix A: Table A2).

In summary, H1 receives support with temporal qualifications. Imitation consistently predicts positive stock performance (stock market recognizes the dynamic model). For operations, imitation corresponds to short-term benefits (dynamic model) that again reverse in the long-term as competitive similarity erodes operational rents (static model).

Early-Movers and Firm Performance

Hypothesis 2 predicts early-movers experience negative performance outcomes. Results provide strong and consistent support. We examine early-mover mentions (novel topic emphasis) and early-mover sentiment (favorable early tone). For stock returns, early-mover mentions show marginally negative short-term coefficients (1-year: β = -7.02, p < 0.1) that attenuate over time. Strikingly, early-mover sentiment has increasingly negative coefficients: non-significant at 1 year but significantly negative at 2 years (β = -12.84, p < 0.05) and 5 years (β = -24.10, p < 0.05), as markets progressively discount pioneering strategies and knowledge spillovers enable imitators to benefit without equivalent costs (Jaffe et al. 1993; Lieberman & Montgomery 1988). EBIT results reveal persistent negative outcomes: early-mover mentions show negative coefficients across all horizons (1-year: $\beta = -8.42$, $p < 0.01$; 5-year: $\beta = -10.85$), indicating pioneering immediately imposes operational costs. Sales show initial capture (1-year: $\beta = 3.62$, $p < 0.05$) that reverses long-term (5-year sentiment: $\beta = -11.22$, $p < 0.05$), reflecting initial market excitement dissipating as e.g., imitators enter with refined products (Suarez & Lanzolla 2005). These findings support three interrelated mechanisms. First, direct pioneering costs: early-movers invest heavily in unproven approaches, market education, and navigating uncertainties without observing others' experiences (Lieberman & Montgomery 1988), directly reducing profitability. Second, knowledge spillover asymmetries: early-movers bear knowledge generation costs while imitators benefit from observing outcomes without equivalent investment (Jaffe et al. 1993; Hoppe 2000), entering with reduced uncertainties and refined strategies. Third, path dependency constraints: early commitments constrain flexibility when superior approaches emerge, whereas imitators adopt refined strategies from the outset, combining observed information with internal knowledge (Cohen & Levinthal 1990).

Critically, these findings further adjudicate between H1's two EBIT interpretations. Recall imitation showed positive short-term (1-2 years: $\beta = 1.31$-1.92, $p < 0.05$) but negative long-term EBIT coefficients (5-year: $\beta = -3.25$, $p < 0.1$). We proposed: (a) initial capability development with later rent erosion, or (b) capability building followed by increased R&D investments. The early-mover results also support explanation (a): if rent erosion drives long-term declines, early-movers should face also negative outcomes as imitators converge and erode differentiation. Consistent with this, early-movers show persistent negative EBIT and sales coefficients, indicating pioneering costs depress profitability while subsequent imitation erodes rents. This pattern supports the temporal reconciliation of imitation as capability builder and rent eroder.

Boundary Conditions

We proceed with the moderating boundary conditions. Hypothesis 3A and 3B posit that the static and dynamic imitation models diverge on their boundary conditions (Posen et al. 2023). We test how uncertainty scope (global vs. sectoral) and firm strength moderate performance outcomes. Table 5 and 6 report the 5-year period. For all other periods see Tables A3-A6 in Appendix A.

Uncertainty's spatial scope: strategic paralysis versus bounded learning. Uncertainty's spatial scope, global versus sectoral, emerges as the critical moderator. Global uncertainty reflects S&P 500-wide conditions; sectoral uncertainty reflects within-industry conditions. A divergence reveals striking magnitude differences and directional reversals. For stock returns, global uncertainty creates strategic paralysis: strong negative interactions with imitation mentions (β = -1.584, $p < 0.05$) and dramatically amplified early-mover disadvantages (early-mover mentions: β = -3.637, $p < 0.05$; early-mover sentiment: β = -3.197, $p < 0.05$), as pioneering under broad uncertainty compounds burdens of market education and navigating unproven approaches (Lieberman & Montgomery 1988). Markets discount both strategies when uncertainty is global. In sharp contrast, sectoral uncertainty enables strategic learning: imitation sentiment shows positive interactions (β = 0.358, $p < 0.1$), and early-mover penalties are half the global magnitude (β = -1.716, $p < 0.01$). The 1.9 percentage point reversal for imitation mentions (global: β = -1.584 versus sectoral: β = 0.311) demonstrates markets reward imitation under sectoral uncertainty while penalizing it under global uncertainty. Operational performance reveals complementary trade-offs. For EBIT, sectoral uncertainty shows stronger negative interactions with imitation mentions (β = -0.310, $p < 0.01$) than global uncertainty (β = -0.133), reflecting operational costs of adapting to sector-specific dynamics: firms sacrifice short-term profitability while building capabilities, consistent with knowledge recombination arguments (Posen et al. 2013; Posen & Martignoni 2018; Wang et al. 2023). Conversely, global uncertainty shows positive interactions with early-mover mentions for EBIT (β = 1.155, $p < 0.05$), suggesting strategic hold-up: firms rather delay pioneering under global uncertainty (Luoma et al. 2017), reducing expenses but destroying market value, as the stock market expects lower returns. Sales show negative moderation, though the global coefficient (β = -0.684, $p < 0.05$) is 1.8x stronger than the sectoral coefficient (β = -0.376, $p < 0.05$).

This divergence provides crucial empirical reconciliation. When uncertainty is sector-specific and bounded, the dynamic model mechanisms seem to operate: firms observe peer responses, integrate knowledge (Cohen & Levinthal 1990), leverage early-mover experiences for refined strategies (Eisenhardt & Martin 2000; Suarez &Lanzolla 2005), and engage in recombination generating competitive advantage while avoiding incumbent failure (Christensen & Bower 1996). When uncertainty is global, neither imitation nor pioneering is associated with positive outcomes: Imitation provides little differentiation, while pioneers face amplified disadvantages. This finding extends Posen et al. (2023)'s dichotomy: it is not whether uncertainty is high or low, but whether it is interpretable and bounded (enabling learning) versus broad and exogenous (disabling differentiation). Spatial scope matter as much as temporal dynamics in determining when imitation builds capabilities or erodes performance.

Firm strength: democratic imitation and asymmetric pioneering costs. The dynamic model predicts strong firms benefit more from imitation. Our results provide limited support. Firm strength shows non-significant interactions with imitation variables across horizons and measures. These null findings suggest imitation benefits accrue equally to strong and weak firms, thus imitation represents a democratic strategic capability. In sharp contrast, strong firms face significantly greater pioneering costs. For EBIT, early-mover mentions interact negatively with both global strength (β = -0.912, $p < 0.01$) and sectoral strength (β = -0.844, $p < 0.01$). Neither model explicitly predicts this. We argue strong firms may face higher opportunity costs diverting resources to unproven efforts, pioneering by leaders attracts intense imitative responses accelerating knowledge spillovers (Jaffe et al. 1993; Hoppe 2000), and established routines create greater disruption when pioneering (Christensen 1997). This asymmetry reveals that firm strength does not amplify imitation benefits but substantially increases pioneering costs.

Collectively from testing H3, uncertainty's spatial scope emerges as a powerful moderator, with 2 to 4 times magnitude differences and directional reversals. Sectoral uncertainty enables dynamic learning while global uncertainty creates strategic paralysis discounting both imitation and early-mover behavior. Firm strength shows minimal moderating on imitation but amplifies pioneering costs. These patterns complement our temporal reconciliation: imitation generates short-term benefits while also erasing long-term rents. Uncertainty's spatial scope determines whether imitation enables strategic learning or reflects undifferentiated responses. Our results point toward an integrated framework where temporal dynamics, environmental scope, and organizational context jointly determine when imitation builds advantage versus erodes rents.

In summary, the main and moderated effects demonstrate that the core predictions of dynamic and static models hold under certain conditions. These findings underscore that imitation is neither universally beneficial nor harmful, but rather a behavior whose outcomes are contingent on temporal horizons and type and degree of uncertainty. Therefore, our text-based innovation measure (Bellstam et al. 2021) and large-scale approach enable us to discover new nuances of imitation behavior. We proceed with implications for theory and further research.

DISCUSSION AND CONCLUSION

In this paper, we show that the performance outcomes of imitation are predictable once key contingencies are made explicit. With this evidence, we contribute to a highly debated theoretical construct within Penrosean-based theories. To the best of our knowledge, this is the first study to systematically extract and interpret *latent* imitation signals from firms' 10-K communications at *S&P 500* scale. We leverage established NLP tools (e.g., dynamic topic modeling and sentiment analysis) to recover firms' stated strategic positioning and vision as communicated to investors, rather than relying only on *ex post* actions. Our contributions are threefold: (i) we perform a deep analyze on S&P 500 firms over fifteen years to extract latent signals of imitation behavior; (ii) we introduce novel text-based variables that translate these signals into measurable insights, by combining well-established machine-learning techniques with econometric modeling in a robust, replicable manner; and (iii) we clarify and extend management theory (Makadok et al. 2018) by testing the performance outcomes and critical boundary conditions of imitation behavior. We unveil how temporal dynamics, as well as the scope of uncertainty (global versus sectoral) and firm strength, moderate between the static and dynamic theoretical models of imitation.

Posen et al. (2023)'s comprehensive synthesis of over three hundred publications in top-ranked management journals documents a field fundamentally divided between two competing perspectives: a static model that predicts rent erosion and a dynamic model that predicts capability building. Prior studies relied on small samples and narrow contexts, thereby hindering theoretical progress. Our study overcomes this impasse and supplies the robust empirical foundation needed to integrate the competing static and dynamic perspectives. We ultimately contribute to a fundamental theoretical question of the strategy field: *why and how* sources of performance heterogeneity arise, manifest, and change (Rumelt 1984). Our findings reveal more granular, empirically driven insights into imitation and how it shapes performance outcomes under different conditions. This shifts the conversation from whether imitation is good to how, and under what conditions, it creates value (Posen et al. 2023; Sharapov & Ross 2023). In what follows, we summarize the theoretical implications with respect to our hypotheses and discuss how our findings advance strategy theory by reconciling static and dynamic views on imitation.

Theoretical Implications

Temporal dynamics of imitation benefits reconcile competing views. Hypothesis 1's findings, that imitation positively predicts firm performance, support the dynamic model's core premise (Posen et al. 2023), yet also reveals theoretically richer temporal patterns. In the short to medium term, imitation is associated with enhanced performance, aligned with the dynamic model that argues firms leverage absorptive capacity (Cohen & Levinthal 1990) to integrate external knowledge, building capabilities (Teece et al. 1997; Eisenhardt & Martin 2000; Posen & Martignoni 2018). The stock markets reward such innovation alignment, recognizing, that e.g., incumbents avoid failure (Christensen & Bower 1996). However, operational performance reverses at five years, revealing the static model's predictions after some time: in the long-term imitation erodes performance. We rule out the possibility that imitators reinvest gains into exploratory activities. Instead, both mechanisms tend to operate sequentially where capability development transitions into rent dissipation.

Early-mover costs validate imitation mechanisms. Hypothesis 2's provides validation by mirrored symmetry: imitation creates value via e.g., spillovers while avoiding early-mover costs (Lieberman & Montgomery 1988; Jaffe et al. 1993). Our findings support this bidirectional pattern and strengthens confidence in coexisting static and dynamic models of imitation.

Boundary conditions reveal mechanisms. Hypotheses 3A and 3B test boundary conditions that critically refine when imitation and early-mover strategies appear to succeed or fail. *Uncertainty's scope* (H3A) shapes which outcomes firms should expect. We find that it is not merely the presence or magnitude of uncertainty, it is the dimensionality that matters. When uncertainty is *sectoral* (bounded), the dynamic model's predictions are observable; sectoral uncertainty *enhances* imitation benefits, supporting that firms engage in meaningful vicarious learning when facing interpretable challenges (Posen et al. 2013; Wang et al. 2023). Conversely, when uncertainty is *global* and firms face identical uncertainty intensities, benefits attenuate substantially, creating *strategic paralysis* where imitation provides minimal differentiation. Operational magnitude differences are striking: global uncertainty is two to four times worse than sectoral. Uncertainty's scope determines whether imitation enables strategic learning (Posen et al. 2023) or undifferentiated herding (Bikhchandani et al. 1992; Banerjee 1992). Lastly, firm strength (H3A, H3B) predictions receive limited support: imitation benefits appear democratic, accruing equally to strong and weak firms. Notably, H3B reveals that strong firms experience *greater* early-mover costs than weak firms, e.g., due to higher opportunity costs and competition.

In summary, we contribute to strategy and management theory by reconciling imitation from a binary discussion to a temporal and dimensional contingency, where time horizons and uncertainty's scope determine whether capability building or rent erosion dominates.

Future Research

We open several avenues for future research to advance theory along multiple fronts: the role of industry characteristics, an extension of boundary conditions, and a theory of imitation depth.

Industry characteristics should shape when imitation's short-run capability gains erode into long-run rent dissipation. Future work should identify each sector's 'imitation window' and 'rent half-life' by mapping knowledge complexity, technological dynamism, and competitive intensity. This would articulate when firms should learn from peers versus pivot to differentiation. Industry-focused studies could leverage natural experiments to support causal claims. Next, uncertainty should be theorized not only by scope and magnitude, but also by nature: disentangling technological, regulatory, demand, or competitive uncertainty could explain how bounded, interpretable uncertainty enhances imitation's payoff. The agenda is to map combinations of uncertainty scope, type, and intensity that amplify versus attenuate imitation outcomes, thereby further investigating the conditions of value creation and strategic paralysis. Lastly, the distinction between topical overlap and evaluative imitation invites a theory of imitation depth. Future measurement innovation building on our approach could reveal which aspects they selectively imitate, and at what pace. Triangulating text-based measures with secondary data (e.g., hiring, patents) would help address endogeneity concerns by distinguishing intentional imitation from spurious correlation driven by common environmental pressures.

Together, this would enable addressing core theoretical questions: Where does optimal imitation depth lie to capture near-term gains without accelerating ren erosion? When does deeper alignment expand the competitive pie rather than hasten commoditization? How do firms balance absorbing external knowledge with maintaining distinctive positions? Tracing finer-grained degrees of imitation would advance strategy research and deepen our understanding on the sources of competitive advantage.

REFERENCES

Argyres, N., Bigelow, L., and Nickerson, J. A. (2015). Dominant designs, innovation shocks, and the follower's dilemma. *Strategic Management Journal*, 36:216–234.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4):1593–1636.

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*,107:797–817.

Banker, R., Cao, Z., Menon, N. M., and Mudambi, R. (2013). The red queen in action: The longitudinal effects of capital investments in the mobile telecommunications sector. *Industrial and Corporate Change*, 22:1195–1228.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*,17:99–120.

Barreto, I. and Baden-Fuller, C. (2006). To conform or to perform? mimetic behaviour, legitimacy-based groups and performance consequences*. *Journal of Management Studies*, 43:1559–1581.

Bayer, E., Tuli, K. R., and Skiera, B. (2017). Do disclosures of customer metrics lower investors' and analysts' uncertainty but hurt firm performance? *Journal of Marketing Research*, 54:239–259.

Bellstam, G., Bhagat, S., and Cookson, J. A. (2021). A text-based analysis of corporate innovation. *Management Science*, 67:4004–4031.

BenMabrouk, H. (2018). Cross-herding behavior between the stock market and the crude oil market during financial distress. *Managerial Finance*, 44:439–458.

Berk, J. and DeMarzo, P. (2007). *Corporate Finance*. Pearson Education, 6 edition.

Berry, W. D. (1993). *Understanding regression assumptions*, volume 92. Sage.

Bikhchandani, S., Hirshleifer, D., and Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 100:992–1026.

Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, 3:993–1022.

Bloom, N., Hassan, T. A., Kalyani, A., Lerner, J., and Tahoun, A. (2021). The diffusion of new technologies.

Choudhury, P., Wang, D., Carlson, N. A., and Khanna, T. (2019). Machine learning approaches to facial and text analysis: Discovering ceo oral communication styles. *Strategic Management Journal*, 40(11):1705–1732.

Christensen, C. M. (1997). *The innovator's dilemma : when new technologies cause great firms to fail*. Harvard Business School Press.

Christensen, C. M. and Bower, J. L. (1996). Customer power, strategic investment, and the failure of leading firms. *Strategic Management Journal*, 17:197–218.

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35:128.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13:319.

Davis, J. P. and Aggarwal, V. A. (2020). Knowledge mobilization in the face of imitation: Microfoundations of knowledge aggregation and firm-level innovation. *Strategic Management Journal*, 41:1983–2014.

Deephouse, D. L. (1999). To be different or to be the same? it's a question (and a theory) of strategic balance. *Strategic Management Journal*, 20.

Devaraj, S., Easley, R. F., and Crant, J. M. (2008). How does personality matter? relating the five-factor model to technology acceptance and use. *Information Systems Research*, 19:93–105.

Devenow, A. and Welch, I. (1996). Rational herding in financial economics. *European Economic Review*, 40:603–615.

DiMaggio, P. J., Powell, W. W., et al. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American sociological review*, 48(2):147–160.

Dye, K. C., Eggers, J. P., and Shapira, Z. (2014). Trade-offs in a tempest: Stakeholder influence on hurricane evacuation decisions. *Organization Science*, 25:1009–1025.

Eisenhardt, K. M. and Martin, J. A. (2000). Dynamic capabilities: what are they? *Strategic Management Journal*, 21:1105–1121.

Ethiraj, S. K. and Zhu, D. H. (2008). Performance effects of imitative entry. *Strategic management journal*, 29(8):797–817.

Fung, W. and Hsieh, D. A. (1997). Survivorship bias and investment style in the returns of ctas. *The Journal of Portfolio Management*, 24:30–41.

Giachetti, C., Lampel, J., and Pira, S. L. (2017). Red queen competitive imitation in the u.k. mobile phone industry. *Academy of Management Journal*, 60:1882–1914.

Giachetti, C. and Pira, S. L. (2022). Catching up with the market leader: Does it pay to rapidly imitate its innovations? *Research Policy*, 51:104505.

Haunschild, P. R. and Miner, A. S. (1997). Modes of interorganizational imitation: The effects of outcome salience and uncertainty. *Administrative Science Quarterly*, 42:472.

Haveman, H. A. (1993). Follow the leader: Mimetic isomorphism and entry into new markets. *Administrative Science Quarterly*, 38:593.

Hoppe, H. C. (2000). Second-mover advantages in the strategic adoption of new technology under uncertainty. *International Journal of Industrial Organization*, 18:315–338.

Hutto, C. and Gilbert, E. (2014). Vader: A parsimonious rule-based model for sentiment analysis of social media text. *Proceedings of the International AAAI Conference on Web and Social Media*, 8:216–225.

Hwang, S. and Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance*,11:585–616.

Jaffe, A. B., Trajtenberg, M., and Fogarty, M. S. (2000). Knowledge spillovers and patent citations: Evidence from a survey of inventors. *American Economic Review*, 90:215–218.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, 108:577–598.

Jiang, H. and Verardo, M. (2013). Does herding behavior reveal skill? an analysis of mutual fund performance. *SSRN Electronic Journal*.

Keister, L. A. (2004). Capital structure in transition: The transformation of financial strategies in china's emerging economy. *Organization Science*, 15:145–158.

Keynes, J. M. (1937). The general theory of employment. *The Quarterly Journal of Economics*, 51:209.

Komalasari, P. T., Asri, M., Purwanto, B. M., and Setiyono, B. (2022). Herding behaviour in the capital market: What do we know and what is next? *Management Review Quarterly*, 72:745–787.

Korn, H. J. and Baum, J. A. C. (1999). Chance, imitative, and strategic antecedents to multimarket contact. *Academy of Management Journal*, 42:171–193.

Levinthal, D. A. (1997). Adaptation on rugged landscapes. *Management Science*, 43:934–950.
Levinthal, D. A. (2011). A behavioral approach to strategy—what's the alternative? *Strategic Management Journal*, 32:1517–1523.
Levitt, B. and March, J. G. (1988). Organizational learning. *Annual Review of Sociology*, 14:319–338.
Li, F., Lundholm, R., and Minnis, M. (2013). A measure of competition based on 10-k filings. *Journal of Accounting Research*, 51:399–436.
Lieberman, M. B. and Montgomery, D. B. (1988). First-mover advantages. *Strategic Management Journal*, 9:41–58.
Lippman, S. A. and Rumelt, R. P. (1982). Uncertain imitability: An analysis of interfirm differences in efficiency under competition. *The Bell Journal of Economics*, 13:418.
Luoma, J., Ruutu, S., King, A. W., and Tikkanen, H. (2017). Time delays, competitive interdependence, and firm performance. *Strategic Management Journal*, 38(3):506–525.
Makadok, R., Burton, R., & Barney, J. (2018). A practical guide for making theory contributions in strategic management. *Strategic Management Journal*, 39(6), 1530-1545.
Malone, T. W., Weill, P., Lai, R. K., D'Urso, V. T., Herman, G., Apel, T. G., and Woerner, S. (2006). Do some business models perform better than others? *SSRN Electronic Journal*.
March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2:71–87.
Miric, M., Jia, N., and Huang, K. G. (2023). Using supervised machine learning for large-scale classification in management research: The case for identifying artificial intelligence patents. *Strategic Management Journal*, 44:491–519.
Nauhaus, S., Luger, J., and Raisch, S. (2021). Strategic decision making in the digital age: Expert sentiment and corporate capital allocation. *Journal of Management Studies*, 58(7):1933–1961.
Nguyen, H. and Agrawal, A. (2023). Disruptive innovation and ipo outcomes: Evidence from machine learning. *SSRN Electronic Journal*.
Nofsinger, J. R. and Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *The Journal of Finance*, 54:2263–2295.
Nousiainen, E., Ranta, M., Ylinen, M., and Järvenpää, M. (2022). Using machine learning and 10-k filings to measure innovation. *SSRN Electronic Journal*.
Peteraf, M. A. (1993). The cornerstones of competitive advantage: A resource-based view. *Strategic Management Journal*, 14:179–191.
Posen, H. E., Lee, J., and Yi, S. (2013). The power of imperfect imitation. *Strategic Management Journal*, 34:149–164.
Posen, H. E. and Martignoni, D. (2018). Revisiting the imitation assumption: Why imitation may increase, rather than decrease, performance heterogeneity. *Strategic Management Journal*, 39:1350–1369.
Posen, H. E., Ross, J. M., Wu, B., Benigni, S., and Cao, Z. (2023). Reconceptualizing imitation: Implications for dynamic capabilities, innovation, and competitive advantage. *Academy of Management Annals*, 17:74–112.
Rivkin, J. W. (2000). Imitation of complex strategies. *Management Science*, 46:824–844.Ross, S. A. (1973). The economic theory of agency: The principal's problem. *The American Economic Review*, 63:134–139.
Rumelt, R. P. (1984). Towards a strategic theory of the firm. *Competitive Strategic Management*, 26:556–570.
Scharfstein, D. S. and Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, 80:465–479.
Schepman, A. and Rodway, P. (2023). The general attitudes towards artificial intelligence scale (gaais): Confirmatory validation and associations with personality, corporate distrust, and general trust. *International Journal of Human–Computer Interaction*, 39:2724–2741.
Sharapov, D. and Ross, J. (2023). Whom should a leader imitate? using rivalry-based imitation to manage strategic risk in changing environments. *Strategic Management Journal*, 44:311–342.
Simon, D. H. and Lieberman, M. B. (2010). Internal and external influences on adoption decisions in multi-unit firms: the moderating effect of experience. *Strategic Organization*, 8:132–154.
Sirmon, D. G. and Hitt, M. A. (2009). Contingencies within dynamic managerial capabilities: Interdependent effects of resource investment and deployment on firm performance. *Strategic management journal*, 30(13):1375–1394.
Sirmon, D. G., Hitt, M. A., Arregle, J.-L., and Campbell, J. T. (2010). The dynamic interplay of capability strengths and weaknesses: investigating the bases of temporary competitive advantage. *Strategic Management Journal*, 31(13):1386–1409.
S&P Global (2024). S&5 500 equity.
Strang, D. and Soule, S. A. (1998). Diffusion in organizations and social movements: From hybrid corn to poison pills. *Annual Review of Sociology*, 24:265–290.
Suarez, F. and Lanzolla, G. (2005). The half-truth of first-mover advantage. *Harvard Business Review*.
Sutcliffe, K. M. and Zaheer, A. (1998). Uncertainty in the transaction environment: an empirical test. *Strategic management journal*, 19(1):1–23.
Teece, D. J., Pisano, G., and Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18:509–533.
Terlaak, A. and Gong, Y. (2008). Vicarious learning and inferential accuracy in adoption processes. *Academy of Management Review*, 33:846–868.
Uotila, J., Maula, M., Keil, T., and Zahra, S. A. (2009). Exploration, exploitation, and financial performance: analysis of sp 500 corporations. *Strategic Management Journal*, 30:221–231.
Vasudeva, G. (2013). Weaving together the normative and regulative roles of government: How the norwegian sovereign wealth fund's responsible conduct is shaping firms' cross-border investments. *Organization Science*, 24:1662–1682.

Wang, L., Wu, B., Pechmann, C., and Wang, Y. (2023). The performance effects of creative imitation on original products: Evidence from lab and field experiments. *Strategic Management Journal*, 44:171–196.
Wolf, C. and Best, H. (2013). *The SAGE Handbook of Regression Analysis and Causal Inference*. SAGE Publications Ltd.
Wu, Z. and Salomon, R. (2016). Does imitation reduce the liability of foreignness? linking distance, isomorphism, and performance. *Strategic Management Journal*, 37:2441–2462.
Zhou, K. Z., Yim, C. K. B., and Tse, D. K. (2005). The effects of strategic orientations on technology- and market-based breakthrough innovations. *Journal of Marketing*, 69:42–60.

Figure 1. Conceptual Framework

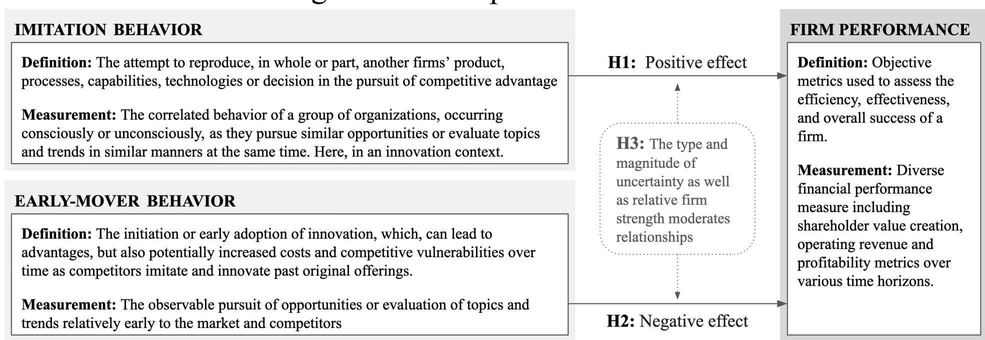

Figure 2. Operationalizing the Framework

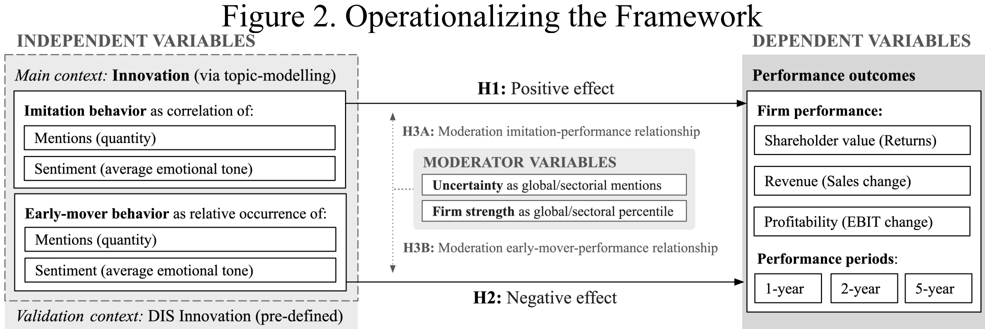

Figure 3. Imitation and Early-mover Variable Construction

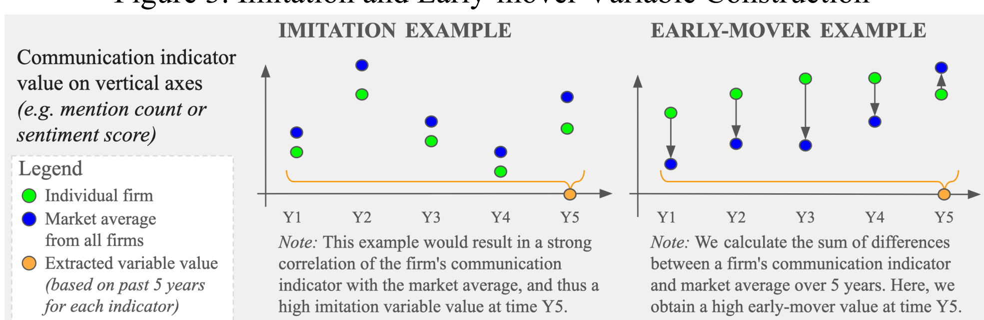

Figure 4. Panel Data Structure: Observation and Performance Periods

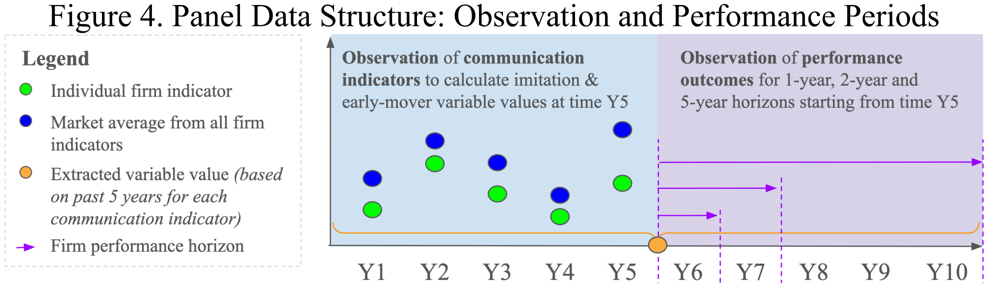

Figure 5. Method: From Data to Results

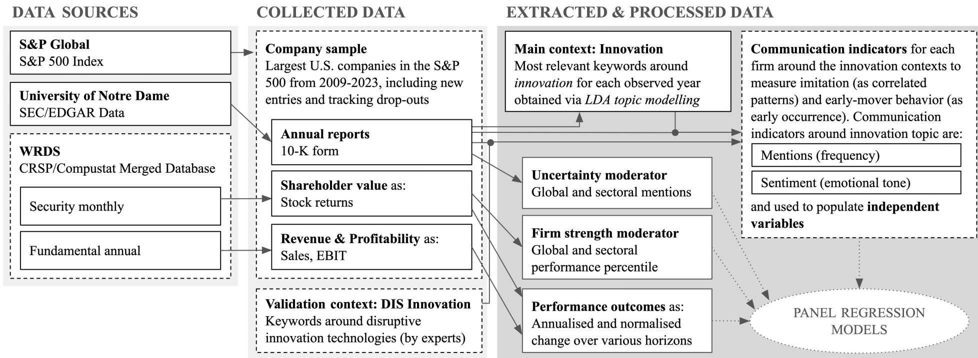

Table 1. Summary of Variables

Variable Category	Measure	Literature
Communication Indicator Variables		
Mentions	Frequency counts of innovation topic occurrences	Giachetti et al. (2017); Li et al. (2013)
Sentiment	Sentiment analysis scores on innovation topic discussions	Hutto and Gilbert (2014); Ribeiro et al. (2016)
Imitation Variables		
Imitation mentions	Correlation of topic mentions with market/peers	Both novel approaches based on Hwang & Salmon (2004); Nofsinger & Sias (1999)
Imitation sentiment	Correlation of topic sentiment with market/peers	
Early-mover Variables		
E.-m. mentions	Sum of above-average mentions	Lieberman & Montgomery (1988)
E.-m. sentiment	Sum of above-average sentiment	Lieberman & Montgomery (1988)
Boundary Condition Variables		
Uncertainty	Global or sectoral frequency counts of “uncertainty” or “uncertain” mentions	Baker et al. (2016); Sutcliffe and Zaheer, 1998; Posen et al., 2023
Strength	Global or sectoral 5-year stock performance percentile	Sirmon et al. (2010)
Performance Variables		
Stock returns	1-, 2-, 5-year annualized returns	Posen et al. (2023); Berk & DeMarzo (2007)
Sales change	1-, 2-, 5-year revenue changes	Posen et al. (2023), Berk & DeMarzo (2007)
EBIT change	1-, 2-, 5-year profitability changes	Posen et al. (2023), Berk & DeMarzo (2007)

Table 2. Descriptive Statistics

Variable	mean	std	min	25%	50%	75%	max
Imitation mentions	-0.023	0.500	-1.000	-0.400	0.000	0.300	1.000
Imitation sentiment	0.012	0.516	-1.000	-0.400	0.000	0.400	1.000
E.-m. mentions	123.727	5255.1067	-9445.157	-3394.641	-965.935	2371.4331	41068.897
E.-m. sentiment	0.003	0.227	-1.116	-0.131	0.0164	0.147	0.829

Note on Early-mover mentions: For the regressions the values are rescaled between 0-2, so an increase in one unit is comparable to the other variables.

Table 3. Model-Free Evidence: Correlations with Performance

Variable	Returns			Sales Change			EBIT Change		
	1 Year	2 Year	5 Year	1 Year	2 Year	5 Year	1 Year	2 Year	5 Year
Im. mentions	0.045***	-0.014	-0.002	-0.003	-0.014	-0.014	0.005	-0.005	0.007
Im. sentiment	-0.016	0.024*	-0.004	0.025*	0.024**	-0.002	0.030**	0.009	-0.022
E.-m. mentions	-0.0801***	-0.028**	-0.031*	-0.036***	-0.028**	-0.016	-0.042***	-0.031**	-0.053***
E.-m. sentiment	-0.019	0.010	-0.103***	0.011	0.010	0.016	-0.008	0.004	0.020

Note. *p < 0.1; **p < 0.05; ***p < 0.01

Table 4. Main Regression Results: Imitation, Early-movers and Firm Performance

Variable	Stock Return [%]			EBIT Change [%]			Sales Change [%]		
	1y	2y	5y	1y	2y	5y	1y	2y	5y
Imitation mentions	1.75** (0.85)	0.55 (1.18)	3.36 (2.56)	0.69 (0.63)	0.28 (1.00)	1.65 (1.90)	0.66** (0.31)	0.91* (0.54)	-1.56 (1.06)

Imitation sentiment	0.37 (0.81)	2.36** (1.14)	8.25*** (2.45)	1.31** (0.60)	1.92** (0.96)	-3.25* (1.91)	0.40 (0.29)	0.67 (0.52)	-2.14** (1.08)
E.-m. mentions	-7.02* (4.01)	-1.61 (5.58)	16.90 (11.61)	-8.42*** (3.24)	-10.21* (5.40)	-10.85 (9.39)	-3.62** (1.54)	-4.73* (2.64)	-4.68 (5.84)
E.-m. sentiment	-4.54 (3.88)	-12.84** (5.49)	-24.10** (12.27)	1.64 (3.02)	-13.66*** (4.86)	-14.31 (9.52)	0.22 (1.44)	-2.08 (2.55)	-11.22** (5.36)
Adj. R^2	0.27	0.28	0.59	0.13	0.2	0.43	0.27	0.33	0.53
N obs.	5009	4895	3198	4404	4515	4167	4719	4811	4390
Specifications	All models estimated with firm FEs & year FEs								

Note: Models are estimated using OLS with robust standard errors (in parentheses). *p < 0.1; **p < 0.05; ***p < 0.01.

Table 5. Boundary Condition Regression Results: Global Moderators

	Stock Return 5y Period [%]				EBIT Change 5y Period [%]				Sales Change 5y Period [%]			
	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined
Imitation mentions	3.359 (2.559)	4.922 (3.181)	-4.250 (7.408)	4.678 (3.080)	1.653 (1.899)	2.266 (1.963)	12.940 (53.608)	1.466 (1.691)	-1.556 (1.064)	-2.207* (1.155)	-9.674** (4.711)	-2.686** (1.076)
Imitation sentiment	8.255*** (2.449)	7.343** (3.248)	-7.934 (12.524)	7.565** (3.173)	-3.247* (1.906)	-2.047 (1.960)	28.306 (53.485)	-1.060 (1.692)	-2.140** (1.083)	-1.374 (1.151)	5.918 (8.601)	-0.776 (1.064)
E.-m. mentions	16.896 (11.609)	13.154 (12.780)	-7.586 (26.092)	13.946 (12.527)	-10.847 (9.392)	-6.240 (9.796)	258.343 (1136.445)	-16.122* (9.783)	-4.685 (5.839)	-8.804 (6.410)	-33.817 (20.898)	-8.276 (6.131)
E.-m. sentiment	-23.001** (11.709)	-3.102 (14.031)	-42.317 (33.931)	-6.365 (13.680)	-13.918 (9.261)	-11.889 (9.821)	-454.701 (517.758)	-8.828 (8.385)	-10.917** (5.213)	-6.296 (5.767)	-71.731*** (26.723)	-4.509 (5.138)
Uncertainty (centered)	—	4.460*** (0.969)	—	3.971*** (0.939)	—	-2.020*** (0.603)	—	-1.895*** (0.466)	—	-0.976*** (0.217)	—	-0.894*** (0.172)
Strength (centered)	—	—	-1.668*** (0.630)	-0.718*** (0.117)	—	—	2.575 (3.138)	1.212*** (0.076)	—	—	1.429*** (0.398)	0.598*** (0.048)
Im. mentions × Uncertainty	—	-1.584** (0.774)	—	-1.312* (0.747)	—	-0.133 (0.234)	—	-0.188 (0.196)	—	-0.134 (0.133)	—	-0.174 (0.121)
Im. mentions × Strength	—	—	0.346 (0.223)	0.134 (0.097)	—	—	0.024 (3.109)	-0.042 (0.063)	—	—	-0.417 (0.301)	-0.055 (0.040)
Im. sentiment × Uncertainty	—	0.164 (0.770)	—	0.154 (0.738)	—	-0.035 (0.230)	—	0.019 (0.200)	—	0.178 (0.141)	—	0.203 (0.130)
Im. sentiment × Strength	—	—	0.119 (0.293)	0.051 (0.100)	—	—	1.383 (2.727)	0.070 (0.064)	—	—	0.214 (0.359)	0.044 (0.041)
E.-m. mentions × Uncertainty	—	-3.637** (1.660)	—	-2.683* (1.630)	—	1.155** (0.518)	—	1.070** (0.484)	—	-0.153 (0.347)	—	-0.041 (0.329)
E.-m. mentions × Strength	—	—	1.191 (0.888)	0.186 (0.231)	—	—	0.432 (24.338)	-0.912*** (0.216)	—	—	-0.126 (0.334)	0.006 (0.124)
E.-m. sentiment × Uncertainty	—	-3.197** (1.602)	—	-3.862** (1.565)	—	-0.675 (0.471)	—	-0.211 (0.402)	—	-0.684** (0.300)	—	-0.402 (0.278)
E.-m. sentiment × Strength	—	—	-0.005 (1.096)	-0.189 (0.264)	—	—	-10.870 (10.120)	-0.158 (0.196)	—	—	-0.813 (0.602)	0.025 (0.125)
N obs.	3198	2500	2644	2500	4167	3828	4375	3828	4390	4047	4375	4047
Specification	All models estimated with firm FEs & year FEs											

Note: Models are estimated using OLS with robust standard errors (in parentheses). *p < 0.1; **p < 0.05; ***p < 0.01.

Table 6. Boundary Condition Regression Results: Sectoral Moderators

	Stock Return 5y Period [%]				EBIT Change 5y Period [%]				Sales Change 5y Period [%]			
	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined
Imitation mentions	3.359 (2.559)	-1.131 (2.944)	1.587 (2.747)	-0.982 (2.877)	1.653 (1.899)	3.473* (1.956)	2.108 (1.754)	3.325* (1.781)	-1.556 (1.064)	-1.940* (1.175)	-2.280** (1.107)	-2.026* (1.132)
Imitation sentiment	8.255*** (2.449)	6.052** (2.952)	8.122*** (2.764)	6.366** (2.912)	-3.247* (1.906)	-2.505 (2.023)	-0.788 (1.729)	-1.420 (1.812)	-2.140** (1.083)	-1.214 (1.190)	-0.905 (1.084)	-0.709 (1.126)
E.-m. mentions	16.896 (11.609)	4.374 (9.251)	5.871 (12.489)	4.057 (9.177)	-10.847 (9.392)	-18.256** (8.149)	-17.055* (9.585)	-25.558*** (8.030)	-4.685 (5.839)	-14.092*** (5.335)	-6.853 (6.029)	-13.181** (5.290)
E.-m. sentiment	-23.001** (11.709)	—	-9.613 (13.612)	-53.744*** (12.812)	-13.918 (9.261)	5.638 (9.243)	-11.936 (8.451)	6.118 (8.170)	-10.917** (5.213)	5.518 (5.454)	-6.891 (5.252)	6.177 (5.033)
Uncertainty (centered)	—	0.408* (0.245)	—	0.392 (0.243)	—	0.049 (0.124)	—	0.022 (0.105)	—	0.073 (0.074)	—	0.060 (0.069)
Strength (centered)	—	—	-0.618*** (0.110)	-0.632*** (0.116)	—	—	1.091*** (0.073)	1.080*** (0.077)	—	—	0.492*** (0.046)	0.494*** (0.048)
Im. mentions × Uncertainty	—	0.311 (0.197)	—	0.304 (0.196)	—	-0.310*** (0.110)	—	-0.290*** (0.097)	—	-0.160** (0.065)	—	-0.146** (0.062)
Im. mentions × Strength	—	—	0.099 (0.092)	0.113 (0.097)	—	—	-0.061 (0.062)	-0.084 (0.064)	—	—	-0.046 (0.039)	-0.058 (0.040)

	Stock Return Model 1	Model 2	Model 3	Model 4	EBIT Change Model 1	Model 2	Model 3	Model 4	Sales Change Model 1	Model 2	Model 3	Model 4
Im. sentiment × Uncertainty	—	0.358* (0.202)	—	0.444** (0.199)	—	0.132 (0.113)	—	0.069 (0.102)	—	0.080 (0.069)	—	0.066 (0.066)
Im. sentiment × Strength	—	—	0.056 (0.091)	0.083 (0.095)	—	—	0.068 (0.060)	0.077 (0.062)	—	—	0.024 (0.038)	0.031 (0.040)
E.-m. mentions × Uncertainty	—	-1.716*** (0.655)	—	-1.728*** (0.655)	—	0.159 (0.317)	—	0.160 (0.286)	—	-0.288 (0.212)	—	-0.233 (0.201)
E.-m. mentions × Strength	—	—	0.211 (0.226)	0.344 (0.233)	—	—	-0.844*** (0.205)	-0.893*** (0.207)	—	—	-0.051 (0.119)	-0.088 (0.120)
E.-m. sentiment × Uncertainty	—	—	—	-0.778 (0.546)	—	-0.575** (0.285)	—	-0.243 (0.234)	—	-0.376** (0.169)	—	-0.199 (0.158)
E.-m. sentiment × Strength	—	—	-0.131 (0.248)	0.021 (0.259)	—	—	-0.346* (0.180)	-0.335* (0.189)	—	—	-0.007 (0.118)	-0.039 (0.122)
N obs.	3198	2493	2493	2493	4167	3821	3821	3821	4390	4040	4040	4040
Specification	All models estimated with firm FEs & year FEs											

Note: Models are estimated using OLS with robust standard errors (in parentheses). *p < 0.1; **p < 0.05; ***p < 0.01.

APPENDIX A

Table A1. Alternative Main Regression with RE: Imitation, Early-movers and Firm Performance

	Stock Return [%]			EBIT Change [%]			Sales Change [%]		
	1y	2y	5y	1y	2y	5y	1y	2y	5y
Imitation mentions	1.02 (0.73)	0.26 (1.09)	2.78 (2.40)	0.47 (0.55)	0.29 (0.91)	1.92 (1.77)	0.63** (0.28)	0.90* (0.51)	-1.17 (1.01)
Imitation sentiment	0.15 (0.69)	1.97* (1.04)	6.68*** (2.32)	1.00* (0.53)	1.50* (0.88)	-3.17* (1.78)	0.36 (0.26)	0.75 (0.48)	-1.88* (1.03)
E.-m. mentions	-2.14 (1.78)	-2.66 (3.32)	7.02 (9.05)	-3.98** (1.74)	-6.35** (3.20)	-11.05* (6.58)	-1.79** (0.90)	-3.05* (1.78)	-3.54 (4.57)
E.-m. sentiment	-2.46 (1.66)	-9.31*** (3.15)	-28.24*** (9.01)	1.31 (1.72)	-0.87 (2.96)	2.87 (7.13)	0.71 (0.89)	0.12 (1.72)	-6.22 (4.17)
Adj. R^2	0.25	0.16	0.14	0.05	0.03	0.06	0.11	0.09	0.06
N obs.	5009	4895	3198	4404	4515	4167	4719	4811	4390
Specifications	All models estimated with random-effects and year dummies								

Note: Models are estimated using OLS with robust standard errors (in parentheses). *p < 0.1; **p < 0.05; ***p < 0.01.

Table A2. Additional Testing: Imitation and Changes R&D Spending

	Change in R&D spending [%]		
	1y	2y	5y
Imitation mentions	-0.01* (0.01)	-0.01 (0.01)	0.03 (0.02)
Imitation sentiment	0.00 (0.01)	0.00 (0.01)	-0.01 (0.02)
Adj. R^2	0.23	0.32	0.65
N obs.	2034	2009	1360
Specifications	All models estimated with firm FEs & year FEs		

Note: Models are estimated using OLS with robust standard errors (in parentheses). *p < 0.1; **p < 0.05; ***p < 0.01.

Table A3. Boundary Condition Regression Results: Global Moderators, 1y Period

	Stock Return 1y Period [%]				EBIT Change 1y Period [%]				Sales Change 1y Period [%]			
	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined
Imitation mentions	1.750** (0.848)	1.489 (0.953)	1.235 (1.457)	1.616* (0.900)	0.694 (0.632)	1.546** (0.705)	11.216 (16.859)	1.744** (0.689)	0.661** (0.307)	0.844** (0.348)	0.071 (0.734)	0.884*** (0.339)
Imitation sentiment	0.367 (0.806)	0.734 (0.908)	2.505* (1.390)	1.031 (0.858)	1.312** (0.596)	1.426** (0.694)	6.935 (17.856)	1.582** (0.675)	0.403 (0.289)	0.738** (0.340)	1.512** (0.756)	0.804** (0.330)
E.-m. mentions	-7.021* (4.007)	-12.135*** (4.218)	-5.721 (8.094)	-10.910*** (3.936)	-8.423*** (3.240)	-5.399 (3.538)	71.145 (60.041)	-5.212 (3.510)	-3.620** (1.545)	-2.070 (1.762)	7.233 (8.924)	-2.366 (1.722)
E.-m. sentiment	-4.418 (3.773)	-7.258 (4.491)	-9.223 (6.493)	-6.916 (4.255)	1.591 (2.937)	-1.642 (3.411)	-103.221 (71.922)	-2.199 (3.309)	0.218 (1.402)	-0.739 (1.713)	-4.282 (4.446)	-0.933 (1.655)
Uncertainty (centered)	—	-0.176 (0.155)	—	-0.051 (0.133)	—	-0.090 (0.097)	—	-0.036 (0.094)	—	0.101* (0.060)	—	0.120** (0.054)
Strength (centered)	—	—	0.446*** (0.060)	0.402*** (0.040)	—	—	1.755** (0.830)	0.220*** (0.031)	—	—	0.137*** (0.038)	0.086*** (0.014)
Im. mentions × Uncertainty	—	-0.040 (0.106)	—	-0.086 (0.104)	—	0.044 (0.081)	—	0.057 (0.077)	—	-0.018 (0.041)	—	-0.018 (0.040)
Im. mentions × Strength	—	—	0.047 (0.052)	-0.023 (0.034)	—	—	-1.137* (0.677)	-0.029 (0.026)	—	—	0.043 (0.027)	0.017 (0.012)
Im. sentiment × Uncertainty	—	0.061 (0.106)	—	0.112 (0.103)	—	-0.025 (0.083)	—	0.001 (0.080)	—	-0.001 (0.042)	—	0.008 (0.040)

Im. sentiment × Strength	—	—	0.114*	0.025	—	—	0.224	-0.033	—	—	-0.008	-0.008
			(0.064)	(0.033)			(0.554)	(0.025)			(0.038)	(0.012)
E.-m. mentions × Uncertainty	—	-0.294	—	-0.194	—	-0.109	—	-0.071	—	-0.360***	—	-0.354***
		(0.262)		(0.261)		(0.232)		(0.226)		(0.098)		(0.095)
E.-m. mentions × Strength	—	—	0.366**	0.109	—	—	2.056	-0.007	—	—	-0.227	0.005
			(0.154)	(0.086)			(1.941)	(0.073)			(0.194)	(0.033)
E.-m. sentiment × Uncertainty	—	-0.158	—	0.045	—	-0.063	—	0.008	—	-0.097	—	-0.049
		(0.213)		(0.206)		(0.180)		(0.177)		(0.092)		(0.088)
E.-m. sentiment × Strength	—	—	0.019	-0.031	—	—	2.582	-0.010	—	—	-0.197	0.005
			(0.158)	(0.095)			(1.814)	(0.071)			(0.150)	(0.037)
N obs.	5009	4087	4205	4087	4404	3642	4373	3642	4719	3906	4374	3906
Specification	All models estimated with firm FEs & year FEs											

Note: Models are estimated using OLS with robust standard errors (in parentheses). *p < 0.1; **p < 0.05; ***p < 0.01.

Table A4. Boundary Condition Regression Results: Sectoral Moderators, 1y Period

	Stock Return 1y Period [%]				EBIT Change 1y Period [%]				Sales Change 1y Period [%]			
	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined
Imitation mentions	1.750**	3.563***	1.614*	3.718***	0.694	1.593**	1.870***	1.815***	0.661**	0.477	0.963***	0.564
	(0.848)	(1.063)	(0.929)	(1.034)	(0.632)	(0.719)	(0.692)	(0.702)	(0.307)	(0.357)	(0.340)	(0.349)
Imitation sentiment	0.367	-0.984	1.162	-0.682	1.312**	1.012	1.531**	1.130	0.403	0.656*	0.801**	0.707**
	(0.806)	(1.054)	(0.878)	(1.028)	(0.596)	(0.704)	(0.674)	(0.688)	(0.289)	(0.352)	(0.331)	(0.345)
E.-m. mentions	-7.021*	-34.412***	-9.642**	-32.981***	-8.423***	-10.337***	-4.461	-9.777***	-3.620**	-6.422***	-1.009	-6.290***
	(4.007)	(3.960)	(3.997)	(3.834)	(3.240)	(2.963)	(3.493)	(2.933)	(1.545)	(1.533)	(1.756)	(1.512)
E.-m. sentiment	-4.418	5.301	-7.290*	5.121	1.591	0.693	-2.813	-0.181	0.218	0.897	-1.299	0.596
	(3.773)	(4.691)	(4.283)	(4.564)	(2.937)	(3.214)	(3.318)	(3.140)	(1.402)	(1.656)	(1.650)	(1.614)
Uncertainty (centered)	—	0.133**	—	0.126**	—	0.080**	—	0.071*	—	0.145***	—	0.142***
		(0.066)		(0.063)		(0.041)		(0.040)		(0.021)		(0.021)
Strength (centered)	—	—	0.291***	0.250***	—	—	0.192***	0.197***	—	—	0.065***	0.072***
			(0.038)	(0.042)			(0.030)	(0.030)			(0.014)	(0.014)
Im. mentions × Uncertainty	—	-0.040	—	-0.027	—	-0.009	—	0.005	—	-0.021	—	-0.017
		(0.061)		(0.058)		(0.037)		(0.036)		(0.019)		(0.019)
Im. mentions × Strength	—	—	0.002	0.039	—	—	-0.029	-0.035	—	—	0.021*	0.012
			(0.033)	(0.037)			(0.025)	(0.025)			(0.012)	(0.012)
Im. sentiment × Uncertainty	—	0.050	—	0.041	—	0.012	—	0.010	—	0.011	—	0.008
		(0.059)		(0.057)		(0.039)		(0.038)		(0.020)		(0.020)
Im. sentiment × Strength	—	—	0.018	0.033	—	—	-0.036	-0.031	—	—	-0.002	-0.004
			(0.032)	(0.036)			(0.024)	(0.024)			(0.011)	(0.012)
E.-m. mentions × Uncertainty	—	-0.254	—	-0.197	—	-0.058	—	-0.030	—	-0.066	—	-0.060
		(0.175)		(0.172)		(0.142)		(0.141)		(0.066)		(0.067)
E.-m. mentions × Strength	—	—	0.066	0.068	—	—	0.006	-0.020	—	—	0.041	0.026
			(0.084)	(0.099)			(0.068)	(0.070)			(0.032)	(0.034)
E.-m. sentiment × Uncertainty	—	-0.140	—	-0.009	—	0.007	—	0.042	—	-0.026	—	-0.001
		(0.136)		(0.131)		(0.101)		(0.100)		(0.053)		(0.052)
E.-m. sentiment × Strength	—	—	-0.038	0.035	—	—	-0.022	-0.005	—	—	-0.002	0.012
			(0.088)	(0.099)			(0.066)	(0.069)			(0.035)	(0.036)
N obs.	5009	4078	4078	4078	4404	3634	3634	3634	4719	3897	3897	3897
Specification	All models estimated with firm FEs & year FEs											

Note: Models are estimated using OLS with robust standard errors (in parentheses). *p < 0.1; **p < 0.05; ***p < 0.01.

Table A5. Boundary Condition Regression Results: Global Moderators, 2y Period

	Stock Return 2y Period [%]				EBIT Change 2y Period [%]				Sales Change 2y Period [%]			
	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined
Imitation mentions	0.757	0.557	1.323	0.637	0.285	0.683	18.860	0.798	0.910*	0.691	-1.553	0.735
	(1.387)	(1.348)	(2.983)	(1.343)	(1.001)	(1.101)	(26.171)	(1.059)	(0.538)	(0.600)	(1.236)	(0.576)
Imitation sentiment	2.260*	2.635**	7.171***	2.758**	1.919**	2.791**	-7.700	2.891***	0.668	0.805	1.430	0.753
	(1.352)	(1.320)	(2.759)	(1.311)	(0.963)	(1.113)	(19.306)	(1.069)	(0.521)	(0.598)	(1.207)	(0.571)
E.-m. mentions	-1.881	-10.373*	-8.054	-10.222*	-10.214*	-14.356***	-15.539	-14.669***	-4.727*	-4.802	-5.130	-4.658*
	(6.777)	(6.213)	(18.124)	(6.193)	(5.399)	(5.235)	(97.228)	(5.220)	(2.641)	(2.925)	(8.020)	(2.798)
E.-m. sentiment	-11.937*	-12.888**	-6.414	-12.603**	-13.295***	-16.638***	64.702	-16.551***	-2.027	-2.207	-7.588	-2.056
	(6.344)	(6.399)	(13.161)	(6.368)	(4.726)	(5.499)	(91.031)	(5.219)	(2.476)	(2.934)	(5.840)	(2.783)
Uncertainty (centered)	—	0.245	—	0.287	—	0.177	—	0.218	—	-0.039	—	0.025
		(0.201)		(0.197)		(0.152)		(0.143)		(0.108)		(0.092)
Strength (centered)	—	—	0.145	0.017	—	—	-0.091	0.395***	—	—	0.334***	0.212***
			(0.141)	(0.061)			(1.194)	(0.046)			(0.064)	(0.025)
Im. mentions × Uncertainty	—	-0.146	—	-0.153	—	-0.005	—	-0.003	—	0.044	—	0.020
		(0.155)		(0.156)		(0.122)		(0.115)		(0.071)		(0.067)

Im. mentions ×	—	—	0.239**	0.141***	—	—	0.960	-0.013	—	—	0.058	0.009
Strength			(0.113)	(0.052)			(1.052)	(0.039)			(0.043)	(0.021)
Im. sentiment ×	—	-0.017	—	0.004	—	-0.053	—	-0.016	—	0.025	—	0.045
Uncertainty		(0.155)		(0.155)		(0.130)		(0.124)		(0.074)		(0.070)
Im. sentiment ×	—	—	0.194	-0.018	—	—	-0.243	-0.029	—	—	0.031	0.015
Strength			(0.119)	(0.049)			(0.738)	(0.040)			(0.056)	(0.022)
E.-m. mentions ×	—	-0.593	—	-0.586	—	0.036	—	0.066	—	-0.535***	—	-0.512***
Uncertainty		(0.387)		(0.389)		(0.323)		(0.319)		(0.183)		(0.174)
E.-m. mentions ×	—	—	-0.154	-0.041	—	—	1.649	-0.003	—	—	-0.162	0.081
Strength			(0.340)	(0.131)			(1.734)	(0.113)			(0.165)	(0.059)
E.-m. sentiment	—	-0.343	—	-0.267	—	-0.288	—	-0.111	—	-0.394**	—	-0.278*
× Uncertainty		(0.349)		(0.349)		(0.254)		(0.242)		(0.155)		(0.143)
E.-m. sentiment	—	—	0.084	-0.144	—	—	3.639	0.013	—	—	-0.098	0.048
× Strength			(0.319)	(0.144)			(2.245)	(0.105)			(0.142)	(0.062)
N obs.	4895	4036	4201	4036	4515	3721	4374	3721	4811	3973	4375	3973
Specification	All models estimated with firm FEs & year FEs											

Note: Models are estimated using OLS with robust standard errors (in parentheses). *p < 0.1; **p < 0.05; ***p < 0.01.

Table A6. Boundary Condition Regression Results: Sectoral Moderators, 2y Period

	Stock Return 2y Period [%]				EBIT Change 2y Period [%]				Sales Change 2y Period [%]			
	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined	Model 1 Base	Model 2 Uncertainty	Model 3 Strength	Model 4 Combined
Imitation	0.757	2.066	0.457	2.179	0.285	0.449	0.987	0.694	0.910*	0.224	0.961	0.341
mentions	(1.387)	(1.411)	(1.338)	(1.405)	(1.001)	(1.101)	(1.069)	(1.065)	(0.538)	(0.608)	(0.588)	(0.595)
Imitation	2.260*	1.864	2.717**	1.942	1.919**	3.013***	2.858***	3.105***	0.668	1.220**	0.863	1.239**
sentiment	(1.352)	(1.411)	(1.308)	(1.410)	(0.963)	(1.117)	(1.068)	(1.080)	(0.521)	(0.619)	(0.577)	(0.601)
E.-m. mentions	-1.881	-21.507***	-8.325	-21.004***	-10.214*	-18.119***	-13.901***	-17.289***	-4.727*	-8.997***	-2.511	-8.145***
	(6.777)	(5.099)	(6.148)	(5.110)	(5.399)	(4.168)	(5.187)	(4.204)	(2.641)	(2.480)	(2.842)	(2.440)
E.-m. sentiment	-11.937*	-13.767**	-14.074**	-13.793**	-13.295***	-11.064**	-18.343***	-12.184**	-2.027	0.829	-3.634	0.767
	(6.344)	(6.256)	(6.352)	(6.236)	(4.726)	(5.090)	(5.178)	(4.866)	(2.476)	(2.867)	(2.769)	(2.764)
Uncertainty	—	-0.284***	—	-0.284***	—	0.197***	—	0.187***	—	0.176***	—	0.177***
(centered)		(0.080)		(0.079)		(0.062)		(0.059)		(0.038)		(0.037)
Strength	—	—	-0.033	-0.068	—	—	0.332***	0.344***	—	—	0.176***	0.189***
(centered)			(0.057)	(0.059)			(0.043)	(0.044)			(0.024)	(0.026)
Im. mentions ×	—	0.021	—	0.023	—	-0.081	—	-0.061	—	-0.023	—	-0.021
Uncertainty		(0.073)		(0.073)		(0.056)		(0.054)		(0.035)		(0.034)
Im. mentions ×	—	—	0.140***	0.168***	—	—	0.002	-0.013	—	—	0.008	-0.006
Strength			(0.050)	(0.052)			(0.038)	(0.038)			(0.021)	(0.022)
Im. sentiment ×	—	0.033	—	0.030	—	0.077	—	0.055	—	0.036	—	0.027
Uncertainty		(0.075)		(0.075)		(0.063)		(0.061)		(0.037)		(0.036)
Im. sentiment ×	—	—	-0.039	-0.044	—	—	-0.051	-0.047	—	—	0.007	0.006
Strength			(0.046)	(0.049)			(0.038)	(0.038)			(0.021)	(0.022)
E.-m. mentions ×	—	-0.275	—	-0.259	—	-0.145	—	-0.117	—	-0.231**	—	-0.215*
Uncertainty		(0.212)		(0.212)		(0.186)		(0.189)		(0.116)		(0.113)
E.-m. mentions ×	—	—	0.064	0.042	—	—	-0.041	-0.060	—	—	0.071	0.049
Strength			(0.126)	(0.133)			(0.107)	(0.110)			(0.058)	(0.061)
E.-m. sentiment	—	-0.311*	—	-0.274	—	-0.016	—	0.059	—	-0.188**	—	-0.113
× Uncertainty		(0.168)		(0.168)		(0.144)		(0.145)		(0.095)		(0.091)
E.-m. sentiment	—	—	0.007	-0.021	—	—	-0.070	-0.063	—	—	-0.004	0.008
× Strength			(0.139)	(0.143)			(0.099)	(0.101)			(0.060)	(0.062)
N obs.	4895	4027	4027	4027	4515	3712	3712	3712	4811	3964	3964	3964
Specification	All models estimated with firm FEs & year FEs											

Note: Models are estimated using OLS with robust standard errors (in parentheses). *p < 0.1; **p < 0.05; ***p < 0.01.