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Cover Page Footnote

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Firm-Generated Online Content in Social Media and Stock Performance: An Event Window Study of Twitter and the S&P 500

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Abstract:

This study explores how different types of firm-generated online content (FGOC) on social media affect stock performance. Employing signaling theory and limited attention theory, we analyze stock market data from 141 companies in the S&P 500 index and categorize FGOC on Twitter into distinct signal types through semantic analysis. Using econometric models, we estimate the relationships between these FGOC signals and abnormal stock returns. Our findings reveal that disseminating a greater number of strong image-enhancing FGOC signals, particularly those related to new products and financial matters, significantly enhances stock performance, resulting in higher abnormal stock returns. In contrast, weak image-enhancing FGOC signals not only fail to improve stock performance but also diminish the positive relationship between strong image-enhancing signals, especially those pertaining to financial information, and stock performance. This study contributes to the literature by illuminating the interplay between different types of FGOC, addressing the need for research on how varying informational elements interact in social media contexts. It provides practical guidance for managers on managing digital communication strategies to enhance investor engagement and optimize market outcomes.

Keywords: Social Media, Firm-Generated Online Content (FGOC), User-Generated Content (UGC), Information Disclosure, Stock Performance, Weak and Strong Signals.

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1 Introduction

Firm disclosures about performance and strategic initiatives frequently fail to reach all investors, resulting in market imperfections such as information asymmetry, which in turn reduces market liquidity (Blankespoor et al., 2014; Xu & Zhang, 2013). This asymmetry poses challenges not only for investors but also for companies seeking efficient ways to communicate corporate information. Over the years, firms have sought alternative, more effective communication channels, with social media emerging as a dominant platform in recent decades (Bartov et al., 2018; Chen et al., 2014; Macchioni et al., 2024). Today, social media is deeply integrated into both everyday life and corporate practices, providing companies with a direct and rapid medium to disseminate information and engage with investors and the public (Cheng et al., 2021; Sprenger et al., 2014; Sul et al., 2017). A pertinent question arises: Can firm-generated content on social media substantively influence stock market movements? This question is not only relevant for practitioners but also of significant academic concern (Ajjoub et al., 2021; Jung et al., 2018; Yuan et al., 2021).

Publicly traded firms use social media to communicate consistently and continuously with customers and stakeholders, offering a channel unrestricted by the frequency limitations seen in traditional disclosures. This form of communication enables firms to signal their quality and engage directly with investors. However, not all social media interactions convey substantial information about firm value. To address this disparity, we categorize firm-generated market information into two types: (1) strong signals, which are clearly visible and reveal the fundamental quality of the company, and (2) weak signals, which have low observability and provide little or no information about the company's value. While previous research highlights the role of strong signals in enhancing signaling effectiveness, there is limited research on the effects of weak signals in influencing market behavior (de Haan et al., 2011).

Existing literature on social media has largely focused on user-generated content (UGC), examining its effects on consumer behavior, such as purchase intentions (Qin et al., 2024), customer satisfaction (Li et al., 2024), and product competitiveness (Ma et al., 2024). Several studies have explored the impact of UGC or social media sentiment on the stock market (Ajjoub et al., 2021; Guan et al., 2022; Yuan et al., 2021). Some studies have explored the value of UGC according to different scenarios (Du et al., 2023; Ho-Dac, 2020). Others focus on how UGC interacts with traditional media marketing (Stephen & Galak, 2012). As firms increasingly rely on interactions with customers within social media, recent research has attempted to shed light on the impact of firms' social media generated content (FGOC). Research shows that FGOC can drive product sales (Wan & Ren, 2017), boost brand value (de Vries et al., 2012), enhance customer engagement (Cheng et al., 2021; Yang et al., 2019), improve stock liquidity (Blankespoor et al., 2014), and even mitigate negative effects of crises like product recalls (Lee et al., 2015). Additionally, studies indicate that while UGC primarily impacts brand awareness and customer satisfaction, FGOC tends to have a stronger effect on influencing purchase decisions (Colicev et al., 2019).

This study builds upon several foundational works that investigate the impact of firm-generated online content (FGOC) on company performance and stock market outcomes. For instance, Lacka et al. (2021) utilize high-frequency stock market data to reveal that the content of a firm’s tweets can have both permanent and temporary effects on stock prices, highlighting the significance of tweet subject matter and value. Cheng et al. (2021) empirically examine the influence of firm-generated information and consumer digital engagement on theater sales performance, demonstrating that consumer digital engagement serves as a critical mediator in the relationship between FGOC and firm sales. Bai and Yan (2020) categorize corporate user-generated content on Sina Weibo as either persuasive or informative, finding that both types significantly impact firm performance and consumer engagement. Additionally, Peng et al. (2022) leverage Twitter data to show that increased corporate tweeting correlates with higher stock returns, emphasizing the moderating effects of news sentiment and firm size.

While existing studies provide valuable insights into the effects of firm-generated online content (FGOC) on firm performance, they often overlook the nuanced interplay between strong and weak signals. This research advances the literature by distinguishing FGOC into strong and weak image-enhancing signals and applying signaling theory and limited attention theory to uncover their complex interactions. Our findings indicate that strong FGOC signals positively impact stock returns; however, the presence of weak FGOCs diminishes this effect by consuming valuable cognitive resources. Given that attention is a scarce resource and individuals have limited capacity to process information (Kahneman, 1973; Shen & Wang, 2023), investors typically focus on strong signals that are relevant to their decisions. In contrast, weaker,

less relevant signals (e.g., unexpected disruptions) can passively attract investor attention, leading to suboptimal decision-making and market inefficiency (Israeli et al., 2022; Shen & Wang, 2023). By emphasizing the interactions between strong and weak FGOC signals, this study highlights the importance of effectively guiding investor attention to enhance decision-making and market efficiency. Thus, our research contributes significantly by exploring how firms can optimize their digital communication strategies to minimize inefficiencies and direct investor attention toward meaningful signals.

To address research gaps in the literature, we collected social media and stock market data from 141 publicly traded companies in the S&P 500 index. We then used machine learning tools to conduct semantic analysis of firm-generated online content (FGOC) on the Twitter platform. The tweets from these companies were categorized into two types: (1) strong image-enhancing FGOC and (2) weak image-enhancing FGOC. Strong image-enhancing FGOC was further divided into three subcategories: (a) product-related FGOC; (b) finance-related FGOC; and (c) other strong image-enhancing FGOC. Finally, econometric models were used to examine the relationship between these FGOC types and stock abnormal returns, as well as the interactive effects of weak image-enhancing FGOC on strong image-enhancing FGOC.

2 Theoretical Background

2.1 Signaling Theory

Signaling theory addresses behaviors stemming from information asymmetry, where insiders possess information that outsiders lack (Connelly et al., 2011). The core elements of signaling theory include signalers, receivers, and signals. Signalers, such as firms, hold private information about the market, while receivers, such as investors, must make decisions with incomplete information. In the stock market, firms act as signalers, investors as receivers, and corporate disclosures—such as financial reports and voluntary communications—serve as signals intended to reflect firm quality (Guo et al., 2024). Both regulated disclosures (e.g., earnings announcements) and broader signals, like media coverage, have been shown to influence stock performance (Guldiken et al., 2017; Liu et al., 2023).

Signals in capital markets differ in strength, with strong signals generally being more observable and closely aligned with the signaler's true underlying quality (Connelly et al., 2011). Strong signals are those that are highly visible, rich in content, and designed to effectively communicate value to investors. In the context of corporate communication, these signals are particularly beneficial in reducing information asymmetry and guiding investment decisions. For example, in financial markets, positive earnings reports or strategic announcements are often perceived as strong signals that significantly influence investor behavior (Gu & Kurov, 2020; Lacka et al., 2021).

Weak signals, on the other hand, tend to be less observable and carry ambiguous or incomplete information, containing only a small amount of information about the value of the firm (Connelly et al., 2011). Due to their ambiguous nature, weak signals may fail to provide a reliable basis for predicting stock market behavior, leading scholars to often overlook their potential influence on market outcomes (Sprenger et al., 2014). However, some studies suggest that while weak signals might not always be directly impactful, their presence could still shape investor perceptions (Macca et al., 2024). Therefore, although weak signals are not typically seen as reliable predictors of market trends, their role in investor decision-making cannot be entirely discounted. As such, understanding the interaction between strong and weak signals may provide deeper insights into capital market behavior.

2.2 Limited Attention Theory

Attention is a limited cognitive resource essential for processing external information and forming thoughts, but its finite nature requires individuals to allocate it across multiple stimuli (Hirshleifer & Teoh, 2003). When attention is focused on one stimulus, less is available for others, leading to decision biases during signaling (Hirshleifer et al., 2011).

In capital markets, limited attention influences investor behavior and stock prices. Investors often focus on attention-grabbing stocks and exhibit selective attention toward positive or negative portfolio information (Sicherman et al., 2016). This selective attention implies that the more attention is paid to one detail, the less attention is paid to another (Lu, 2022). Moreover, competing news or information overload can reduce the effectiveness of post-earnings announcements (Hirshleifer et al., 2011).

Limited attention is a consequence of information overload. Due to the vast amount of information available in the environment, attentional resources are quickly depleted, thereby overwhelming investors' information-processing capacity to cope with and analyze new stimuli (Zhao & Gan, 2024). Although investors attempt to focus on the most relevant signals, the sheer volume of available information often draws attention passively, further straining their cognitive resources (Lu, 2022).

While existing research shows that selective attention influences portfolio information, it often neglects the role of signal strength. Few studies integrate limited attention with signal strength, leaving a theoretical gap in understanding how strong and weak signals impact attention (Sicherman et al., 2016). This gap highlights the need to explore how weak signals affect stock prices and how signal strength influences attention.

3 Hypothesis Development

Based on signal transmission theory and the theory of limited attention, we propose a theoretical model focusing on stock returns to provide a more comprehensive understanding of these two theories. By analyzing various signals from FGOC, this study advances the field. First, we argue that FGOC signals with strong image enhancement can lead to actual investments by increasing investors' attention, thereby improving stock performance. Second, the presence of weak image-enhancing FGOC signals consumes investors' limited attention, which in turn diminishes the impact of strong signals on stock returns. Third, the weakening effect of weak image-enhanced FGOC signals on financial-related FGOC signals is more pronounced than on product-related FGOC signals. To avoid measurement bias and comprehensively address the key concept of attention, we hypothesize that stock performance represents the “realized” attention (Chen et al., 2014; Xu & Zhang, 2013). Figure 1 shows our theoretical model.

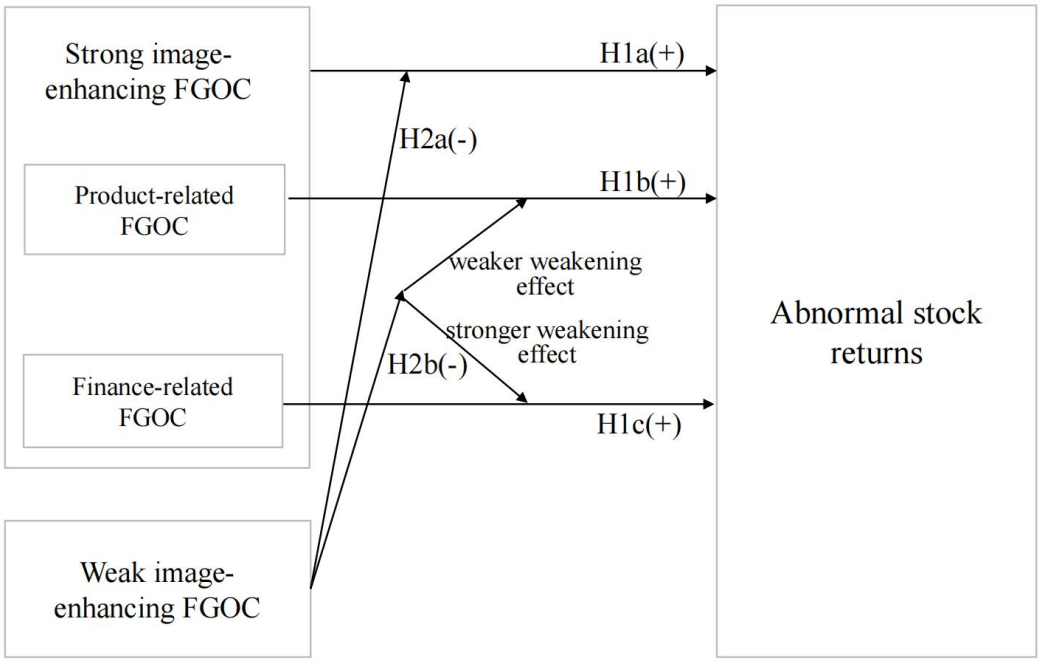

Figure 1. Theoretical Model

3.1 Research Context: FGOC Signaling and Classification

What is FGOC signaling? By definition, FGOC is firm-initiated marketing communication residing on official social media pages (Kumar et al., 2016). Event categories in the present study were first categorized into two large groups: strong image-enhancing FGOC signals and weak image-enhancing FGOC signals. The former meets the requirements of being a strong signal; that is, it is in a form salient enough to readily catch investor attention and contains the most relevant information about the firm value (Chiou et al., 2019). By contrast, the weak image-enhancing FGOC signals contained less structured interaction information and less firm-related evaluative information, hence weakly related to firm value (Xie

et al., 2020). In other words, weak signals make it difficult for investors to locate and perceive economic importance and firm value in tweets.

The reasons for this classification are twofold. First, communicating corporate image to the target group is a fundamental marketing activity, as corporate image is important for corporate brand positioning and can serve as a signal of corporate quality (Balmer & Podnar, 2021). Given that firms can control the information disclosed on their official social media accounts, they tend to send image-enhancing FGOC signals to reveal firm value to the public (Hernández-Ortega et al., 2020). Second, social media allow firms to both disseminate firm news and interact personally with investors and customers. The differential nature of these two communication activities generates signals of varying strength (Lee et al., 2015). Therefore, we distinguish between strong image-enhancing FGOC signals and weak image-enhancing FGOC signals.

3.2 Strong Image-Enhancing FGOC Signals and Stock Performance

The relationship between strong image-enhancing firm-generated online content (FGOC) and stock performance fundamentally involves the allocation of investor attention (Falkinger, 2008). According to limited attention theory, investors—facing cognitive resource constraints—focus selectively on information they perceive as valuable (Sprenger et al., 2014). To influence decision-making, information must first surpass a perceptual threshold and capture the attention of investors. Signals with heightened salience are therefore more likely to attract attention and influence financial decisions.

Strong image-enhancing FGOC signals are perceived to have such strength by investors due to two key factors: observability and relevance. First, high levels of signal observability of strong image-enhancing FGOC signals reduce the difficulty investors face in detecting firm quality information by grabbing their attention, which in turn increases the likelihood of stock trading. As a result, this increased visibility boosts the likelihood of triggering investor actions (Hirshleifer & Teoh, 2003). This is consistent with the visibility-attraction hypothesis, which posits that stocks with higher visibility attract more investor attention, potentially leading to positive effects on stock performance (Nose et al., 2021).

Second, the relevance of these signals to investor needs further enhances their appeal. When FGOC aligns closely with investor expectations, it is perceived as a credible indicator of firm quality, providing valuable decision-relevant information. Empirical studies have shown that investors are skilled at filtering out irrelevant noise, focusing on signals that offer substantive informational content (Sprenger et al., 2014). As such, strong FGOC signals that meet investor expectations act as reliable indicators of firm performance, amplifying their influence on investment decisions (Connelly et al., 2011). What is noteworthy in this specific context is that a rich literature regarding the dissemination of firm-initiated-disclosure via Twitter has suggested a definite positive effect from strong FGOC signals (Bartov et al., 2018; Chen et al., 2014; Jung et al., 2018; Lee et al., 2015).

Based on this theoretical foundation, we propose the following hypothesis:

Hypothesis 1a: The extent of strong image-enhancement FGOC on firm social media accounts is positively correlated with abnormal stock returns.

In order to study the impact of strong image-enhancing FGOC in depth, we further categorized strong image-enhancing signals into three distinct types: product launch information (product-related FGOC signals) and (2) financial information (finance-related FGOC signals), and (3) other strong image-enhancing signals excluding those related to product and financial information. Among these strong image-enhancing FGOC signals, we argue, product- and finance-related FGOC signals are the two most important signals presented via social media. These two lightly studied types of signals enable a firm's valuable quality information to pass the perceptual gate and attract investor attention (Baum et al., 2019; Kundu & Banerjee, 2021).

First, product-related FGOC signals attract attention by revealing critical information about firm quality. This kind of signal relates primarily to launching new products and introducing product innovation, activities that show competitiveness, which have a positive impact on consumer attitudes (Baum et al., 2019). These unobservable firm attributes are exactly what customers and investors use to valuate a firm. Thus, signaling consumers about product quality helps firms to attract attention, charge premium prices, and enhance access to capital markets (Baum et al., 2019; Poirier et al., 2024). As a logical derivation of this line of thinking, product-related FGOC signals are likely to positively influence stock prices.

Second, online generated content, particularly related to product introductions, plays a significant role in shaping investor perceptions and influencing stock returns (Warren & Sorescu, 2017). Drawing from behavioral finance, investors are often influenced by the information they consume, and firms' online activities can trigger positive market reactions. Product announcements via digital platforms generate heightened attention, which often leads to increased trading activity and upward price movement (Chu et al., 2024).

Moreover, online engagement surrounding new product launches often correlates with future sales growth, which in turn affects stock returns. Higher levels of online interaction create expectations of increased profitability, encouraging speculative buying and driving stock prices upward. Research by Luo et al. (2013) supports this notion, indicating that firms' social media activity and digital marketing efforts can significantly shape equity value. Therefore, we hypothesize that:

Hypothesis 1b: The extent of product-related FGOC on firm social media accounts is positively correlated with abnormal stock returns.

Finance-related FGOC signals have the same effect on stock performance. This kind of information undoubtedly attracts investor attention because it directly reveals a public firm's earnings performance and profitability. The impact of financial disclosures on market behavior has been extensively studied in academic literature. Traditional financial reports, such as quarterly earnings announcements, are known to significantly reduce information asymmetry between firms and investors, thereby enhancing market efficiency and influencing stock prices (Kundu & Banerjee, 2021).

In the contemporary landscape, the rise of social media platforms like Twitter has introduced a new dimension to financial communication. Firms now use social media to extend their financial disclosure strategies, with finance-related Firm Generated Online Content (FGOC) offering real-time updates on a company's financial health. Unlike traditional financial reports, FGOC can be rapidly disseminated, amplifying the speed and reach of financial information. Research by Ranco et al. (2015) and Broadstock and Zhang (2019) indicates that social media activity, including finance-related content, can significantly influence stock prices due to its immediacy and broad audience. This suggests that the extent of finance-related FGOC on firm social media can directly impact investor sentiment and behavior.

Based on the above analysis, we formulate the research hypothesis:

Hypothesis 1c: The extent of finance-related FGOC on firm social media accounts is positively correlated with abnormal stock returns.

3.3 The Moderating Effect of Weak Image-Enhancing FGOC Signals

Weak image-enhancing FGOC signals refer to personalized, non-financial interactions between firms and their followers on social media platforms such as Twitter (Naaman et al., 2010). Such signals typically include casual greetings (e.g., "Happy New Year") or responses to individual user comments (e.g., "Thank you for sharing"), which may foster a warmer, more personal connection between the firm and its audience. While these signals may foster goodwill among consumers and humanize the brand, their potential impact on investor behavior is limited (van Veen & Ortt, 2021).

According to cognitive load theory (Sweller, 1988), individuals have a limited capacity for processing information. Information overload is particularly apparent when investors face a large volume of information, causing their cognitive load to increase rapidly and limiting their ability to process information effectively. In the context of information overload, investors' attentional resources become highly constrained. They are often unable to process all available information, leading them to make choices between different sources and types of information (Lu, 2022). Although investors may try to focus their attention on more important strong signals, the abundance of weak signals can create cognitive interference, passively capturing their attention and further diminishing their ability to process strong signals (Falkinger, 2008).

This phenomenon is referred to as attention dilution, meaning that investors are forced to distribute their limited cognitive resources and are unable to fully process the value information carried by strong signals (Drover et al., 2018; Zhao & Gan, 2024). Specifically, when the visibility of information increases, its ability to capture investors' attention also increases, thereby influencing their judgment (Drover et al., 2018). While individual weak signals have a minor impact on investors' decisions, as their quantity and visibility rise, these weak signals compete with strong signals for investors' attention. In this process, weak signals not only fail to enhance the effect of strong signals but also dilute investors' attention, weakening the

positive impact of strong signals on stock prices. This competitive effect prevents investors from fully recognizing and responding to the truly valuable information conveyed by strong signals, thereby affecting fluctuations in abnormal stock returns.

Therefore, we hypothesize the following:

Hypothesis 2a: The number of weak image-enhancing FGOC on firm social media accounts weakens the positive relationship between strong image-enhancement FGOC and abnormal stock returns.

As noted earlier in this paper, in the realm of stock market performance, both finance-related and product-related FGOCs play a critical role in shaping investor perceptions and decisions. However, compared to product-related FGOC signals, the weakening effect of weak image-enhancing FGOCs may be more pronounced on finance-related FGOC signals.

Finance-related FGOCs typically encompass critical financial metrics such as earnings announcements, profit forecasts, and cash flow insights. These signals are intrinsically tied to a firm's immediate profitability and risk profile, making them paramount for investors focused on short-term market movements (Chen et al., 2018). Research indicates that financial information can lead to rapid adjustments in market expectations and stock price volatility (Bourveau & Schoenfeld, 2017). As a result, investors prioritize these signals, using them as benchmarks for immediate decision-making.

Conversely, product-related FGOCs often reflect a firm's long-term strategic positioning, including its capacity for innovation, market share, and brand equity (Koski & Kretschmer, 2010). While these signals are undoubtedly important, they typically require a longer timeframe for investors to fully appreciate their implications. As a result, in contexts with high market volatility or strong short-term information shocks, investors may prioritize their attention on immediate signals related to financial health, while reacting relatively more slowly to long-term product-related signals (Sorescu et al., 2007).

Since financial information is critical to investors' short-term decision-making, weak image-enhancing FGOC signals may generate noise that distracts investors and weakens their focus on these critical signals. This distraction weakens the impact of financial signals, resulting in investors' inability to adequately respond to financial information, which can have a delaying or weakening effect on stock price adjustments (Hirshleifer & Teoh, 2003). In contrast, while weak image-enhancing FGOC signals can also dilute the impact of product-related signals, these signals focus on long-term brand value and competitive positioning, making investors generally less susceptible to short-term distractions (Koski & Kretschmer, 2010). Thus, while both types of FGOC signals may be affected by the weakening effects of weak image-enhancing FGOC, finance-related FGOC signals are more significantly impacted due to their direct association with investor behavior.

Therefore, we hypothesize the following:

Hypothesis 2b: The weakening effect of weak image-enhancing FGOC signals on finance-related FGOC signals is more pronounced than the effect of weak image-enhancing FGOC signals on product-related FGOC signals.

4 Methods

The method adopted in this work is an event window field study of the stock market. The data collection is threefold. First, it consisted of Twitter activity associated with selected public firms over a designated period. The second was data on traditional media press released over the same period. Third was period-aligned, publicly reported stock prices.

4.1 Measures

The most difficult construct to measure is the social media signal. To capture the attention-grabbing aspects of this signal, consistent with the rich disclosure literature (Lacka et al., 2021; Peng et al., 2022), we investigated each category of tweets released on a firm's official Twitter account over a one-day period. This served as a proxy for the quantity of the social media signal (Jung & Jeong, 2020). Furthermore, tweets were classified according to their content. Strong image-enhancing information includes tweets about new product introductions, revenues and profits, honors and awards, important activities and social responsibility, executive opinions, recruitment and employee news, and alliances and acquisitions, etc. Weak image-enhancing information includes retweeting, daily greetings, and responses

to followers. Table A1 and Table A2 in Appendix A show text examples of strong image-enhancing and weak image-enhancing signals of Twitter and traditional press releases.

To account for the extent of each category of signals on a daily basis, a three-round semantic analysis assessed the content of each tweet. To pilot the classification procedure, every tweet was read and then manually classified as a subset of tweets. Next, a machine learning model automatically categorized the same tweet sample. After comparing results, we focused on disputed tweets to determine the category to which they belonged. In general, each tweet was reviewed at least twice, making this information classification scheme fairly robust. Next, we chose a meta-learning model for text classification. The measurement and details of the subsequent machine learning model appears in Table B1 in Appendix B. Definitions of theoretical constructs appear in Appendix B, Table B2.

Another essential construct in this study is attention. Although some research has been able to directly measure attention through online survey questions and online account logins, it is intractable to match the daily attention of Twitter users to stocks because potential investors are only a small part of the thousands of followers and, moreover, their retweeting behavior cannot be distinguished from that of any other user. For this reason, directly measuring the attention of investors on Twitter was infeasible. However, the efficient markets hypothesis suggests that stock market fluctuations are captured in the abnormal price reaction measured over the course of this event, given that the information is unexpected (Fama & French, 1993). Therefore, to capture investor attention to portfolios, we followed Bank et al. (2019) in using abnormal returns, a metric that is likely to be associated with attention-grabbing events.

A tweet released from a firm's official social media page is such an event, an assumption that led us to choose the event study method as the best way to assess the market value of information. This is consistent with usage in the finance, economics, accounting, management, and marketing literatures (Sprenger et al., 2014; Xu & Zhang, 2013). In line with previous event studies, cumulative abnormal returns (CAR) served as the proxy to assess the stock market response to tweets (Chen et al., 2014; Xu & Zhang, 2013).

The design choice was for a short three-day window that included the releasing day and two additional days following the tweet (event window [0, 2]). This allowed firm social media signals to be fully interpreted by the market and to capture the daily price reaction without overlap (Lee et al., 2015; Sprenger et al., 2014). This is reasonable considering that Twitter users react readily to this short, real-time news whereas others take a little longer time.

Using this window, we first calculated abnormal returns by employing the Fama-French three-factor model (Fama & French, 1993), running a rolling regression for 250 trading days before the target day to estimate the factor coefficients and then taking the difference between actual and expected returns as abnormal returns. Finally, CAR was computed as the sum of abnormal returns from the beginning and end of the event window [0, 2]. As a robustness check, abnormal returns were also assessed in a distinctly different three-day event window [1, 3] to include the following three days after sending tweets.

4.2 Regression Models, Endogeneity Concerns, and Statistical Assumptions

First, the precise regression models for this study appear in Appendix C. Second, there are inevitably endogeneity concerns about the relationship between FGOC and abnormal returns and, although FGOC such as image-enhancing FGOC on Twitter did indeed influence stock performance, as predicted, any increase in stock price might, in turn, increase the information being subsequently disclosed on social media. The logic here is that when profitable, firms naturally release even more information on their social media account. If this is the case, the estimation results will be biased (Stock & Watson, 2019).

To address this form of endogeneity, our two-stage least square (2SLS) regression model employed two-event-day lagged CAR as instrumental variables (IVs) (Antonakis et al., 2014). Then we tested whether these IVs were indeed weak instruments by calculating the first-stage F statistics. These instruments also qualified because the increased FGOC of the current period cannot possibly improve CAR of the previous two event days, but will correlate with the CAR of the current event day because stock price usually varies daily within 10% (Xu & Zhang, 2013).

Moreover, to mitigate concerns related to heteroscedasticity and autocorrelation, we employed clustered standard errors. This method allows for the correlation of regression errors within groups, such as individual firms, while treating errors across different groups as uncorrelated (Stock & Watson, 2019). By clustering standard errors at the firm level, we enhance the robustness of our results.

In our panel data analysis, we incorporated both firm dummy variables and time dummy variables to control for entity fixed effects and time-specific effects. Firm dummy variables account for unobserved characteristics that may influence stock performance but remain constant over time, such as management practices or company culture. Time dummy variables capture effects that are common across all firms during specific periods, such as economic events or market trends. This dual approach allows us to isolate the effect of FGOC on stock returns more accurately.

4.3 Data and Sample

Data sources included: (1) Twitter data from Gnip Company; (2) press release data from the Factiva database; and (3) financial market data from Compustat and the Center for Research in Security Prices (CRSP). The number of official Twitter accounts classified firms into two types: firms having only one official account and firms having multiple accounts (ACC). For the former type of firm, the FGOC on their Twitter accounts was obtained; for the later type, the FGOC on their most-visited Twitter accounts was used. These Twitter data allowed us to calculate the quantity of each type of social media signal, strong image-enhancing FGOC signal (SIE_T), weak image-enhancing FGOC signal (WIE_T), product-related FGOC signal (PRO_T), finance-related FGOC signal (FIN_T) and other strong image-enhancing FGOC signal (OTH_T), as well as the logarithm of followers (FOL). It is also important to note that Sprenger et al. (2014) used the method of searching for tweets with dollar tags and company codes when collecting UGC from sample companies on Twitter (for instance, "$MMM" was used as a keyword to search for tweets related to the 3M company). For FGOC on traditional media, we queried Factiva with each company name as it appeared in the CRSP database. The tag "press release" was used to ensure that the news was indeed released by enterprises. Using the news articles, the number of traditional media signals (PR) was obtained. Accessed through the Wharton Research Data Services, CRSP stock data was used to calculate CAR. Firm data was manipulated to compute the logarithm of firm size (SIZE), market-to-book ratio (MtB), and institutional ownership proportion (INST).

In this study, we focus on the constituents of the S&P 500 Index, with a sample period from January 1 to July 31, 2013, with sample collection occurring in February 2014. The S&P 500 Index tracks well-known companies that represent a broad spectrum of the U.S. stock market, and the performance of these companies, along with their social media activity, is widely monitored (Sprenger et al., 2014).

To ensure the integrity and relevance of the data, we initially filtered out 217 companies that posted tweets during the sample period. After preliminary filtering, we excluded 46 companies that had significant gaps in their tweet data, ensuring that the remaining firms had at least 120 days of available daily stock market data from the CRSP database prior to the event. Additionally, we established criteria of an average daily stock price exceeding $1 and an average daily trading volume of over 50,000 shares to further enhance sample quality. As a result, our final sample comprised 141 companies, representing 65% of the original set.

The relatively high retention rate of 65% indicates that our sample is robust and representative of the broader population of the S&P 500. By selecting companies with consistent social media engagement and sufficient trading activity, we aim to ensure that our findings accurately reflect genuine market behavior. Moreover, our sample includes companies from diverse sectors within the S&P 500, enhancing the generalizability of our results across various market contexts. For every firm, the variables shown in Table B2 were computed, see Appendix B. The interpretation of the summary statistics is shown in Appendix E.

5 Results

5.1 Main Results

Table 1 displays the main results. None of the first-stage F statistics are zero, indicating there is no weakness in the instrumental variables (Cragg & Donald, 1993). Significant coefficients of firm dummy variables mean the model captures the fixed effect of the firms, but we do not report these coefficients due to the page limitation.

Columns (1) to (4) of Table 1 indicate that the coefficients for SIE_T, PRO_T, and FIN_T are positive and statistically significant, while the coefficient for OTH_T is positive but not significant. Specifically, each additional 100 units of strong image-enhancing FGOC signals posted by the company on Twitter is associated with a 5-unit increase in CAR. Product-related FGOC signals and finance-related FGOC

signals each lead to increases in CAR by 4 units and 9 units respectively, per 100 units increase. These findings highlight that strong image-enhancing FGOC signals, particularly those related to products and finances, positively impact stock performance. These results support hypotheses H1a, H1b, and H1c, and underscore the importance of signaling theory in the communication of information between firms and investors.

Product-related FGOC signals suggest positive attributes such as innovation capability or market performance, while finance-related FGOC signals convey strong positive information about the company's profitability and financial health. Such signals reduce information asymmetry, enhance investor confidence in the company's future, and drive stock price increases (Guay et al., 2016). This is consistent with Drover et al. (2018), who emphasized that decision-makers rely on information signals perceived to be associated with organizational quality when direct observation is unfeasible. In contrast, the coefficient for OTH_T, while positive, is not significant, suggesting that other forms of strong image-enhancing FGOC signals do not significantly impact stock returns. This may relate to the nature of these signals. The effectiveness of a signal depends on its ability to address critical information asymmetry and investor concerns (Bergh et al., 2014). Although these signals may enhance corporate image to some degree, they may not deliver the financial or product-related information most crucial to investors, thereby lacking a substantial impact on stock prices.

We also tested the direct effect of weak image-enhancing FGOC signals on stock performance. Column (5) of Table 1 shows that the coefficient for WIE_T is not significant (coefficient = 0.012, $p > 0.1$), indicating that weak image-enhancing FGOC signals do not significantly impact stock performance. According to signaling theory, weak signals, due to their insufficient informational strength, fail to effectively mitigate information asymmetry between investors and the firm, thus lacking a significant impact on stock prices. This suggests that only signals with adequate strength and informational content are recognized by the market, further supporting signaling theory (Drover et al., 2018).

Columns (6) to (8) of Table 1 then present results for hypotheses H2a and H2b. Here, we focus on the coefficients and significance of the interaction terms. Column (6) supports H2a (the coefficient for SIE_T*WIE_T is -0.029, $p < 0.05$), indicating that the positive relationship between strong image-enhancing FGOC signals and stock returns is weakened by weak image-enhancing FGOC signals. This finding suggests that weak signals may obscure valuable information from investors (Cao et al., 2021). This phenomenon can be explained by limited attention theory, which posits that investors' cognitive resources are often diverted by weak signals, thereby diminishing their responsiveness to important information (Ben-Rephael et al., 2017; Hirshleifer et al., 2011).

The results in Columns (7) and (8) show that weak image-enhancing FGOC signals significantly weaken the effect of finance-related FGOC signals on stock returns (coefficient for FIN_T*WIE_T is -0.012, $p < 0.01$) , but have no significant impact on the effect of product-related FGOC signals (coefficient for PRO_T*WIE_T is -0.003, $p > 0.1$). These findings support hypothesis H2b. As discussed earlier, financial information is typically more immediate and relevant to investor decision-making. Financial signals, such as earnings announcements and cash flow updates, provide direct insights into a company's future profitability and risk, which makes investors more sensitive to these signals (Chen et al., 2018). Limited attention theory suggests that, when faced with multiple signals, investors—due to their finite cognitive resources—focus on those most pertinent to short-term financial decisions. Consequently, weak signals can divert attention away from these critical financial signals, diminishing their impact on stock prices.

In contrast, product-related information generally reflects market performance and long-term brand value, which takes more time to manifest in stock prices (Koski & Kretschmer, 2010). As such, during periods of short-term market fluctuation, investors may be less focused on product-related signals (Sorescu et al., 2007). This is consistent with the results from Columns (2) and (3) of Table 1, where the coefficient for FIN_T is 0.093, significantly higher than the coefficient for PRO_T at 0.040, indicating that investors respond more strongly to financial signals than product-related ones. Thus, the weakening effect of weak FGOC signals is more pronounced for financial signals, as these signals play a more immediate role in investor decision-making. In summary, our study suggests that while stronger signals are generally more attractive, they are also more susceptible to interference from other information.

Regarding control variables, the results remain consistent across models. The PR coefficient is positive, indicating that news published in traditional media significantly positively affects stock prices. The MtB coefficient is negative and significant, suggesting the BM effect (i.e., higher book-to-market ratios correlate with poorer stock performance). The ACC coefficient is significantly positive, showing that the use of

multiple social media platforms enhances stock performance. Although the UGC coefficient is positive, it is not significant, indicating that failing to consider FGOC may bias the research results on UGC. Future research should integrate UGC with FGOC to provide a more comprehensive analysis.

Table 1. Estimation Results

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAR	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**
Theoretical Variables								
SIE_{Tit}	0.052*** (0.014)					0.063*** (0.017)		
PRO_{Tit}		0.040*** (0.015)					0.050*** (0.019)	
FIN_{Tit}			0.093*** (0.020)					0.095*** (0.020)
OTH_{Tit}				0.012 (0.009)				
WIE_{Tit}					0.016 (0.019)	0.014 (0.022)	0.012 (0.020)	0.017 (0.019)
SIE_{Tit}*WIE_{Tit}						-0.029** (0.014)		
PRO_{Tit}*WIE_{Tit}							-0.003 (0.002)	
FIN_{Tit}*WIE_{Tit}								-0.012*** (0.002)
Control Variables								
FOL_{it}	-0.885*** (0.085)	-0.886*** (0.085)	-0.888*** (0.085)	-0.888*** (0.085)	-0.890*** (0.085)	-0.884*** (0.085)	-0.885*** (0.085)	-0.889*** (0.085)
ACC_{it}	0.036** (0.014)	0.036** (0.014)	0.033** (0.014)	0.036** (0.014)	0.036** (0.014)	0.036** (0.014)	0.036** (0.014)	0.033** (0.014)
UGC_{Tit}	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
PR_{it}	0.086*** (0.017)	0.091*** (0.017)	0.088*** (0.017)	0.092*** (0.017)	0.093*** (0.017)	0.084*** (0.017)	0.090*** (0.017)	0.087*** (0.017)
$SIZE_{it}$	-0.026 (0.257)	-0.015 (0.257)	-0.010 (0.251)	-0.0112 (0.259)	-0.014 (0.259)	-0.035 (0.257)	-0.021 (0.257)	-0.016 (0.251)
MtB_{it}	-0.490*** (0.069)	-0.490*** (0.067)	-0.481*** (0.067)	-0.488*** (0.069)	-0.486*** (0.069)	-0.490*** (0.069)	-0.490*** (0.069)	-0.480*** (0.067)
$INST_{it}$	-1.210 (1.948)	-1.195 (1.950)	-1.084 (1.897)	-1.104 (1.959)	-1.149 (1.960)	-1.275 (1.949)	-1.265 (1.952)	-1.146 (1.899)
Constants	14.084*** (3.905)	13.963*** (3.904)	13.818*** (3.802)	13.882*** (3.925)	13.956*** (3.927)	14.214*** (3.906)	14.084*** (3.905)	13.948*** (3.806)
R^2	0.116	0.116	0.119	0.115	0.115	0.116	0.116	0.119
F statistics	15.890	15.871	16.025	15.851	15.844	15.682	15.767	16.032
N	17457	17457	17457	17457	17457	17457	17457	17457

Notes: (1) Cluster-robust standard errors in parentheses; (2) ***p < 0.01, **p < 0.05, *p < 0.10.

5.2 Additional Analysis

No more than any other non-experimental study can consider all the factors that influence investors and stock returns, endogeneity is still possible here. Testing variables and linkages found in previous research is a good way of examining this endogeneity issue, in effect conducting a reverse form of nomological validity. Xu and Zhang (2013) research offers three sets of proxy variables through which the public perceives listed companies to be visible: firm characteristics, media coverage, and capital market visibility.

Following these scholars, we included seven control variables to examine rival explanations. The details of this testing in Appendix D suggest that endogeneity concerns are not serious. Results of subsample analysis ruling out unobserved heterogeneity appear in Appendix F. As another robustness check, abnormal returns were also assessed in a distinctly different three-day event window [1, 3] to include the following three days after sending tweets, and the results in Appendix G show that the findings in this paper remain robust.

6 Discussion

This study contributes to the literature on firm-generated content (FGOC) and its impact on stock performance by applying the theoretical frameworks of signaling theory (Connelly et al., 2011) and limited attention theory (Kahneman, 1973). We empirically tested the effects of strong and weak image-enhancing FGOC signals on stock performance, and the results are summarized in Appendix H. Our findings indicate that strong image-enhancing FGOC signals such as FGOC signals related to new products and finances are significantly and positively related to stock performance. Specifically, when companies leverage their official Twitter accounts to disseminate more image-enhancing information in these two areas, they can achieve higher abnormal returns.

Conversely, our analysis reveals that weak image-enhancing signals do not contribute positively to firm stock performance. Furthermore, these weak signals can undermine the beneficial effects of strong image-enhancing FGOC signals, particularly in the context of finance-related information. This suggests that while strong signals are crucial for enhancing investor perceptions and driving stock performance, the presence of weak signals can detract from these efforts.

Overall, these results highlight the importance of carefully managing the types of FGOC signals a firm communicates to investors, as both the strength and nature of the signals can significantly influence market outcomes.

6.1 Theoretical Implications

This study contributes to several important areas of financial and communication theory by examining how firm-generated online content (FGOC) influences stock market reactions. While existing research provides valuable insights into the effects of FGOC on firm performance, it often overlooks the nuanced interplay between strong and weak signals. By focusing on different types of FGOC signals—specifically strong image-enhancing, weak image-enhancing, and their interactions—this research advances the literature and offers new insights into how firms' digital communication strategies affect investor behavior.

One key theoretical contribution lies in the application of signaling theory to the digital sphere. Traditional signaling theory has typically focused on formal announcements or corporate actions that reduce information asymmetry between firms and investors. In this study, we extend this framework by demonstrating that signals transmitted through digital platforms like Twitter can effectively influence stock market performance when they contain strong, relevant information. The results show that signals related to financial and product performance are particularly impactful, providing further validation of signaling theory in the context of social media. This contribution is relevant for understanding how companies can leverage digital platforms to strategically manage their communications with investors, reducing uncertainty and enhancing confidence in the firm’s future prospects.

The study also engages with limited attention theory, which suggests that investors’ cognitive resources are finite, leading them to prioritize certain information while potentially ignoring other signals. Our findings indicate that while weak signals do not directly impact stock returns, they can interfere with the effectiveness of strong signals. Specifically, signals related to financial information tend to be more attention-grabbing than those related to product information; however, these financial signals are also more vulnerable to interference from competing signals. This offers a more nuanced understanding of how investor attention is allocated in an environment where firms continuously broadcast information across multiple channels. The weakening effect of weak signals on finance-related content emphasizes the importance of clarity and relevance in digital communications, as investors may overlook key information when overwhelmed by less important signals. This aligns with limited attention theory but adds specificity by identifying the conditions under which signal interference occurs.

At the same time, the study’s results regarding the interaction between strong and weak signals provide a more refined perspective on signaling theory. The finding that weak signals can dilute the effect of strong

ones suggests that firms need to carefully manage the volume and content of their communications. This underscores the complexity of signal interpretation in a digital environment, where investors are bombarded with information from various sources. It also challenges the assumption that more communication is always beneficial, providing a theoretical basis for further exploration of how signal overload might impact investor decision-making.

In conclusion, this study provides a meaningful extension of established theories, offering new perspectives on how digital signals influence stock market behavior. By examining the interactions between different types of FGOC and their effects on stock returns, the research contributes to a deeper understanding of how firms can strategically manage their communications in the digital age.

6.2 Managerial Implications

The findings of this study reveal actionable insights for firms and key stakeholders on leveraging Firm Generated Online Content (FGOC) to improve stock performance. By strategically managing the content and presentation of FGOC signals, companies can significantly influence investor perceptions and stock valuations.

Firms should focus on generating and amplifying strong FGOC signals, such as major product innovations, strategic financial announcements, or significant partnerships. For instance, when Tesla announces the release of a new electric vehicle model or a groundbreaking technological advancement, it should post these announcements on high-traffic platforms like Twitter. This approach ensures that strong signals are prominently visible, capturing the attention of investors who are seeking substantial updates that can directly influence their investment decisions.

On the other hand, companies with less established market positions, such as emerging technology firms, can benefit from adopting a balanced signaling strategy. While these companies may need to release weak firm-generated online content (FGOC) signals—such as updates on incremental research progress or minor partnerships—to maintain market visibility, it is equally crucial to communicate occasional strong signals. Examples of strong signals include securing significant funding rounds or achieving breakthroughs in product innovation. This balanced approach allows companies to effectively manage uncertainty, maintain a positive image, and foster investor trust, ensuring that weak signals do not undermine investor expectations or dilute the impact of more substantial achievements.

Presentation is equally critical. For instance, when Amazon releases its quarterly earnings report, it can enhance this strong signal by using dynamic visuals such as infographics or interactive charts, making the information more accessible and engaging for both investors and analysts. In contrast, weaker signals—such as minor personnel changes—should be conveyed more subtly to avoid cluttering the communication flow. This ensures that investors remain focused on critical information, preventing less important updates from diluting the impact of key signals.

Additionally, social media platforms like Twitter and LinkedIn already provide firms with tools to pin or highlight important posts, helping crucial signals remain visible. To further support firms, platforms could enhance these features by offering customized solutions—such as time-based pinning for earnings announcements or automatic boosts during peak trading hours. AI-powered tools could further support firms by recommending optimal posting times, personalized content strategies, or relevant tags to maximize reach among target groups like institutional investors and analysts. Moreover, platforms might develop premium services that boost the visibility of financial announcements during critical market periods, such as earnings seasons. These efforts would enable firms to cut through the noise, ensuring that their most valuable signals effectively drive investor decision-making and market outcomes.

Furthermore, stock market operators could benefit from incorporating FGOC signal analysis into their assessments. For example, stock exchanges could track the frequency and impact of certain types of FGOC signals to predict stock price movements more accurately. By analyzing how different content types affect market trends, stock operators could offer valuable insights into how public communication influences market dynamics.

In summary, firms can optimize the impact of their FGOC by focusing on the strategic dissemination of strong signals, balancing the use of weak signals, and ensuring that these messages are delivered in a vivid, compelling format. This nuanced management of FGOC not only helps enhance investor engagement but also contributes to improved stock performance, benefiting both the firm and the broader market ecosystem.

6.3 Limitations and Future Research Directions

While this study provides meaningful insights into the impact of firm-generated content (FGOC) on stock returns through the lens of signaling theory and limited attention theory, there are several limitations that should be acknowledged. First, the research focuses exclusively on firm-generated content on Twitter, which may not fully capture the broader dynamics of digital communication. Future research could explore whether similar effects hold on other social media channels, thereby expanding the scope of digital communication research.

Additionally, while we apply limited attention theory to explain the differential impact of signals, we do not directly measure investor attention. Future studies could employ proxies such as trading volume or search trends to better capture this construct, providing a deeper understanding of how attention allocation affects investor behavior in information-rich environments.

Another limitation relates to the specific sample used in this study. We focus on 141 publicly traded enterprises over a 7-month period, which, while sufficient for the analysis, represents a relatively short time frame and a modest sample size. Extending the time horizon and increasing the number of firms in future studies could help ensure that the findings are more generalizable. This would also allow researchers to capture longer-term trends and better understand how sustained FGOC impacts stock market performance over time.

While this study emphasizes the positive impact of strong FGOC signals on stock returns, it is important to note that the presence of weak FGOC signals does not negate their value. Although our findings suggest that weak signals may diminish the effectiveness of strong signals, they can still serve important functions, such as maintaining visibility in the market and supporting ongoing communication with investors. Future research could investigate the potential benefits of weak FGOC signals in various contexts, exploring how they can complement strong signals and contribute to a more nuanced understanding of investor perceptions and decision-making.

Lastly, while this study focuses on abnormal stock returns, other indicators such as firm value or volatility could be explored to provide a more comprehensive view of the market impact of FGOC.

In summary, while this research offers valuable insights into the relationship between FGOC and stock returns, future work can expand upon these findings by incorporating new measurement approaches, broader datasets, and alternative performance indicators. These extensions would not only enrich the theoretical contributions but also provide deeper practical insights for firms aiming to optimize their digital communication strategies.

6.4 Conclusion

The impact of social media on businesses is likely to play out over time. The current research advances the scientific inquiry into this phenomenon by investigating social media messages and the financial markets. Firms can better control their own destinies if they understand the ramifications of the types and volume of online messages they are sending to the public and investors. Although companies have little power over UGC on social media platforms, they can dictate what FGOC appears on their own sites. This simple ability appears to have sizable implications for worldwide enterprises.

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Appendix A: Text Samples of Social Media

Table A1. Texts of Strong Image-enhancing Information

Strong Image-Enhancing Information	Texts from X(Twitter)
New product introductions	3M designs cheaper fuel tank for natural gas vehicles in Chesapeake collaboration http://t.co/KW9apxww via @tulsaworld ; 3M launches fast Salmonella detection system http://t.co/0c3GakhbrF via @FoodProdDaily ; New 3M eyewear range offering eye protection and high quality optics http://t.co/4PH89F9Kys
Revenues and Profits	3M Delivers Q4 Sales of $7.4B andamp; Earnings of $1.41 per Share; Company Posts Record Full-Year Sales Read more http://t.co/mfxMbd5Q ; 3M Board Declares Quarterly Dividend http://t.co/cifmtBUtix via @sharethis ; 3M Reports Record 2nd Quarter Results; Company Posts Sales of $7.8 Billion andamp; Earnings per Share of $1.71 http://t.co/KgL8HgrEM2 @sharethis
Honors and Awards	BCG Names 3M One of the World's 50 Most Innovative Companies http://t.co/gmsdzoph ; 3M Listed as One of the Best Employers in America - Yahoo! Finance http://t.co/BX0j91tI via @YahooFinance ; Inventing every day! Dow was named a 2012 Top 100 Global #Innovator by @ThompsonReuters #IPDay
Important Activities and Social Responsibility	3M Thinsulate sponsors Burton US Open Snowboarding Championships in Vail Feb 25-Mar 2! TV airtimes at http://t.co/drVz6JS3 @burtonsnowboard ; Delphi's 2013 Global Excellence Week activities are underway! http://t.co/jelQNNrr9k ; 3M aids collision schools with $250,000 product donation through CREF | Search Autoparts: http://t.co/weMOE0FamT ;
Executive Opinions	3M CEO Inge Thulin talks about innovation and global business on Squawk Box http://t.co/Bw3XPV28Cf ; Corning CEO: [Corning is] "a company responsible for numerous life-changing innovationsâ€• http://t.co/Oysto06lE3 #innovation #tech $GLW ; Our CEO, Rodney O'Neal shares how important the consumer experience is to Delphi:http://t.co/lJhDDrSb
Recruitment and Employee News	CSX employees and retirees are still spreading good cheer! Hear their stories of good deeds at #BeyondOurRails: http://t.co/vh4uw0XN ; Our employees volunteered 24,000 hours last year, placing us 80% of the way to our 2015 goal of 100,000 hours. Way to go team! #CSR ; Interested in a career at Ameren? Our recruiters will be heading to @Northwoods_Mall for the #Peoria community career fair, 3/27, 10am-2pm!
Alliances and Acquisitions	RT @BudapestBJ: Govt to sign strategic cooperation agreement with Jabil Circuit unit: The local unit of American contract electr... http ... .@GM CEO Akerson: GM andamp; @Honda collaboration â€œhas the potential to help reduce dependence on petroleum andamp; establish #sustainable mobilityâ€• MT @humananews: Humana Foundation continues partnership w/ Festival of New American Plays. http://t.co/6YUj2FlISh via @WFPLNews

Table A2. Texts of Weak Image-enhancing Information

Weak Image-Enhancing Information	Texts from X(Twitter)
Responses to Followers	@beccaflack We don't have that sandwich in the States; what's the issue with it? Thanks! @MommaRossonÂ Glad to hear it! @WSUFrontDoor thank you for the mention!
Retweeting and Daily Greetings	RT @roushfenway: Having a little fun here at Daytona! #NASCAR @DISupdates http://t.co/j3Dqn4VM; Happy New Year from Citi! How do you plan on celebrating #NYE? The only thing as important as your clubs is how they travel to the #golf course. Travel like a pro Http://t.co/GI2yOL7gvA

Appendix B: Meta-Learning Model for Text Classification and Construct Definitions

Table B1 shows the precision, recall, and F1 measure of the machine learning method we used, i.e., a meta-learning model for textual classification. Table B2 offers definitions of our constructs.

Our information classification results appear to be robust when we look at the relatively high precision, recall, and F1 measure of each kind of text. To further understand the classification method of the machine learning model, we briefly introduce this meta-learning model.

Meta-learning is one of the most popular machine learning technologies used in the world. A meta-learning model enhances machine learning by relearning the learning outcomes. This machine learning model emphasizes that models need to gain knowledge about learning tasks and diversify learners as much as possible. They then generate better algorithms by combining all other algorithms (Gomes et al., 2012). Generally speaking, a combination of multiple learners and algorithms includes several types, including: a combination of different algorithms, a combination of different algorithms in different parts of the data set, or a combination of the same algorithm in different settings. Meta-learning integrates the advantages of a variety of base learners to achieve higher learning performance (Gomes et al., 2012).

The meta-learning model in the present research integrates the algorithms of the information gain model (IG), the paragraph vector model, and the latent Dirichlet allocation model (LDA), therefore gaining advantages of these three machine learning algorithms (Le & Mikolov, 2014).

Table B1. Meta Learning Model

X(Twitter) text categories	Precision	Recall	F1 score
product-related	94.87%	96.19%	95.53%
finance-related	91.66%	88.51%	90.05%
other image-enhancing	87.46%	82.13%	84.71%
non image-enhancing	89.33%	88.91%	89.12%

Table B2. Construct Definitions

Variables	Computation	Source
Theoretical Variables		
CAR_{it}	Sum of abnormal returns in two event windows [0, +2] and event window [1, +3], including releasing day and two following days. The abnormal returns are estimated using Fama-French three-factor model (Fama & French, 1993).	CRSP
SIE_{Tit} (strong image-enhancing FGOC signal)	The number of strong image-enhancing tweets released by a firm. Strong image-enhancing FGOC includes three categories: product-related FGOC, finance-related FGOC and other strong image-enhancing FGOC.	Gnip Company
WIE_{Tit} (weak image-enhancing FGOC signal)	The number of weak image-enhancing tweets released by a firm. Weak image-enhancing FGOC includes three categories: responding to followers, retweets, and daily greetings. Once again, we manually and automatically classified each tweet three times.	Gnip Company
PRO_{Tit} (product-related FGOC signal)	The number of tweets about new product introduction released by a firm. These product-related tweets were a subset of all strong image-enhancing tweets.	Gnip Company
FIN_{Tit} (finance-related FGOC signal)	The number of tweets about revenue and profit released by a firm. These finance-related tweets were a subset of all strong image-enhancing tweets.	Gnip Company
OTH_{Tit} (other strong image-enhancing FGOC signal)	The number of strong image-enhancing tweets apart from product-related tweets and profit-related tweets.	Gnip Company
Control Variables		
UGC_{Tit} (UGC on X(Twitter))	The number of tweets that relate to sample firms with dollar tag and firm tickers and released by ordinary X(Twitter) users, which indicates the content relate to sample firms and generated by ordinary users on X(Twitter), can also become an information source for investors to get firm quality and make decision. Control for the impact of UGC enables us to get the marginal impact	Twitter

	of FGOC.	
PR_{Pit} (signal on traditional media)	The number of news on traditional media released by a firm.	Factiva
FOL_{it} (The logarithm of followers)	Natural logarithm of the total number of followers for a firm. The log transformation smooths the distribution of data to meet the assumptions of parametric statistical tests despite large deviations from the mean. The number of followers is an important social media feature that possibly influence stock price (Sul et al., 2017).	CRSP
$SIZE_{it}$ (The logarithm of firm total assets)	Natural logarithm of total assets in the second fiscal quarter of 2013 of a firm. Similar to followers, firm assets are not normally distributed; therefore, the log transformation will make the data much more suitable for fitting with the linear model. Firm size has been widely controlled for in the disclosure literature, because large firms may have different disclosure policies and may attract more media attention than small firms, which in turn may lead to differential effects on stock price (Peng et al. 2022).	CRSP
MtB_{it} (The market-to-book ratio)	The market-to-book ratio for a firm in the second fiscal quarter of 2013. Market-to-book ratios are equal to the current share price divided by the book value per share, and show a significant effect on predicting stock price.	CRSP
$INST_{it}$ (The proportion of institutional ownership)	The proportion of institutional ownership for a firm at the end of 2012. Institutional investors pay more attention to earnings components than individuals, therefore stocks with larger institutional ownership demonstrating a lower volatility in excess returns (Fu et al., 2024).	CRSP
ACC_{it} (The amount of social media account)	Account equals 0 when the firm has only one official X(Twitter) account, and 1 otherwise during the sample period (January 1, 2013–August 2, 2013). The number of social media accounts is an important social media feature that possibly influencing stock price (Sul et al., 2017).	Twitter

Appendix C: Regression Models

To test H1a, H1b and H1c, we posited model (1) – (3) to examine the relationship between strong image-enhancing FGOC signals, product-related FGOC signals and finance-related FGOC signals on social media and stock price. The subscripts "i" indicates firms and "t" indicates time periods.

$$CAR_{it} = \alpha + \beta_{11} SIE_{Tit} + \delta controls_{it} + \varphi fe_i + \tau te_i + \varepsilon_{it} \quad (1)$$

$$CAR_{it} = \alpha + \beta_{12} PRO_{Tit} + \delta controls_{it} + \varphi fe_i + \tau te_i + \varepsilon_{it} \quad (2)$$

$$CAR_{it} = \alpha + \beta_{13} FIN_{Tit} + \delta controls_{it} + \varphi fe_i + \tau te_i + \varepsilon_{it} \quad (3)$$

Consistent with prior research, we included several firm characteristics, namely, firm fixed effects and time period fixed effects, to control for endogeneity and other factors affecting stock price. The control variables are summarized in Table B2.

To test H2a, and H2b, models (4), (5) and (6) represent the moderating effect of weak image-enhancing information on strong image-enhancing FGOC signals, product-related signals and finance-related signals and include the same controls as the previous models.

$$CAR_{it} = \alpha + \beta_{31} SIE_{Tit} + \beta_{32} WIE_{Tit} + \beta_{33} SIE_{Tit} * WIE_{Tit} + \delta controls_{it} + \varphi fe_i + \tau te_i + \varepsilon_{it} \quad (4)$$

$$CAR_{it} = \alpha + \beta_{41} PRO_{Tit} + \beta_{42} WIE_{Tit} + \beta_{43} PRO_{Tit} * WIE_{Tit} + \delta controls_{it} + \varphi fe_i + \tau te_i + \varepsilon_{it} \quad (5)$$

$$CAR_{it} = \alpha + \beta_{51} FIN_{Tit} + \beta_{52} WIE_{Tit} + \beta_{53} FIN_{Tit} * WIE_{Tit} + \delta controls_{it} + \varphi fe_i + \tau te_i + \varepsilon_{it} \quad (6)$$

Appendix D: Possible Endogeneity from Omitted Variables

We included seven statistical control variables for this analysis. For firm characteristics, we first examined whether the firm is in the technology sector (TECH) (SIC codes 3570–3579, 3610–3699, 7370–7379, 3810–3849, and 4800–4899) because tech firms are likely to be at the forefront of changes in technology and often face a larger-than-average risk, thus tending to disclose more information to their shareholders (Xu & Zhang, 2013).

Second, we considered firm age (AGE) because investors could be more familiar with older firms, a factor that could affect investor behavior (Xu & Zhang, 2013).

Third, previous research has shown that mergers and acquisitions can lead to permanent gains in stockholder value (Lubatkin 1987); thus, we obtained a dummy variable indicating whether the firm released information about acquisition (ACQ).

For media coverage and our fourth variable, we included Google's Search Volume Index (SVI) as a measure of online investor attention, given that our research interest is on the effect of online social media (Xu & Zhang, 2013). We used a procedure similar to Xu and Zhang (2013) to obtain the Google SVI data.

Next, our fifth variable, advertisement expenditure (AD) could reflect media coverage from other media such as television and radio and research show that this influences investors (Grullon et al., 2004). Thus, we also obtained advertisement expenditures in the model to capture offline investor attention.

Moreover, for capital market visibility and our sixth variable, a NYSE listing (NYSE) (a dummy variable indicating firms listed on the NYSE) was used since it could be positively related to firm visibility (Xu & Zhang, 2013).

Finally, considering the significant positive impact of new purchase or sales contracts on market value (Yang et al., 2014), we introduce a seventh control variable in our model to account for the effect of businesses signing relevant contracts. This variable, denoted as SIGN, takes the value of 1 to indicate that a contract has been signed and 0 to indicate that it has not. By incorporating this control variable, we aim to more accurately assess the impact of FGOC on abnormal stock returns.

The results of this analysis are presented in Table D1. We conclude that our main findings are robust because the effects of FGOC are unchanged, even though the tech firm dummy, firm age, advertisement expenditure, Google SVI, and NYSE listing are all significant. Consistent with prior studies (e.g., Xu & Zhang, 2013), our findings confirm that firm visibility plays a role in affecting firm stock performance.

Table D1. Estimation Results with Added Controls

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAR	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**
Theoretical Variables								
SIE_{Tit}	0.043*** (0.013)					0.053*** (0.016)		
PRO_{Tit}		0.034** (0.015)					0.042** (0.019)	
FIN_{Tit}			0.086*** (0.020)					0.088*** (0.020)
OTH_{Tit}				0.006 (0.010)				
WIE_{Tit}					0.010 (0.018)	0.008 (0.022)	0.005 (0.020)	0.011 (0.018)
SIE_{Tit}*WIE_{Tit}						-0.023* (0.014)		
PRO_{Tit}*WIE_{Tit}							-0.002 (0.002)	
FIN_{Tit}*WIE_{Tit}								-0.011*** (0.002)
Control Variables								

FOL_{it}	-0.822*** (0.087)	-0.821*** (0.087)	-0.826*** (0.087)	-0.822*** (0.087)	-0.824*** (0.087)	-0.821*** (0.087)	-0.821*** (0.087)	-0.828*** (0.087)
ACC_{it}	0.035** (0.014)	0.034** (0.014)	0.032** (0.014)	0.035** (0.014)	0.035** (0.014)	0.035** (0.014)	0.034** (0.014)	0.031** (0.014)
UGC_{Tit}	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
PR_{it}	0.075*** (0.016)	0.078*** (0.016)	0.076*** (0.016)	0.080*** (0.016)	0.081*** (0.016)	0.073*** (0.016)	0.077*** (0.016)	0.075*** (0.016)
$SIZE_{it}$	-22.173*** (3.098)	-22.192*** (3.104)	-22.979*** (3.118)	-22.677*** (3.109)	-22.503*** (3.151)	-22.393*** (3.141)	-22.235*** (3.139)	-22.818*** (3.153)
MtB_{it}	-5.358*** (0.713)	-5.364*** (0.714)	-5.527*** (0.717)	-5.466*** (0.715)	-5.427*** (0.725)	-5.406*** (0.723)	-5.374*** (0.722)	-5.491*** (0.725)
$INST_{it}$	-85.324*** (12.262)	-85.405*** (12.285)	-88.463*** (12.338)	-87.255*** (12.303)	-86.601*** (12.458)	-86.163*** (12.419)	-85.574*** (12.411)	-87.855*** (12.465)
$TECH_i$	-7.922*** (1.093)	-7.946*** (1.097)	-8.254*** (1.100)	-8.164*** (1.096)	-8.085*** (1.117)	-8.021*** (1.112)	-7.966*** (1.113)	-8.174*** (1.117)
AGE_{it}	71.211*** (9.994)	71.303*** (10.019)	73.850*** (10.054)	72.886*** (10.023)	72.320*** (10.164)	71.889*** (10.130)	71.422*** (10.129)	73.313*** (10.170)
ACQ_{it}	0.430 (0.291)	0.429 (0.291)	0.432 (0.291)	0.431 (0.291)	0.430 (0.291)	0.430 (0.291)	0.429 (0.291)	0.432 (0.291)
SVI_{it}	1.185*** (0.245)	1.202*** (0.244)	1.148*** (0.244)	1.216*** (0.244)	1.216*** (0.242)	1.181*** (0.244)	1.199*** (0.243)	1.141*** (0.244)
AD_{it}	162.568*** (22.486)	162.884*** (22.505)	167.745*** (22.608)	165.944*** (22.595)	164.743*** (22.888)	164.243*** (22.808)	163.320*** (22.784)	166.648*** (22.855)
$NYSE_{it}$	4.130*** (0.958)	4.124*** (0.958)	4.372*** (0.962)	4.248*** (0.961)	4.210*** (0.968)	4.190*** (0.966)	4.138*** (0.965)	4.340*** (0.968)
$SIGN_{it}$	0.069 (0.100)	0.070 (0.100)	0.047 (0.101)	0.071 (0.100)	0.071 (0.100)	0.068 (0.100)	0.067 (0.100)	0.045 (0.101)
Constants	294.108*** (40.264)	294.3618*** (40.342)	304.417*** (40.523)	300.537*** (40.402)	298.327*** (40.935)	296.904*** (40.806)	294.912*** (40.778)	302.365*** (40.962)
R^2	0.120	0.120	0.123	0.120	0.120	0.120	0.120	0.123
F statistics	15.634	15.619	15.756	15.603	15.599	15.439	15.414	15.637
N	17457	17457	17457	17457	17457	17457	17457	17457
Notes: (1) Cluster-robust standard errors in parentheses; (2) ***p < 0.01, **p < 0.05, *p < 0.10.								

Appendix E: Interpretation of Summary Statistics

Table E1 shows summary statistics. In the final sample, the mean strong image-enhancing FGOC signal is 1.777 while the mean number of weak image-enhancing FGOC signal is 4.538, more than two times larger than the former, indicating that firms tend to release many more weak image-enhancing FGOC signals than the alternative. Among the strong image-enhancing FGOC signals, the mean of finance-related FGOC signals is 0.0491, more than ten times smaller than the other two kinds of strong image-enhancing FGOC signals. For UGC, signals related to firms but released by ordinary users on X(Twitter), the mean is 4.70642. For other control variables, the standard deviation of followers and firm size are 697682.7 and 248094.6, respectively, so we log-transformed these variables because of their skewness, we therefore show the summary statistics of log-transformed followers and firm size. Table E1 also presents the variance inflation factors (VIFs). The VIFs are all under 10.0, indicating a small risk of multicollinearity (Petter et al., 2007).

Table E1. Summary Statistics

Variable	N	Mean	SD	Min	Max	VIFs
SIE_{Tit}	21,009	1.777	3.698	0	169	0.81
PRO_{Tit}	21,009	0.671	2.052	0	101	1.25
FIN_{Tit}	21,009	0.049	0.609	0	27	1.01
OTH_{Tit}	21,009	1.056	2.562	0	168	1.1
WIE_{Tit}	21,009	4.538	14.736	0	427	1.31
UGC_{it}	21,009	147.700	85.975	0	298	1.01
SIE_{Pit}	21,009	1.038	2.468	0	40	1.24
WIE_{Pit}	21,009	0.009	0.107	0	5	1.02
FOL_{it}	17,898	9.728	2.025	5.215	15.690	1.25
$SIZE_{it}$	21,009	9.909	1.303	7.517	14.569	1.46
MtB_{it}	21,009	3.493	5.087	-23.500	49.854	1.03
$INST_{it}$	20,413	0.762	0.174	0.081	1.330	1.19
ACC_{it}	21,009	-0.002	0.998	-0.302	18.809	1.06
CAR_{it}	21,009	1.657	2.132	-2.024	54.009	-

Appendix F: Subsample Analysis to Test for Unobserved Heterogeneity

This appendix covers the results of subsample analysis to consider the possible effect of number of followers. Since we focus on the effect of information released on X(Twitter), followers are the first to notice the FGOC sent by companies on X(Twitter) and, for this reason, the number of followers becomes one of the important features of X(Twitter) that might influence the outcomes of signaling. In this section, we conduct subsample analysis, comparing the estimation results between firms with a large number of X(Twitter) followers and firms with a small number of X(Twitter) followers. To avoid the influence of extreme values, we employ a median of followers (13678 followers) to categorize sample firms into firms with a large number of X(Twitter) followers and firms with a small number of X(Twitter) followers. The results shown next suggest that the number of followers is possibly influencing the effect of FGOC signals. The results of this analysis are shown in Table F1 and F2.

The positive effects of strong and finance-related FGOC signals and the interaction effects are consistent in both subsamples, while the effects of product-related FGOC signals are only significant in sampled firms with a large number of followers, a finding which indicates that product-related FGOC signals are less salient compared with finance related FGOC signals and that firms with a large followership are better able to convey firm quality to investors. Thus, compared to firms with a small number of followers, firms with a large number of followers are more effective at sending product-related signals.

Table F1. Subsample Estimation Results: Firms with a Large Number of Followers

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAR	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**
Theoretical Variables								
SIE_{Tit}	0.059*** (0.018)					0.074 (0.024)		
PRO_{Tit}		0.047** (0.019)					0.061 (0.023)	
FIN_{Tit}			0.017*** (0.028)					0.113** (0.030)
OTH_{Tit}				0.017 (0.012)				
WIE_{Tit}					0.007 (0.019)	0.004 (0.022)	0.001 (0.020)	0.008 (0.019)
SIE_{Tit}*WIE_{Tit}						-0.028* (0.017)		
PRO_{Tit}*WIE_{Tit}							-0.003 (0.002)	
FIN_{Tit}*WIE_{Tit}								-0.012** (0.002)
Control Variables								
FOL_{it}	-1.078*** (0.161)	-1.079*** (0.161)	-1.084*** (0.161)	-1.081*** (0.161)	-1.083*** (0.161)	-1.075*** (0.161)	-1.078*** (0.161)	-1.085*** (0.161)
ACC_{it}	0.056*** (0.019)	0.055*** (0.019)	0.053*** (0.019)	0.056*** (0.019)	0.055*** (0.019)	0.056*** (0.019)	0.055*** (0.019)	0.053*** (0.019)
UGC_{Tit}	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
PR_{it}	0.076*** (0.020)	0.080*** (0.020)	0.080*** (0.020)	0.082*** (0.020)	0.084*** (0.020)	0.074*** (0.020)	0.079*** (0.020)	0.079*** (0.020)
$SIZE_{it}$	-1.810 (1.602)	-1.790 (1.606)	-1.688 (1.516)	-1.773 (1.624)	-1.771 (1.625)	-1.824 (1.598)	-1.801 (1.602)	-1.703 (1.514)
MtB_{it}	-0.167 (0.501)	-0.170 (0.502)	-0.197 (0.476)	-0.180 (0.507)	-0.178 (0.507)	-0.162 (0.500)	-0.165 (0.501)	-0.190 (0.476)
$INST_{it}$	5.180 (9.887)	5.124 (9.912)	4.469 (9.386)	4.953 (10.020)	4.977 (10.020)	5.262 (9.863)	5.207 (9.892)	4.575 (9.372)

Constants	28.977*** (8.186)	28.844*** (8.201)	28.371*** (7.748)	28.834*** (8.301)	28.816*** (8.303)	29.018*** (8.164)	28.870*** (8.179)	28.437*** (7.736)
R^2	0.122	0.122	0.125	0.121	0.121	0.123	0.122	0.126
F statistics	17.905	17.937	18.093	17.901	17.922	17.455	17.471	17.758
N	8854	8854	8854	8854	8854	8854	8854	8854
Notes: (1) Cluster-robust standard errors in parentheses; (2) ***p < 0.01, **p < 0.05, *p < 0.10.								

Table F2. Subsample Estimation Results: Firms with a Small Number of Followers

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAR	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**	**CAR**
Theoretical Variables								
SIE_{Tit}	0.039** (0.019)					0.033 (0.023)		
PRO_{Tit}		0.021 (0.0217)					0.018 (0.027)	
FIN_{Tit}			0.0775*** (0.026)					0.056** (0.027)
OTH_{Tit}				-0.001 (0.018)				
WIE_{Tit}					0.126 (0.081)	0.185 (0.122)	0.171* (0.101)	0.122 (0.082)
SIE_{Tit}*WIE_{Tit}						-0.086** (0.043)		
PRO_{Tit}*WIE_{Tit}							-0.157 (0.110)	
FIN_{Tit}*WIE_{Tit}								-0.009** (0.004)
Control Variables								
FOL_{it}	-0.769*** (0.092)	-0.768*** (0.092)	-0.767*** (0.092)	-0.769*** (0.092)	-0.780*** (0.091)	-0.781*** (0.091)	-0.782*** (0.091)	-0.777*** (0.091)
ACC_{it}	-0.008 (0.019)	-0.007 (0.019)	-0.012 (0.020)	-0.007 (0.019)	-0.006 (0.019)	-0.007 (0.019)	-0.007 (0.019)	-0.013 (0.020)
UGC_{Tit}	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
PR_{it}	0.117*** (0.036)	0.123*** (0.036)	0.115*** (0.036)	0.124*** (0.036)	0.121*** (0.035)	0.114*** (0.035)	0.118*** (0.035)	0.110*** (0.035)
$SIZE_{it}$	-2.112*** (0.274)	-2.094*** (0.274)	-2.100*** (0.274)	-2.101*** (0.275)	-2.103*** (0.274)	-2.107*** (0.275)	-2.093*** (0.274)	-2.102*** (0.274)
MtB_{it}	-5.837*** (0.933)	-5.843*** (0.931)	-5.795*** (0.936)	-5.817*** (0.930)	-5.995*** (0.930)	-5.962*** (0.932)	-5.984*** (0.930)	-5.982*** (0.935)
$INST_{it}$	37.473*** (7.031)	37.624*** (7.019)	37.196*** (7.050)	37.386*** (7.016)	38.954*** (7.028)	38.588*** (7.047)	38.856*** (7.025)	38.841*** (7.065)
Constants	15.865*** (4.324)	15.590*** (4.329)	15.841*** (4.318)	15.783*** (4.334)	15.168*** (4.359)	15.418*** (4.363)	15.143*** (4.350)	15.187*** (4.349)
R^2	0.110	0.110	0.112	0.110	0.110	0.111	0.110	0.113
F statistics	13.820	13.768	13.852	13.746	13.713	13.490	13.747	13.495
N	8603	8603	8603	8603	8603	8603	8603	8603
Notes: (1) Cluster-robust standard errors in parentheses; (2) ***p < 0.01, **p < 0.05, *p < 0.10.								

Appendix G: Sensitivity Tests for Time Windows

Table G1. The Results of the Time Window Sensitivity Test

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CAR[1,3]	**CAR[1,3]**	**CAR[1,3]**	**CAR[1,3]**	**CAR[1,3]**	**CAR[1,3]**	**CAR[1,3]**	**CAR[1,3]**
Theoretical Variables								
SIE_{Tit}	0.069*** (0.018)					0.086*** (0.023)		
PRO_{Tit}		0.046** (0.019)					0.061** (0.024)	
FIN_{Tit}			0.086*** (0.021)					0.089*** (0.021)
OTH_{Tit}				0.031** (0.015)				
WIE_{Tit}					0.011 (0.021)	0.007 (0.025)	0.007 (0.023)	0.013 (0.021)
SIE_{Tit}*WIE_{Tit}						-0.037** (0.018)		
PRO_{Tit}*WIE_{Tit}							-0.003 (0.003)	
FIN_{Tit}*WIE_{Tit}								-0.014** (0.002)
Control Variables								
FOL_{it}	-1.384*** (0.107)	-1.385*** (0.107)	-1.388*** (0.107)	-1.387*** (0.107)	-1.389*** (0.107)	-1.381*** (0.107)	-1.384*** (0.107)	-1.389*** (0.107)
ACC_{it}	0.036** (0.017)	0.035** (0.017)	0.033* (0.017)	0.036** (0.017)	0.036** (0.017)	0.036** (0.017)	0.035** (0.017)	0.033* (0.017)
UGC_{Tit}	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
PR_{it}	0.085*** (0.020)	0.092*** (0.020)	0.090*** (0.020)	0.091*** (0.020)	0.095*** (0.020)	0.082*** (0.020)	0.090*** (0.020)	0.089*** (0.020)
$SIZE_{it}$	-0.060 (0.319)	-0.043 (0.319)	-0.037 (0.315)	-0.046 (0.320)	-0.039 (0.320)	-0.068 (0.319)	-0.049 (0.319)	-0.042 (0.315)
MtB_{it}	-0.756*** (0.085)	-0.755*** (0.085)	-0.746*** (0.084)	-0.754*** (0.085)	-0.752*** (0.085)	-0.757*** (0.085)	-0.756*** (0.085)	-0.745*** (0.084)
$INST_{it}$	-2.138 (2.409)	-2.100 (2.411)	-1.974 (2.377)	-2.018 (2.420)	-2.019 (2.419)	-2.188 (2.409)	-2.164 (2.411)	-2.020 (2.379)
Constants	19.189*** (4.826)	19.007*** (4.825)	18.842*** (4.760)	18.994*** (4.846)	18.939*** (4.844)	19.285*** (4.825)	19.103*** (4.823)	18.938*** (4.764)
R^2	0.157	0.156	0.158	0.156	0.156	0.157	0.156	0.158
F statistics	22.939	22.934	23.039	22.915	22.908	22.647	22.627	22.963
N	-1.384*** (0.107)	-1.385*** (0.107)	-1.388*** (0.107)	-1.387*** (0.107)	-1.389*** (0.107)	-1.381*** (0.107)	-1.384*** (0.107)	-1.389*** (0.107)

Notes: (1) Cluster-robust standard errors in parentheses; (2) ***p < 0.01, **p < 0.05, *p < 0.10.

Appendix H: Summary of Hypothesis Testing

Table H1. The Results of Hypotheses Testing

#	Description	Supported?
H1a	The extent of strong image-enhancement FGOC on firm X(Twitter) accounts is positively correlated with abnormal stock return.	Yes
H1b	The extent of product-related FGOC on firm X(Twitter) accounts is positively correlated with abnormal stock returns.	Yes
H1c	The extent of finance-related FGOC on firm X(Twitter) accounts is positively correlated with abnormal stock returns.	Yes
H2a	The number of weak image-enhancing FGOC on firm X(Twitter) accounts weakens the positive relationship between strong image-enhancement FGOC and abnormal stock returns.	Yes
H2b	The weakening effect of weak image-enhancing FGOC signals on financial-related FGOC signals is more pronounced than the effect of weak image-enhancing FGOC signals on product-related FGOC signals.	Yes

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