Social Media Reactions to Product Announcements and Competitive Response*

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Abstract:

Using data from a popular social media platform, we examine whether firms' product market strategies are associated with social media reactions to competitors' product announcements. We document that product announcements trigger heightened discussions on social media. Firms adjust their product offerings to a greater extent in the following year when their competitors' new products attract strong social media attention, especially if accompanied by favorable sentiment. Furthermore, high attention is associated with greater product differentiation, while positive sentiment correlates with convergence in product offerings when attention is moderate. These effects persist after controlling for alternative information channels, product market dynamics, and firm characteristics. We argue that social media serves as a valuable external source of real-time, crowdsourced information on the consumer side, reflecting potential consumer bases and preferences for new products. This is evidenced by results showing the baseline associations are driven by product-related discussions and stronger in market-oriented industries.

Keywords: Social Media Signals; Product Announcements; Consumer Feedback; Competitive Response; Product Market Dynamics

JEL Codes: D22; D83; G14; G32; L10; L25

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I. Introduction

With the rapid rise of social media platforms in recent years, the ways in which investors express their opinions about firms and market-moving events have changed dramatically. Social media enables a wide range of users to share their views instantaneously and at minimal cost, creating a rich source of real-time, crowdsourced feedback. These features have spurred considerable research into the informativeness of social media and its role in financial markets. For example, Grennan and Michaely (2021) find that sophisticated investors, such as hedge funds, utilize real-time trading signals derived from social media for investment recommendations, and Farrell, Green, Jame, and Markov (2022) show that social media improves the informativeness of retail trading.[1] Despite these advances, the relation between social media and corporate decisions remains under-explored. Recent studies have begun to address this gap: Cookson, Niessner, and Schiller (2024) show that social media sentiment serves as a valuable signal of the likelihood of merger withdrawal, while He, Leung, Qiu, and Zhou (2024) show that social media disseminates innovation-related information that promotes corporate innovation activities.

In this paper, we extend this line of research by focusing specifically on firms' competitive interactions in the product market. Understanding this dynamic is crucial because firms must continuously adapt their product offerings to maintain competitiveness in rapidly evolving markets, especially in industries with intensive innovation and short product life cycles. We investigate whether social media signals following competitors' product announcements are associated with focal firms' strategic responses and explore the information content reflected in these signals. Our baseline findings show that when competitors' new products trigger strong reactions on social media, proxied by abnormal attention and sentiment, focal firms adjust their product portfolios to a greater extent. We

[1] There is ongoing debate in the current literature about whether social media benefits investors. On one hand, social media has been found to exacerbate behavioral biases (Heimer, 2016), trigger trading frenzies (Pedersen, 2022), impair the efficiency of information processing (Bradley, Hanousek Jr, Jame, and Xiao, 2023), and amplify retail investor optimism (Bali, Hirshleifer, Peng, Tang, and Wang, 2025). On the other hand, social media can reduce information asymmetry by disseminating corporate news broadly and rapidly (Blankespoor, Miller, and White, 2014). Its content has demonstrated predictive value for firms' quarterly earnings (Bartov, Faurel, and Mohanram, 2018) and has been shown to improve return predictability (Giannini, Irvine, and Shu, 2018). However, despite these debates, the literature consistently indicates that investor behavior is influenced by social media.

hypothesize that this association arises because social media signals around product announcements are likely to reflect underlying consumer reactions. Consumers—many of whom are also investors—actively and promptly express their opinions and excitement about new products on social media, providing real-time insights into a potential consumer base and their preferences.

To empirically measure social media reactions to corporate events, two considerations must be addressed. First, it is essential to ensure that the social media signals are responses specifically to the product announcement, rather than to other confounding events. Second, firm-specific measures are required to establish a clear and direct link between the social media signals and the announcing firm. Our datasets effectively address both these requirements. We obtain product announcement data for U.S. publicly listed firms from Capital IQ and restrict our sample to announcements with clean windows free from confounding events, which ensures that observed social media reactions can be more confidently attributed to the product announcements themselves. For firm-level social media signals, we use data from Stocktwits, which allows users to post short messages—commonly referred to as "tweets"—and express their opinions about a specific firm by including a "cashtag" followed by the firm's ticker symbol (e.g., $AAPL for Apple). Users can voluntarily label their tweets as bullish or bearish, allowing us to measure social media sentiment directly. Additionally, Stocktwits organizes all tweets related to a given company in a dedicated feed on the firm's page, creating a centralized, and real-time stream of crowd-sourced insights. These features enable us to track firm-day level variations in social media attention and sentiment following particular events. The platform's large and active user base ensures a rich pool of real-time discussions, making it a valuable source for capturing diverse and timely discussions. Together, these databases offer comprehensive coverage, ensuring a thorough representation of firms operating in the U.S. product market.

Using these datasets, we show that product announcements attract substantial attention on social media, supported by three pieces of evidence. First, we observe a sharp increase in the number of tweets and users discussing the firm on the product announcement day. Second, through structural topic modelling, we analyze the tweet content and find a significant surge in product-related discussions when the new product is announced, while tweets on other topics remain stable. Third, we find that product announcements attract the most attention on social media in industries such as Pharmaceutical Products, Consumer Goods, Recreation, and Automobile and Trucks—sectors characterized by market-oriented firms that prioritize understanding and responding to consumer preferences and competitive dynamics (Jaworski and Kohli, 1993, 1996; Kohli, Jaworski, and Kumar, 1993).[2]

We argue that social media reactions to product announcements can reflect consumer-side information. Stocktwits users, while engaging in financial discussions, also contribute product-related insights from a consumer perspective, particularly following product announcements. Unlike traditional consumer review platforms such as Amazon, where feedback accumulates gradually, Stocktwits users' investment focus motivates immediate reactions to product announcements, as new products are perceived to have a direct and timely impact on firms' future earnings and valuation. Moreover, social media attention and sentiment capture distinct dimensions of information, as discussed in Cookson, Lu, Mullins, and Niessner (2024). In this paper, we propose that abnormal social media attention signals consumer's interest in new products, indicating the size of the potential consumer base, while abnormal sentiment reflects consumer enthusiasm, signaling the degree of liking or disliking toward the new product. Notably, when a product announcement generates both high attention and positive sentiment, this combination serves as a strong signal of substantial market potential. We hypothesize that abnormal attention and sentiment following competitors' product announcements are associated with significant adjustments in focal firms' product offerings in the subsequent year. We emphasize that we do not claim that managers are guided in their product market strategies by these signals—indeed, managers may already know what these signals reflect. Our contribution lies in showing that these signals can predict subsequent managerial responses, and that they go beyond typical observable signals such as market reactions to competitors' product announcements or media coverage, in anticipating these responses.

To test this hypothesis, we identify a focal firm's competitors using the Hoberg and Phillips three-digit TNIC industry classification and measure adjustments in product offerings via the firm's

[2] In our sample, product announcements generate a statistically significant abnormal return of 0.3% on the announcement days. It suggests that investors pay close attention to these announcements and generally respond positively, viewing new products as signals of potential future value creation for the firm.

self-fluidity (Hoberg, Philips, and Prabhala, 2014). An increase in self-fluidity implies that the firm is adjusting its product offerings more aggressively. Our dependent variable is the focal firm's self-fluidity in the year following competitors' product announcements.[3] For our key independent variables, for each product announcement made by a product market competitor of a focal firm, we calculate the abnormal attention it receives as the percentage change in the average number of tweets per day from the benchmark window [-13, -7] to the event window [0, 3]. Following Cookson, Niessner, and Schiller (2024), we also construct a measure of abnormal sentiment as the difference in the average sentiment scores between these two windows. To construct focal firm-year level measures of social media reactions to competitors' product announcements, we aggregate these event-level measures across all competitors' announcements within the same year.[4] In all specifications, we include firm fixed effects to control for time-invariant firm characteristics and year fixed effects to account for shocks that affect all firms in a given year.

Our empirical results support the hypothesis that focal firms significantly adjust their product offering in the year following competitors' products announcements that receive strong social media reactions. A one-standard-deviation increase in abnormal attention to competitors' product announcements is associated with an 0.836 increase in the focal firm's self-fluidity for the next year ($p < 0.01$), corresponding to 4.742% of its unconditional mean. Meanwhile, the effect of abnormal sentiment is relatively modest but remains statistically significant, with an increase of 0.206 in self-fluidity, or 1.170% of the unconditional mean ($p < 0.05$). Moreover, high abnormal sentiment amplifies the effect of abnormal attention, underscoring their interactive relation in reflecting product market strategies. To ensure that the observed correlations are not confounded by other sources of information, we control for stock market reactions, abnormal news coverage and news sentiment, and changes in recommendations by sell-side analysts. We further control for variables that are likely to influence product market strategies, such as the focal firm's product announcement history, market share,

[3] Throughout, we refer to firms whose product market strategies are the focus of our research as *focal firms.* Their strategies constitute our dependent variables. The peer firms which make product announcements and are in the same TNIC3 industry as focal firms are called *competitors* or *rivals.*

[4] We discuss these measurement choices in section 2.2.2.

corporate innovation, common ownership, product similarity with the competitors, and various firm characteristics. After including these controls, the effects of abnormal attention and abnormal sentiment remain statistically and economically significant (4.658% and 1.220%, respectively). Our results remain robust when replacing year fixed effects with industries-by-year fixed effects to control for industry-specific economic shocks.

Next, we examine the *direction* of focal firms' adjustments in product offerings. Given the complexity of competitive dynamics, the direction of these adjustments is theoretically ambiguous ex ante: firms may choose to converge with competitors to capture shared market opportunities or differentiate themselves to avoid direct competition.[5] Different signals may be associated with distinct strategies as the underlying information differs. Specifically, we hypothesize that high abnormal social media attention to a competitor's product launch, reflecting broad consumer interest for a particular type of product, may be associated with more divergence in product offerings, as focal firms seek to differentiate themselves to avoid head-to-head competition. Conversely, positive abnormal sentiment, especially when not attracting wide attention, is likely to reflect consumers' approval for a specific product feature, and may be associated with a higher likelihood of convergence, as firms have more incentives to align their offerings to new innovations positively received by consumers, but not necessarily dominating the market. The combination of widespread consumer interest (high attention) and enthusiasm (favorable sentiment), on the other hand, is a particularly strong signal of a significant new product introduction by a rival with major market potential, and is likely to strongly encourage differentiation and divergence in product offerings. While our hypothesis reflects one plausible interpretation, alternative hypothesis points to opposite effects. For example, high attention might signal a large market opportunity that encourages convergence, whereas strong positive sentiment might be associated with more differentiations as firms pursue unique features that set them apart in the market. Therefore, empirical analysis is necessary to uncover which strategic response predominates in practice.

[5] For related concepts in the innovation literature, see Aghion, Bloom, Blundell, Griffith, and Howitt (2005), Bloom, Schankerman, and Van Reenen (2013), and Foster, Haltiwanger, and Syverson (2008).

We conduct the analysis at the firm pair-year level, using the product similarity data from Hoberg and Phillips (2010, 2016) to construct our dependent variables for the subsequent year: (1) a dummy variable indicating whether the product offerings of a focal firm and its competitor become more similar, and (2) a dummy variable indicating whether both firms remain in the same TNIC3 industry. Our key explanatory variables are abnormal attention and sentiment for competitors' product announcements, while controlling for a range of factors that could affect the direction of adjustments. All specifications include firm pair-year fixed effects and year fixed effects to control for unobserved heterogeneity and common temporal shocks.

We find that abnormal attention and sentiment predict opposite directions in firm's adjustment of product offerings. First, higher abnormal attention toward competitor's product announcement is associated with a higher likelihood of differentiation: focal firms are less likely to increase product similarity with those competitors or to remain in the same TNIC3 industry in the following year. We interpret this pattern as a form of *strategic differentiation*. When the competitor's new products capture significant consumer interest—as reflected by high abnormal attention—the focal firm tends to redirect their product offerings towards less-contested market spaces. In contrast, when the competitor's new products receive favorable sentiment on social media, firm pairs exhibit great product similarity and a higher likelihood of remaining in the same industry. This suggests a *strategic convergence* effect, where positive abnormal sentiment signals consumers' enthusiasm toward the new product, reducing uncertainty about the product's future earnings potential and making convergence a less risky strategy. However, this effect is reversed when attention is high. When high sentiment is associated with high attention, the differentiation effect is even more pronounced. This result indicates that focal firms are especially likely to circumvent direct competition when the competitor's new products attract broad interests (high attention) and strong approval (positive sentiment) from consumers. Overall, our findings highlight the nuanced ways in which firms adjust product offering when the underlying consumer insights differ.

We next investigate the information content of the social media signals through two sets of tests. First, if social media signals capture consumer interest relevant to product market dynamics, we expect that signals derived from contents specifically related to products exhibit stronger correlations with changes in focal firms' product market strategies than those derived from irrelevant contents. To test this, we apply structural topic modelling (STM) to extract topic distributions for each tweet and manually classify the topics into three categories: product-related, trading-related, and other. We then assign each tweet to the category corresponding to its highest topic score and construct measures of abnormal attention for each category.

Our results support the expectation. We show that higher abnormal attention derived from product-related tweets is significantly associated with stronger adjustments in focal firms' product portfolios in the subsequent year. These tweets typically discuss regulatory approvals for new products and consumer-facing innovations, mainly in industries such as biotechnology, healthcare, and technology. This finding supports our expectation that social media signals capture consumer interest in new products. Additionally, abnormal attention derived from trading-related tweets also exhibits a significant association, with an economic magnitude comparable to that of product-related abnormal attention. This aligns with the nature of investor-oriented platform like Stocktwits, where discussions often reflect investment evaluations based on the potential revenue of new products and changes competitive positioning. In contrast, abnormal attention based on 'other' topics—such as unrelated discussions, broad market commentary—shows no significant correlation with product adjustments, suggesting that only social media signals relevant to product market dynamics are associated with changes in firms' product market strategies.

Second, if social media signals reflect consumer-side information, we expect the associations between social media signals and focal firms' product market strategies to be more pronounced for market-oriented firms which place greater emphasize on actively understanding and responding to consumer needs throughout the product development and decision-making process. Our empirical tests support this expectation: such associations remain statistically and economically significant in the subsample of industries characterized by market-oriented firms. In contrast, we observe no significant effect in the subsample where none of the competitors from market-oriented industries. Overall, our findings suggest that social media signals serve as a meaningful information channel for consumer insights that resonate with firms' strategic adjustments in their product offerings.

Furthermore, we examine how firm heterogeneity affects patterns of product convergence and differentiation. We find that pairs of firms covered by common analysts are more likely to remain in the same industry and offer more similar products in the subsequent year when the competitor's new products receive strong attention on social media. This result aligns with the idea that common analyst coverage serves as an important channel for information transmission (Chu, Dasgupta, and Ma, 2025; Martens and Sextroh, 2021), enabling the spillover of technological knowledge and promoting convergence in product offerings. Similarly, technological capabilities also promote convergence: we find that convergence is stronger among firm pairs with stronger technological similarity. Furthermore, convergence is more likely when the focal firm is relatively larger than its competitor, possibly indicating a preemptive strategy by the large focal firm to limit the growth potential of the smaller competitor.

Finally, we examine focal firms' performance in the subsequent year when competitors' product announcements attract strong reactions on social media. First, we analyze stock market reactions and social media responses to the focal firm's first product announcement in the subsequent year. Our results show that when competitors' new products attract substantial social media attention accompanied with favorable sentiment, the focal firm's product announcement elicits stronger stock market reactions and higher abnormal sentiment on social media. Second, we find that focal firms experience greater sales growth in the year following competitor's new products attracting substantial attention and favorable sentiment. Together, these findings suggest that social media signals—by reflecting consumer interest and enthusiasm—can serve as valuable indicators that reflect focal firms' beneficial strategic decisions in a competitive product market.

Our paper makes several contributions to the current literature. First, we contribute to the growing body of literature examining the informativeness of social media. Our results show that attention and sentiment can serve as valuable consumer-side signals. Specifically, abnormal social media attention reflects consumer interest in new products, while abnormal sentiment indicates consumer enthusiasm—the degree of liking or disliking these products. The existing literature has documented mixed findings on the informativeness of social media and its impact on financial markets. On the one hand, social media amplifies market volatility (Antweiler and Frank, 2004), exacerbates behavioral biases (Heimer, 2016), distort prices (Giannini, Irvine, and Shu, 2018), disseminate stale news (Chawla, Da, Xu, and Ye, 2022), and causes inefficient information process (Bradley, Hanousek Jr, Jame, and Xiao, 2023). On the other hand, it has been found to predict quarterly earnings (Bartov, Faurel, and Mohanram, 2018), support institutional decision-making (Grennan and Michaely, 2021), improve the informativeness of retail trading (Farrell, Green, Jame, and Markov, 2022), and facilitate the incorporation of information into stock price (Hirshleifer, Peng, and Wang, 2025). Our findings add to this literature by showing that social media signals can serve as a valuable external source of consumer-side information. While managers and their research teams may already possess substantial consumer insights gathered through market research, post-purchase feedback, and direct interactions with distributors and retails, social media functions as a public channel that makes such information visible and accessible to external stakeholders who do not have privileged access to internal information but can make use of observable public signals to understand consumer demand in a timely manner and anticipate firms' strategic market moves.

Our paper also connects to the extensive literature investigating the interaction between financial market and corporate decisions (Bond, Edmans, and Goldstein, 2012; Goldstein, 2023) from various perspectives. These include the impact of stock market on corporate decisions (Giammarino, Heinkel, Hollifield, and Li, 2004; Luo, 2005; Kau, Linck, and Rubin, 2008; Foucault and Fresard, 2014; Zuo, 2016), the effect of traditional news media (Liu and McConnell, 2013; Baloria, Lo, and Shu, 2025; Gao, Wu, You, and Smith, 2025), and the role of other important information channels such as analyst coverage (To, Navone, Wu, 2018). Specifically, our paper contributes to the literature examining the relationship between social media and corporate decisions. Cookson, Niessner, and Schiller (2024) use Stocktwits data to show that social media sentiment can predict merger withdrawals. He, Leung, Qiu, and Zhou (2024) find that coverage initiation on Seeking Alpha significantly promotes corporate innovation activities. Koenraadt, Martens, and Sextroh (2024) show that firms are more likely to invest into technologies similar to firms covered by the same analyst on social media. We extend this literature by showing that social media signals convey consumer-side information that cannot be fully explained by other important information channels such as the stock market, traditional news media, and analyst coverage. Moreover, our findings suggest that such signals serve as valuable indicators, reflecting firms' strategic decisions in competitive product markets which potentially improves firms' market performance.

Product market strategies are central to a firm's competitive positioning and long-term growth, and information plays a vital role in informing and guiding these strategic choices. Our paper also speaks to the literature at the intersection of corporate finance and industrial organization, which has grown substantially in the past 35 years (Sertsios, 2020). Specifically, we contribute to the literature examining the effect of a firm's financial information environment on its product market outcome. Billett, Garfinkel, and Yu (2017) show that a worsened information environment reduces firms' industry-adjusted sales growth. Ferracuti (2022) shows the information uncertainty affects firms' organizational design. In this paper, we show that firms adjust their product offerings to a greater extent in the subsequent year when their competitors' new products attract strong attention and favorable sentiment on the social media. In addition, we provide evidence on the direction of such adjustment and show that higher attention is associated with a high likelihood of adopting the differentiation strategy in the next year while sentiment predicts the opposite.

II. Data and Variable Construction

2.1 Product Market Data

We obtain product announcement data from Capital IQ Key Development. This database compiles information from regulatory filings, press releases, and company websites, providing summaries of over 100 types of events that may impact the market value of securities. Product-related announcements are one category of corporate events, encompassing the entire product lifecycle—from the research phase to final launch and subsequent enhancements. Following Chu, Dasgupta, and Ma (2025), we identify announcements of new products among all the product-related events by searching for relevant keywords (e.g., "announce," "introduce," "unveil") in announcement headlines and summary texts. To mitigate the impact of any confounding events, we only retain the new product announcement with a clean event window [-7, 7] during which it is a standalone announcement. Our sample comprises 2,766 new product announcements from the first quarter of 2010 to the last quarter of 2021, made by 1,226 non-financial firms listed on the U.S. three main stock exchanges.

To measure changes in focal firms' product offerings, we employ the self-fluidity measure (referred to as "fluidity" in this paper) proposed by Hoberg, Phillips, and Prabhala (2014). This measure quantifies the extent to which firms alter their product descriptions in 10-K filings year-over-year by assessing vocabulary overlap, capturing shifts in product portfolios. Higher fluidity values indicate greater changes in product offerings.

We identify competitors for each focal firm using the Hoberg and Phillips TNIC3 industry classification, which dynamically groups firms based on product similarities derived from textual analysis of product descriptions in 0-K filings. In Section 3.4, to study the direction of a focal firm adjusting its product offerings, we use the similarity scores introduced by Hoberg and Phillips (2010, 2016) for each focal-rival firm pair and construct dummy indicators of whether firm pairs become more similar in their product offerings over time and whether they are more likely to remain in the same industry.[6]

2.2 Social Media Data

2.2.1 Introduction to Stocktwits

We measure social media signals through short messages posted on Stocktwits[7], a specialized financial social media platform for individuals to share financial market-related insights and ideas. Stocktwits has experienced substantial growth in recent years, and as of January 2025, the platform boasts an active

[6] All Hoberg and Phillips' data are available at http://hobergphillips.tuck.dartmouth.edu/.

[7] The character limit on the Stocktwits platform was 140 per post. On May 9, 2019, it was increased to 1000.

user base exceeding 10 million members.[8] Unlike more general platforms such as Twitter, which mix financial conversations with other topics like politics, entertainment, and sports, Stocktwits caters to a unique demographic of users who are highly engaged in trading and investing.

Stocktwits encourages users to reference a firm's ticker symbol in the format "$TICKER" (a dollar sign followed by the stock ticker) when posting contents related to a particular firm.[9] This structured tagging system enables Stocktwits to aggregate all posts mentioning a specific firm's ticker symbol ($TICKER) and display them in the "Feed" section of that firm's webpage, providing users with convenient access to consolidated discussions about each firm. In Figure 1, we show an example of tweets posted by Stocktwits users in the [0, 3] window following Mannkind's announcement of new drug *Afrezza* on February 3rd, 2015.

[Insert Figure 1 here.]

For our analysis, we merge Stocktwits data with product announcement data and collect tweets referencing the product-announcing company's $TICKER. Figure 2(a) plots the average daily post volume (measured by the average number of tweets per day) surrounding the announcements of new products. It shows a notable spike in posting activity on the announcement day, with an average of 10 posts per event-day after winsorizing at the 1% level, significantly exceeding pre-announcement levels.[10] Figure 2(b) demonstrates a parallel trend in the number of unique users engaging with these posts. These findings indicate that product announcements attract substantial attention on social media. Notably, we observe no significant increase in posting activities (whether measured by volume or unique users) prior to announcements in both figures, supporting our use of a clean event window to isolate the effect of the product announcement on social media engagement.

[Insert Figure 2 here.]

[8] https://www.etoro.com/en-us/news-and-analysis/latest-news/press-release/stocktwits-etoro-new-partnership/

[9] The Stocktwits platform provides clear and straightforward instructions for users to send posts. The post box includes pre-written guidance, such as "Share an idea (use $ before ticker: e.g., $SYMBL)," to assist users in correctly referencing a stock in their posts.

[10] There is an average of 15 posts per event-day without winsorizing.

2.2.2 Construct the Measures of Social Media Signals

2.2.2.1 Abnormal Attention

We construct the measure of abnormal attention to a firm's product announcement, denoted as *AbnAtten*, based on all tweets referencing the firm's ticker symbol around the announcement date. Following Cookson, Niessner, and Schiller (2024), we define the benchmark window as [-13, -7], which ends one week before the announcement to mitigate concerns about information leakage, and the event window as days [0, 3]. For each product announcement, *AbnAtten* is calculated as the fractional increase in tweet volume during the event window relative to the benchmark window:

$$AbnAtten_{j,n} = \frac{\left(\frac{1}{4}\sum_{d=0}^{3} Tweets_{j,d}\right) - \left(\frac{1}{7}\sum_{d=-13}^{-7} Tweets_{j,d}\right)}{\frac{1}{7}\sum_{d=-13}^{-7} Tweets_{j,d}} \tag{1}$$

where *j* denotes the rival firm making product announcement, *n* denotes a specific product announcement by firm *j*, and *d* denotes the days surrounding it with 0 as the announcement day. This normalized measure controls for event-specific baseline activity levels, ensuring comparability across announcements with different posting volumes. After winsorizing at the 1% tails to reduce outlier influence, the abnormal attention shows a mean value of 0.854 ($p < 0.01$), suggesting an average increase of 85.4% in tweet volume following the announcement.

In the empirical section, we examine whether abnormal attention to competitors' product announcements is associated with changes in focal firms' product offerings in the subsequent year. This analysis is conducted at the focal firm-year level. Abnormal attention, denoted as *AbnAtten_FY,* is constructed by summing the daily average tweet volume (number of tweets) of the event window across all product announcements made by competitors in the same TNIC-3 industry as the focal firm in each year, subtracting the corresponding total daily average tweet volume during the benchmark window, and then scaling this difference by the total daily average tweet volume of the benchmark window.[11]

[11] In this paper, we use the suffix *FY* to denote variables calculated at the *focal firm-year level*. Similarly, in our focal-rival pairwise analysis in Section 3.4, we use the suffix *RY* to denote variables calculated at the *rival firm-year level* to avoid confusion.

The formula is as follows, where *i* denotes the focal firm, *j* denotes the competitor making the product announcement in the year *t* (with $j = 1, \ldots, J_t$), *n* denotes a product announcement made by competitor *j* (with $n = 1, \ldots, N_j$), and *d* denotes the days around each announcement (with 0 as the announcement day). The mean value of abnormal attention at focal firm-year level is 0.308.

$$AbnAtten\_FY_{i,t} = \frac{\sum_{j=1}^{J_t} \sum_{n=1}^{N_j} \left(\frac{1}{4}\sum_{d=0}^{3} Tweets_{i,j,n,d}\right) - \sum_{j=1}^{J_t} \sum_{n=1}^{N_j} \left(\frac{1}{7}\sum_{d=-13}^{-7} Tweets_{i,j,n,d}\right)}{\sum_{j=1}^{J_t} \sum_{n=1}^{N_j} \left(\frac{1}{7}\sum_{d=-13}^{-7} Tweets_{i,j,n,d}\right)} \quad (2)$$

In Section 3.4, we conduct a firm pair-year level analysis to examine the association between the social media signal and the direction of the focal firm's strategic adjustments in product offerings. Since a competitor can make multiple announcements within a year, we measure the abnormal attention at the rival firm-year level, denoted as $AbnAtten\_RY_{j,t}$. It represents the fractional increase in the total tweet volume in the event window across all product announcements by the same competitor *j* in the year *t,* relative to the benchmark window.

2.2.2.2 Abnormal Sentiment

On Stocktwits, users can express their sentiment by clicking the green "Bullish" button, the red "Bearish" button, or opting not to select either option when posting their ideas. We quantify sentiment at the individual tweet level by assigning a score of 1 for 'Bullish' posts and -1 for 'Bearish' posts. Following Cookson, Niessner, and Schiller (2024), we construct a measure of abnormal sentiment for each product announcement, denoted as *AbnSent.* It is calculated as the difference between the daily average sentiment score during the event window [0, 3] and that of the benchmark window [-13, -7]. The mean value of *AbnSent* across all product announcements in our sample is 0.029. We construct a focal firm-year level measure of abnormal sentiment (*AbnSent_FY*) toward competitors' product announcements. It equals the weighted-average of *AbnSent* for all product announcements made by competitors in the same TNIC3 industry as the focal firm *i* in a given year *t*, using the average tweet volume per day in the event window as the weight, as announcements with more discussions should carry greater influence. The mean value of *AbnSent_FY* is 0.019 ($p < 0.01$). Additionally, for tests in

Section 3.4, we calculate the tweet volume weighted-average abnormal sentiment for all product announcements made by each competitor in each year, denoted as *AbnSent_RY*.[12]

2.2.3 Structural Topic Modelling and Topic-Specific Tweets

To analyze tweets contents, we employ Structural Topic Modeling (STM), an unsupervised machine learning technique developed by Roberts, Stewart, and Airoldi (2016). This approach allows us to identify latent discussion topics emerging from user posts, and quantitatively assess how topic prevalence shifts following product announcements.

The first step in implementing STM involves data preparation. We treat each tweet as a separate document—the basic unit of analysis in STM—and perform standardized pre-processing procedure. We remove stock ticker symbols, hyperlinks, and a customized list of stop words, followed by tokenizing and stemming the texts. To reduce noise from infrequent or idiosyncratic terms that could impair the quality of topic estimation, we exclude tokens that appear in fewer than ten documents. Following Dasgupta, Harford, Ma, Wang, and Xie (2020), we incorporate the industry of the announcing firm for topic prevalence of the STM. This adaptation enhances model's capacity to capture systematic variations in industries, particularly within the context of financial and technical discussions on Stocktwits.

Following pre-processing, we determine the optimal number of topics by estimating models with topic counts ranging from 15 to 30. Based on a balance of semantic coherence and interpretability, we select a 21-topic specification. To identify and label each topic, we analyze the top 10 highest-probability words and manually assign a descriptive label based on their semantic coherence. Our

[12] Note that we measure abnormal sentiment and abnormal attention using different approaches. Since tweet volume can vary widely across announcements, expressing abnormal attention as a fraction standardizes the metric, making it comparable across events with different baseline activity levels. Using a simple difference would not account for differences in scale and could bias results toward events with already high tweet volumes. On the other hand, abnormal sentiment is constructed as the difference in daily average sentiment scores, consistent with the approach in Cookson, Niessner, and Schiller (2024). Since sentiment scores are naturally bounded between –1 and +1, calculating the difference will not create extremely high value. If we calculate it as a fraction, a very small average sentiment in the benchmark window could lead to inflated values. Hence, using a simple difference ensures that changes in sentiment are not distorted by low baseline value and also consistent with the literature.

examination indicates that topics #2 and #18 are predominantly associated with product-related terminology. Accordingly, we designate these as ‘product-related’ topics.

STM generates a probability score for each topic at the document level, with these scores summing to one. A higher topic score indicates that the document is more closely related to that topic. In Figure 3(a), we compare the average topic scores of Stocktwits tweets in the benchmark window [-13, -7] with those in the event window [0, 3]. Topics are presented in descending order based on their average topic scores in the benchmark period. We observe a substantial increase in the scores of product-related topics following product announcements, with topic #2 increased by 62.67% and topic #18 increased by 23.27%. In contrast, we do not observe significant change in other topics.

[Insert Figure 3 here.]

We assign each document to the topic with the highest probability score. In Figure 3(b), we present the distribution of tweets under each topic in both pre- and post-event periods. The topics are presented in descending order based on the proportion of tweets under each topic in the pre-event period. We find that the proportion of tweets under the product-related topics increases substantially following product announcements, with topic #2 increased by 116.10% and topic #18 increased by 57.29%. However, no such significant increase is observed in other topics.

The results presented in both figures provide evidence that social media users actively engage in real-time product-related discussions following product announcements. These heightened engagements underscore the responsiveness of social media users in their capacity as consumers, revealing a demand-side reaction to corporate disclosures.

In Section 4.1.1, we measure social media signals by categorizing tweets based on their contents. Specifically, we classify 21 STM topics into three broad categories: (1) product-related (topic #2 and #18), (2) trading-related (topics #1, #3, #9, #10, #12, #14, and #19), and (3) other topics. Each tweet is assigned to one of these categories based on the topic with the highest probability score. Product-related tweets are characterized by high-probability words such as approval, FDA, announce, drug, patient, new, launch, and cost, which reflect contents related to product developments, regulatory approvals, and consumer-facing innovations, primarily in industries such as biotech, healthcare, and technology. Trading-related tweets include highest-probability words such as high, low, trade, profit, run, wait, sell, buy, short, market, capturing investor discussions around trading strategies, profitability, and price movement. These tweets constitute a significant share of the sample, consistent with the investor-oriented nature of the Stocktwits platform. The remaining topics are classified under the 'other' category, which reflects general market commentary.[13] The top 10 highest-probability words for each topic are reported in the Online Appendix A.

2.2.4 Industry Distribution

Firms that prioritize understanding and responding to consumer demand and competitive landscape are defined as market-oriented (Jaworski and Kohli, 1993, 1996; Kohli and Jaworski, 1993). Since consumers naturally gravitate toward companies that meet their needs and offer products aligned with their preferences, they are more likely to actively engage with and discuss offerings from these firms. Hence, we expect to find that product announcements from market-oriented firms are more likely to attract elevated reactions on social media.

In Table 1, we examine the average abnormal attention and sentiment for 2,766 product announcements across the Fama-French 48 industries. Industries are ranked from highest to lowest based on average daily tweet volume within the event window, with the top 20 industries reported in the table. Using ChatGPT 4.0, we assess whether each industry is market oriented. We find that the top four industries by tweet volume — Pharmaceutical Products, Consumer Goods, Recreation, and Automobiles and Trucks—are all identified as market-oriented. Notably, the Pharmaceutical Products industry exhibits a substantial increase of 492% in tweet volume and a favorable abnormal sentiment of 0.805 associated with a product announcement, reflecting a strong positive and response to announcements of new therapeutic breakthroughs. These findings support our expectation that product

[13] We classify the two topics that have concentrated product-related contents and show a sharp increase after product announcements as 'product-related' tweets. This classification is conservative as some tweets in the 'other' category may also contain product-related keywords; however, that category tends to be relatively noisy and less focused.

announcements attract heightened reactions on social media, particularly for market-oriented firms that are closely attuned to consumer needs, thereby underscoring social media's potential value as a window into consumer-side information.

[Insert Table 1 here.]

2.3 Other Information Sources

To account for the effects of alternative information channels, we incorporate the following measures: news media coverage and sentiment, stock market reactions, and analyst recommendations. First, we construct a measure of traditional news media coverage related to product announcements using RavenPack Analytics (RPA) data. It is a comprehensive news analytics platform that aggregates and analyses real-time news from a wide range of sources. We retain only articles and stories classified under the "Products" category by RPA, along with their "Event Sentiment Score" (ESS). For each product announcement, we calculate abnormal news media coverage, denoted as *AbnNewCoverage*, as the fractional increase in the average number of news articles per day from the benchmark window [-13, -7] to the event window [0, 3]. Consistent with the methodology used to construct focal firm-year and rival firm-year measures of abnormal social media signals, we derive analogous measures for traditional news media: abnormal news coverage (*AbnNewsCoverage_FY* and *AbnNewsCoverage_RY*) and abnormal news sentiment (*AbnNewsSent_FY* and *AbnNewsSent_RY*).

For each product announcement made by a competitor, we estimate cumulative abnormal returns (CARs) over a four-day window [0,3] for both the announcing competitor (denoted as *RivalPA_RivalCAR[0,3],* where PA stands for 'product announcement') and the focal firm (*RivalPA_FocalCAR[0,3]*). Market reaction measures are calculated using the Fama-French 5-Factor model (Fama and French, 2018), based on daily stock return data obtained from Centre for Research in Security Prices (CRSP). We aggregate each of these event-level abnormal return measures by taking the average to the focal firm-year level (*RivalPA_RivalCAR[0,3]_FY* and *RivalPA_FocalCAR[0,3]_FY*) and the rival firm-year level (*RivalPA_RivalCAR[0,3]_RY* and *RivalPA_FocalCAR[0,3]_RY*).

We obtain the analyst stock recommendation data from I/B/E/S Detail. Analyst recommendations are key metrics for understanding how market professionals perceive a firm's prospects following product announcements. Revisions in these recommendations indicate shifts in their expectations. We convert recommendation categories into numerical scores (i.e., 5 for 'strong buy', 4 for 'buy', 3 for 'hold', 2 for 'sell', and 1 for 'strong sell') and calculate recommendation revisions as the difference between the first stock recommendation issued within seven days following the product announcement and the most recent recommendation prior to the announcement. Analyst recommendation revisions for competitors following their product announcements are aggregated by calculating the average at the focal-year level and rival-year levels, denoted as *AvgAnalystRevisions_FY* and *AvgAnalystRevisions_RY*, respectively.

2.4 Factors that Affect Product Market Strategies

We construct a comprehensive set of control variables to account for additional factors that may affect product market dynamics. First, we control for the intensity of product announcements. Specifically, we include the number of product announcements made by the focal firm in a given year (*Focal_#NewProducts*) to capture the baseline level of product development activity, as firms more active in announcing new products may exhibit inherently different strategic behaviors in changing product offerings. Similarly, we control for the intensity of competitors' product announcements in both focal firm-year tests (*Rival_Avg#NewProducts_FY*) and firm-pair tests (*Rival_#NewProducts_RY*). A higher intensity of announcing new products by competitors may signal the focal firm's awareness of market threats and opportunities, prompting adjustments in its own product offerings to maintain competitiveness and market share (Chen, Tribbitt, Yang, and Li, 2017).

Second, we incorporate the focal firm's market share (*Focal_MktShare*) in the firm-year level analyses, which equals its total assets divided by the sum of total assets of the focal firm and its competitors with product announcements in a given year. It captures whether firms with greater market dominance exhibit different competitive responses than smaller, less-established firms.

Third, we control for the role of innovation in competitive interactions. At the firm-year level, we include the total number of patents held by the focal firm (*Focal_#Patents*) as a proxy for its technological capabilities and flexibility. Firms with larger patent portfolio likely possess greater adaptive capacity and exhibit differently in adjusting their product offerings in response to competitive threats. In the firm pair-level, we introduce technology similarity between the focal firm and its competitor (*TechSimilarity*). This measure is calculated as the fraction of the competitor's patents that belong to the same three-digit Cooperative Patent Classification (CPC) categories as the patents held by focal firm.[14] Focal firms with varying degrees of technological overlap with their competitors may exhibit different strategic behaviors in the competitive product market.

Next, we introduce common ownership (*ComOwnership*) as a potential signal of strategic coordination between competitors. At the firm pair-year level, *ComOwnership* is defined as the total ownership held by institutional blockholders owning more than 3% of the outstanding shares in both the focal firm and its competitor, scaled by the combined market capitalization of the two firms. In the focal firm-level tests, we use the average common ownership across all competitors with product announcements in a given year, denoted as *AvgComOwnership*.[15]

Finally, we control for product market similarity using the textual product similarity scores from Hoberg and Phillips (2010, 2016). For firm-year analyses, we include the average product similarity between the focal firm and its competitors (*AvgScore_FY*). In firm pair-year regressions, we use the raw similarity score between each focal-competitor pair (*SimilarityScore*). Product similarity has potential implications for strategic interaction between firms. Higher overlap may intensify rivalry and prompt product differentiation, whereas lower similarity may provide greater latitude for firms to adjust their portfolios without triggering competitive retaliation.

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[14] We obtain patent data from Kogan, Papanikolaou, Seru, and Stoffman (2017), accessible via their public dataset repository: https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

[15] The current literature provides mixed evidence on how common ownership affects product market competition. Some studies suggest that common ownership has an anticompetitive effect (Azar, Schmalz, and Tecu, 2018; He and Huang, 2017), while others argue that the observed relations between common ownership and industry competition are not robust (Dennis, Gerardi, and Schenone, 2022; Koch, Panayides, and Thomas 2021).

2.5 Firm Characteristics

In all firm-year level tests, we include a standard set of firm characteristics as control variables. These include Firm Size (log of total assets), Return on Assets (ROA) (operating income before depreciation divided by average total assets), Leverage Ratio (total liabilities and long-term debt divided by total assets), R&D (research and development expenditure divided by total assets), and Market-to-Book Ratio (market value of assets divided by book value). All variables are winsorized at the 1% level on both sides to mitigate outliers' impact. In firm pair-year level tests, we include the same set of firm characteristics for both focal firms and competitors.

2.6 Summary Statistics

Table 2 presents the summary statistics of the variables used in our analysis. We compare the signals from social media with those from other information channels. The abnormal social media attention to competitors' product announcements (*AbnAtten_FY*) has a mean (median) value of 0.308 (0.008). It is moderately correlated with the abnormal news coverage (*AbnNewCoverage_FY*), with a correlation coefficient of 0.223. This suggests that while social media and news media partly overlaps, each source captures distinct facets of public and investor interest in product announcements. Social media signals tend to reflect immediate, crowdsourced, and possibly consumer reactions, whereas new media offers more formal, curated information. We further analyze sentiment-related variables. The mean value of abnormal social media sentiment (*AbnSent_FY)* is 0.019, statistically different from zero at the 1% level, while average abnormal news sentiment (*AbnNewsSent_FY*) has a mean of 0.001, statistically indifferent from zero. The correlation between the two sentiment measures is 0.002, highlighting the non-overlapping nature of the sentiment conveyed across these information sources. This lack of correlation suggests that social media sentiment contains unique information following product announcements, which are not captured by traditional news coverage.

We also examine the correlation between social media sentiment and stock market reaction to competitors' product announcements. The average cumulative abnormal return for competitors over the three-day window surrounding their product announcements (*RivalPA_RivalCAR[0,3]_FY*) has a mean (median) of 0.175 (0.082), statistically different from zero at the 1% level. This suggests that product announcements elicit a strong positive market reaction, reflecting investor optimism about the potential increase in the rival firms' future cash flow from these new products. *RivalPA_RivalCAR[0,3]_FY* is positively correlated with abnormal social media sentiment, with a correlation coefficient of 0.172. This implies that social media sentiment captures information consistent with investor optimism and market valuation around product announcements, while also conveying unique insights. Conversely, the average cumulative abnormal return for the focal firm following competitors' product announcements (*RivalPA_FocalCAR[0,3]_FY*) is negative, with a mean (median) of -0.136 (-0.119), statistically significant at the 1% level. This suggests that the market perceives competitors' product introductions as a threat, leading to a negative reassessment of the focal firm's prospects.

In addition to market reactions, we analyze responses from sell-side analysts. The average recommendation revision (*AvgAnalystRevisions_FY*) for competitors following their product announcements is 0.070, which is statistically different from zero at the 1% level. This indicates that product announcements attract attention from analysts and lead to shifts in their expectations. However, recommendation revisions are uncorrelated with abnormal social media sentiment, suggests that the information reflected in analyst recommendations differs from that embedded in social media sentiment.

III. Empirical Results

3.1 Baseline Setting

Our baseline analyses examine whether abnormal social media attention and sentiment in response to competitors' product announcements serve as predictive signals regarding changes in the focal firms' product offerings in the subsequent year. We conduct ordinary least squares (OLS) regressions at the focal firm-year level, based on the following empirical specifications:

$$Fluidity_{i,t+1} = \beta_1 * AbnAtten\_FY_{i,t} + \Gamma * Control\ variables + \delta_i + \varepsilon_t \tag{3}$$

$$Fluidity_{i,t+1} = \beta_1 * AbnSent\_FY_{i,t} + \Gamma * Control\ variables + \delta_i + \varepsilon_t \tag{4}$$

$$Fluidity_{i,t+1} = \beta_1 * AbnAtten\_FY_{i,t} + \beta_2 * AbnSent\_FY_{i,t} + \beta_3 * AbnAtten\_FY_{i,t} * AbnSent\_FY_{i,t} + \Gamma * Control\ variables + \delta_i + \varepsilon_t \quad (5)$$

where $Fluidity_{i,t+1}$ measures the extent of change in focal firm *i*'s product offerings in year *t+1* relative to year *t*, and $AbnAtten\_FY_{i,t}$ ($AbnSent\_FY_{i,t}$) represents the focal firm-year level abnormal social media attention (sentiment) following product announcements by competitors within the same TNIC3 industry as the focal firm in year *t*. The coefficients on $AbnAtten\_FY_{i,t}$ and $AbnSent\_FY_{i,t}$ in models (3) and (4) are of primary interest, as they examine whether social media signals following competitors' product announcements are associated with focal firms' adjustments to their product offerings in the subsequent year. In model (5), we include an interaction term to explore whether the effect of abnormal attention is further affected by sentiment.

In all specifications, we include a set of control variables as outlined in the previous section. First, we account for alternative channels of information by including: (1) the abnormal news coverage of competitors' product announcements (*AbnNewsCoverage_FY*), abnormal news sentiment (*AbnNewsSent_FY*), along with a dummy variable (*D[miss_News]_FY*) indicating firm-years with missing Ravenpack news data; (2) the average four-day cumulative abnormal return of focal firm *i* following its competitors' product announcements (*RivalPA_FocalCAR[0,3]_FY*); (3) the average four-day cumulative abnormal returns of competitors following their product announcements (*RivalPA_RivalCAR [0,3]_FY*); (4) the average recommendation revisions issued by sell-side analysts for competitors within seven days of their product announcements by (*AvgAnalystRevisions_FY*), as well as a dummy variable (*D[miss_Revisions_FY]*) indicating focal-years where no such revisions are observed.

In addition, we control for a range of factors that may relate to competitive dynamics in the product market. Specifically, we include: (5) the intensity of product announcements by the focal firm (*Focal_#NewProducts_FY*) and the average intensity of those by its competitors in a given year (*Rival_Avg#NewProducts_FY*); (6) the market share of the focal firm (*Focal_MktShare*); (7) the number of patents held by the focal firm (*Focal_#Patents*); (8) the average common ownership between the focal firm and its competitors (*AvgComOwnership*); and (9) the average product similarity score between the focal firm and its competitors (*AvgScore_FY*).

We further control for a series of firm characteristics including return on assets (ROA), market-to-book ratio, firm size, book leverage ratio, and R&D. We include firm fixed effects δ_i to control for time-invariant firm characteristics and year fixed effects ε_t to account for shocks that affect all firms equally in a year. Additionally, we also explore the specification with year fixed effects replaced by Fama French 48 industry interacted with year fixed effects to account for industry-specific economic shocks. Standard errors are clustered at the industry-year level.

3.2 Social Media Signals and Adjustment in Product Offerings

In Table 3, Panel A show that focal firms significantly adjust their product offerings in the subsequent year when competitors' product announcements attract substantial social media attention. In column (1), a one-standard-deviation increase in abnormal attention is associated with a 0.836 increase in focal firm's product fluidity ($p < 0.01$), corresponding to 4.742% of its unconditional mean. Such an effect strengthens in column (2), where we control for industry-specific economic shocks by including industry-year fixed effects. In this specification, a one-standard-deviation increase in abnormal attention is associated with a 5.353% increase in focal firm's product fluidity ($p < 0.01$).

[Insert Table 3 here.]

Column (3) presents evidence that after accounting for a comprehensive set of control variables, abnormal attention remains both economically (4.658%) and statistically significant ($p < 0.01$). In column (4), where we account for industry-year fixed effects, a one-standard-deviation increase in abnormal attention corresponds to a 5.357% increase in focal firm's product fluidity ($p < 0.01$). Comparatively, we find generally weaker or insignificant correlations from other information channels, highlighting the unique role of social media in providing timely and distinctive signals relevant to firms' strategic decisions—beyond what is conveyed through conventional market and media channels. For example, stock market reactions to the focal firm following its competitors' product announcements (*RivalPA_FocalCAR[0,3]_FY*) are positively associated with higher focal firm fluidity in the next year after controlling for industry-level shocks, suggesting that stock market's positive assessment of the focal firm has a similar effect as abnormal attention reflected in social media.[16]

In addition, we control for factors that may affect focal firms' product market strategy. We find that focal firms with more patents in the current year exhibit higher fluidity in the following year ($p < 0.01$), suggesting that firms with greater technological capabilities are better positioned to modify their product offerings. The negative and significant effect ($p < 0.01$) of *Focal_MktShare* suggests firms with smaller market share are less immune to the competitive pressure from competitors and are more likely to adjust their product offerings. Finally, we find that average common ownership between the focal firm and its competitors (*AvgComOwnership*) has a negative and significant effect ($p < 0.10$) on fluidity, indicating that concentrated ownership is associated with a tendency toward softer competition.

For firm characteristics, we find that smaller focal firms exhibit significantly higher product fluidity in the following year. These firms are often more adaptable and flexible, as they are less bound by established product lines and can respond quickly to market opportunities and changes. In contrast, larger firms may focus more on maintaining established product lines and leveraging economies of scale. Additionally, firms with higher market-to-book ratios are less likely to change their product offerings. Perceived by investors as having strong growth potential, these firms may prioritize enhancing their existing operations and reinforcing their market position.

Next, we use model (4) to examine whether abnormal social media sentiment is associated with the focal firm's adjustment in its product portfolio in the subsequent year. The results are presented in Panel B of Table 3. We find a positive and statistically significant association between the abnormal

[16] In Appendix Table A1, we examine the effect of each information channel separately on the focal firm's fluidity and assess whether the presence of abnormal social media attention attenuates these effects. Abnormal news coverage (*AbnNewsCoverage_FY)* is positively associated with higher focal firm's fluidity in the next year ($p < 0.05$), controlling for firm fixed effects and year fixed effects. Its effects weakens once we control for industry-year fixed effects, suggesting that news coverage may capture broader economic shocks common to all firms within an industry. Additionally, the stock market reaction to the focal firm following competitors' product announcements (*RivalPA_FocalCAR[0,3]_FY*) is also positively associated with the focal firm's fluidity in the next year ($p < 0.10$), which holds after we control industry-level shocks ($p < 0.05$). Notably, the effects of both news coverage and stock market reactions attenuate once abnormal social media attention is included, while abnormal attention itself shows a robust and positive association with the focal firm's product fluidity ($p < 0.01$). We find no significant associations between the focal firm's fluidity and either the stock market reaction to competitors following their product announcements (*RivalPA_RivalCAR[0,3]_FY*) or the average analyst recommendation revisions (*AvgAnalystRevisions_FY*).

sentiment and focal firm's fluidity in the following year. A one-standard-deviation increase in abnormal sentiment corresponds to a 0.206 increase in focal firm's product fluidity without controls ($p < 0.05$), corresponding to 1.170% of its unconditional mean. This effect increases to 1.220% after including all control variables and further strengthens to 1.303% when year fixed effects are replaced with industry-year fixed effects. Favorable sentiment indicates the new products are likely to resonate well with consumers, reducing the uncertainty about consumer demand. Our findings in Panel A and Panel B suggest that both volume and tone of social media discussions matter in signaling firms' strategic decisions.

Finally, we examine the joint effect of abnormal attention and sentiment, based on the model (3). The results are presented in Table 3, Panel C. We find that the interaction term has a positive and statistically significant coefficient.[17] This finding suggests that the high attention accompanied by favorable sentiment toward competitors' product announcements serves as a strong signal of robust consumer interest and approval.[18] In addition, the attention measure itself has a positive and statistically significant coefficient, while the sentiment measure alone does not show a significant effect. This implies that when competitors' product announcements fail to attract sufficient consumer interest—potentially reflected by low social media attention—focal firms are less likely to adjust their product offerings, even if some consumers express positive sentiment toward the new products.[19]

[17] The correlation coefficient between *AbnAtten_FY* and *AbnSent_FY* is 0.071. The low correlation reduces concerns about multicollinearity in regression models. More importantly, it indicates these measures capture distinct aspects of social media signals. In this paper, while attention reflects the volume of consumer focus, sentiment conveys the tone of their discussions. Cookson, Lu, Mullins, and Niessner (2024) also support the idea that attention and sentiment reflect different dimensions of social media activity. They find that social media attention tends to be consistent across platforms and user groups, while sentiment is more idiosyncratic and varies more widely.

[18] In untabulated results, we decompose abnormal social media sentiment into two components: positive and negative abnormal sentiment. We find that adjustments in the focal firm's product offerings are only significantly associated with positive abnormal sentiment, while no significant association is observed for negative sentiment. Moreover, the effect of abnormal attention is amplified to a greater extent when accompanied with positive abnormal sentiment.

[19] We also examine the results with the simple-average abnormal sentiment instead of the weighted average version. This alternative sentiment measure shows a positive association with the focal firm's fluidity in the year $t+1$ but is statistically insignificant with a t-statistic of 1.393. When including the interaction of abnormal attention and this simple-average sentiment, the sentiment itself remains insignificant. These results suggest the information conveyed in sentiment matters only when attention is high, which is consistent with the implication in Panel C of Table 3 that focal firms are less likely to adjust their product offerings when few consumers express interest in competitors' new products, even if they are enthusiastic.

3.3 Robustness

To ensure the validity and reliability of our findings, we conduct a series of robustness checks that test whether our main results hold under alternative specifications and additional controls. First, we focus on a subset of tweets that specifically mention the announcing competitor, which constitute over 87% of tweets used in our baseline models. These competitor-specific tweets allow for a more focused and precise measurement of social media signals that are highly relevant to the announcements. In the Panel A of Appendix Table A2, we construct measures of abnormal attention and sentiment (*AbnAtten_OnlyRival_FY* and *AbnSent_OnlyRival_FY*) from these tweets, demonstrating that our baseline findings remain robust when using this focused data subset.

In addition, we show in Panel B of Appendix Table A2 that our baseline results for abnormal attention and sentiment remain robust using an alternative four-day benchmark window of [-10, -7], which matches the length of the event window. In Panel C, we follow Da, Engelberg, and Gao (2011) and construct the alternative measure of abnormal attention by taking the difference between the log of daily average tweet volume of the event window [0, 3] and that of the benchmark window [-13, -7]. Abnormal sentiment is not reconstructed as the daily average sentiment is bounded between -1 and +1. Our baseline results still hold with this alternative measure.

Next, we extend our robustness analysis by incorporating additional control variables to account for underlying market conditions that may influence firms' product market behavior. As shown in Appendix A3, we control for product market competitiveness using the measure of product market fluidity proposed by Hoberg, Phillips, and Prabhala (2014) in Panel A, and the Herfindahl-Hirschman Index (HHI) for the focal firm in Panel B, which help isolate the effect of social media signals from wider market dynamics. Our baseline findings remain robust with these controls.

Finally, to address potential persistence in firms' product strategies, we include the focal firm's self-fluidity in the current year as an additional control in Panel C. The robustness of our baseline findings with this inclusion strengthens our confidence that the observed associations between social media signals and focal firms' fluidity are not driven by prior product market behavior.

3.4 Direction of Adjustment in Product Offerings: Differentiation and Convergence

We next examine the association between social media reactions to competitors' product announcements and the direction in which focal firms adjust their product offerings in the subsequent year. We implement tests at the firm pair-year level, which allows us to study whether the focal firm and the competitor become more similar or diverge further in the product space. The models are presented as follows:

$$D[Score\ Increase]_{i,j,t+1} = X_{i,j,t} + Control\ variables + \delta_{i,j} + \varepsilon_t \tag{6}$$

$$D[Same\ TNIC3]_{i,j,t+1} = X_{i,j,t} + Control\ variables + \delta_{i,j} + \varepsilon_t \tag{7}$$

We construct two dependent variables based on the Hoberg and Phillips similarity score: (1) a dummy indicator which equals one if the product similarity score between the focal firm *i* and rival firm *j* increases from year *t* to year *t+1*, and zero otherwise, denoted as $D[Score\ Increase]_{i,j,t+1}$, and (2) a dummy indicator which equals one if the focal firm *i* and its rival firm *j* remain in the same TNIC-3 industry in year *t+1*, denoted as $D[Same\ TNIC3]_{i,j,t+1}$. Our key explanatory variables, $X_{i,j,t}$, include abnormal attention ($AbnAtten\_RY_{i,j,t}$) and abnormal sentiment ($AbnSent\_RY_{i,j,t}$)—aggregated over all product announcements by rival firm *j* within the same TNIC3 industry as focal firm *i* in the year *t*—and the interaction between these two.

We include a set of control variables: (1) the abnormal news coverage and abnormal news sentiment of competitor *j*'s product announcements in year *t* ($AbnNewsCoverage\_RY_{j,t}$ and $AbnNewsSent\_RY_{j,t}$) along with a dummy variable indicating missing values for these news measures (*D[missing_News]*); (2) the average four-day cumulative abnormal return of focal firm *i* following competitor *j*'s product announcements in year *t* (*RivalPA_FocalCAR[0,3]*); (3) the average four-day cumulative abnormal return of competitor *j* across its product announcements in year *t* (*RivalPA_RivalCAR[0,3]*), (4) the average recommendation revision issued by sell-side analysts for competitor *j* within seven days following its product announcements (*AvgAnalystRevisions_RY*), with a dummy indicator for rival firm-years lacking such analyst revisions (*D[missing_Revisions_RY]*); (5) the number of product announcements made by competitor *j* in year *t* (*Rival_#NewProducts*); (6) the number of product announcement made by focal firm *i* in year *t* (*Focal_#NewProducts*); and a series of pair-year level factors that may affect competitive dynamics in the product market: (7) technology similarity (*TechSimilarity*), (8) common ownership (*ComOwnership*), and (9) Hoberg and Phillips similarity score (*SimilarityScore*). Finally, we control for firm characteristics for both the focal firm and the competitor, including return on assets (ROA), market-to-book ratio, firm size, book leverage ratio, and R&D. We include firm-pair fixed effects δ_{ij} to control for time-invariant characteristics specific to each firm pair, and year fixed effects ε_t to account for common shocks that affect all firms within a year. Additionally, we examine the robustness of our results by replace pair fixed effects with focal firm fixed effects and rival firm fixed effects, as pair fixed effects may not fully capture all unobserved firm-level characteristics. Standard errors are clustered at the focal firm-year level. The results are presented in Table 4.

[Insert Table 4 here.]

In Panel A, we find strong evidence that heightened social media attention to a competitor's new product is associated with a higher likelihood that the focal firm differentiates its product offerings from the competitor in the following year. In column (1), where firm-pair fixed effects and year fixed effects are included, the coefficient on abnormal attention (*AbnAtten_RY*) is negative and statistically significant ($p < 0.01$), with a one standard deviation increase in abnormal attention associated with a 3.477% decrease in the likelihood that the firm pair becomes more similar in terms of product offerings, as measured by Hoberg and Philips similarity score, corresponding to 10.357% of the unconditional mean. This effect remains robust in column (2), where we replace firm-pair fixed effects with focal fixed effects and rival fixed effects. When changing the dependent variable to $D[Same\ TNIC3]_{i,j,t+1}$, column (3) shows that increased abnormal attention is associated with a lower probability for the firm pairs to remain in the same TNIC-3 industry in the next year. Specifically, a one standard deviation increase in abnormal attention is associated with a 4.392% decrease in the probability of remaining in the same industry, corresponding to 5.842% of the unconditional mean. This result also holds in column (4), where we replace the pair fixed effects with focal fixed effects and rival fixed effects. Together, these results suggest that a focal firm tends to pursue a differentiation strategy when the competitor's new products attract strong social media attention. The focal firm has more incentives to differentiate themselves to avoid direct competition with the rival whose new products have attracted more interest from potential consumers.[20]

In contrast, abnormal sentiment—when unaccompanied with high attention— signals increased convergence in product offerings. As shown in Panel B, column (1), a one standard deviation increase in the abnormal sentiment (*AbnSent_RY*) is associated with a 1.927% increase in the likelihood that the firm pair becomes more similar in their product offerings, corresponding to 5.738% of the unconditional mean. When the dependent variable is changed to $D[Same\ TNIC3]_{i,j,t+1}$, column (3) reports that a one standard deviation increase in the abnormal sentiment is associated with a 0.407% increase in likelihood that the focal firm and its rival remain in the same TNIC3 industry next year, corresponding to 0.542% of the unconditional mean. These results remain robust in columns (2) and (4), where we replace firm-pair fixed effects with focal firm fixed effects and rival firm fixed effects. These findings suggest that positive abnormal sentiment—which likely reflects consumer enthusiasm toward the new products, but not necessarily market dominance—signals a convergence strategy by focal firms to align their offerings with new innovations that have promising earnings potential.

In Panel C, we explore the interaction between abnormal attention and abnormal sentiment. We find that the positive association between abnormal attention and the likelihood of focal firms adopting a product differentiation strategy is amplified when abnormal sentiment is more favorable, as evidenced by the negative and statistically significant coefficient of the interaction term ($p < 0.01$). This combined signal — elevated social media attention accompanied by favorable sentiment—indicates the introduction of a notably strong product by the competitor, which not only attracts widespread attention

[20] Alternatively, we conduct tests at the focal firm-year level. The dependent variables are: (1) the fraction of focal-competitor pairs with increased product similarity score and (2) the fraction of focal-competitor pairs remaining in the same TNIC-3 industry in the next year. These fractions are calculated across all rival firms that announced new products in a given year. We use a fractional probit model, controlling for Fama French 48 industry fixed effects and year fixed effects. Standard errors are clustered at the Fama French 48 industry-year level. Results, reported in Appendix Table A4, indicate that higher abnormal attention (*AbnAtten_FY*) is significantly associated with a lower fraction of firm pairs with higher similarity score and firm pairs remaining in the same industry. These findings further support the interpretation that elevated social media attention signals a shift toward product differentiation at the focal firm level.

but also receives strong approval. Under these conditions, focal firms are more likely to pursue strategic differentiation to avoid direct competition when competitors' new products garner strong positive feedback from potential consumers.

IV. Mechanism and Heterogeneity

4.1 Informational Contents of Tweets

We argue that social media provides timely and informative signals by capturing real-time insights from the consumer-side of the market. In investor-oriented platforms such as Stocktwits, users possess a dual role: they are both participants in the financial market and potential consumers in the product market. This dual identity uniquely positions them to respond promptly to corporate events—particularly product announcements—that carry implications for both earnings potential and consumer demand. Consequently, user-generated content on such platforms reflects not only investor insights but also immediate consumer feedback. In this section, we provide two sets of evidence supporting the premise that social media activities reflect consumer-based perceptions.

4.1.1 Tweets under Different Topics

If social media signals capture consumer interest toward the new product, we expect that signals originating from product-related content will demonstrate stronger associations with changes in focal firms' product offerings compared to signals derived from irrelevant content. To test this, we employ a structural topic modeling approach to analyze tweets from Stocktwits. As detailed in Section 2.2.3, tweets posted around product announcements are categorized into three broad groups—product-related, trading-related, and other content. Based on this classification, we decompose the measure of abnormal attention (*AbnAtten_FY*) into category-specific measures, denoted as *AbnAtten_FY_Product, AbnAtten_FY_Trade*, and *AbnAtten_FY_Other*. We then estimate the baseline model (3), incorporating these measures as primary explanatory variables of interest. The results are presented in Table 5.

[Insert Table 5 here.]

Our results support the expectation. As shown in column (1) of Table 5, abnormal attention derived from product-related tweets (*AbnAtten_FY_Product*) is significantly associated with subsequent changes in focal firms' product portfolios. A one-standard-deviation increase in product-related attention is associated with a 0.621 increase in focal firm's fluidity in the next year ($p < 0.01$), corresponding to 3.318% of the unconditional mean. The model controls for other information channels, factors affecting product market decisions, firm characteristics, firm fixed effects, and year fixed effects being controlled. In column (2), the effect rises to 4.435% after further accounting for industry-year level shocks. In columns (3) and (4), we address the issue of undefined attention measures—arising when competitors have no product-related tweets in the benchmark period—by filling missing values as zero and including a dummy indicator, *D[miss_AbnAtten_Product],* to identify these cases. The positive correlation of product-related attention and fluidity remains robust under this specification. Notably, the dummy indicator is negative and statistically significant, suggesting that when competitors' new products trigger little or no product-related discussions on social media—likely reflecting limited consumer interest or a less dynamic product market environment—the focal firm tends to maintain a more stable product strategy.[21]

In addition, trading-related attention is also positively associated with changes in a focal firm's product fluidity, with an economic magnitude comparable to that of product-related attention (4.551% and 4.796% in columns (1) and (2) respectively). Users on financial social media platforms may generate product insights from a consumer perspective and translate them into trading-related commentary, such as buy or sell recommendations, thereby reflecting underlying consumer perceptions toward the new product. Overall, these results underscore that product-related signals are non-trivial and informative in understanding firms' product market strategies, while trading-related attention complements this by providing additional investment-driven perspectives.

[21] For the product announcements without product-related tweets in the benchmark window [-13, -7], we observe that these announcements tend to be the ones with low social media attention and have fewer product-related tweets during the event window [0, 3]. To be more specific, firms without product tweets in the benchmark window have an average of 0.270 product tweets in the event window, which is significantly lower than the average of 4.925 product-related tweets for firms with product-related tweets in the benchmark window.

Importantly, we find no significant association between the abnormal attention derived from other topics—such as unrelated discussions, general market commentary—and adjustments in the focal firm's product portfolio. This suggests that not all social media discussions are informative for understanding firm strategic behavior in the product market. Specifically, social media content that are directly related to products provide meaningful insights into consumer interest that are associated with firms' product market decisions. In contrast, attention generated by unrelated or broader market topics appears to lack the specificity necessary to signal shifts in consumer demand.

4.1.2 Market-Oriented Firms

If social media discussions collectively reflect real-time, firm-specific signals of consumer-side information, we expect such signals to be particularly salient for market-oriented firms—those placing greater emphasize on understanding and responding to consumer preferences and competitive dynamics. In this section, we partition the focal firm-year sample into two groups based on whether at least one competitor with product announcements operates in an industry characterized as market-oriented.[22] The results are presented in Table 6.

[Insert Table 6 here.]

Table 6 shows that our baseline correlations of abnormal attention and abnormal sentiment with focal firms' product fluidity remain positive and statistically significant in the subsample of Panel A, which includes industries characterized by market-oriented firms. On the contrary, we do not find significant relationship in the subsample reported in Panel B where none of the competitors are from market-oriented industries. These results support the argument that social media signals capture

[22] Market-oriented industries are identified based on the Fama-French 48 Industry Classification (FF48) because it provides a widely used, manageable grouping of firms into economically meaningful sectors defined by their primary business activities (Fama and French, 1997), such as Pharmaceutical Products, Consumer Goods, and Recreation. In contrast, the Hoberg and Phillips TNIC3 classification identifies firm-specific competitors based on textual similarity in product descriptions and does not assign broad industry labels. Consequently, these two classifications do not perfectly overlap. For each focal firm in a given year, it is possible that not all competitors identified by the TNIC3 classification belong to the same market-oriented industry as defined by FF48.

consumer-side information, which more accurately reflects the product market strategies of the focal firm that actively align their strategies, products, and services with consumers' interest and preference.

4.2 Firm Heterogeneity

Common analyst coverage can potentially exhibit mixed effects on the adjustment of product offerings. On the one hand, firm pairs covered by common analysts show greater similarity in fundamentals (Ali and Hirshleifer, 2020; Kaustia and Rantala, 2021), which may indicate more direct competition and potentially motivate firms to differentiate and avoid head-to-head rivalry. On the other hand, common analyst linkages serve as important channels for information transmission (Banerjee, Dasgupta, Shi, and Yan, 2024; Martens and Sextroh, 2021). The technology spillover through the common analyst link can bring more convergence in product offerings. Our empirical results in Panel A of Table 7 show a more pronounced positive association between abnormal attention to competitors' product announcements and the likelihood of the firm pair becoming more similar in product offerings or remaining in the same industry in the following year, when the focal firm and its competitor are covered by more common analysts. Furthermore, in Panel B, we use the fraction of competitor's patents in the same three-digit CPC category as the focal firm's patents to indicate the technology similarity between two firms. We show similar results when firms are more technologically similar. Taken together, the results from both panels may reflect the underlying flows of technology information — possibly facilitated by common analyst links—that contribute to convergence in product offerings.

[Insert Table 7 here.]

In Panel C, we examine how the relative firm size of the focal firm compared to its competitor influences the relationship between social media attention to the competitor' product announcements and the direction of focal firm's strategic adjustments in product offerings. Larger firms typically possess more resources, a more established market position, and greater capacity for innovation. In competitive product markets, these advantages allow these firms either to differentiate themselves by developing distinctive products to protect their dominant market position. Alternatively, they may adopt features or innovations similar to those introduced by competitors to stay with market trends, potentially undermining the peer firms' market positions and limiting their growth.

To test this, we include an interaction term between abnormal attention to the competitor's new product announcements (*AbnAtten_RY*) and the focal firm's relative size (*Focal_RelativeSize*), measured as its total assets divided by the total assets of the competitor. We find that when the focal firm is relatively larger than the competitor, strong social media attention to competitors' new products is associated with a higher likelihood that the firm pair will remain in the same industry and an increased similarity in product offerings in the following year. This finding supports the argument that larger firms may engage in preemptive imitation strategy when threatened by smaller competitors' growth potential. On the other hand, the coefficient on relative size alone is significantly negative, suggesting that in the absence of strong competitive threats, larger firms tend to pursue differentiation strategy—likely reflecting their ability to carve out unique market niches rather than follow smaller peers.

4.3 Focal Firms' Performance and Growth

While previous analyses provide evidence that social media information can signal changes in focal firms' product offerings, the economic value of these changes—whether value-enhancing or value-destroying—is unknown. In this section, we conduct two sets of analyses to investigate whether the focal firm's subsequent performance improves after its competitor's new products trigger heightened discussions on social media.

To assess the performance implications of these signals, first, we examine the stock market reactions and social media responses to the focal firm's first product announcement in the year subsequent to the competitor's product announcement. Results are presented in Table 8. We find that when the competitor's new products attract substantial attention and high sentiment on the social media, the focal firm's product announcement in the next year receives positive stock market reactions, as measured by the four-day cumulative abnormal returns (*CAR[0,3]_Focal_1stPA*). Additionally, it attracts favorable sentiment on social media (*AbnSent_Focal_1stPA*), though the level of attention is moderate (*AbnAtten_Focal_1stPA*). Second, we examine the focal firm's overall performance in the product market in the following year. As shown in Panel B, the focal firm exhibits higher sales growth in the next year if the competitor's new products in the current year attract substantial attention and favorable sentiment on social media.

[Insert Table 8 here.]

Overall, the results in Table 8 suggest that social media signals—generated in response to competitors' product announcements—not only have the potential to serve as valuable indicators of the focal firm's strategic changes in product offering, but also indicate that these changes bring value to the firm.

V. Conclusion

This paper explores whether firms' product market strategies are associated with social media reactions to competitors' product announcements and the information reflected in these reactions. Using Stocktwits data, we observe that product announcements trigger heightened discussions on social media, which in turn are significantly associated with strategic adjustments in focal firms' product offerings. We argue that social media attention and sentiment reflect distinct but complementary facets of consumer demand — attention signals consumer interest in the new products, whereas sentiment captures consumer enthusiasm or aversion. Specifically, our analysis reveals nuanced dynamics in the direction of these adjustments: while high abnormal attention to competitor's new products is associated with greater product differentiation by the focal firm, favorable sentiment is linked to a higher likelihood of convergence when attention is moderate, but amplifies the differentiation effect when attention is high. These results remain robust when controlling for alternative information channels, such as traditional news coverage, stock market reactions, and analyst recommendation revisions, highlighting that the unique value of social media signals in capturing real-time, consumer-side market insights.

In further support of the argument that social media reflects facets of consumer preference, we present two sets of evidence. First, we categorize tweet into groups using structural topic modeling and show that only product-related signal is significantly correlated with focal firms' product adjustments, while signals derived from unrelated discussions show no such association. Second, the associations between social media signals and adjustments of focal firms' product offerings are concentrated in market-driven industries where firms place great emphasize on consumer preference and competitive dynamics.

Next, our findings highlight the roles of technological similarity and common analyst coverage: firm pairs covered by more common analysts or sharing high technology similarity are more likely to converge in product offerings, indicating potential spillovers of technological information through common analyst linkages. Additionally, relatively large focal firms are more likely to converge with smaller competitors whose new products receive substantial social media attention, suggesting a preemptive imitation strategy.

Finally, we show that focal firms show higher sales growth in the subsequent year and their new products are positively received by the stock market and the social media when their competitors' new products attract strong social media reactions, indicating that changes in their product offerings bring value to firms.

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Figure 1. Examples of Tweets posted by Stocktwits Users Following Product Announcement
In this figure, we show examples of tweets posted by Stocktwits users following Mannkind Corporation ($MNKD)'s announcement of new drug *Afrezza* on February 3rd, 2015. *Afrezza* is a rapid-acting inhalable insulin designed to improve blood sugar control in adults with diabetes, offering a needle-free alternative to traditional insulin delivery methods.

Money_Templar February 3, 2015 12:20 PM

$MNKD Wow! 🤝 Now what was it this company came out with? A life changing device for diabetes without the needle? Bullish

Money_Templar February 3, 2015 12:22 PM

$MNKD I'm teasing but shocked. This thing should be SCREAMING by now! Bullish

Rockingrollingfun. February 3, 2015 12:33 PM

$MNKD Just google afrezza and it was top hit as an ad.

atee February 3, 2015 12:37 PM

$MNKD Not in this anymore, but with the news today why isn't it moving? Any guess?

Mitchdubb February 3, 2015 12:43 PM

$MNKD Biotechs getting slammed today. I'll take the green

GKSbay February 3, 2015 12:45 PM

$MNKD All reporting today show the price comparison to existing insulin far too expensive and total BS, that's part of the PPS issue today.

Mellifera February 3, 2015 12:51 PM

$MNKD If you want to know why the stock isn't moving, check out the market cap for MNKD and consider that sales is just now starting. Bullish

_ MoneyMike_ February 3, 2015 12:52 PM

$MNKD Adding Bullish

BullMarket75 February 3, 2015 12:53 PM

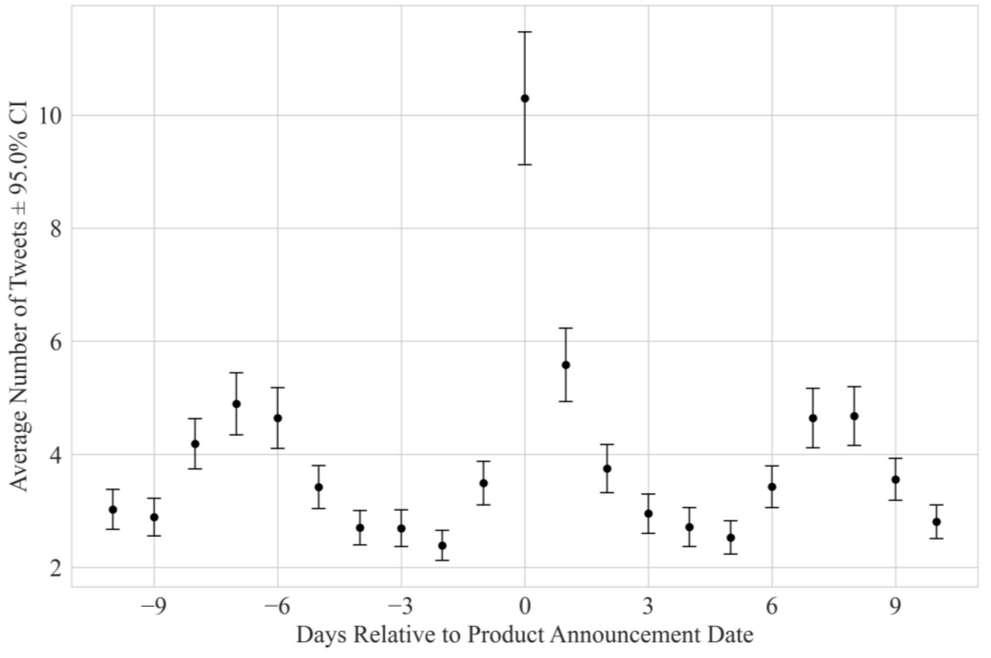
$MNKD 1500 Sanofi sales reps pushing Afrezza exclusively....that's BIG! Just getting started.. Bullish

Verticalmojo February 3, 2015 12:59 PM

$MNKD chart $MNKD Golden cross, a bullish sign Bullish

Figure 2. Tweet Volume and User Engagement on Stocktwits around Product Announcements
This figure shows tweeting activity by Stocktwits users around product announcements. The sample only includes *clean* product announcements—those for which no other events occur within a 15-day event window spanning from day t-7 to t+7, with t = 0 denoting the product announcement date. Panel A presents the daily average number of tweets per event mentioning the announcing firm. Panel B plots the daily average number of unique Stocktwits users who posted tweets mentioning the announcing firm. The bars indicate the 95% confidence intervals. In both panels, the average number of tweets is winsorized at the 1% level on both tails of the distribution.

Panel A. Tweet volume



Panel B. User Engagement

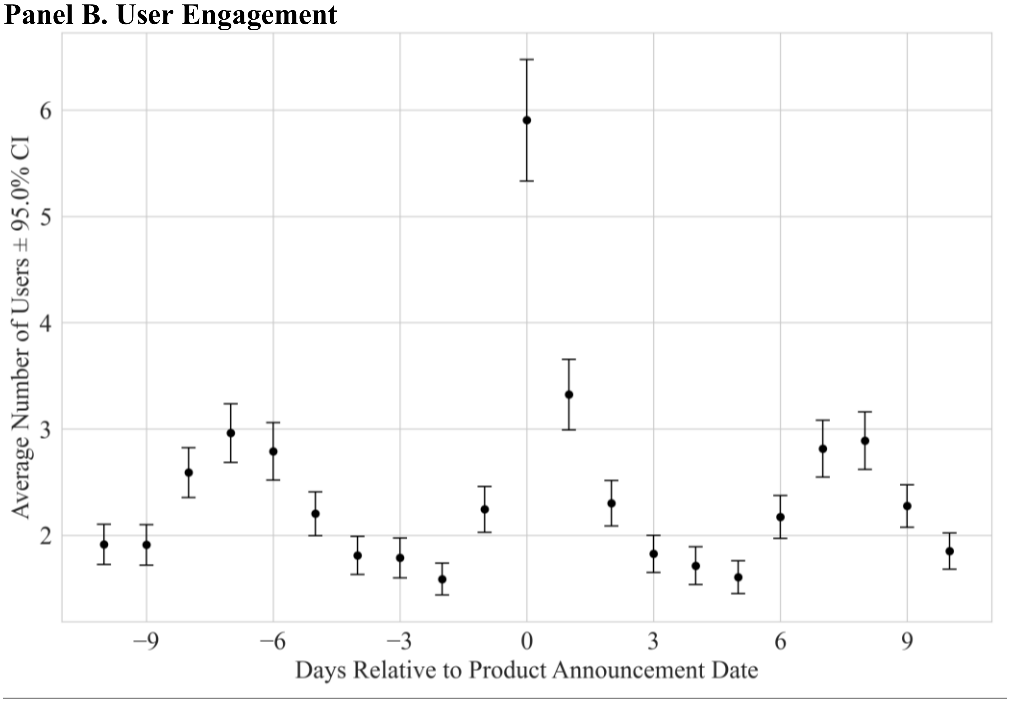
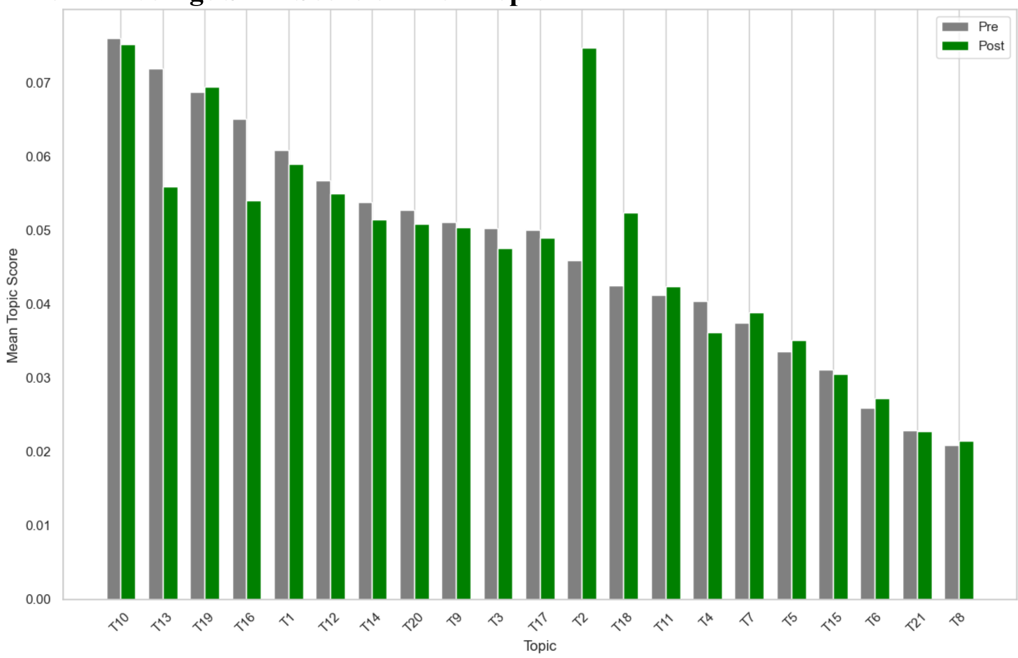


Figure 3. Tweets Topic Distribution around Product Announcements

This figure shows the proportion of topics discussed by Stocktwits users in the pre-event period ([-13, -7]) and the post-event period ([0, 3]), relative to the firm's product announcement date (t=0). A Structural Topic Modeling (STM) with 21 topics is used to identify themes in the tweets and estimate the probability of each topic for every tweet. Among these topics, #2 and #18 predominately feature vocabulary associated with products. Panel A presents the average probability score for each topic across tweets posted in the pre-event and post-event periods. Topics are presented in descending order based on their average scores in the pre-event period. Panel B assigns each tweet to the topic with the highest probability score and displays the proportion of tweets attributed to each topic in the pre-event and post-event period. Topics are presented in descending order based on the proportion of tweets under each topic in the pre-event period.

Panel A. Average STM Score of Each Topic



Panel B. Proportion of Tweets Belonged to Each Topic

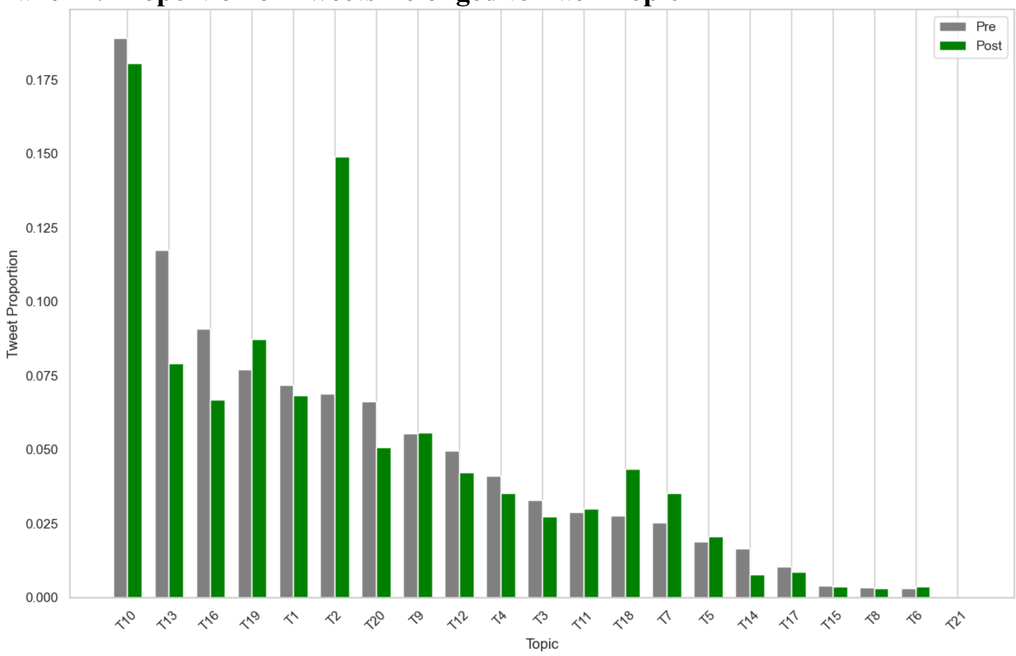


Table 1. Market-Driven Industries and Social Media Reactions to Product Announcements

This table presents the distribution of social media reactions to product announcements across industries The sample includes 2,766 clean announcements from 2010 to 2021, classified by the Fama French 48 Industry Classification. Industries are ranked by average daily tweet volume per event (column (5)) from highest to the lowest. Column (3) flags the *Market-Oriented* industries, where firms prioritize understanding and responding to customer demand and competitive dynamics. Column (4) shows the total number of clean announcements in each industry. Column (5) and (6) display the average daily tweet volume (number of tweets mentioning the announcing firm) for each product announcement during the post-event period [0, 3] and pre-event period [-13, -7], respectively. Column (7) shows the average abnormal attention across all product announcements in the industry (*AbnAtten*), which equals the fractional increase of daily tweet volume from [-13, -7] to [0, 3]. Columns (8) and (9) show the average sentiment score for each product announcement during [0, 3] and [-13, -7] respectively, which are calculated based on the voluntarily disclosed sentiment on Stocktwits (where -1 is bearish and 1 is bullish). Column (10) shows the average abnormal sentiment for each product announcement (*AbnSent*), which equals the difference between average sentiment in [0, 3] and [-13, -7].

(1) *Rank*	(2) *Fama French 48 Industry Classification*	(3) *Market Oriented*	(4) *#New Product Announce*	(5) *Avg. #Tweets in [0, 3]*	(6) *Avg. #Tweets in [-13, -7]*	(7) *Average AbnAtten*	(8) *Avg. Sentiment in [0, 3]*	(9) *Avg. Sentiment in [-13, -7]*	(10) *Average AbnSent*
1	Pharmaceutical Products	1	273	40.788	25.070	4.921	0.754	0.012	0.805
2	Consumer Goods	1	64	32.840	12.266	0.247	0.420	-0.086	0.431
3	Recreation	1	54	30.954	37.132	1.527	0.756	0.107	0.859
4	Automobiles and Trucks	1	86	25.735	13.512	4.041	0.662	0.168	0.496
5	Electrical Equipment	0	62	23.778	9.138	0.966	0.732	-0.033	0.816
6	Electronic Equipment	0	475	14.058	13.068	0.578	0.700	0.007	0.726
7	Medical Equipment	0	160	13.933	7.465	2.445	0.607	0.108	0.719
8	Steel Works Etc	0	15	13.383	7.352	0.316	0.550	0.019	0.813
9	Wholesale	0	41	8.244	3.397	0.668	0.672	-0.184	0.555
10	Retail	1	120	8.144	7.075	0.512	0.372	0.139	0.503
11	Candy & Soda	1	10	8.100	10.843	1.136	0.881	0.034	0.925
12	Business Services	0	567	7.634	7.374	0.876	0.683	0.000	0.724
13	Entertainment	1	25	6.260	9.063	0.349	0.499	-0.058	0.554
14	Apparel	1	47	5.324	8.978	0.448	0.493	-0.026	0.630
15	Healthcare	1	17	4.706	4.168	1.436	0.830	-0.225	0.609
16	Chemicals	0	41	4.512	4.070	0.773	0.536	0.265	0.798
17	Communication	0	98	4.240	2.494	0.772	0.673	-0.042	0.627
18	Food Products	1	86	4.195	5.364	0.296	0.452	-0.113	0.513
19	Restaurants, Hotels, Motels	1	58	4.060	4.283	0.272	0.547	0.137	0.704
20	Transportation	0	36	3.799	5.821	0.397	0.466	0.096	0.523

Table 2: Summary Statistics for Variables used in Regressions

This table presents summary statistics for the variables used in the empirical sections. The sample period spans from 2010 to 2021. The left panel shows the variables we use in the focal firm-year level tests, with 15,632 observations. The right panel shows the variables in the firm pair-year level tests, with 166,071 observations.

Variables for Focal-Year Sample	Mean	Med	S.D.	Variables for Pair-Year Sample	Mean	Median	S.D.
Fluidity	17.768	14.125	13.859	*D[Score Increase]*	0.252	0.000	0.434
AbnAtten_FY	0.308	0.008	1.294	*D[Same TNIC]*	0.609	1.000	0.488
AbnSent_FY	0.019	0.000	0.308	*AbnAtten_RY*	2.597	0.375	7.453
D[miss_AbnSent_FY]	0.347	0.000	0.476	*AbnSent_RY*	0.009	0.000	0.422
AbnAtten_FY_Product	1.609	1.008	2.595	*D[miss_AbnSent_RY]*	0.405	0.000	0.491
AbnAtten_FY_Trade	0.382	-0.125	1.816	*AbnNewsCoverage_RY*	-0.170	0.000	0.521
AbnAtten_FY_Other	0.129	-0.140	1.354	*AbnNewsSent_RY*	-0.000	0.000	0.109
D[miss_AbnAtten_Product]	0.303	0.000	0.460	*D[miss_News]_RY*	0.736	1.000	0.441
D[miss_AbnAtten_Trade]	0.100	0.000	0.299	*RivalPA_FocalCAR[0,3]_RY*	-0.250	-0.274	7.895
D[miss_AbnAtten_Other]	0.077	0.000	0.267	*RivalPA_RivalCAR[0,3]_RY*	0.720	0.357	7.803
AbnNewsCoverage_FY	-0.138	-0.344	1.069	*Rival_#NewProducts_RY*	3.351	2.000	4.934
AbnNewsSent_FY	0.001	0.000	0.215	*AvgAnalystRevisions_RY*	0.009	0.000	0.229
D[miss_News]_FY	0.267	0.000	0.443	*D[miss_Revisions_RY]*	0.970	1.000	0.169
RivalPA_RivalCAR[0,3]_FY	0.175	0.082	3.723	*ComOwnership*	0.111	0.077	0.118
RivalPA_FocalCAR[0,3]_FY	-0.136	-0.119	3.720	*TechSimilarity*	0.038	0.000	0.146
Rival_Avg#NewProducts_FY	5.897	3.500	8.692	*SimilarityScore*	0.058	0.041	0.054
AvgAnalystRevisions_FY	0.070	0.000	0.602	*Rival_ROA*	-0.476	-0.186	1.199
D[miss_Revisions]_FY	0.787	1.000	0.410	*Rival_M/B*	3.759	2.569	3.817
AvgComOwnership	0.133	0.130	0.106	*Rival_log(Asset)*	5.583	5.618	1.896
AvgScore_FY	0.037	0.029	0.031	*Rival_Book Leverage*	0.237	0.148	0.345
Focal_#Patent	50.062	0.000	217.329	*Rival_R&D*	0.265	0.166	0.312
Focal_MktShare	0.229	0.077	0.295	*Nbr[CA]*	0.817	0.000	2.806
Focal_#NewProducts	1.806	0.000	5.460	*Focal_RelativeSize*	1.132	0.996	0.613
Focal_ROA	-0.222	0.010	1.050				
Focal_M/B	2.784	1.919	3.324				
Focal_FirmSize	6.282	6.195	2.178				
Focal_Book Leverage	0.227	0.160	0.293				
Focal_R&D	0.161	0.055	0.275				

Table 3. Social Media Signals and Adjustment in Product Offerings

This table reports OLS regression results examining whether focal firms adjust their product offerings when competitors' new products receive strong reactions on social media. The sample consists of 14,824 focal firm-year level observations from 2010 to 2021. The dependent variable $Fluidity_{t+1}$ measures the changes in the product offerings of focal firm in year *t+1* relative to year *t*. Our key explanatory variables are $AbnAtten\_FY_t$ and $AbnSent\_FY_t$, representing abnormal social media attention and sentiment, respectively, for products announcements by competitors within the same TNIC-3 industry as the focal firm in year t. These variables are constructed at the focal firm-year level by aggregating across multiple competitors making announcements within the industry. Columns (1) and (3) include focal firm fixed effects and year fixed effects. Columns (2) and (4) replace year fixed effects to Fama French 48 industry-by-year fixed effects. Columns (1) and (2) present the effects of social media signals without control variables. In columns (3) and (4), we account for alternative information channels, including (a) abnormal news coverage of competitors' announcements (*AbnNewsCoverage_FY),* abnormal news sentiment (*AbnNewsSent_FY*), and a dummy indicator for missing news coverage data (*D[miss_News]_FY*), (b) the average cumulative abnormal returns of the focal firm and the competitor in the [0, 3] window after the competitor's product announcement (*RivalPA_FocalCAR[0,3]_FY* and *RivalPA_RivalCAR[0,3]_FY)*, (c) average recommendation revisions issued by sell-side analysts for the competitor (*AvgAnalystRevisions_FY)* within seven days after its product announcement and the dummy indicator for missing recommendation revisions (*D[miss_Revisions]_FY*). In addition, we also control for factors that may affect competitive dynamics in the product market: (d) the number of product announcements by the focal firm (*Focal_#NewProducts*) and competitors (*Rival_Avg#NewProducts*) in year *t*, (e) the market share of focal firm *i* (*Focal_MktShare*), (f) the number of patents held by the focal firm (*Focal_#Patents*), (g) the average common ownership between the focal firm and its competitors (*AvgComOwnership*), and (h) the average product similarity score between focal firm *i* and its competitors (*AvgScore_FY*). Finally, we control for a series of firm characteristics including ROA, market-to-book ratio, firm size, book leverage ratio, and R&D. Panel A reports the effects of abnormal attention ($AbnAtten\_FY_t$), Panel B reports the effects of abnormal sentiment ($AbnSent\_FY_t$), and Panel C reports the effect of their interaction. In all specifications, standard errors are clustered at the Fama French 48 industry-by-year levels. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Panel A. Abnormal Attention and Focal Firms' Product Offerings

	(1)	(2)	(3)	(4)
		Fluidity [t+1]		
AbnAtten_FY[t]	0.646***	0.730***	0.635***	0.731***
	(4.880)	(4.678)	(4.921)	(4.802)
AbnNewsCoverage_FY[t]			0.215	0.159
			(1.599)	(0.944)
AbnNewsSent_FY[t]			0.360	-0.201
			(0.588)	(-0.298)
D[miss_News]_FY[t]			-0.340	-0.751**
			(-1.028)	(-2.130)
RivalPA_FocalCAR[0,3]_FY[t]			0.051	0.064*
			(1.549)	(1.892)
RivalPA_RivalCAR[0,3]_FY[t]			-0.006	-0.015
			(-0.184)	(-0.372)
Focal_#NewProducts[t]			-0.019	-0.021
			(-0.684)	(-0.748)
Rival_Avg#NewProducts_FY[t]			0.006	0.014
			(0.345)	(0.726)
AvgAnalystRevisions_FY[t]			-0.180	-0.088
			(-1.069)	(-0.415)
D[miss_Revisions]_FY[t]			-0.193	-0.046
			(-0.689)	(-0.151)
Focal_MktShare[t]			-1.826***	-1.229
			(-2.606)	(-1.604)
Focal_#Patents[t]			0.008***	0.009***
			(2.773)	(3.055)
AvgComOwnership[t]			-3.249*	-3.268
			(-1.656)	(-1.455)
AvgScore_FY[t]			6.483	5.861
			(1.057)	(0.828)
Focal_ROA[t]			0.066	0.076
			(0.395)	(0.442)
Focal_M/B[t]			-0.090*	-0.102*
			(-1.724)	(-1.816)
Focal_FirmSize[t]			-0.794**	-0.910***
			(-2.559)	(-2.917)
Focal_Book Leverage[t]			0.494	0.119
			(0.875)	(0.199)
Focal_R&D[t]			0.341	0.686
			(0.364)	(0.778)
Focal Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	NO	YES	NO
Year*FF48 Fixed Effects	NO	YES	NO	YES
Cluster S.E. at FF48 * Year	YES	YES	YES	YES
Observations	14,824	14,766	14,824	14,766
Adjusted R^2	0.259	0.261	0.261	0.263

Panel B. Abnormal Sentiment and Focal Firms' Product Offerings

	(1)	(2)	(3)	(4)
		Fluidity [t+1]		
AbnSent_FY[t]	0.669**	0.785*	0.698**	0.746*
	(2.055)	(1.792)	(2.049)	(1.721)
D[miss_AbnSent_FY][t]	-0.331	-0.071	0.049	0.186
	(-0.980)	(-0.183)	(0.139)	(0.471)
AbnNewsCoverage_FY[t]			0.327**	0.260
			(2.318)	(1.439)
AbnNewsSent_FY[t]			0.358	-0.057
			(0.599)	(-0.085)
D[miss_News]_FY[t]			-0.290	-0.686*
			(-0.864)	(-1.932)
RivalPA_FocalCAR[0,3]_FY[t]			0.053	0.065*
			(1.594)	(1.907)
RivalPA_RivalCAR[0,3]_FY[t]			0.014	0.013
			(0.409)	(0.320)
Focal_#NewProducts[t]			-0.017	-0.018
			(-0.605)	(-0.615)
Rival_Avg#NewProducts_FY[t]			0.005	0.014
			(0.318)	(0.706)
AvgAnalystRevisions_FY[t]			-0.216	-0.152
			(-1.212)	(-0.711)
D[miss_Revisions]_FY[t]			-0.239	-0.027
			(-0.831)	(-0.088)
Focal_MktShare[t]			-1.651**	-1.192
			(-2.319)	(-1.497)
Focal_#Patents[t]			0.008***	0.009***
			(2.638)	(2.898)
AvgComOwnership[t]			-3.524*	-3.550
			(-1.815)	(-1.575)
AvgScore_FY[t]			5.712	6.035
			(0.929)	(0.840)
Focal_ROA[t]			0.066	0.076
			(0.399)	(0.455)
Focal_M/B[t]			-0.086	-0.101*
			(-1.639)	(-1.797)
Focal_FirmSize[t]			-0.812***	-0.930***
			(-2.619)	(-2.979)
Focal_Book Leverage[t]			0.520	0.109
			(0.906)	(0.181)
Focal_R&D[t]			0.293	0.629
			(0.318)	(0.722)
Focal Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	NO	YES	NO
Year*FF48 Fixed Effects	NO	YES	NO	YES
Cluster S.E. at FF48 * Year	YES	YES	YES	YES
Observations	14,832	14,774	14,832	14,774
Adjusted R^2	0.256	0.258	0.258	0.260

Panel C. Interaction of Abnormal Attention and Sentiment

	(1)	(2)	(3)	(4)
		Fluidity [t+1]		
AbnAtten_FY[t]	0.575***	0.675***	0.570***	0.686***
	(4.519)	(4.535)	(4.570)	(4.658)
*AbnAtten_FY * AbnSent_FY[t]*	0.937**	0.835*	0.969***	0.795*
	(2.494)	(1.918)	(2.619)	(1.873)
AbnSent_FY[t]	0.044	0.349	0.091	0.366
	(0.127)	(0.786)	(0.264)	(0.833)
D[miss_AbnSent]_FY[t]	-0.110	0.129	0.275	0.402
	(-0.315)	(0.323)	(0.774)	(0.998)
AbnNewsCoverage_FY[t]			0.225*	0.150
			(1.698)	(0.911)
AbnNewsSent_FY[t]			0.422	-0.196
			(0.686)	(-0.291)
D[miss_News]_FY[t]			-0.388	-0.766**
			(-1.177)	(-2.198)
RivalPA_FocalCAR[0,3]_FY[t]			0.050	0.064*
			(1.509)	(1.882)
RivalPA_RivalCAR[0,3]_FY[t]			-0.008	-0.021
			(-0.219)	(-0.500)
Focal_#NewProducts[t]			-0.020	-0.022
			(-0.718)	(-0.770)
Rival_Avg#NewProducts_FY[t]			0.005	0.013
			(0.314)	(0.683)
AvgAnalystRevisions_FY[t]			-0.219	-0.097
			(-1.264)	(-0.458)
D[miss_Revisions]_FY[t]			-0.245	-0.090
			(-0.878)	(-0.295)
Focal_MktShare[t]			-1.912***	-1.384*
			(-2.681)	(-1.777)
Focal_#Patents[t]			0.008***	0.009***
			(2.755)	(3.040)
AvgComOwnership[t]			-3.543*	-3.511
			(-1.808)	(-1.566)
AvgScore_FY[t]			6.451	5.370
			(1.060)	(0.756)
Focal_ROA[t]			0.066	0.075
			(0.392)	(0.441)
Focal_M/B[t]			-0.091*	-0.100*
			(-1.763)	(-1.777)
Focal_FirmSize[t]			-0.781**	-0.889***
			(-2.523)	(-2.847)
Focal_Book Leverage[t]			0.487	0.119
			(0.861)	(0.199)
Focal_R&D[t]			0.350	0.708
			(0.380)	(0.813)
Focal Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	NO	YES	NO
Year*Focal FF48 Fixed Effects	NO	YES	NO	YES
Cluster S.E. at Focal FF48 * Year	YES	YES	YES	YES
Observations	14,824	14,766	14,824	14,766
Adjusted R^2	0.260	0.261	0.261	0.263

Table 4. Focal Firm's Product Market Strategies: Differentiation and Convergence

This table reports OLS regression results examining the direction in which focal firms adjust their product offerings when competitors' new products attract strong social media reactions. The tests implement at the firm pair-year level, with competitors defined as firms within the same TNIC-3 industry as the focal firm in year *t*. We construct two dependent variables based on the Hoberg and Phillips similarity score: (a) $D[Score\ Increase]_{i,j,t+1}$, a dummy indicator which takes the value of one if the product similarity score between the pair increases in the following year and zero otherwise, and (b) $D[Same\ TNIC3]_{i,j,t+1}$, a dummy indicator which takes the value of one if the focal firm *i* and its competitor *j* remain in the same TNIC-3 industry in the following year. For each focal-rival pair in a given year, $AbnAtten\_RY_{i,j,t}$ ($AbnSent\_RY_{i,j,t}$) is the abnormal attention (sentiment) for competitors' product announcements in year *t*. Since one competitor can make multiple product announcements in a year, the abnormal attention (sentiment) is aggregated to the rival firm-year level. Columns (1) and (3) include firm pair fixed effects and year fixed effects, while columns (2) and (4) replace pair fixed effects with focal firm fixed effects and rival firm fixed effects. All regressions control for alternative information channels, product market competition factors, and firm characteristics. Panel A reports the effects of abnormal attention ($AbnAtten\_RY_{i,j,t}$), Panel B reports the effects of abnormal sentiment ($AbnSent\_RY_{i,j,t}$), and Panel C reports the interaction effects of the two. Standard errors are clustered at the focal firm interacted with year levels. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Panel A. Abnormal Attention and Focal Firm's Product Market Strategies

Model: OLS	(1)	(2)	(3)	(4)
Dependent Variable:	*D[Score Increase] [t+1]*		*D[Same TNIC] [t+1]*	
AbnAtten_RY[t]	-0.005***	-0.005***	-0.006***	-0.004***
	(-11.831)	(-15.781)	(-18.543)	(-16.536)
AbnNewsCoverage_RY[t]	-0.004	-0.001	-0.009**	-0.006*
	(-0.878)	(-0.342)	(-2.116)	(-1.870)
AbnNewsSent_RY[t]	-0.160***	-0.151***	-0.107***	-0.124***
	(-7.901)	(-9.076)	(-7.044)	(-9.708)
RivalPA_FocalCAR[0,3]_RY[t]	0.000	-0.000	-0.000	0.000
	(0.704)	(-0.111)	(-0.496)	(0.689)
RivalPA_RivalCAR[0,3]_RY[t]	0.002***	0.002***	-0.001**	0.000
	(4.427)	(7.976)	(-2.420)	(0.452)
AvgAnalystRevisions_RY[t]	-0.007	-0.003	0.028***	0.025***
	(-0.782)	(-0.356)	(3.911)	(3.972)
Focal_#NewProducts[t]	-0.000	0.000	-0.000	-0.000
	(-0.441)	(0.133)	(-0.523)	(-0.667)
Rival_#NewProducts_RY[t]	-0.000	-0.001*	-0.000	-0.002***
	(-0.384)	(-1.793)	(-0.231)	(-4.389)
TechSimilarity[t]	-0.082	-0.022**	-0.041	-0.014*
	(-1.044)	(-2.353)	(-0.580)	(-1.660)
ComOwnership[t]	0.049	0.070***	0.084**	0.048***
	(1.092)	(4.065)	(2.244)	(2.940)
SimilarityScore[t]	-9.427***	-0.938***	2.150***	1.738***
	(-54.115)	(-25.081)	(18.466)	(45.273)
Rival_ROA[t]	-0.008**	0.001	-0.002	0.003
	(-2.218)	(0.315)	(-0.545)	(1.210)
Rival_M/B[t]	0.003**	0.000	0.003***	0.001**
	(2.545)	(0.639)	(2.586)	(1.968)
Rival_log(Asset)[t]	0.017**	0.006	0.032***	0.030***
	(2.508)	(1.384)	(5.117)	(6.293)
Rival_Book Leverage[t]	0.004	0.001	-0.008	-0.020**
	(0.267)	(0.084)	(-0.739)	(-1.969)
Rival_R&D[t]	0.002	0.015	0.039***	0.055***
	(0.114)	(1.269)	(2.730)	(4.773)
Focal_ROA[t]	0.043***	0.034***	0.016***	0.009***
	(7.834)	(8.453)	(4.613)	(3.028)
Focal_M/B[t]	-0.000	0.000	-0.003**	-0.002**
	(-0.214)	(0.242)	(-2.548)	(-2.213)
Focal_log(Asset)[t]	0.052***	0.033***	0.073***	0.068***
	(6.993)	(7.076)	(13.138)	(16.793)
Focal_Book Leverage[t]	0.055***	-0.026**	-0.019	-0.048***
	(3.157)	(-2.068)	(-1.532)	(-4.686)
Focal_R&D[t]	0.176***	0.119***	0.151***	0.100***
	(8.636)	(7.408)	(10.948)	(8.490)
D[miss_News_RY]	0.033***	0.012**	0.039***	0.024***
	(5.043)	(2.425)	(7.417)	(5.617)
D[miss_Revisions_RY]	0.011	0.006	-0.008	-0.030***
	(0.838)	(0.589)	(-0.750)	(-3.260)
Pair FE + Year FE	YES	NO	YES	NO
Rival FE + Focal FE + Year FE	NO	YES	NO	YES
Observations	59,693	165,467	59,693	165,467
Adjusted-R^2	0.176	0.220	0.377	0.562

Panel B. Abnormal Sentiment and Focal Firm's Product Market Strategies

Model: OLS	(1)	(2)	(3)	(4)
Dependent Variable:	*D[Score Increase] [t+1]*		*D[Same TNIC] [t+1]*	
AbnSent RY[t]	0.045***	0.060***	0.008*	0.029***
	(8.109)	(13.505)	(1.941)	(8.235)
AbnNewsCoverage RY[t]	-0.008*	-0.005	-0.016***	-0.010***
	(-1.719)	(-1.272)	(-3.700)	(-2.808)
AbnNewsSent RY[t]	-0.180***	-0.171***	-0.128***	-0.142***
	(-8.840)	(-10.243)	(-8.340)	(-11.017)
RivalPA FocalCAR[0,3] RY[t]	0.000	0.000	0.000	0.000
	(1.081)	(0.149)	(0.291)	(0.985)
RivalPA RivalCAR[0,3] RY[t]	0.001**	0.001***	-0.001***	-0.001***
	(2.392)	(4.604)	(-4.706)	(-2.750)
AvgAnalystRevisions RY[t]	-0.012	-0.006	0.017**	0.020***
	(-1.371)	(-0.793)	(2.483)	(3.189)
Focal #NewProducts[t]	-0.000	0.000	-0.000	-0.000
	(-0.475)	(0.159)	(-0.566)	(-0.696)
Rival #NewProducts RY[t]	0.000	-0.001	0.000	-0.002***
	(0.088)	(-1.178)	(0.705)	(-3.598)
TechSimilarity [t]	-0.084	-0.022**	-0.042	-0.013
	(-1.067)	(-2.268)	(-0.606)	(-1.581)
ComOwnership[t]	0.043	0.069***	0.071*	0.046***
	(0.948)	(3.986)	(1.896)	(2.830)
SimilarityScore[t]	-9.512***	-0.945***	2.028***	1.732***
	(-54.790)	(-25.278)	(17.502)	(45.151)
Rival_ROA[t]	-0.008**	0.001	-0.001	0.003
	(-2.099)	(0.340)	(-0.415)	(1.222)
Rival M/B[t]	0.003**	0.000	0.003**	0.001*
	(2.537)	(0.578)	(2.515)	(1.937)
Rival log(Asset)[t]	0.017**	0.006	0.031***	0.030***
	(2.517)	(1.321)	(5.045)	(6.255)
Rival Book Leverage[t]	0.002	0.000	-0.010	-0.021**
	(0.169)	(0.027)	(-0.893)	(-2.008)
Rival R&D[t]	0.003	0.015	0.040***	0.055***
	(0.174)	(1.326)	(2.793)	(4.827)
Focal ROA[t]	0.036***	0.030***	0.008**	0.004
	(6.691)	(7.525)	(2.280)	(1.213)
Focal M/B[t]	-0.000	0.001	-0.003***	-0.002**
	(-0.048)	(0.631)	(-2.734)	(-2.238)
Focal log(Asset)[t]	0.058***	0.037***	0.079***	0.071***
	(7.815)	(7.850)	(14.420)	(17.529)
Focal Book Leverage[t]	0.046***	-0.027**	-0.020	-0.047***
	(2.640)	(-2.167)	(-1.606)	(-4.564)
Focal R&D[t]	0.143***	0.096***	0.115***	0.075***
	(7.051)	(5.996)	(8.297)	(6.396)
D[miss News RY][t]	0.032***	0.013**	0.036***	0.023***
	(4.872)	(2.523)	(6.802)	(5.170)
D[miss Revisions RY][t]	0.025*	0.023**	-0.001	-0.016*
	(1.851)	(2.077)	(-0.123)	(-1.700)
D[miss AbnSent RY][t]	-0.032***	-0.022***	-0.041***	-0.038***
	(-4.717)	(-4.087)	(-7.282)	(-8.182)
Pair FE + Year FE	YES	NO	YES	NO
Rival FE + Focal FE + Year FE	NO	YES	NO	YES
Observations	59,720	165,500	59,720	165,500
Adjusted-R^2	0.176	0.220	0.373	0.562

Panel C. Interaction of Attention and Sentiment and Focal Firm's Product Market Strategies

Model: OLS	(1)	(2)	(3)	(4)
Dependent Variable:	*D[Score Increase] [t+1]*		*D[Same TNIC] [t+1]*	
AbnAtten RY[t]	-0.004***	-0.005***	-0.005***	-0.004***
	(-9.310)	(-13.735)	(-14.833)	(-13.616)
*AbnAtten RY * AbnSent RY[t]*	-0.016***	-0.012***	-0.024***	-0.014***
	(-8.222)	(-8.405)	(-13.694)	(-10.398)
AbnSent RY[t]	0.064***	0.077***	0.038***	0.047***
	(10.351)	(15.628)	(7.716)	(12.098)
AbnNewsCoverage RY[t]	0.004	0.007*	0.002	0.001
	(0.910)	(1.666)	(0.405)	(0.269)
AbnNewsSent RY[t]	-0.163***	-0.154***	-0.104***	-0.126***
	(-7.994)	(-9.254)	(-6.865)	(-9.844)
RivalPA FocalCAR[0,3] RY[t]	0.000	-0.000	-0.000	0.000
	(0.645)	(-0.183)	(-0.349)	(0.657)
RivalPA RivalCAR[0,3] RY[t]	0.002***	0.002***	0.000	0.000
	(5.271)	(8.114)	(0.755)	(1.499)
AvgAnalystRevisions RY[t]	-0.001	0.007	0.031***	0.030***
	(-0.067)	(0.899)	(4.432)	(4.715)
Focal #NewProducts[t]	-0.000	0.000	-0.001	-0.000
	(-0.505)	(0.180)	(-0.662)	(-0.716)
Rival #NewProducts RY[t]	-0.000	-0.001*	-0.000	-0.002***
	(-0.329)	(-1.755)	(-0.025)	(-4.253)
TechSimilarity [t]	-0.081	-0.021**	-0.038	-0.013
	(-1.037)	(-2.249)	(-0.538)	(-1.552)
ComOwnership[t]	0.054	0.071***	0.087**	0.049***
	(1.188)	(4.124)	(2.351)	(2.992)
SimilarityScore[t]	-9.414***	-0.937***	2.162***	1.739***
	(-54.130)	(-25.055)	(18.682)	(45.286)
Rival ROA[t]	-0.008**	0.001	-0.001	0.003
	(-2.144)	(0.280)	(-0.449)	(1.166)
Rival M/B[t]	0.003**	0.000	0.003**	0.001**
	(2.558)	(0.611)	(2.565)	(1.964)
Rival log(Asset)[t]	0.018**	0.006	0.032***	0.030***
	(2.549)	(1.391)	(5.126)	(6.309)
Rival Book Leverage[t]	0.003	0.001	-0.009	-0.021**
	(0.236)	(0.061)	(-0.800)	(-1.993)
Rival R&D[t]	0.003	0.015	0.040***	0.055***
	(0.160)	(1.313)	(2.781)	(4.820)
Focal ROA[t]	0.037***	0.030***	0.008**	0.002
	(6.824)	(7.281)	(2.420)	(0.635)
Focal M/B[t]	-0.001	0.000	-0.005***	-0.003***
	(-0.806)	(0.071)	(-4.302)	(-3.092)
Focal log(Asset)[t]	0.055***	0.037***	0.076***	0.072***
	(7.403)	(7.824)	(13.620)	(17.544)
Focal Book Leverage[t]	0.039**	-0.045***	-0.030**	-0.063***
	(2.245)	(-3.541)	(-2.372)	(-6.110)
Focal R&D[t]	0.173***	0.117***	0.156***	0.094***
	(8.473)	(7.281)	(11.211)	(7.994)
D[miss News RY][t]	0.022***	0.006	0.020***	0.014***
	(3.231)	(1.216)	(3.737)	(3.270)
D[miss Revisions RY][t]	0.035***	0.037***	0.009	-0.006
	(2.612)	(3.330)	(0.815)	(-0.631)
D[miss AbnSent RY][t]	-0.030***	-0.020***	-0.040***	-0.038***
	(-4.418)	(-3.735)	(-7.128)	(-8.182)
Pair FE + Year FE	YES	NO	YES	NO
Focal FE + Rival FE + Year FE	NO	YES	NO	YES
Observations	59,693	165,467	59,693	165,467
Adjusted R^2	0.180	0.221	0.382	0.563

Table 5. Topic-Specific Tweets and Focal Firm's Product Offerings

In this table, we examine the effects of abnormal social media attention derived from tweets categorized under different topics. Using structural topic modelling with 21 topics, each tweet is classified to its highest probability topic. We further group them as product-related (topic #2 and #18), trading-related (topic #1, #3, #9, #10, #12, #14, and #19), and other topics. Then we construct three measures of abnormal attention based on these groups using the same approach as we construct *AbnAtten_FY,* denoted as *AbnAtten_FY_Product, AbnAtten_FY_Trade*, and *AbnAtten_FY_Other*. Columns (1) and (3) include firm fixed effects and year fixed effects. Columns (2) and (4) replace year fixed effects to Fama French industry-year fixed effects. All regressions include the same set of control variables as Table 3. Additionally, columns (3) and (4) incorporate dummy indicators that capture whether competitors lack tweets in the respective topic groups. In all specifications, standard errors are clustered at the Fama French 48 industry-year levels. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)
		Fluidity [t+1]		
AbnAtten_FY_Product[t]	0.239***	0.320***	0.217***	0.247***
	(3.092)	(3.337)	(2.722)	(2.861)
AbnAtten_FY_Trade[t]	0.469***	0.494***	0.408***	0.485***
	(3.668)	(3.831)	(4.550)	(4.711)
AbnAtten_FY_Other[t]	-0.069	-0.116	-0.024	0.016
	(-0.409)	(-0.550)	(-0.212)	(0.126)
D[miss_AbnAtten_Product]			-0.685*	-0.778*
			(-1.928)	(-1.883)
D[miss_AbnAtten_Trade]			0.520	0.595
			(1.202)	(1.117)
D[miss_AbnAtten_Other]			0.752	-0.022
			(1.444)	(-0.041)
Control variables	YES	YES	YES	YES
Focal Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	NO	YES	NO
Year*FF48 Fixed Effects	NO	YES	NO	YES
Cluster S.E. at FF48*Year	YES	YES	YES	YES
Observations	9,640	9,562	14,832	14,774
Adjusted R^2	0.271	0.275	0.263	0.265

Table 6. Market-Oriented Firms

In this table, we partition the focal firm-year sample into two groups based on whether at least one competitor with product announcements operates in the industry characterized as market-oriented. The dependent variable $Fluidity_{t+1}$ measures the changes in the product offerings of focal firm in year *t+1* relative to year *t*. Our key explanatory variables are $AbnAtten\_FY_t$ and $AbnSent\_FY_t$, referring to the abnormal attention and sentiment for the product announcements by competitors within the same TNIC-3 industry as the focal firm in year t. Columns (1), (3), and (5) include firm fixed effects and year fixed effects. Columns (2), (4), and (6) replace year fixed effects to Fama French 48 industry-year fixed effects. All regressions include the same set of control variables in Table 3. In Panel A, the results are based on the subsample where at least one competitor's industry is characterized as market-driven, while Panel B reports the results with the remaining sample where none of the competitors are from market-driven industries. In all specifications, standard errors are clustered at the Fama French 48 industries interacted with year levels. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Market-Oriented Firms	*Fluidity[t+1]*	*Fluidity[t+1]*	*Fluidity[t+1]*	*Fluidity[t+1]*	*Fluidity[t+1]*	*Fluidity[t+1]*
AbnAtten_FY [t]	0.697***	0.727***			0.624***	0.678***
	(3.736)	(3.346)			(3.375)	(3.165)
AbnSent_FY[t]			1.027**	0.687	0.145	0.140
			(2.377)	(1.079)	(0.289)	(0.211)
*AbnAtten_FY * AbnSent_FY[t]*					1.018**	0.967*
					(2.010)	(1.706)
Observations	7,039	6,956	7,047	6,964	7,039	6,956
Adjusted R^2	0.280	0.280	0.278	0.277	0.281	0.280
Panel B. Other Firms	*Fluidity[t+1]*	*Fluidity[t+1]*	*Fluidity[t+1]*	*Fluidity[t+1]*	*Fluidity[t+1]*	*Fluidity[t+1]*
AbnAtten_FY [t]	0.197	0.193			0.195	0.208
	(1.501)	(1.226)			(1.436)	(1.273)
AbnSent_FY[t]			0.034	0.271	-0.029	0.334
			(0.065)	(0.448)	(-0.055)	(0.563)
*AbnAtten_FY * AbnSent_FY[t]*					0.225	-0.149
					(0.648)	(-0.443)
Observations	7,338	7,257	7,338	7,257	7,338	7,257
Adjusted R^2	0.252	0.252	0.252	0.251	0.252	0.251
Control Variables	YES	YES	YES	YES	YES	YES
Focal Firm FE + Year FE	YES	YES	YES	YES	YES	YES
Focal Firm FE + Year*FF48 Fixed Effects	NO	YES	NO	YES	NO	YES

Table 7. Heterogeneity

In this table, we conduct heterogeneity analyses to explore the factors influencing the direction of adjustments in focal firms' product offerings when competitors' new products attract strong abnormal attention on social media. Panel A, B, and C examine the effects of common analyst coverage, technology similarity, and the relative firm size between the focal firm and its competitors, respectively. The dependent variables are two dummy indicators. *D[Score Increase]$_{t+1}$*, equals one if the product similarity between a competitor-focal pair increases in the following year, and zero otherwise. *D[Same TNIC3]$_{t+1}$*, equals one if the pair remains in the same TNIC-3 industry in the following year, and zero otherwise. *AbnAtten_RY* represents the abnormal attention for competitors' product announcements in year *t*. This measure is aggregated at the rival-year level for all announcements made by the same competitor. In Panel A, *Nbr[CA]* denotes the number of common analysts following the focal firm and the competitor in year *t*. In Panel B, *TechSimilarity* denotes the fraction of competitor's patents that belong to the same three-digit CPC categories as the patents held by the focal firm. In Panel C, *Focal_RelativeSize* equals the focal firm's total assets divided by the total assets of the competitors. Columns (1) and (3) includes pair fixed effects and the year fixed effects. Columns (2) and (4) replace pair fixed effects with focal firm fixed effects and rival firm fixed effects. All regressions include the control variables in Table 4. Standard errors are clustered at the focal firm interacted with year levels. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)
Panel A. Common Analyst Coverage	*D[Score Increase] [t+1]*		*D[Same TNIC] [t+1]*	
AbnAttent_RY	-0.005***	-0.005***	-0.006***	-0.004***
	(-12.282)	(-16.300)	(-18.540)	(-16.592)
*Nbr[CA] * AbnAttent_RY*	0.001***	0.001***	0.001**	0.000
	(2.667)	(3.991)	(2.205)	(1.136)
Nbr[CA]	0.001	0.006***	0.002***	0.006***
	(0.906)	(10.075)	(2.587)	(13.329)
Observations	59,693	165,467	59,693	165,467
Adjusted R^2	0.177	0.221	0.377	0.563
Panel B. Technology Similarity	*D[Score Increase] [t+1]*		*D[Same TNIC] [t+1]*	
AbnAttent_RY	-0.006***	-0.007***	-0.008***	-0.007***
	(-8.930)	(-12.858)	(-17.464)	(-16.866)
*TechSimilarity * AbnAttent_RY*	0.008*	0.002	0.005*	0.003*
	(1.814)	(0.752)	(1.702)	(1.905)
TechSimilarity	-0.091	-0.025**	-0.047	-0.018**
	(-1.156)	(-2.465)	(-0.665)	(-2.057)
Observations	59,693	165,467	59,693	165,467
Adjusted R^2	0.175	0.219	0.376	0.562
Panel C. Relative Firm Size	*D[Score Increase] [t+1]*		*D[Same TNIC] [t+1]*	
AbnAttent_RY	-0.009***	-0.006***	-0.015***	-0.007***
	(-9.482)	(-14.071)	(-19.995)	(-18.265)
Focal_RelativeSize AbnAttent_RY*	0.003***	0.001***	0.008***	0.002***
	(4.738)	(2.684)	(14.103)	(9.629)
Focal_RelativeSize	-0.137***	-0.029***	-0.038**	-0.014**
	(-5.967)	(-4.761)	(-2.072)	(-2.249)
Observations	59,693	165,467	59,693	165,467
Adjusted R^2	0.178	0.220	0.380	0.562
Rival FE + Focal FE + Year FE	NO	YES	NO	YES
Pair FE + Year FE	YES	NO	YES	NO

Table 8. Focal Firms' Product Announcements and Sales Growth

In Panel A, we examine the stock market and social media reactions to the focal firm's first product announcement in the year subsequent to the competitor's product announcement. The sample consists of pair-event observations. Dependent variables include four-day cumulative abnormal returns (*CAR[0, 3]_Focal 1stPA*) and abnormal social media attention and sentiment (*AbnAtten_Focal 1stPA* and *AbnSent_Focal 1stPA*) for focal firm's first product announcement. Our key explanatory variables are the abnormal social media attention (*AbnAtten*) and sentiment (*AbnSent*) for each competitor's product announcement in year *t* and their interaction. We include the same set of control variables as in Table 4. Columns (1), (3), and (5) include pair fixed effects and year fixed effects. Columns (2), (4), and (6) replace pair fixed effects with focal firm fixed effects and rival firm fixed effects. Standard errors are clustered at the focal firm-year levels. In Panel B, we use the focal firm-year level sample to examine focal firms' sales growth in the subsequent year. Our dependent variable is focal firm's sales growth in year *t+1*. Our explanatory variables include abnormal social media attention (*AbnAtten_FY),* sentiment (*AbnSent_FY*), and their interaction. We include the same set of control variables as Table 3. Columns (1), (3), and (5) include firm fixed effects and year fixed effects. Columns (2), (4), and (6) replace year fixed effects to industry-year fixed effects. Standard errors are clustered at the industry-year levels. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Panel A. Stock Market and Social Media Reactions to Focal Firm's First Product Announcements

	(1)	(2)	(3)	(4)	(1)	(2)
	CAR[0, 3] Focal 1stPA		*AbnAtten Focal 1stPA*		*AbnSent Focal 1stPA*	
AbnAtten[t]	-0.162	0.008	0.059	-0.010	0.925***	0.001
	(-1.280)	(0.357)	(0.756)	(-0.661)	(3.669)	(0.413)
AbnSent[t]	-0.540	0.142	-0.920	0.167	0.133	-0.026
	(-0.717)	(0.528)	(-1.190)	(0.847)	(0.363)	(-0.681)
*AbnAtten * AbnSent[t]*	0.937***	0.166*	-0.115	0.104*	7.146***	0.014
	(4.478)	(1.951)	(-0.877)	(1.871)	(3.527)	(1.445)
Observations	13,949	19,821	11,637	15,487	4,603	7,010
Adjusted-R^2	0.973	0.777	0.968	0.771	0.997	0.885
Control Vars	YES	YES	YES	YES	YES	YES
Pair + Year FE	YES	NO	YES	NO	YES	NO
Rival + Focal + Year FE	NO	YES	NO	YES	NO	YES
Cluster S.E. at Focal*Year	YES	YES	YES	YES	YES	YES

Panel B. Focal Firm's Sales Growth in the Next Year

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Sales Growth)[t+1]					
AbnAtten_FY[t]	-0.003	-0.005			-0.006	-0.007
	(-0.615)	(-0.896)			(-1.182)	(-1.231)
AbnSent_FY[t]			0.037**	-0.001	0.022	-0.015
			(1.977)	(-0.055)	(1.280)	(-0.901)
*AbnAtten_FY*AbnSent_FY[t]*					0.033	0.031*
					(1.621)	(1.729)
Adjusted-R^2	13,867	13,807	13,875	13,815	13,867	13,807
Observations	0.136	0.118	0.136	0.117	0.136	0.117
Control Vars	YES	YES	YES	YES	YES	YES
Focal FE + Year FE	YES	NO	YES	NO	YES	NO
Focal FE + FF48*Year FE	NO	YES	NO	YES	NO	YES
Cluster S.E. at FF48*Year	YES	YES	YES	YES	YES	YES

Appendix

Table A1. Alternative Information Channels and Focal Firms' Product Offerings

The table shows the effects of alternative information channels on the focal firms' product fluidity in the year after competitors' product announcements. Panel A examines the effect of traditional news media using Ravenpack data. The explanatory variables in columns (1) and (2) include abnormal news coverage (*AbnNewsCoverage_FY*), abnormal news sentiment (*AbnNewsSent_FY*), and a dummy indicator for observations without Ravenpack data (*D[miss_News]_FY*). Columns (3) and (4) further include the abnormal social media attention (*AbnAtten_FY*). Panel B and Panel C analyze the effect of stock market reactions, proxied by four-day cumulative abnormal returns for the focal firm following competitors' product announcements (*RivalPA_FocalCAR[0,3]_FY*) and for competitors following their own product announcements (*RivalPA_RivalCAR[0,3]_FY*), respectively. Panel D examines recommendation revisions issued by common analysts for competitors within seven days after product announcements (*AvgAnalystRevisions_FY*) and a dummy indicator for firm-years without revisions (*D[miss_Revisions_FY]*). In this table, we present the results without control variables. Columns (1) and (3) include firm fixed effects and year fixed effects. Columns (2) and (4) replace year fixed effects to industry-year fixed effects. Standard errors are clustered at the industry-year levels. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)
		Fluidity [t+1]		
Panel A. News Coverage				
AbnNewsCoverage_FY[t]	0.341**	0.261	0.227*	0.154
	(2.432)	(1.447)	(1.713)	(0.921)
AbnNewsSent_FY[t]	0.326	-0.029	0.316	-0.154
	(0.546)	(-0.043)	(0.509)	(-0.226)
D[miss_News]_FY[t]	-0.339	-0.728**	-0.422	-0.813**
	(-1.053)	(-2.088)	(-1.327)	(-2.345)
AbnAtten_FY [t]			0.621***	0.725***
			(4.795)	(4.763)
Panel B. Market reactions to the *focal firm* following competitor's product announcements				
RivalPA_FocalCAR[0,3]_FY	0.055*	0.068**	0.051	0.066*
	(1.654)	(1.973)	(1.530)	(1.921)
AbnAtten_FY [t]			0.642***	0.727***
			(4.865)	(4.663)
Panel C. Market reactions to the competitor following its product announcements				
RivalPA_RivalCAR[0,3]_FY	0.033	0.032	0.001	-0.006
	(0.954)	(0.745)	(0.025)	(-0.134)
AbnAtten_FY [t]			0.646***	0.732***
			(4.871)	(4.731)
Panel D. Recommendation revisions from sell-side analysts for competitors following their product announcements				
AvgAnalystRevisions_FY	-0.235	-0.150	-0.190	-0.079
	(-1.397)	(-0.708)	(-1.206)	(-0.371)
D[miss_Revisions_FY]	-0.425	-0.146	-0.356	-0.185
	(-1.549)	(-0.484)	(-1.332)	(-0.614)
AbnAtten_FY [t]			0.641***	0.730***
			(4.867)	(4.660)
Observations	14,832	14,774	14,824	14,766
Focal Firm Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	NO	YES	NO
Year*FF48 Fixed Effects	NO	YES	NO	YES
Cluster S.E. at FF48 * Year	YES	YES	YES	YES

Table A2. Robustness Checks: Alternative Definitions of Social Media Signals

In this table, we examine the robustness of our baseline results from Table 3 with alternative definitions of social media signals. In Panel A, we construct the abnormal attention and sentiment based on tweets only mentioning the ticker of the competitor making the product announcement, denoted as *AbnAtten_OnlyRival_FY* and *AbnSent_OnlyRival_FY*. In Panel B, we construct the focal firm-year level measures of abnormal attention and sentiment using an alternative benchmark window [-10, -7], denoted as *AbnAtten_[-10,-7]_FY* and *AbnSent_[-10,-7]_FY.* In Panel C, we follow Da, Engelberg, and Gao (2011) and construct the abnormal attention as the difference between the log of daily average tweet volume in the even window [0, 3] and that of the benchmark window [-13, -7], denoted as *AbnAtten_alter_FY*. Abnormal sentiment (*AbnSent_FY)* is not re-constructed as daily average sentiment is bounded between -1 and +1. In all panels, the dependent variable is $Fluidity_{t+1}$, which measures the changes in the product offerings of focal firm in year *t+1* relative to year *t*. We include the same set of control variables as in Table 3. Columns (1), (3) and (5) include focal firm fixed effects and year fixed effects. Columns (2), (4) and (6) replace year fixed effects to Fama French 48 industry-year fixed effects. In all specifications, standard errors are clustered at the Fama French 48 industry-year level. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

Panel A. Competitor-Specific Tweets	(1)	(2)	(3)	(4)	(3)	(4)
Dependent Variable:			*Fluidity[t+1]*			
AbnAtten_OnlyRival_FY[t]	0.384***	0.407***			0.352***	0.384***
	(3.311)	(3.106)			(3.232)	(3.067)
AbnSent_OnlyRival_FY[t]			1.170***	1.460***	0.363	0.935*
			(3.243)	(3.049)	(0.963)	(1.954)
*AbnAtten_OnlyRival_FY * AbnSent_OnlyRival_FY[t]*					0.829**	0.614
					(2.119)	(1.396)
Observations	14,481	14,425	14,832	14,774	14,473	14,417
Adjusted R^2	0.263	0.265	0.258	0.260	0.264	0.266
Panel B. Alternative Benchmark Window [-10, -7]						
Dependent Variable:			*Fluidity[t+1]*			
AbnAtten_[-10,-7]_FY[t]	0.461***	0.584***			0.379***	0.508***
	(4.733)	(5.034)			(4.223)	(4.600)
AbnSent_[-10,-7]_FY[t]			0.714*	0.753	-0.504	-0.243
			(1.886)	(1.519)	(-1.169)	(-0.440)
*AbnAtten_[-10,-7]_FY * AbnSent_[-10,-7]_FY[t]*					1.457***	1.396***
					(3.912)	(3.302)
Observations	14,226	14,167	14,832	14,774	14,226	14,167
Adjusted R^2	0.267	0.268	0.258	0.260	0.269	0.270
Panel C. Alternative Attention Measure Following Da, Engelberg, and Gao. (2011)						
Dependent Variable:			*Fluidity[t+1]*			
AbnAtten_alter_FY[t]	1.041***	1.262***			0.966***	1.235***
	(4.182)	(4.076)			(3.917)	(4.005)
AbnSent_FY[t]			0.698**	0.746*	0.476	0.720
			(2.049)	(1.721)	(1.393)	(1.615)
*AbnAtten_alter_FY * AbnSent_FY[t]*					1.924***	1.739**
					(2.836)	(2.054)
Observations	14,832	14,774	14,832	14,774	14,832	14,774
Adjusted R^2	0.260	0.261	0.258	0.260	0.260	0.262
Focal Firm FE + Year Fixed Effects	YES	NO	YES	NO	YES	NO
Focal Firm FE + Year*FF48 Fixed Effects	NO	YES	NO	YES	NO	YES
Control Variables	YES	YES	YES	YES	YES	YES

Table A3. Robustness Checks: Additional Control Variables

In this table, we examine the robustness of our baseline results from Table 3 with additional control variables. The dependent variable $Fluidity_{t+1}$ measures the changes in the product offerings of focal firm in year $t+1$ relative to year t. Our key explanatory variables are abnormal social media attention and sentiment (*AbnAtten_FY* and *AbnSent_FY*). We include the same set of control variables as in Table 3. Additionally, we control for the product market fluidity proposed by Hoberg and Phillips (2014), Herfindahl-Hirschman Index (HHI), and focal firm's self-fluidity in the current year in Panel A, B, and C, respectively. In each panel, columns (1), (3) and (5) include focal firm fixed effects and year fixed effects, while columns (2), (4) and (6) replace year fixed effects with Fama French 48 industry-year fixed effects. Standard errors are clustered at the Fama French 48 industry-year levels. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			*Fluidity [t+1]*			
Panel A. Control Product Market Fluidity						
AbnAtten_FY	0.571***	0.629***			0.514***	0.598***
	(4.645)	(4.407)			(4.215)	(4.243)
AbnSent_FY			0.714**	0.692*	0.147	0.366
			(2.097)	(1.650)	(0.438)	(0.868)
*AbnAtten_FY * AbnSent_FY*					0.915***	0.687*
					(2.668)	(1.770)
Focal_ProductMarketFluidity	1.186***	1.305***	1.210***	1.343***	1.188***	1.309***
	(6.181)	(6.318)	(6.236)	(6.429)	(6.184)	(6.305)
Observations	14,821	14,763	14,829	14,771	14,821	14,763
Adjusted R^2	0.275	0.278	0.273	0.276	0.276	0.279
Panel B. Control Herfindahl-Hirschman Index (HHI)						
Dependent Variable:			*Fluidity [t+1]*			
AbnAtten_FY	0.637***	0.733***			0.575***	0.690***
	(4.970)	(4.821)			(4.639)	(4.689)
AbnSent_FY			0.686**	0.748*	0.082	0.370
			(2.018)	(1.726)	(0.238)	(0.840)
*AbnAtten_FY * AbnSent_FY*					0.958***	0.791*
					(2.601)	(1.871)
HHI	-1.369*	-0.900	-1.298*	-0.851	-1.353*	-0.961
	(-1.782)	(-1.086)	(-1.705)	(-1.048)	(-1.753)	(-1.165)
Observations	14,824	14,766	14,832	14,774	14,824	14,766
Adjusted R^2	0.261	0.263	0.258	0.260	0.262	0.263
Panel C. Control Focal Firms' Self-Fluidity in the Current Year						
Dependent Variable:			*Fluidity [t+1]*			
AbnAtten_FY	0.704***	0.801***			0.642***	0.758***
	(5.118)	(4.931)			(4.847)	(4.839)
AbnSent_FY			0.637*	0.573	0.003	0.164
			(1.809)	(1.279)	(0.009)	(0.356)
*AbnAtten_FY * AbnSent_FY*					0.998**	0.839*
					(2.492)	(1.818)
Focal_SelfFluidity[t]	-0.008	-0.019	-0.006	-0.017	-0.008	-0.019
	(-0.384)	(-0.922)	(-0.318)	(-0.841)	(-0.411)	(-0.929)
Observations	13,970	13,910	13,978	13,918	13,970	13,910
Adjusted R^2	0.263	0.265	0.260	0.261	0.264	0.265
Control Variables	YES	YES	YES	YES	YES	YES
Focal Firm FE + Year FE	YES	NO	YES	NO	YES	NO
Focal Firm FE + Year*FF48 FE	NO	YES	NO	YES	NO	YES

Table A4. Fractional Probit Model

In this table, we use the fractional probit model to examine direction of focal firms' adjustment in product offerings. Our dependent variables are *Frac[Score Increase]*$_{t+1}$ and *Frac[Same TNIC3]*$_{t+1}$. These variables measure, among all focal-competitor pairs where competitors make product announcements in the current year, the fraction of pairs (1) with an increased product similarity score in the next year, and (2) remaining in the same TNIC3 industry in the next year, respectively. Our key explanatory variables are abnormal social media attention and sentiment (*AbnAtten_FY* and *AbnSent_FY*). We include the same set of control variables as in Table 3 and account for year fixed effects and Fama French 48 industry fixed effects. Standard errors are clustered at the Fama French 48 industry-year levels. ***, **, and * indicate the 1%, 5%, and 10% levels of significance, respectively.

	(1) *Frac[Score Increase]*	(2) *Frac[Same TNIC3]*
AbnAtten_FY [t]	-0.039***	-0.023**
	(-3.690)	(-2.433)
AbnNewsCoverage_FY[t]	0.019	0.037***
	(1.492)	(4.313)
AbnNewsSent_FY[t]	0.115	0.115***
	(1.477)	(2.630)
D[miss_News]_FY[t]	0.011	0.013
	(0.401)	(0.551)
RivalPA_FocalCAR[0,3]_FY[t]	0.007**	0.003
	(2.573)	(1.155)
RivalPA_RivalCAR[0,3]_FY[t]	0.004	0.007**
	(0.951)	(2.068)
Focal_#NewProducts [t]	0.004***	0.002
	(2.776)	(1.312)
Rival_Avg#NewProducts_FY [t]	0.000	0.001
	(0.158)	(0.886)
AvgAnalystRevisions_FY[t]	-0.034	-0.032*
	(-1.443)	(-1.907)
D[miss_Revisions]_FY[t]	-0.054	-0.054*
	(-1.194)	(-1.749)
Focal_MktShare[t]	0.036	0.080
	(0.545)	(1.466)
Focal_#Patents[t]	-0.000	-0.000
	(-0.367)	(-0.388)
AvgComOwnership[t]	0.532***	0.372***
	(3.646)	(3.181)
AvgScore_FY[t]	14.816***	0.172
	(11.795)	(0.366)
Focal_ROA[t]	-0.004	0.007
	(-0.399)	(0.857)
Focal_M/B[t]	0.006**	0.000
	(2.322)	(0.152)
Focal_FirmSize[t]	0.001	-0.002
	(0.112)	(-0.218)
Focal_Book Leverage[t]	-0.007	0.011
	(-0.247)	(0.485)
Focal_R&D[t]	0.045	0.065*
	(1.023)	(1.821)
Year FE + FF48 FE	YES	YES
Cluster S.E. at FF48 * Year	YES	YES
Observations	15,592	15,592
Adjusted R^2	0.0197	0.0197