**The Impact of Social Media Influencers on the Financial Market Performance of Firms**

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## Abstract

Despite the huge growth in the number of influencers and their use by firms, there is a lack of analysis of how social media influencers affect the financial market performance of firms. Anecdotal evidence suggests mega influencers can impact the stock prices of firms via social media. We ask whether such an effect is generalizable to all mega influencers and other financial market characteristics of firms. Using a hand-collected dataset of 16,156,419 mega influencer posts on Instagram, we find that mega influencers affect investors' attention, volatility and trading volume but not stock returns. It takes top influencers with extreme sentiment posts to affect returns and, even here, the effect is short-lived.

**Keywords**: Influencers; Mega Influencers; Investors; Sentiment; Firms; Financial Market Performance

**JEL Codes**: G1; G12

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## 1. Introduction

A key development in social media has been the remarkable growth of influencers and their increasing use by firms to manage their online presence and image. Instagram is the leading influencer marketing platform worldwide having, as of 2023, approximately 2bn monthly active users globally,[1] and hosting 200m businesses on the platform.[2] Firms worldwide spent \$50bn on advertising on Instagram in 2022 and this is forecast to reach \$71bn by 2024.[3] Among them, 61% of firms report collaborating with at least 10 influencers, while 54% (23%) state they allocate at least 20% (40%) of their marketing budget to influencer marketing activities.[4] The development of influencers has led the marketing literature (De Veirman et al., 2017; Zhang et al., 2018; Lou and Yuan, 2019; Hughes et al., 2019) to examine their role and find they lead to herding via the desire to mimic (Ki and Kim, 2019). There has been no equivalent analysis in finance. In one sense, this is surprising, given the increasing pervasiveness of influencers and their interest to firms and regulators. In another sense, however, it is not surprising given the absence of available data and the costs of manually collecting it. This paper addresses this gap by combining the insights of noise trader models (for a survey see Dow and Gorton, 2018) with a unique and powerful dataset of Instagram influencer posts to examine the power of mega influencers to affect investors and the stock market performance of firms.

Anecdotal evidence suggests 'mega influencers' (i.e., those with, at least, one million of followers, according to the standard industry classification)[5] are able to affect the stock prices of firms via social media. For example, Spotify's stock price dropped from \$193.56 per share on the 24th January 2022 to \$173 per share on the 28th January 2022 because Neil Young and Joni Mitchell protested on social media against Joe Rogan's views on COVID-19, and against Spotify for hosting Rogan's podcast and his views on COVID-19. On the 30th January, Joe Rogan (15m followers)

[1] https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/
[2] https://dataprot.net/statistics/instagram-statistics/
[3] https://www.warc.com/content/feed/instagram-forecast-to-hit-71bn-revenue-by-2024/en-GB/8650
[4] https://sproutsocial.com/insights/influencer-marketing-statistics/
[5] https://sproutsocial.com/insights/influencer-marketing/

posted an apology video on Instagram and Spotify's stock price went back to $195.36 in the following days. It is important to note that while Instagram is not an investment platform for investors to discuss their views on stock prices and the performance of firms, the comments/posts of influencers, whether positive or negative,[6] have the potential to influence investors because of the sheer number of their followers and their consequent newsworthiness. We ask whether the effect on stock prices identified in anecdotal evidence is generalizable to all 'mega influencers' and other financial market characteristics (investor attention, volatility and volume) of firms.

To examine the impact of social media influencers on financial markets we bring together marketing fundamentals with insights from the noise trader literature in finance, in the manner of Tetlock (2007) who examines the role of traditional media in stock markets within the noise trader theoretical framework. From marketing fundamentals we focus on two dimensions of influencers' posts to create the key variables of our analysis, namely abnormal sentiment and the number of comments. Sentiment is used in the marketing literature to measure the positive or negative tone of social media posts (e.g., Schweidel and Moe, 2014; Leung et al., 2022), and it has also been used in the finance literature to examine the effect of social media posts on stock returns (e.g., Renault, 2017; Gu and Kurov, 2020; Cookson et al., 2024). Accordingly, we employ sentiment to measure the positive or negative tone of a post by an influencer, specifically using abnormal sentiment, because a change from the normal level is more likely to be noticed by an influencer's followers. Having measured the positivity or negativity of posts, we assess their impact on followers via the number of comments a post receives. This captures the level of attention and engagement that a post by an influencer will generate among the influencer's followers (Hughes et al., 2019; Leung et al., 2022).

[6] While influencers can be rewarded by firms for their posts, they have their own agency and this is important. Though influencers tend to post positive content to promote products, they also make negative comments about firms or products. For instance, Snap shares dropped significantly (4.26%) on Thursday, 15th March 2018 after Rihanna condemned – via Instagram – Snapchat for its offence to victims of domestic violence (https://www.ft.com/content/9cf3773c-2872-11e8-b27e-cc62a39d57a0). Influencers, like other important stakeholders of a firm (e.g., activist CEOs [Andreou et al., 2016]), can sometimes take public stands on issues reflecting their personal beliefs, even though these might not align with the firm's interests.

While the informational value of influencer posts cannot be entirely ruled out, prior evidence has shown that most social media posts are not value relevant and are likely to just add noise to the financial markets by motivating uninformed investors to trade (Heimer, 2016; Pedersen, 2022; Eliner and Kobilov, 2023). Therefore, we use findings from the noise trader and social sentiment literatures to develop our hypotheses as to how the above influencer variables will affect the market characteristics of investor attention, volatility, volume and returns. When noise traders experience a positive (negative) belief shock, they will buy (sell) stocks from (to) informed traders, increasing trading volume and volatility and causing a temporary increase (reduction) in prices that is soon reversed (DeLong et al., 1990; Peress and Schmidt, 2020).[7] Therefore, if a post triggers noise trading, then attention, volatility and volume should rise after the post is shared. However, a necessary condition for a post to be influential and motivate noise traders to trade is it needs to be noticed (Barber and Odean, 2008; Da et al., 2011). A plausible way to capture the level of attention a post is able to grab is by the number of comments it attracts. Therefore, investor attention, volatility and volume are predicted to be positively associated with the number of comments. In contrast, returns should not be related to the number of comments, as the direction of a stock price change depends on post sentiment. Thus, we expect returns to be positively associated with a post's sentiment. Finally, if a post triggers noise trading, then any post-induced price changes should be temporary. Therefore, we expect any return effects to be short-lived.

In line with our hypotheses, we find that the number of comments has a significantly positive effect on investor attention, trading volume and volatility, and no effect on Fama-French adjusted returns. Regarding the sentiment of influencer posts, when we consider all posts, we find that it has no effect on returns. Given that attention is a necessary condition for a post to be influential

[7] Alternatively, if influencer posts typically contain information that is relevant for stock value and is not already incorporated into prices, then the implications are different. We should still observe increased investor attention and a change in the stock price, which will not reverse. Also, there is no clear prediction about volatility and volume. New information can cause disagreement among investors that could lead to increased volume and volatility. However, it is equally likely that the opinions of investors will converge when they observe the same piece of information (Tetlock, 2007).

and induce traders to act, there is the possibility that sentiment is insufficient to cut through and lead to an impact on returns. To account for this possibility we identify cases where the post signal is more likely to reach a broader audience and come from influencers who typically have users engaging with their posts, by focusing on posts coming from top influencers, namely those with the highest historical impact power.[8] In addition, given the features of the anecdotal evidence presented at the start of the paper, where not only the influencers seem to be 'top influencers' with many millions of followers, but also the sentiments/actions expressed are quite extreme, we examine whether the effect of posts on returns occurs when top influencers issue extreme sentiment posts. These results show that the posts by top influencers with the most extreme sentiment (as defined by the top 5% [most positive] and bottom 5% [most negative] sampled posts by top influencers with the most extreme sentiment changes) are able to significantly shift returns. Using a battery of tests, including daily abnormal returns, cumulative abnormal returns, and trading strategies, we also find that the effect on returns from extreme sentiment posts by top influencers is short-lived. In sum, while mega influencers, in general, influence investor attention, volume and volatility, the ability to influence returns is a function of being a top influencer and of extreme sentiment. In the 'busy world' of social media (see the facts given at the start of the introduction), it is perhaps not surprising that it takes extreme posts by top influencers to affect investors with limited attention to the point where their reactions are sufficient to shift returns. Finally, we find that influencer posts have no predictive ability for firms' operating performance. This finding, combined with the temporary nature of post-induced returns, is consistent with the conjecture that influencer posts foster noise trading.

This study has three contributions. First, we offer insights to firms on how to utilize social media analytics to identify risks arising from the potential impact of influencers on their stock market performance. Thereby, we contribute to the literature investigating the organizational value

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[8] We define historical impact power as the 12-month average (calculated on day $t$–1) number of comments an influencer's posts were able to attract. Posts by top influencers are defined as those in the top 5% of posts, as ranked by the prior year's average number of comments.

of big data analytics (e.g., Batistič and Laken, 2019). Second, we contribute to the literature that studies how interactions of investors on social media shape trading activity and asset price dynamics (e.g., Bartov et al., 2018; Cookson and Niessner, 2020; Chen and Hwang, 2022) by providing evidence that influencers have the power to affect stock market variables. Finally, our findings contribute to the literature on investor attention (e.g., Blankespoor et al., 2014; Lou, 2014) and its important role in the acquisition/pricing of information by indicating that influencers are able to attract the attention of both retail and institutional investors through their posts.

## 2. Literature, Model and Hypotheses

In general, influencers share their lives, product experiences, knowledge, and other content on social media platforms, with their followers recognizing them as opinion leaders (Sánchez-Fernández and Jiménez-Castillo, 2021). Influencers are trusted and supposedly expert and knowledgeable (Ki and Kim, 2019). With increasing numbers of followers, influencers build up their impact power and have the potential to change their followers' behavior and attitudes towards firms.

There is a range of literature that is relevant to this paper's investigation of the impact of social media influencers on stock market variables (investor attention, volume, volatility and returns). First, within the literature linking the use of big data by firms with their performance, there is a large research stream focusing on the utilization of big data to produce valuable finance and customer analytics (see Batistič and Laken, 2019, for a review). Recent papers have shown the increasing use of big data, artificial intelligence, and machine learning techniques to investigate finance phenomena (Aziz et al., 2022; Nguyen et al., 2023), including how big data analytics can be used to effectively measure the market orientation of firms (Andreou et al., 2020).

Second, there is a growing literature that studies how interactions of investors on social media shape trading activity and asset price dynamics. It is important to note that prior studies have used data mostly from investor social networks, typically Seeking Alpha (e.g., Chen et al., 2014; Chen and Hwang, 2022; Farrel et al., 2022), StockTwits (e.g., Giannini et al., 2019; Cookson and Niessner, 2020), Reddit's Wallstreetbets (e.g., Anand and Pathak, 2022; Shaen et al., 2022; Bradley et al., 2023), and Twitter (e.g., Sprenger et al., 2014; Bartov et al., 2018; Fan et al., 2020; Gu and Kurov, 2020; Karampatsas et al., 2023). Unlike the studies mentioned above, which primarily rely on overall user opinions and sentiment, the focus of our research on influencers is entirely novel. We concentrate on the influence of social media influencers, specifically the most impactful users within the social media landscape, typically active on Instagram, to examine their impact on the stock market performance of firms.

To further emphasize Instagram is different from other social media platforms, it is worth considering a number of features and statistics. While other platforms have grown their market presence (for example, TikTok), Instagram retains its preeminent position with influencers and marketers.[9] Various surveys[10] agree that Instagram is the top platform for influencers, who are the main focus of this paper given the sentiment they generate. Instagram has the following advantages. First, it has a broader multi-media approach than its competitors and this offers influencers the ability to tailor their approach according to the message and the intended audience. Second, Instagram has a greater user base compared to other platforms. For instance, Instagram has nearly three times as many active users as Twitter. As of October 2023, Instagram has about 2 billion users.[11] Hence, given the broader audience, focusing on Instagram allows for better sample representativeness. Of the users on Instagram, 90% follow at least one business account, 83% discover new products and services on the platform, and 59% believe they get the best engagement on Instagram.[12] In terms of demographics it has a good representation from the 18-34 age group (61% of its users are from this group) but still has good coverage of older adults

[9] https://www.insiderintelligence.com/content/instagram-still-crucial-influencer-marketing-even-tiktok-on-rise
[10] https://www.statista.com/statistics/803492/social-media-platforms-social-influencers-brand-collaborations/; https://blog.hubspot.com/marketing/influencer-platforms; https://www.spiceworks.com/marketing/content-marketing/articles/social-media-influencers-are-active-on-instagram/
[11] https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/
[12] https://www.socialpilot.co/blog/instagram-over-other-social-media-platform

(31% plus are for adults over 35).[13] Third, Instagram has been in operation since 2010 and has a very well established and understood influencer ecosystem.[14] Influencers have experience of working with brands and many have agents to connect with businesses in terms of payment, goals, etc. The processes and terms of engagement are understood and standardized. The above supports the conclusion that Instagram is the major site for influencers (the focus of this study) and echoes the fact that the world's biggest brands use it to reach out via influencers to the various target markets. Fourth, and not least, previous research (Cookson et al., 2024) suggests that sentiment from three major platforms (i.e., Twitter, StockTwits, and Seeking Alpha) is not correlated due to the distinct features of each social media platform. Factors such as character limits and varying user bases across social media platforms are shown to influence the informativeness of sentiment. If sentiment from those three platforms is not correlated, then we would not expect it to be correlated with Instagram, especially given the different focus Instagram influencers have compared to users posting on the three aforementioned media.

Third, there is a literature stream exploring whether social media posts draw investor attention. For instance, Blankespoor et al. (2014) find that the use of Twitter by firms can help draw investors' attention and affect outcome variables, such as stock market liquidity. Yang et al. (2023), Huang and Morozov (2023), and Li et al. (2023) show that non-investor-targeted social media posts increase consumer attention. There is also evidence that greater consumer attention comes with greater investor attention and affects financial market outcome variables (e.g., Keloharju et al., 2012; Lou, 2014; Madsen and Niessner, 2019).

Fourth, there is a literature that studies the role of social media in shaping economic and financial thinking and decision-making (e.g., Pedersen, 2022; Goldstein et al., 2023). Previous studies have shown that social connectedness, as estimated through social media networks, affects institutional investor decisions (Kuchler et al., 2022) and international trade and financial flows

[13] https://www.statista.com/statistics/325587/instagram-global-age-group/
[14] https://influencehunter.com/2021/11/16/why-instagram-is-the-top-platform-for-influencer-marketing/

between countries and regions (Bailey et al., 2021). Furthermore, interactions on social media networks can generate echo chambers (Cookson et al., 2023) and promote disagreement (Hirshleifer et al., 2023) among investors.

To examine the impact of social media influencers on the financial market performance of firms we meld marketing fundamentals (e.g., Schweidel and Moe, 2014; Hughes et al., 2019; Leung et al., 2022) with insights from the noise trader literature (e.g., DeLong et al., 1990, Peress and Schmidt, 2020) from finance. From the marketing insights we focus on two dimensions of influencers' posts to create the key variables of our analysis. The first of these is "Log of Comments", which we calculate as the natural logarithm of the sum of the number of comments influencers were able to attract when posting, in a given day, on a specific company. The second is "Abnormal Sentiment", which we calculate as the difference between the average sentiment score of an influencer's posts about a specific company in a given day *t* and the average sentiment score of the influencer's posts uploaded from the time of the influencer's initial posting until day *t*–1. If a firm is being advertised/discussed by more than one influencer on a given day, then our "Abnormal Sentiment" variable will be calculated as the average abnormal sentiment of all influencers who posted about the firm on that day. We thoroughly discuss in the appendix how we calculate the sentiment score of a post.

Given that a lot of social media posts will not be value relevant and are likely to just add noise to the financial markets (Heimer, 2016; Pedersen, 2022; Eliner and Kobilov, 2023), we then use the literature on noise traders to develop our hypotheses as to how the above influencer variables will affect the market characteristics of investor attention, volatility, volume and returns. While noise trader models (e.g., Kyle, 1985, DeLong et al., 1990, and Peress and Schmidt, 2020) have a number of features, there are a few key elements which are important for the current analysis. One key feature is the two types of investors – noise traders and informed traders. Noise traders are seen as trading without possessing or using all available information or as trading based on spurious signals which they incorrectly believe to be informative. Their trading decisions are often influenced by emotions, market rumors, or irrelevant factors rather than the careful analysis of fundamental or technical information. In contrast, informed traders are seen as being rational and making decisions based on available information. Their trading is based on value relevant information such as market trends, economic indicators, company financials, or any other relevant data.

Noise traders are seen as introducing noise or irrelevant information into the market and engaging in trend-chasing behavior, leading to temporary deviations of prices from their fundamental values. Whereas, rational traders will correct any mispricing created by noise traders, subject to limits to arbitrage, the interaction between noise traders and informed traders contributes to market dynamics. In fact, an increase in noise trading has three important implications for market dynamics: *i*) prices will temporarily deviate from their fundamental values, as limits to arbitrage deter informed traders from aggressively trading against noise traders and preventing any mispricing from occurring (DeLong et al., 1990); *ii*) noise traders, by driving prices away from fundamentals, will create short-term price fluctuations and increased volatility (DeLong et al., 1990; Peress and Schmidt, 2020); *iii*) noise traders through their interaction with informed traders, who seek to capitalize on mispricing and trends in the market (DeLong at al., 1990) or conceal their superior information from market makers (Peress and Schmidt, 2020), will increase trading volume. Since the discussion of noise traders entered the economics and finance literature from the late 1970s onwards (see, for example, Grossman, 1977; Grossman and Stiglitz, 1980; Glosten and Milgrom 1985; Kyle, 1985; Black, 1986) there has been a lot of literature (see Dow and Gorton, 2018, for a review) exploring the specifics of the model. There is also empirical evidence indicating that noise traders are indeed associated with increased volatility and volume in the market (e.g., Bloomfield et al., 2009; Peress and Schmidt, 2020; Dai et al., 2023) and with short-term price runs followed by price reversals (e.g., Tetlock, 2007; Renault, 2017).

We now link our measures of influencers to the categories of noise and informed traders to develop our hypotheses. While the informational value of influencer posts cannot be entirely ruled out, a lot of them arguably contain no value-relevant information, despite attracting investor attention. In fact, prior evidence has shown that social media causes uninformed trading (Pedersen, 2022), exacerbates investor behavioral biases (Heimer, 2016), and induces retail trading more than other known traditional attention-grabbing factors, such as traditional news, momentum and trading volume (Eliner and Kobilov, 2023). More importantly, compared to regular retail investors, social media-induced retail investors tend to be younger, with less trading experience and financial knowledge (Eliner and Kobilov, 2023). Given the above, we conjecture that a post by an influencer is likely to foster noise trading. According to the three aforementioned implications of noise trading for market dynamics, when noise traders experience a positive (negative) belief shock, they will buy (sell) stocks from (to) informed traders, increasing trading volume and volatility and causing a temporary increase (reduction) in prices that is eventually reversed.[15] Alternatively, if influencer posts typically contain information that is relevant for stock value and is not already incorporated into prices, then the implications are different. We should still observe increased investor attention and a change in the stock price, which will not reverse. Also, there is no clear prediction about volatility and volume.[16]

If a post triggers noise trading, then attention, volatility and volume[17] should rise after the post is shared. However, a necessary condition for a post to be influential and motivate noise traders to trade is it needs to be noticed. A plausible way to capture the level of attention that a post is able to grab is by the number of comments it attracts. In the marketing literature, the number of

[15] Tetlock (2007) uses a similar noise trader theoretical framework to analyse the effect of traditional media on stock markets.

[16] New information can cause disagreement among investors that could lead to increased volume and volatility. However, it is equally likely that the opinions of investors will converge when they observe the same piece of information (Tetlock, 2007).

[17] Inventory risk models (e.g., Ho and Stoll, 1981; Grossman and Miller, 1988) show that increased noise trading can also have a negative effect on trading volume and liquidity. An increase in noise trading may lead market makers to reduce liquidity due to inventory risk (i.e., fluctuations in market makers' inventory value), which is increasing in noise trading. However, Peress and Schmidt (2020) show that this occurs only if the change in noise trading is permanent (as seen, for example, in regulatory reforms discouraging retail trading in Foucault et al., 2011), while in cases where the increase in noise trading is temporary, the impact on trading volume and liquidity is still expected to be positive. Given the transient nature of social media, a spike in noise trading triggered by a specific post will be short-lived, as noise traders swiftly shift attention to the next big trend on social platforms.

comments a post receives is one of the typical variables used to measure a post's reach and the user engagement it generates (Hughes et al., 2019; Leung et al., 2022). Therefore, investor attention, volatility and volume are predicted to be positively associated with the number of comments. In contrast, the number of comments should not be related to returns, as the direction of a stock price change depends on post sentiment. Accordingly, we formulate hypothesis 1.

**H1**: Investor Attention, Volatility and Volume are positively related to the number of comments that a post by an influencer receives.

Sentiment measures the positive or negative nature of a post by an influencer. If a post induces investors to trade, then the direction of the trade should be related to the post's sentiment. Indeed, prior literature has shown that sentiment on social media is positively associated with stock returns (e.g., Renault, 2017; Gu and Kurov, 2020; Cookson et al., 2024). Therefore, we expect a post's sentiment to be positively associated with returns. In contrast, the expected effect of sentiment on attention, volatility and volume is ambiguous, as posts with either extreme negative or positive sentiment could be more likely than those with intermediate sentiment to grab investors' attention and induce them to trade.[18]

**H2***:* Returns are positively related to the sentiment of an influencer's post.

Given that attention is a necessary condition for a post to be influential and induce traders to act, there is the possibility that sentiment is insufficient to cut through and lead to an impact on returns. Considering the analyses by Barber and Odean (2008) and Da et al. (2011) on noise traders and the stock market, particularly regarding the importance of attention in affecting returns, we argue here that an influencer will only have an impact if there are sufficient people paying attention. To account for this possibility we identify cases where the post signal is more likely to reach a broader audience and come from influencers who typically make users engage with their posts, by focusing on posts coming from the influencers with the highest historical impact power. We define

[18] Indeed, in unreported tests we find a positive effect of the absolute value of abnormal sentiment on attention, volatility and volume, albeit the effect is statistically insignificant.

historical impact power as the 12-month average (calculated on day $t$–1) number of comments an influencer's posts were able to attract. In other words, historical impact power is the influencer's $i$ number of comments divided by the same influencer's number of posts, across the preceding 12 months, excluding day $t$. Accordingly, we formulate hypothesis 3.

**H3**: Returns are only positively related to the sentiment of posts from influencers with high impact power.

Within the framework of DeLong et al. (1990), the impact of a noise trader's shock on a stock price will be short-lived, as the price will eventually revert to fundamentals, provided that the duration of noise traders' pessimism or optimism toward the stock is not too long relative to the investment horizon of informed traders.[19] Given the transient nature of social media, a spike in noise trading triggered by a specific post will be short-lived, as noise traders swiftly shift attention to the next big trend on social platforms. Therefore, in the current context, if a post triggers noise trading, then any post-induced price changes (returns) should be temporary. Accordingly, we formulate hypothesis 4.

**H4**: The returns effects of posts from influencers with high impact power are short-lived.

The hypothesized relationships are summarized in Table 1.

[Table 1]

## 3. Data and Methodology

### 3.1. Instagram Data

Instagram is a photo and video-sharing social media platform which was founded in 2010 and acquired by Facebook Inc. (now Meta Platforms, Inc.) in 2012. It is the largest social media platform for running influencer accounts and a popular platform for influencer research (De Veirman et al., 2017; Lou and Yuan, 2019; Rust et al., 2021). To mitigate the impact of fake

[19] Empirical studies show that noise traders are indeed associated with with short-term price runs followed by price reversals (e.g., Tetlock, 2007; Da et al., 2011; Renault, 2017).

followers and engagements, Instagram has implemented a series of methods for auto-detecting and deleting the inauthentic activities from suspended accounts.[20] Also, Instagram introduced strict policies of mandatory disclosure for firm-sponsored posting. All these policies reliably improve the credibility of the interactions generated by posts from Instagram influencers.

We construct the Instagram dataset using web-crawling. Initially, we identify mega influencers on Trackalytics.com. Following standard industry classification, we define mega influencers as those with at least one million followers. We then upload the account names of mega influencers to the Supermetrics API (Application Programming Interface) by Google Data Studio, enabling the retrieval of all posts from the mega influencer accounts spanning 2011 to 2022. We, therefore, end up collecting 16,156,419 posts from 5,743 mega influencers. We then identify posts related to firms. Instagram introduced the hashtag function in January 2011, enabling users to post content and comments with a '#' followed by a character string for cross-referencing to the link of a specific topic. In this way, anyone can tap on a hashtag and browse all photos carrying the same hashtag. We use the hashtags contained in the content of a post to determine whether the post is related to a firm. Employing this technique, we identified 368,677 posts from 4,763 mega influencers related to 546 listed firms. Given this is the first time data on influencers have been used in the academic finance literature, we offer quite a lot of detail on our data collection approach and methodology in the appendix.

## 3.2. Dataset and Variables

### 3.2.1. *Dataset*

We construct a firm-day panel dataset using the 546 U.S. public firms identified in Instagram influencer posts from March 2011 to December 2022. Besides the daily firm-level variables constructed with Instagram data, the other firm-level and market-level explanatory and dependent

[20] https://about.instagram.com/blog/announcements/reducing-inauthentic-activity-on-instagram

variables are constructed with data drawn from CRSP (Centre for Research in Security Prices). We also identify, manually, the Wikipedia page associated to each firm in our sample in a similar fashion to Focke et al. (2020). Then, by employing the official API package through Python, we download daily Wikipedia page views data from July 2015 (i.e., first time available on the API) to December 2022, and match it to our dataset. See, for example, Figure 1 illustrating the sharp increase of Snapchat Wikipedia Page Views after Rihanna's criticism. Finally, we download the "NW016 – News Heat – Daily Max Readership" data from the Bloomberg Terminal, and match it to our sampled companies.[21] Based on Bloomberg's description, News Heat data captures "*the amount of unexpected readership activity compared to the last 30 days of activity on the company*", and its value ranges from 0 to 4, with higher values being suggestive of greater unexpected readership activity.[22]

[Figure 1]

Our final sample is made up of 111,561 daily observations related to 546 unique U.S. public firms between 2012 and 2022. The drop in the number of observations from 368,677 posts to 111,561 firm-day observations is due to three reasons: first, there are days on which an influencer posts more than once about a firm and/or more than one influencer posts about the same firm (we explain in detail in the appendix how we aggregate posts about a firm at a daily level); second, we allocate posts shared on weekends and holidays (non-trading days) to the previous trading day; and third, there is no availability of financial data to match with some posts. Indicatively, out of the 111,561 firm-day observations, 42,786 include more than one post. The summary statistics are shown in Table 2. All the variables are winsorized at the 1% and 99% levels to minimize the effects of outliers.

[Table 2]

[21] Bloomberg code: NEWS_HEAT_READ_DMAX; "News Heat" in the rest of this paper.

[22] "News Heat" captures the amount of unexpected readership activity. A value of 4 presents readership activity in the top 96 percentile of readership for that company. A value of 3 presents readership activity in the top 94 percentile of readership for that company. A value of 2 presents readership activity in the top 90 percentile of readership for that company. A value of 1 presents readership activity in the top 80 percentile of readership for that company. A value of 0 presents readership activity below the top 80 percentile of readership for that company.

Panel A of Table 2 reports the data of Instagram influencers' posts. "Log of Comments" is the natural logarithm of the aggregated number of comments generated by all posts about the related firm on day *t*. "Abnormal Sentiment" is the average abnormal sentiment score of all posts about the related firm on day *t*. The detailed calculation is given in the appendix. On average, mega influencers receive about 665 comments per day on their posts. The mean and median of abnormal sentiment are larger than 0, indicating that influencers maintain a positive tone, on average, in their firm-related posts.

### 3.2.2. *Dependent Variables*

We use Wikipedia Views and Bloomberg News Heat to examine the relationship between influencer posts and investor attention. In terms of volatility, volume and returns, we have the following: "Daily Volatility" – which is a stock's volatility computed as (highest price – lowest price)/[(highest price + lowest price)/2] (see, for instance, Albuquerque et al., 2020; Onali and Mascia, 2022), "Log Dollar Trading Volume" – which is the natural logarithm of a stock's daily trading volume to represent the stock's liquidity (Brennan and Subrahmanyam, 1995; Madsen and Niessner, 2019), and "Abnormal returns" – which is the daily abnormal return adjusted by the Fama-French-Carhart four-factor model (Carhart, 1997).

The related summary statistics are reported in Panel B of Table 2. The mean value of Daily Volatility is 2.804% and the mean value of Log Dollar Trading Volume is 18.699. The mean and median of Abnormal Returns are around 0, whereas the 25th and 75th percentile are –0.798% and 0.785%, respectively.

### 3.2.3. *Control Variables*

Panel C of Table 2 provides summary statistics of the firm-level variables that we include as controls in our analyses. Similarly to Focke et al. (2020), we include the holding period return (Return %), the trading volume (Turnover), the volatility of realized returns (Realized Volatility) –

all of which are computed over the 30 day period ending 1 week prior to the day of the respective observation –, the natural logarithm of the firm's market capitalization (Log Market Size) on day *t*–7, and a dummy variable indicating whether a firm has an earnings announcement on day *t*.

We also calculate "Posting Frequency" to control for how often, in daily terms, an influencer posts, regardless of the firm being advertised and/or discussed.[23] If a firm is being advertised/discussed by more than one influencer in a given day, then our "Posting Frequency" variable will be calculated as the average posting frequency of all influencers who posted about the firm in that day. Frequency helps an influencer to be noticed and to remain salient. It also helps followers to become familiar and comfortable with the messages offered by an influencer. On average, influencers post approximately 1.6 times per day.

The average company's size in our sample is $25.80 bn, whereas the average capitalization of all available firms in CRSP is $3.33 bn. This size difference reflects influencers with more than 1 million followers tend to cooperate with the largest companies. Additionally, since we exclude hashtags used less than five times from 2011 to 2022, this is likely to filter out smaller firms whose hashtags appear only a few times. Table 3 shows that multicollinearity does not appear to be a major concern in our analysis.

[Table 3]

## 4. Empirical Results

We first examine in Section 4.1 the relation between influencers' posts and investors' attention as represented by Wikipedia view times and the Bloomberg News Heat index. We then report in Section 4.2 the various results regarding influencers' posts and stock market variables, including baseline results (Section 4.2.1) and the role of top influencers and extreme sentiment on abnormal

[23] For a given day *t*, it is indeed calculated as the number of posts divided by the number of days since an influencer started posting until day *t*–1.

returns (Section 4.2.2). Section 4.2.3 examines the longevity of the top influencer and extreme sentiment effects found in Section 4.2.2.

All our regressions control for firm, week, and day-of-the-week fixed effects (French, 1980; De Bondt and Thaler, 1987; Wang et al., 1997 Leung et al., 2022). All the standard errors in the following regressions are double-clustered by firm and week.

### 4.1. Influencers and Investors' Attention

Following Moat et al. (2013) and Focke et al. (2020), we use the times a Wikipedia page is viewed to represent retail investors' attention and the Bloomberg News Heat index to represent institutional investors' attention.[24]

More specifically, following equation (3), we regress daily attention – as captured by the number of Wikipedia page views – for firm $i$ on day $t$+1, on our Instagram-related variables (i.e., Log of Comments, Abnormal Sentiment) on day $t$, a set of firm-level controls lagged by 7 days (in a similar fashion to Focke et al., 2020),[25] and 5 lags of the dependent variable to control for potential autocorrelation in the dependent variable.

$$Wikipedia_{i,\,t+1} = \alpha + \beta_1\ Instagram\ Influencers\ Variables_{i,t} + \gamma\ Controls_{i,t-7} + \sum_{j=1}^{5} \xi_j\, Wikipedia_{i,t-j} + \varepsilon_{i,t} \quad (1)$$

The regression results in Table 4 show that the next day's Wikipedia page views are significantly related to the influencer posts' number of comments, but not their abnormal sentiment. The significance is maintained after accounting for lags of the dependent variable, even though the magnitude of the coefficient decreases. In terms of economic significance, when the log number of comments is increased from one standard deviation below to one standard deviation above

[24] Comparing with Wikipedia Pageviews, which provide the exact number of view times, the GSV (Google Search Volume) data only provide the relative number from 1 to 100 each day for the search term. Also, if tickers are used to represent firms when employing the GSV index, it might lead to some ambiguous search results and investor who knows the firm's ticker is not 'unsophisticated enough' (Focke et al., 2020).
[25] Following Focke et al. (2020), we lag the control variables by seven days, instead of one day, to avoid endogeneity with the lag of our Instagram influencers variables.

their mean value in Table 4, Wikepedia page views increase by 3% relative to the median number of views.

[Table 4]

We then investigate the relationship with institutional investors' attention by replacing Wikipedia with the Bloomberg News Heat index in Equation (3). Given that the Bloomberg News Heat index captures the unexpected/abnormal readership activity, for consistency we replace "Log of Comments" with "Abnormal Comments" as defined by the following equation (4):

$$\textit{Abnormal Comments}_{i,t} = \textit{Log (Comments}_{i,t} \textit{ / Average Number of Comments over the past 12 months}_{i,t}\textit{)} \qquad (2)$$

The abnormal comments variable captures the excess number of comments on day *t* relative to the average number of comments (calculated across the preceding 12 months),[26] as of day *t*, from all influencers who posted on a specific firm *i*. We use the average number of comments during the preceding 12 months to characterize the typical level of engagement generated by the posts of an influencer. A higher "Abnormal Comments" means that the number of comments on day *t* is larger than the historical average number of comments, and hence that the post on day *t* generates an unexpectedly extensive engagement among followers. The results are shown in Table 5.

[Table 5]

We find that the next day's Bloomberg News Heat index is only significantly related to the abnormal number of comments and the result holds after adding a lagged News Heat index and firm financial controls. In terms of economic significance, when abnormal comments are increased from one standard deviation below to one standard deviation above their mean value in Table 5, Bloomberg News Heat index change by 0.035 units. As previously described, the Bloomberg News Heat index is an ordinal variable ranging from 0 to 4, where higher values indicate greater abnormal readership. In this context, this change can be interpreted as a 3.5% increase in the probability that the abnormal readership activity will move to a higher category. This implies that influencers only

[26] We use a relatively long time period (one year) to smooth the possible extreme values of the outperforming posts that might impact the estimation of the typical level of engagement with an influencer's posts.

marginally change institutional investors' attention, which is not surprising given that posts are expected to draw institutional investor attention to a lesser extent compared to retail investors, who are more likely to behave like noise traders.

## 4.2. Results for Influencers and the Financial Market

### 4.2.1. *Baseline Results – Financial Market Variables*

The baseline regression is as follows:

$$DV_{i,t+1} = \alpha + \beta_1 \, Instagram\ Influencers\ Variables_{i,t} + \gamma \, Controls_{i,t-7} + \sum_{j=1}^{5} \xi_j DV_{i,t-j} + \varepsilon_{i,t} \quad (3)$$

where DV (short for dependent variable) is Daily Volatility, Log Dollar Trading Volume or Abnormal Returns on day $t$+1 in respective regressions; $\alpha$ is the constant term; $Instagram\ Influencers\ Variables_{i,t}$ is the vector of Instagram influencers' variables (i.e., Log of Comments, Abnormal Sentiment) on day $t$; $Controls_{i,t-7}$ is the vector of firms' data variables seven days before the posting date; $\sum_{j=1}^{5} \xi_j DV_{i,t-j}$ is the vector including 5 lags of the dependent variable before the posting date; $\varepsilon_{i,t}$ is the residual.

The results in Table 6 show that the firms' trading volume and stock volatility are significantly affected by the log of comments at the 1% level. The significance is maintained after accounting for lags of the dependent variable, even though the magnitude of the coefficients decreases. The results suggest that when a mega influencer generates extensive user engagement (log of the number of comments), this affects investor attention and this feeds through to stock trading volume and volatility. However, abnormal returns are not found to be related to the posts of mega influencers. These results on volatility and trading volume align with hypothesis 1, the theoretical predictions (DeLong et al., 1990; Peress and Schmidt, 2020), and prior empirical results on noise trading (Bloomfield et al., 2009; Peress and Schmidt, 2020; Dai et al., 2023). In terms of returns, Table 6 shows no significant results for the key variables, which runs counter to hypothesis 2 and the supporting literature (e.g., DeLong et al., 1990; Renault, 2017; Gu and Kurov, 2020; Cookson et al., 2024).

[Table 6]

4.2.2. *The Influence of Extreme Sentiment Posts by Top Influencers*

Given the results so far have shown that mega influencers have little effect on the returns of firms, we rerun, following hypothesis 3, the regressions on abnormal returns taking account of the historical impact power of influencers and the level of sentiment of the posts. This is also in line with the features of the anecdotal evidence presented at the start of the paper, where the influencers seem to be 'top influencers' with many millions of followers and the sentiments/actions expressed are quite extreme. Accordingly, we examine whether the effect of posts on returns occurs when top influencers issue extreme sentiment posts.

The first column of Table 7 reports regression results obtained from a subsample that only includes posts from top influencers, which we define as those in the top 5% of historical impact power based on the prior year's average number of comments. This selection criterion leads to a subsample of 5,269 observations. We find that the abnormal sentiment of top influencers' posts can significantly impact the next day's abnormal return. Albeit the effect is mild in terms of statistical significance, this is a first indication that returns are affected by posts which are more likely to be noticed.[27]

The remaining columns of Table 7 report the main results for this subsection, namely the results of regressions run on a subsample that only includes extreme sentiment posts coming from top influencers. To do so, we first select the top influencers and, within this subsample, we then select their posts carrying extreme sentiment changes. This sample is, therefore, obtained considering the top 5% and bottom 5% of posts according to the abnormal sentiment distribution, which

[27] Unreported summary statistics reveal that the corresponding average raw return on day t+1 — when abnormal returns are located in the bottom (top) 5% of the distribution for this subsample — equals –3.67% (+4.16%).

pertain to top influencers (as defined by the top 5% of posts, as ranked by the prior year's average number of comments).[28] These two criteria lead us to the narrowest sample of 500 observations.

[Table 7]

Table 7 shows that extreme sentiment posts by top influencers have a strong effect on the next day's abnormal return, both in terms of statistical (significant at the 1% level) and economic significance. Specifically, when abnormal sentiment is increased from one standard deviation below to one standard deviation above its mean value for this subsample, abnormal returns change by 53.5 basis points.[29] The findings provided in this subsection support hypothesis 3 and are in line with the findings of Barber and Odean (2008) and Da et al. (2011), as well as the anecdotal examples used at the beginning of the paper; namely, extreme sentiment posts from top influencers have the power to affect abnormal returns to quite a degree.[30]

#### 4.2.3. *Is the Effect of Influencers on Abnormal Returns Short-Lived?*

Table 8 reports regression results regarding the effect exerted on abnormal returns subsequent to day $t$+1 by extreme sentiment posts from top influencers. The sample is hence obtained using the same filtering criteria used in Table 7 and described in section 4.2.2. The dependent variables, shown from column (1) to column (6), represent the cumulative abnormal returns over the holding periods of [$t$+1, $t$+2], [$t$+1, $t$+3], [$t$+1, $t$+4], [$t$+1, $t$+5], [$t$+1, $t$+6], and [$t$+1, $t$+7], respectively.

[Table 8]

The results reported in Table 8 reveal that the cumulative abnormal return effects from extreme sentiment from top influencers become gradually weaker as we extend the end of the holding

[28] For a given post uploaded by an influencer on day $t$, we calculate the 12-month average (calculated on day $t$–1) number of comments the influencer's posts were able to attract.
[29] Indicatively, Focke et al. (2020) use an abnormal return of 5 basis points per day as an "economically meaningful" daily return effect in their tests.
[30] Miller (1977) proposes a model where investor disagreement leads to overvaluation because short-selling constraints prevent some of the pessimistic investors from trading, resulting in valuations that mostly reflect the views of optimistic investors. Accordingly, when new information is released, it will drive prices lower if it resolves disagreement among investors and higher if it propagates it. If short selling constraints are in operation and binding, our findings, indicating a positive short-term impact of influencer posts on returns, suggest that influencer posts lead to increasing disagreement.

period from day *t*+2 to *t*+4, and eventually become insignificantly different from zero when extending it to day *t*+5 and beyond. These results suggest that, on average, the cumulative effect of a post persists for only up to 4 trading days after its publication. So, while top influencers have the ability to affect company returns by extreme sentiment posts, the effect is very short lived and this may well reflect the involvement of noise traders.

Next, we develop a long-short trading strategy as an alternative method to assess the impact of extreme sentiment posts from top influencers on abnormal returns. On a given day *t*+1, we buy (short) firms for which a post by a top influencer was published on the previous day t, provided that the post belongs to the top (bottom) 5% of posts according to the abnormal sentiment distribution. If this strategy is active only in one leg on a given day, we short (long) the market for the missing long (short) leg.

[Table 9]

Table 9 presents the results, with Panels A and B displaying results for value-weighted and equally-weighted portfolios, respectively. In columns (1) to (7), the position is held from day *t*+1 to *t*+1, *t*+2, *t*+3, *t*+4, *t*+5, *t*+6 and *t*+7, respectively, with day counts corresponding to trading days. Column (1) of Panel A indicates that the strategy generates a statistically significant daily alpha return of 25 basis points if the portfolio is held only on day *t*+1.[31] This would equate to an abnormal annual return of 86% if the strategy could be implemented every trading day throughout the year. This is not the case though, as several trading days do not contain posts. In our sample, we can implement the strategy for 40 days per year on average (approximately 16% of total trading days), which would equate to an annual abnormal return of 10%. Columns (2) to (6) of Panel A show that the alpha return of the strategy drops to 10 basis points if the position is held until *t*+2, while the strategy does not yield any abnormal returns if the positions are held to day *t*+3 and

[31] Using the median trading cost estimates of 7 to 10 basis points as estimated by Frazzini et al. (2015), the strategy would remain profitable even after transaction costs. However, transaction costs vary significantly across different time periods, securities, and trader types. Therefore, we refrain from taking a stance on whether these results withstand transaction costs. Besides, the purpose of this analysis is to test the robustness of our results with a different methodology, rather than estimating the maximum abnormal returns traders can attain.

beyond. We find a similar pattern for equal-weighted portfolios, presented in Panel B. These findings corroborate the results from the analysis on CARs, indicating that post-induced abnormal returns are significant but short-lived, persisting only for a few days after a post is published. Overall, the results presented here support hypothesis 4 and are in line with prior theoretical (DeLong et al., 1990) and empirical literature (Tetlock, 2007; Da et el., 2011; Renault, 2017).

## 5. Additional Analyses

This section contains tests on the potential association between influencer posts and firm operating performance, and placebo tests using firms not mentioned in the posts.

The results presented in the previous sections suggest that the abnormal returns following influencer posts may be more attributable to noise rather than to information. If this conclusion holds true, post sentiment should not impact firm operating performance and/or earnings surprises. To assess whether this conjecture holds, we focus on quarterly-based operating performance and earnings surprises covering all quarters which have firm-related posts from 2011 to 2022.

If a post contains novel information about a firm, it is very likely to affect the firm's future cash flows. For instance, influencer posts might influence consumer behavior, thereby impacting a firm's future sales and earnings. We use the change in return on equity (*ROE*) as a proxy for operating performance. *ROE* is the ratio of net income to equity, with the change in return on equity ($\Delta ROE_{i,q}$) being calculated by $ROE_{i,q} - ROE_{i,q-4}$. Additionally, if posts affect future cash flows, and analysts do not fully incorporate this information into their forecasts, this will lead to earnings surprises. We use the Standardised Unanticipated Earnings (SUE) score as a proxy for earnings surprises. SUE score, obtained from I/B/E/S, is calculated as the difference between actual (reported) quarterly earnings per share (EPS) and the average earnings per share (EPS) forecasts by analysts for a company for the fiscal period indicated, divided by the standard deviation of those forecasts. Following Green et al. (2019) and Huang (2018), to test the effect of posts on firm operating performance and earnings surprises we use the following regression:

$$DV_{i,q} = \alpha + \beta_1 \, Instagram\ Influencers\ Variables_{i,q} + \gamma X_{i,q} + \xi \gamma Z_{i,q-1} + DV_{i,q-1} + \varepsilon_{i,q} \tag{4}$$

where *DV* (short for dependent variable) is either $\Delta ROE$ or SUE in quarter *q* in respective regressions; $\alpha$ is the constant term; *Instagram Influencers Variables* is the vector of the Instagram influencers' variables (i.e., Log of Comments, Abnormal Sentiment) aggregated for quarter *q*; *X* and *Z* are the vectors of firm-level control variables in quarters *q* and *q–1*, respectively; *DV* is the lagged dependent variable in *q–1*; $\varepsilon$ is the residual.

[Table 10]

Table 10 reports the regression results. The dependent variable in the models presented in the first three columns is $\Delta ROE$ for the related firm from quarter *q*–4 to quarter *q*. Columns (1), (2) and (3) report the regression results by employing the samples from the baseline (Table 6), top influencer (Column 1 in Table 7) and top influencer with extreme sentiment (Column 1 in Table 7) posts, respectively. The dependent variable in the models presented in the last three columns is the SUE score for the related firm in quarter *q*. Columns (4), (5) and (6) report the regression results by employing the samples from the baseline (Table 6), top influencer (Column 1 in Table 7) and top influencer with extreme sentiment (Column 5 in Table 7) posts, respectively. The results indicate that influencer posts do not significantly affect firm operating performance, nor can they predict earnings surprises. Overall, these findings support the conjecture that influencer posts, on average, do not contain information relevant to firm value.

To mitigate concerns that our results in Section 4.2 are spurious, we carry out the following placebo test involving firms not mentioned in the posts. Using the nearest neighbour algorithm, we identify out-of-sample listed firms that have similar characteristics. More specifically, the selection of 'nearest neighbour' is based on the firm-specific characteristics including volatility, dollar trading volume, abnormal return, return, log market size, turnover and realized volatility. To facilitate the matching, all variables are standardized. We employ the Python package "sklearn"[32] to locate the out-of-sample firm that has a minimum Euclidean distance in terms of these standardized firm characteristics compared to the original firm. Once the out-of-sample firms are matched, we allocate the Instagram data to them, on the same day as it was for the original firms. If the increase in volatility and volume (observed in Table 6) and in abnormal returns (observed in Table 7) stems from unobserved characteristics rather than truly reflecting the effect of influencers, then our placebo test should roughly replicate the findings in Tables 6–8. As shown in Panel B of Table 11, our results cannot be replicated as our Instagram influencers variables are never significant, therefore mitigating the possibility of our main findings being spurious.

[Table 11]

## 6. Discussion and Conclusion

The results show that while the normal activities of mega influencers affect investor attention, volatility and volume, in the busy world of social media, it takes extreme posts by top influencers to grab the attention of investors sufficiently to affect the abnormal returns of 'posted companies'. Furthermore, the attention of the investors is limited to the extent that they move onto the 'next big thing' in very short order.

From a company perspective, the impact of influencers, in general, on volatility and volume, and, via top influencers and extreme sentiment, on returns should be a cause for reflection. As noted in the main part of the paper, influencers are not the same as plain advertising because they have their own agency and cannot be fully controlled by a firm. Therefore, while an influencer marketing strategy can bring substantial benefits to a company, the power of influencers to affect investors poses some risks to the company and its shareholders. Not surprisingly and in line with

[32] https://scikit-learn.org/stable/

our results, in two relatively recent IPOs, firms listed influencers as a stock market listing risk factor in their offering documents.[33]

Similarly, such extreme sentiment posts by top influencers may need to be monitored and regulated, given the potential for abuse. However, the exact nature of regulation will need a lot of thought. One possibility is to put more onus on monitoring and then dealing with exceptional cases as they arise under current corporate/financial rules and regulations.

Moving onto limitations and extensions, while the use of Wikipedia views as a proxy for retail investor attention is quite common (e.g., Moat et al., 2013; Focke et al., 2020) other measures should be considered. For example, if we consider these attention measures in the order of Wikipedia views, Google SVI, EDGAR views, and Bloomberg readership, we see a progression in investor sophistication: from first-time or potential investors, to those with market knowledge (who know the ticker), to more advanced investors capable of reading financial disclosures, and finally, to professionals. Leveraging the differences in these attention measures in future work could significantly extend the initial analysis presented here. Furthermore, given the explosion of AI tools in the past couple of years, future work could focus on exploiting AI-generated descriptions of the content shown in Instagram images as an alternative way to capture influencers' sentiment.

Finally, it should be feasible in future work to employ topic classification or topic modeling techniques to better understand the exact content of these posts. However, the data collection for the current analysis was lengthy and very time consuming, and the costs of undertaking topic modelling will be substantial.

[33] https://www.ft.com/content/0dacea5c-3402-11ea-9703-eea0cae3f0de

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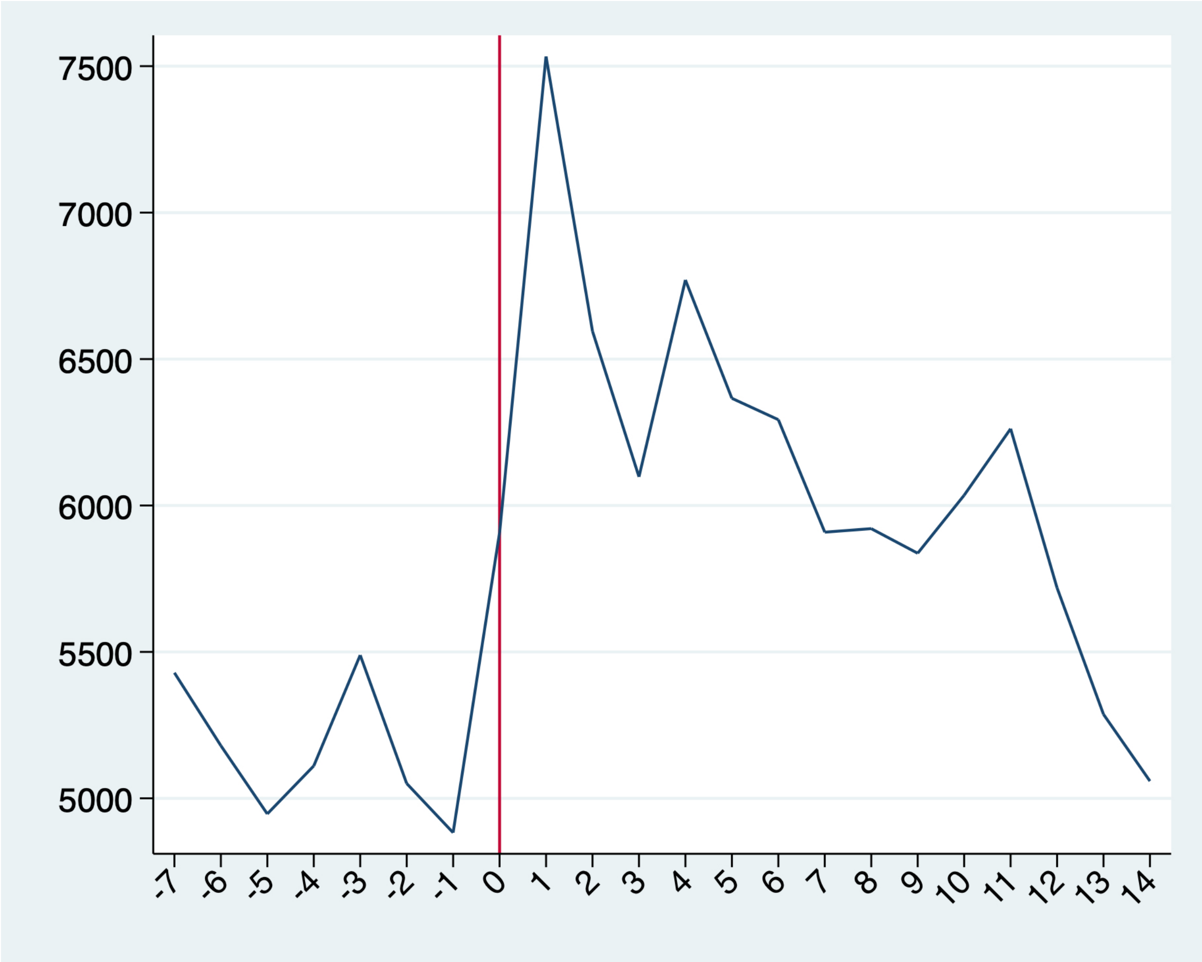


**Figure 1: Snapchat Wikipedia Page Views around Rihanna's Criticism**
This figure illustrates the three-week period of daily Wikipedia page views of the Snapchat firm from March 8, 2018 (7 days before posting) to March 29, 2018 (14 days after posting). Day 0 is March 15, 2018, which is the day that Rihanna posted the criticism content on Snapchat.

## Table 1: Hypotheses

This table illustrates the hypotheses tested by the empirical analysis. Log of Comments is the natural logarithm of the aggregated number of comments generated by all posts about the related firm on day *t*. Abnormal Sentiment is the sentiment change about the related firm on day *t*, the detailed calculation is given in the appendix. Investor Attention is the Bloomberg News Heat or the number of daily firm's Wikipedia page views, the detailed calculation is given in the text. Daily Volatility is the daily stock price volatility in percent, calculated by (highest price – lowest price)/[(highest price + lowest price)/2]. Log of Dollar Trading Volume is the natural logarithm of daily dollar volume of stock trading. Abnormal Returns is the daily abnormal return adjusted by the Fama-French-Carhart four-factor model in percent. NR indicates that the two variables are not expected to be related. ? indicates that the relationship between the two variables is unclear. ^ indicates that we run additional tests on subsamples with posts by top influencers and with extreme sentiment posts.

| | Investor Attention | Daily Volatility | Log of Dollar Trading Volume | Abnormal Returns |
|---|---|---|---|---|
| Log of Comments | + | + | + | NR |
| Abnormal Sentiment | ? | ? | ? | +^ |

## Table 2: Summary Statistics

This table illustrates the summary statistics of Instagram and firm-level data from March 2011 (the date of the first post in our sample) to December 2022. Panel A reports the daily Instagram post and influencers' statistics. The Number of Comments is the aggregated number of comments generated by all posts about the related firm on day *t*. Log of Comments is the natural logarithm of the aggregated number of comments generated by all posts about the related firm on day *t*. Abnormal Sentiment is the sentiment change about the related firm on day *t*, the detailed calculation is given in the appendix. Bloomberg News Heat is abnormal investor attention from Bloomberg. Wikipedia is the daily number of a firm's Wikipedia page views. Daily Volatility (%) is the daily stock price volatility in percent, calculated by (highest price – lowest price)/[(highest price + lowest price)/2]. Log of Dollar Trading Volume is the natural logarithm of daily dollar volume of stock trading. Abnormal Returns (%) is the daily abnormal return adjusted by the Fama-French-Carhart four-factor model in percent. Posting Frequency is the number of posts that the related influencer posts per day, the detailed calculation is given in the text. Return (%) is the holding period return over the 30 days up to *t*–7, in percent. Log Market Size is the natural logarithm of the firm's market capitalization in thousands, on day *t*–7. Turnover is the trading volume over the 30 days up to *t*–7, divided by average shares outstanding. Realized Volatility is the volatility of realized returns over the 30 days up to *t*–7. Earnings Announcement is a dummy variable equal to one if a firm has an earnings announcement on day *t*. All the variables are winsorized at the 1% and 99% levels.

| | N | Mean | Std. Dev. | p25 | Median | p75 |
|---|---|---|---|---|---|---|
| Panel A: Instagram Data | | | | | | |
| Number of Comments | 111,561 | 664.834 | 1,731.760 | 38.000 | 128.000 | 427.000 |
| Log of Comments | 111,561 | 4.864 | 1.860 | 3.638 | 4.852 | 6.057 |
| Abnormal Sentiment | 111,374 | 0.021 | 0.358 | -0.208 | 0.064 | 0.286 |
| Panel B: Dependent variables | | | | | | |
| Bloomberg News Heat | 64,422 | 1.072 | 1.473 | 0.000 | 0.000 | 2.000 |
| Wikipedia | 56,063 | 2,139.375 | 3,026.333 | 200.000 | 762.000 | 2,756.000 |
| Daily Volatility (%) | 111,561 | 2.804 | 2.052 | 1.469 | 2.221 | 3.429 |
| Log of Dollar Trading Volume | 111,561 | 18.699 | 1.969 | 17.69 | 18.903 | 20.114 |
| Abnormal Returns (%) | 111,552 | 0.001 | 1.783 | -0.798 | -0.014 | 0.785 |
| Panel C: Control variables | | | | | | |
| Posting Frequency | 111,456 | 1.579 | 1.175 | 0.768 | 1.249 | 1.993 |
| Return (%) | 111,464 | 0.818 | 8.993 | -3.740 | 0.795 | 5.156 |
| Log Market Size | 111,530 | 16.608 | 2.004 | 15.259 | 16.657 | 18.176 |
| Turnover | 111,464 | 181.996 | 171.428 | 76.096 | 121.376 | 217.902 |
| Realized Volatility | 111,389 | 45.524 | 31.022 | 25.752 | 36.464 | 53.815 |
| Earnings Announcement | 111,561 | 0.009 | 0.097 | 0.000 | 0.000 | 0.000 |

## Table 3: Correlation Table

This table reports the correlation between the main explanatory variables. Log of Comments is the natural logarithm of the aggregated number of comments generated by all posts about the related firm on day *t*. Abnormal Sentiment is the sentiment change about the related firm on day *t*, the detailed calculation is given in the appendix. Posting Frequency is the number of posts that the related influencer posts per day, the detailed calculation is given in the text. Return (%) is the holding period return over the 30 days up to *t*–7, in percent. Log Market Size is the natural logarithm of the firm's market capitalization, on day *t*–7. Turnover is the trading volume over the 30 days up to *t*–7, divided by average shares outstanding. Realized Volatility is the volatility of realized returns over the 30 days up to *t*–7. Earnings Announcement is a dummy variable equal to one if a firm has an earnings announcement on day *t*.

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| (1) Log of Comments | 1.000 | | | | | | | |
| (2) Abnormal Sentiment | -0.014 | 1.000 | | | | | | |
| (3) Posting Frequency | 0.018 | -0.006 | 1.000 | | | | | |
| (4) Return (%) | 0.008 | 0.001 | -0.011 | 1.000 | | | | |
| (5) Log Market Size | 0.148 | 0.005 | 0.069 | 0.049 | 1.000 | | | |
| (6) Turnover | -0.060 | 0.002 | 0.020 | 0.010 | -0.293 | 1.000 | | |
| (7) Realized Volatility | -0.013 | -0.008 | -0.012 | 0.068 | -0.520 | 0.501 | 1.000 | |
| (8) Earnings Announcement | -0.011 | -0.006 | 0.004 | 0.005 | -0.004 | -0.004 | 0.001 | 1.000 |

## Table 4: Influencers and Wikipedia View Times

This table shows the regression results of Instagram influencers' post characteristics on Wikipedia view times from July 2015 to December 2022. $\text{Wikipedia}_{t+1}$ is the number of Wikipedia page views (in thousands) of the related firm on the day after a post. Log of $\text{Comments}_t$ is the natural logarithm of the aggregated number of comments generated by all posts about the related firm on day *t*. Abnormal $\text{Sentiment}_t$ is the sentiment change about the related firm on day *t,* the detailed calculation is given in the appendix. Posting $\text{Frequency}_t$ is the number of posts that the related influencer posts per day, the detailed calculation is given in the text. $\text{Return}_{t-30,t-7}$ is the holding period return over the 30 days up to *t*–7, in percent. Log Market $\text{Size}_{t-7}$ is the natural logarithm of the firm's market capitalization, on day *t*–7. $\text{Turnover}_{t-30,t-7}$ is the trading volume over the 30 days up to *t*–7, divided by average shares outstanding. Realized $\text{Volatility}_{t-30,t-7}$ is the volatility of realized returns over the 30 days up to *t*–7. Earnings Announcement is a dummy variable equal to one if a firm has an earnings announcement on day *t*. Standard errors are clustered by firm and week. Robust *t*-statistics are shown in parentheses. Significance level at 10%, 5% or 1% is indicated by *, ** or ***.

| | $\text{Wikipedia}_{t+1}$ | | | |
|---|---|---|---|---|
| Log of $\text{Comments}_t$ | 0.020** | 0.016** | 0.006** | 0.006** |
| | (2.15) | (2.13) | (2.35) | (2.28) |
| Abnormal $\text{Sentiment}_t$ | -0.007 | -0.004 | -0.005 | -0.004 |
| | (-0.48) | (-0.28) | (-0.61) | (-0.52) |
| Posting $\text{Frequency}_t$ | 0.047*** | 0.033*** | 0.009** | 0.007* |
| | (3.11) | (2.78) | (2.18) | (1.86) |
| $\text{Return}_{t-30,t-7}$ | | 0.000 | | 0.000 |
| | | (0.07) | | (1.27) |
| Log Market $\text{Size}_{t-7}$ | | 0.000*** | | 0.000*** |
| | | (6.96) | | (3.90) |
| $\text{Turnover}_{t-30,t-7}$ | | 0.001** | | 0.000** |
| | | (2.63) | | (2.31) |
| Realized $\text{Volatility}_{t-30,t-7}$ | | 0.002** | | 0.000* |
| | | (2.43) | | (2.00) |
| Earnings $\text{Announcement}_t$ | | 0.165*** | | 0.190*** |
| | | (3.35) | | (4.57) |
| $\text{Wikipedia}_{t-1}$ | | | 0.459*** | 0.456*** |
| | | | (14.68) | (14.57) |
| $\text{Wikipedia}_{t-2}$ | | | 0.080*** | 0.079*** |
| | | | (4.10) | (4.04) |
| $\text{Wikipedia}_{t-3}$ | | | 0.087*** | 0.086*** |
| | | | (5.07) | (5.03) |
| $\text{Wikipedia}_{t-4}$ | | | 0.088*** | 0.087*** |
| | | | (4.39) | (4.30) |
| $\text{Wikipedia}_{t-5}$ | | | 0.115*** | 0.111*** |
| | | | (6.76) | (6.57) |
| Firm FEs | Yes | Yes | Yes | Yes |
| Week FEs | Yes | Yes | Yes | Yes |
| Day-of-week FEs | Yes | Yes | Yes | Yes |
| Observations | 55,912 | 55,880 | 54,925 | 54,901 |
| R-squared | 0.922 | 0.925 | 0.965 | 0.965 |

## Table 5: Influencers and the Bloomberg News Heat Index

This table shows the regression results of Instagram influencers' post characteristics on the Bloomberg News Heat (Daily Max Readership) index from March 2011 to December 2022. The Bloomberg News Heat$_{t+1}$ is the Bloomberg News Heat index on the day after a post. Log of Abnormal Comments$_t$ is the excess number of comments generated from all posts about the related firm on day $t$ relative to the average number of comments (calculated across the preceding 12 months), the detailed calculation is given in the text. Abnormal Sentiment$_t$ is the sentiment change about the related firm on day $t$, the detailed calculation is given in the appendix. Posting Frequency$_t$ is the number of posts that the related influencer posts per day, the detailed calculation is given in the text. Return$_{t-30,t-7}$ is the holding period return over the 30 days up to $t$–7, in percent. Log Market Size$_{t-7}$ is the natural logarithm of the firm's market capitalization, on day $t$–7. Turnover$_{t-30,t-7}$ is the trading volume over the 30 days up to $t$–7, divided by average shares outstanding. Realized Volatility$_{t-30,t-7}$ is the volatility of realized returns over the 30 days up to $t$–7. Earnings Announcement$_t$ is a dummy variable equal to one if a firm has an earnings announcement on day $t$. Standard errors are clustered by firm and week. Robust $t$-statistics are shown in parentheses. Significance level at 10%, 5% or 1% is indicated by *, ** or ***.

| | Bloomberg News Heat$_{t+1}$ | | | |
|---|---|---|---|---|
| Log of Abnormal Comments$_t$ | 0.023*** | 0.025*** | 0.014** | 0.015** |
| | (3.02) | (3.45) | (2.25) | (2.60) |
| Abnormal Sentiment$_t$ | -0.001 | 0.003 | -0.004 | -0.001 |
| | (-0.10) | (0.28) | (-0.43) | (-0.05) |
| Posting Frequency$_t$ | -0.000 | -0.001 | -0.001 | -0.001 |
| | (-0.04) | (-0.11) | (-0.10) | (-0.15) |
| Return$_{t-30,t-7}$ | | -0.003*** | | -0.002*** |
| | | (-3.25) | | (-3.32) |
| Log Market Size$_{t-7}$ | | 0.000 | | 0.000 |
| | | (0.20) | | (0.09) |
| Turnover$_{t-30,t-7}$ | | -0.001*** | | -0.000*** |
| | | (-3.60) | | (-3.70) |
| Realized Volatility$_{t-30,t-7}$ | | 0.003*** | | 0.002*** |
| | | (2.83) | | (2.98) |
| Earnings Announcement$_t$ | | 1.515*** | | 1.391*** |
| | | (10.93) | | (9.98) |
| Bloomberg News Heat$_{t-1}$ | | | 0.158*** | 0.150*** |
| | | | (16.72) | (15.48) |
| Bloomberg News Heat$_{t-2}$ | | | 0.067*** | 0.066*** |
| | | | (7.87) | (7.68) |
| Bloomberg News Heat$_{t-3}$ | | | 0.045*** | 0.043*** |
| | | | (6.85) | (6.52) |
| Bloomberg News Heat$_{t-4}$ | | | 0.060*** | 0.059*** |
| | | | (8.01) | (7.79) |
| Bloomberg News Heat$_{t-5}$ | | | 0.031*** | 0.030*** |
| | | | (4.91) | (4.69) |
| Firm FEs | Yes | Yes | Yes | Yes |
| Week FEs | Yes | Yes | Yes | Yes |
| Day-of-week FEs | Yes | Yes | Yes | Yes |
| Observations | 63,681 | 63,642 | 63,666 | 63,640 |
| R-squared | 0.241 | 0.257 | 0.287 | 0.299 |

## Table 6: Influencers and Financial Market Variables

This table reports the main results of regressing related firms' financial market performance on influencers' posting factors from March 2011 to December 2022. Daily Volatility (%)$_{t+1}$ is the percentage of price volatility on the next day after a post. Log Dollar Trading Volume$_{t+1}$ is the log number of trading dollar volume on the day after posting. Abnormal Returns$_{t+1}$ is the abnormal return adjusted by the Fama-French-Carhart four-factor model on day after posting. Log of Comments$_t$ is the natural logarithm of the aggregated number of comments generated by all posts about the related firm on day $t$. Abnormal Sentiment$_t$ is the sentiment change about the related firm on day $t$, the detailed calculation is given in the appendix. Posting Frequency$_t$ is the number of posts that the related influencer posts per day, the detailed calculation is given in the text. Return$_{t-30,t-7}$ is the holding period return over the 30 days up to $t$–7, in percent. Log Market Size$_{t-7}$ is the natural logarithm of the firm's market capitalization, on day $t$–7. Turnover$_{t-30,t-7}$ is the trading volume over the 30 days up to $t$–7, divided by average shares outstanding. Realized Volatility$_{t-30,t-7}$ is the volatility of realized returns over the 30 days up to $t$–7. Earnings Announcement$_t$ is a dummy variable equal to one if a firm has an earnings announcement on day $t$. Standard errors are clustered by firm and week. Robust $t$-statistics are shown in parentheses. Significance level at 10%, 5% or 1% is indicated by *, ** or ***.

| | Daily Volatility (%)$_{t+1}$ | | Log Dollar Trading Volume$_{t+1}$ | | Abnormal Returns$_{t+1}$ | |
|---|---|---|---|---|---|---|
| Log of Comments$_t$ | 0.051*** | 0.016*** | 0.031*** | 0.004*** | 0.002 | 0.004 |
| | (4.73) | (4.01) | (4.70) | (3.57) | (0.61) | (0.98) |
| Abnormal Sentiment$_t$ | -0.002 | -0.008 | -0.004 | 0.000 | 0.022 | 0.020 |
| | (-0.10) | (-0.60) | (-0.47) | (0.05) | (1.33) | (1.24) |
| Posting Frequency$_t$ | 0.082*** | 0.026*** | 0.049*** | 0.003* | 0.001 | 0.004 |
| | (4.14) | (4.71) | (3.48) | (1.77) | (0.15) | (0.58) |
| Return$_{t-30,t-7}$ | | -0.009*** | | -0.001** | | 0.001 |
| | | (-5.75) | | (-2.63) | | (0.52) |
| Log Market Size$_{t-7}$ | | -0.117** | | 0.296*** | | -0.069*** |
| | | (-2.64) | | (16.55) | | (-4.02) |
| Turnover$_{t-30,t-7}$ | | 0.000*** | | 0.001*** | | -0.000 |
| | | (3.09) | | (10.33) | | (-0.25) |
| Realized Volatility$_{t-30,t-7}$ | | 0.008*** | | 0.001*** | | -0.000 |
| | | (6.25) | | (3.46) | | (-0.08) |
| Earnings Announcement$_t$ | | 2.044*** | | 0.646*** | | 0.064 |
| | | (11.04) | | (11.51) | | (0.40) |
| Dependent$_{t-1}$ | | 0.237*** | | 0.330*** | | -0.010 |
| | | (12.66) | | (37.55) | | (-1.45) |
| Dependent$_{t-2}$ | | 0.137*** | | 0.118*** | | -0.012** |
| | | (14.31) | | (19.06) | | (-2.50) |
| Dependent$_{t-3}$ | | 0.101*** | | 0.070*** | | -0.001 |
| | | (9.78) | | (9.69) | | (-0.14) |
| Dependent$_{t-4}$ | | 0.081*** | | 0.066*** | | -0.014*** |
| | | (9.54) | | (6.20) | | (-3.06) |
| Dependent$_{t-5}$ | | 0.083*** | | 0.070*** | | -0.004 |
| | | (16.84) | | (9.71) | | (-0.90) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Week FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Day-of-week FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 111243 | 111071 | 111243 | 111071 | 111234 | 111071 |
| R-squared | 0.314 | 0.553 | 0.903 | 0.960 | 0.008 | 0.008 |

## Table 7: The Effect of Posts by Top Influencers with Extreme Sentiment Changes on Abnormal Returns

This table reports the results of the effects of posts by top influencers with extreme sentiment changes on abnormal returns on day $t$+1. Column (1) reports the results obtained from a subsample that only includes posts by top influencers, which we define as those in the top 5% of historical impact power based on the prior year's average number of comments. Columns (2) to (5) report the results from a subsample that only includes the top 5% and bottom 5% of posts according to the abnormal sentiment distribution, which pertain to top influencers (as defined by the top 5% of posts, as ranked by the prior year's average number of comments). Abnormal Returns$_{t+1}$ is the abnormal return adjusted by the Fama-French-Carhart four-factor model on the next day after posting. Log of Comments$_t$ is the natural logarithm of the aggregated number of comments generated by all posts about the related firm on day $t$. Abnormal Sentiment$_t$ is the sentiment change about the related firm on day $t$, the detailed calculation is given in the appendix. Posting Frequency$_t$ is the number of posts that the related influencer posts per day, the detailed calculation is given in the text. Return$_{t-30,t-7}$ is the holding period return over the 30 days up to $t$–7, in percent. Log Market Size$_{t-7}$ is the natural logarithm of the firm's market capitalization, on day $t$–7. Turnover$_{t-30,t-7}$ is the trading volume over the 30 days up to $t$–7, divided by average shares outstanding. Realized Volatility$_{t-30,t-7}$ is the volatility of realized returns over the 30 days up to $t$–7. Earnings Announcement$_t$ is a dummy variable equal to one if a firm has an earnings announcement on day $t$. Standard errors are clustered by firm and week. Robust $t$-statistics are shown in parentheses. Significance level at 10%, 5% or 1% is indicated by *, ** or ***.

| Dependent Variable: Abnormal Returns$_{t+1}$ | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Log of Comments$_t$ | 0.013 | 0.002 | | | -0.024 |
| | (0.26) | (0.01) | | | (-0.15) |
| Abnormal Sentiment$_t$ | 0.162* | | 0.363** | | 0.402*** |
| | (1.76) | | (2.45) | | (2.87) |
| Posting Frequency$_t$ | 0.032 | | | -0.126 | -0.126 |
| | (0.96) | | | (-1.32) | (-1.22) |
| Return$_{t-30,t-7}$ | -0.003 | -0.007 | -0.005 | -0.007 | -0.005 |
| | (-0.99) | (-0.47) | (-0.35) | (-0.48) | (-0.36) |
| Log Market Size$_{t-7}$ | -0.281*** | 0.337 | 0.459** | 0.548** | 0.697*** |
| | (-2.93) | (1.48) | (2.02) | (2.28) | (2.90) |
| Turnover$_{t-30,t-7}$ | -0.001 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (-1.25) | (-0.47) | (-0.57) | (-0.15) | (-0.23) |
| Realized Volatility$_{t-30,t-7}$ | 0.005** | 0.002 | 0.002 | 0.003 | 0.004 |
| | (2.10) | (0.27) | (0.41) | (0.53) | (0.68) |
| Earnings Announcement$_t$ | -0.479 | -3.030* | -3.102* | -3.153* | -3.237** |
| | (-0.64) | (-1.77) | (-1.89) | (-1.88) | (-2.04) |
| Abnormal Returns$_{t-1}$ | 0.015 | 0.022 | 0.023 | 0.022 | 0.024 |
| | (0.63) | (0.45) | (0.49) | (0.44) | (0.49) |
| Abnormal Returns$_{t-2}$ | 0.015 | 0.074 | 0.065 | 0.071 | 0.061 |
| | (0.86) | (1.31) | (1.17) | (1.22) | (1.05) |
| Abnormal Returns$_{t-3}$ | -0.023 | -0.022 | -0.020 | -0.026 | -0.024 |
| | (-1.20) | (-0.38) | (-0.37) | (-0.45) | (-0.43) |
| Abnormal Returns$_{t-4}$ | -0.013 | 0.022 | 0.013 | 0.026 | 0.017 |
| | (-0.53) | (0.33) | (0.20) | (0.39) | (0.26) |
| Abnormal Returns$_{t-5}$ | -0.032 | -0.046 | -0.037 | -0.045 | -0.035 |
| | (-1.46) | (-1.19) | (-0.92) | (-1.13) | (-0.83) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes |
| Week FEs | Yes | Yes | Yes | Yes | Yes |
| Day-of-week FEs | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,269 | 501 | 501 | 500 | 500 |
| R-squared | 0.066 | 0.373 | 0.384 | 0.377 | 0.390 |

## Table 8: CARs for the Effect of Posts by Top Influencers with Extreme Sentiment Changes on Abnormal Returns

This table reports the results of the effects of posts by top influencers with extreme sentiment changes on cumulative abnormal returns across various time intervals. The Abnormal Returns are adjusted by the Fama-French-Carhart four-factor model. The dependent variables, shown from column (1) to column (6), represent the cumulative abnormal returns over the holding periods of [$t$+1, $t$+2], [$t$+1, $t$+3], [$t$+1, $t$+4], [$t$+1, $t$+5], [$t$+1, $t$+6], and [$t$+1, $t$+7], respectively. Log of Comments$_t$ is the natural logarithm of the aggregated number of comments generated by all posts about the related firm on day $t$. Abnormal Sentiment$_t$ is the sentiment change about the related firm on day $t$, the detailed calculation is given in the appendix. Posting Frequency$_t$ is the number of posts that the related influencer posts per day, the detailed calculation is given in the text. Return$_{t-30,t-7}$ is the holding period return over the 30 days up to $t$–7, in percent. Log Market Size$_{t-7}$ is the natural logarithm of the firm's market capitalization, on day $t$–7. Turnover$_{t-30,t-7}$ is the trading volume over the 30 days up to $t$–7, divided by average shares outstanding. Realized Volatility$_{t-30,t-7}$ is the volatility of realized returns over the 30 days up to $t$–7. Earnings Announcement$_t$ is a dummy variable equal to one if a firm has an earnings announcement on day $t$. Standard errors are clustered by firm and week. Robust $t$-statistics are shown in parentheses. Significance level at 10%, 5% or 1% is indicated by *, ** or ***.

| | CAR$_{t+1,\ t+2}$<br>(1) | CAR$_{t+1,\ t+3}$<br>(2) | CAR$_{t+1,\ t+4}$<br>(3) | CAR$_{t+1,\ t+5}$<br>(4) | CAR$_{t+1,\ t+6}$<br>(5) | CAR$_{t+1,\ t+7}$<br>(6) |
|---|---|---|---|---|---|---|
| Log of Comments$_t$ | -0.061 | -0.283 | -0.134 | 0.053 | 0.131 | -0.086 |
| | (-0.26) | (-1.05) | (-0.40) | (0.13) | (0.27) | (-0.18) |
| Abnormal Sentiment$_t$ | 0.523** | 0.391* | 0.463* | 0.428 | 0.330 | 0.434 |
| | (2.54) | (1.69) | (1.70) | (1.36) | (0.96) | (1.08) |
| Posting Frequency$_t$ | -0.059 | -0.061 | -0.123 | 0.007 | -0.183 | -0.036 |
| | (-0.46) | (-0.40) | (-0.71) | (0.05) | (-1.12) | (-0.18) |
| Return$_{t-30,t-7}$ | 0.005 | 0.025 | 0.027 | 0.042* | 0.046** | 0.023 |
| | (0.37) | (1.54) | (1.48) | (1.78) | (2.17) | (0.95) |
| Log Market Size$_{t-7}$ | 0.695* | 0.454 | 0.312 | 0.293 | 0.706 | 0.399 |
| | (1.94) | (1.23) | (0.49) | (0.50) | (1.30) | (0.69) |
| Turnover$_{t-30,t-7}$ | -0.002* | -0.002 | -0.001 | 0.000 | 0.000 | -0.001 |
| | (-1.81) | (-0.97) | (-0.37) | (0.06) | (0.07) | (-0.38) |
| Realized Volatility$_{t-30,t-7}$ | 0.010 | 0.009 | 0.015 | 0.014 | 0.014 | 0.005 |
| | (1.59) | (0.84) | (0.92) | (0.77) | (0.72) | (0.27) |
| Earnings Announcement$_t$ | -3.792* | -2.270 | -3.899** | -4.814*** | -3.839*** | -3.277** |
| | (-1.76) | (-1.18) | (-2.60) | (-5.16) | (-5.61) | (-2.44) |
| Abnormal Returns$_{t-1}$ | -0.023 | 0.019 | 0.002 | 0.002 | 0.011 | 0.174 |
| | (-0.31) | (0.19) | (0.01) | (0.01) | (0.07) | (1.02) |
| Abnormal Returns$_{t-2}$ | 0.107 | 0.184* | 0.208* | 0.223 | 0.298* | 0.334** |
| | (1.20) | (1.80) | (1.71) | (1.65) | (1.91) | (2.02) |
| Abnormal Returns$_{t-3}$ | -0.010 | 0.047 | 0.001 | 0.048 | 0.072 | 0.126 |
| | (-0.12) | (0.40) | (0.01) | (0.32) | (0.48) | (0.78) |
| Abnormal Returns$_{t-4}$ | -0.130** | -0.133 | -0.102 | -0.179 | -0.089 | -0.069 |
| | (-2.37) | (-1.54) | (-1.09) | (-1.46) | (-0.86) | (-0.60) |
| Abnormal Returns$_{t-5}$ | -0.134*** | -0.248*** | -0.226** | -0.180 | -0.096 | -0.166 |
| | (-2.71) | (-4.03) | (-2.30) | (-1.50) | (-0.72) | (-1.30) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Week FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Day-of-week FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 500 | 500 | 500 | 500 | 500 | 500 |
| R-squared | 0.393 | 0.375 | 0.403 | 0.405 | 0.394 | 0.395 |

## Table 9: Trading Strategy

This table presents the returns of the trading strategy based on posts by top influencers with extreme sentiment changes. On day *t*+1, we long the firms with the top 5% abnormal sentiment and short the ones with the bottom 5% abnormal sentiment. If there is only one leg on the day, we long (short) the market. The number of observations denotes the number of days on which a trade is triggered. Panel A reports the performance of value-weighted portfolios that are based on the market value on day *t*–3. Panel B reports the performance of equal-weighted portfolios. In column (1) to column (7), the position is held from day *t*+1 to *t*+1, *t*+2, *t*+3, *t*+4, *t*+5, *t*+6 and *t*+7, respectively. The holding period returns are regressed on the market, SMB, HML and UMD risk factors (consistent with the abnormal returns that we use in other tests). The factors are downloaded from Kenneth R. French Data Library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Alpha (%) represents the abnormal returns generated from the trading strategies. *t*-statistics are shown in parentheses. Significance level at 10%, 5% or 1% is indicated by *, ** or ***.

Panel A: Value-Weighted Portfolios

| | *t*+1 | [*t*+1, *t*+2] | [*t*+1, *t*+3] | [*t*+1, *t*+4] | [*t*+1, *t*+5] | [*t*+1, *t*+6] | [*t*+1, *t*+7] |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Alpha (%) | 0.246*** | 0.096* | 0.057 | 0.082 | 0.038 | 0.060 | 0.071 |
| | (2.76) | (1.67) | (1.06) | (1.60) | (0.77) | (1.26) | (1.54) |
| Mkt | -0.101 | 0.075 | 0.074 | 0.004 | -0.029 | -0.027 | -0.063 |
| | (-1.16) | (1.37) | (1.43) | (0.07) | (-0.62) | (-0.57) | (-1.41) |
| SMB | -0.026 | 0.010 | -0.058 | -0.009 | 0.002 | -0.044 | -0.042 |
| | (-0.19) | (0.11) | (-0.66) | (-0.11) | (0.03) | (-0.57) | (-0.55) |
| HML | 0.146 | -0.061 | -0.050 | -0.008 | -0.032 | -0.033 | -0.055 |
| | (1.39) | (-0.91) | (-0.79) | (-0.13) | (-0.55) | (-0.58) | (-1.00) |
| UMD | 0.092 | 0.045 | 0.003 | -0.035 | -0.046 | -0.046 | -0.062 |
| | (1.13) | (0.88) | (0.05) | (-0.74) | (-1.00) | (-1.02) | (-1.40) |
| Observations | 477 | 477 | 477 | 477 | 477 | 477 | 477 |

Panel B: Equal-Weighted Portfolios

| | *t*+1 | [*t*+1, *t*+2] | [*t*+1, *t*+3] | [*t*+1, *t*+4] | [*t*+1, *t*+5] | [*t*+1, *t*+6] | [*t*+1, *t*+7] |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Alpha (%) | 0.146** | 0.094** | 0.072 | 0.061 | 0.043 | 0.042 | 0.045 |
| | (2.29) | (2.02) | (1.58) | (1.42) | (1.01) | (1.03) | (1.14) |
| Mkt | -0.115* | 0.040 | 0.038 | 0.013 | -0.025 | -0.013 | -0.056 |
| | (-1.84) | (0.91) | (0.89) | (0.31) | (-0.62) | (-0.33) | (-1.45) |
| SMB | -0.115 | 0.021 | -0.029 | -0.003 | -0.010 | -0.019 | -0.049 |
| | (-1.19) | (0.29) | (-0.40) | (-0.05) | (-0.14) | (-0.29) | (-0.75) |
| HML | 0.084 | -0.055 | -0.050 | -0.039 | -0.050 | -0.059 | -0.074 |
| | (1.12) | (-1.02) | (-0.93) | (-0.75) | (-1.00) | (-1.20) | (-1.54) |
| UMD | 0.102* | 0.026 | -0.021 | -0.053 | -0.031 | -0.032 | -0.060 |
| | (1.76) | (0.63) | (-0.51) | (-1.32) | (-0.77) | (-0.81) | (-1.58) |
| Observations | 477 | 477 | 477 | 477 | 477 | 477 | 477 |

## Table 10: Operating Performance

This table reports the results of regressing related firms' operating performance on influencers' posting factors from March 2011 to December 2022. The dependent variable in the models presented in the first three columns is the change in Return on Equity (ROE) for the related firm from quarter *q*–4 to quarter *q*. Columns (1), (2) and (3) report the regression results by employing the samples from baseline (Table 6), top influencer (Column 1 in Table 7) and top influencer with extreme sentiment (Column 5 in Table 7) posts, respectively. The dependent variable in the models presented in the last three columns is the quarterly Standardized Unexpected Earnings (SUE) score for the related firm in quarter *q*. SUE score, obtaimed from I/B/E/S, is calculated as the difference between actual (reported) quarterly earnings per share (EPS) and the average earnings per share (EPS) forecasts by analysts for a company for the fiscal period indicated, divided by the standard deviation of those forecasts. Columns (4), (5) and (6) report the regression results by employing the samples from baseline (Table 6), top influencer (Column 1 in Table 7) and top influencer with extreme sentiment (Column 5 in Table 7) posts, respectively. Log of Comments$_q$ is the natural logarithm of the total number of comments generated by all posts about the related firm in quarter *q*. Abnormal Sentiment$_q$ is the average value of abnormal sentiment of all posts about the related firm in quarter *q*. Posting Frequency$_q$ is the average posting frequency of all influencers who posted about the related firm in quarter *q*. SUE, ROE, market size, return, log dollar volume, illiquidity (Amihud, 2002), ROA (Return on Total Asset), book-to-market ratio, F-score and advertisement to sales are downloaded from CRSP, Compustat, and I/B/E/S. For a given quarter *q*, variables with available market data are measured at the end of quarter q, while variables with book values only available are measured at the end of the previous fiscal quarter. Standard errors are clustered by firm. Robust *t*-statistics are shown in parentheses. Significance level at 10%, 5% or 1% is indicated by *, ** or ***.

| Dependent Variable: | $\Delta ROE_q$ | | | SUE score$_q$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log of Comments$_q$ | 0.013 | 0.011 | 0.048 | 0.055 | 0.104 | -0.453 |
| | (1.26) | (1.02) | (0.88) | (1.42) | (0.54) | (-1.40) |
| Abnormal Sentiment$_q$ | -0.065 | -0.068 | 0.070 | 0.170 | 0.441 | -0.019 |
| | (-0.77) | (-1.02) | (1.15) | (0.47) | (1.10) | (-0.03) |
| Posting Frequency$_q$ | 0.065 | 0.034 | -0.006 | -0.033 | 0.031 | -0.169 |
| | (0.86) | (1.16) | (-0.45) | (-0.37) | (0.18) | (-0.54) |
| Log Market Size$_q$ | 0.037 | 0.021 | 0.012 | 0.046 | 1.352** | 2.197** |
| | (0.76) | (0.50) | (0.10) | (0.13) | (2.01) | (2.11) |
| Return$_q$ | -0.101 | -0.063 | 0.262 | 2.020*** | 1.120 | -1.144 |
| | (-1.17) | (-1.38) | (1.59) | (4.16) | (1.33) | (-0.50) |
| Log Dollar Volume$_q$ | 0.008 | -0.131 | 0.046 | -0.016 | -1.027 | -2.244** |
| | (0.28) | (-1.49) | (0.53) | (-0.05) | (-1.53) | (-2.42) |
| Illiquidity$_q$ | 0.000 | 1.826 | 6.411 | -0.004 | -11.109 | -2.706 |
| | (0.00) | (1.41) | (0.86) | (-0.16) | (-0.98) | (-0.03) |
| ROA$_{q-1}$ | 0.162 | 0.998 | 1.198 | -4.113** | -3.797 | -15.148*** |
| | (0.78) | (1.11) | (0.86) | (-2.13) | (-1.29) | (-3.02) |
| Book to Market Ratio$_{q-1}$ | -0.021 | -0.105* | -0.369 | -1.160** | 2.329* | -1.943 |
| | (-0.35) | (-1.96) | (-1.17) | (-2.25) | (1.70) | (-0.36) |
| F-score$_{q-1}$ | -0.090 | 0.025 | -0.013 | 0.062 | 0.464* | 0.334 |
| | (-1.13) | (1.09) | (-0.49) | (0.82) | (1.93) | (1.36) |
| Advertisement to Sales$_{q-1}$ | 0.020 | 0.018 | 0.005 | -0.039 | -0.018 | -0.271 |
| | (0.98) | (1.18) | (0.22) | (-1.06) | (-0.10) | (-1.31) |
| Dependent Variable$_{q-1}$ | 0.200 | 0.151** | 2.809** | 0.126** | 0.044 | -0.083 |
| | (0.76) | (2.53) | (2.70) | (2.35) | (0.88) | (-1.61) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter FEs | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,193 | 490 | 138 | 3,321 | 510 | 140 |
| R-squared | 0.053 | 0.391 | 0.656 | 0.224 | 0.196 | 0.268 |

## Table 11: Out-Sample Firms Placebo

This table reports the placebo test of out-sample firms. The placebo sample selection is based on the nearest neighbour algorithm for all the US-listed firms. Panel A reports the mean values of the firm characteristics for both the original and matched placebo samples. The first column displays the original sample's mean value; the second column displays the matched placebo sample's mean value; the last column shows the *t*-statistics of the differences across two groups using *t*-tests. Panel B reports the results of the placebo tests: Column (1) and (2) present the placebo test results for daily volatility and log trading volume on day $t$+1 respectively, as derived from the baseline in Table 6; Column (3) shows the placebo test results for abnormal returns on day $t$+1 from the top comments as per the sample in Column 1 of Table 7; and Column (4) presents the results for abnormal returns on day $t$+1 from the top comments with extreme sentiment as per the sample in Column 5 of Table 7. *t*-statistics are shown in parentheses. Significance level at 10%, 5% or 1% is indicated by *, ** or ***.

| Panel A: Firm Characteristics' Comparisons between the Original and Placebo Samples | | | |
|---|---|---|---|
| | Original | Placebo | T-statistics |
| Volatility (%) | 3.127 | 3.145 | -0.179 |
| Log Dollar Trading Volume | 17.526 | 17.127 | 2.913 |
| Abnormal Return (%) | -0.025 | 0.028 | -0.931 |
| Return (%) | 0.802 | 0.942 | -0.455 |
| Log Market Size | 15.301 | 15.002 | 2.317 |
| Turnover | 168.407 | 147.279 | 2.681 |
| Realized Volatility | 51.645 | 50.688 | 0.521 |

| Panel B: Placebo Tests | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | [Table 6] Daily Volatility (%)$_{t+1}$ | [Table 6] Log Dollar Trading Volume$_{t+1}$ | [Table 7 - Column 1] Abnormal Returns$_{t+1}$ | [Table 7 - Column 5] Abnormal Returns$_{t+1}$ |
| Log of Comments$_t$ | -0.001 | 0.000 | 0.000 | 0.122 |
| | (-0.32) | (0.40) | (0.00) | (0.46) |
| Abnormal Sentiment$_t$ | -0.009 | -0.002 | 0.047 | 0.202 |
| | (-0.77) | (-0.53) | (0.41) | (1.35) |
| Posting Frequency$_t$ | -0.001 | 0.002 | -0.028 | -0.130 |
| | (-0.39) | (1.27) | (-0.56) | (-0.98) |
| Return$_{t-30,t-7}$ | -0.003*** | -0.001*** | -0.006* | 0.017** |
| | (-3.69) | (-3.04) | (-1.93) | (2.10) |
| Log Market Size$_{t-7}$ | -0.149*** | 0.302*** | 0.070* | 0.019 |
| | (-3.94) | (10.84) | (1.94) | (0.13) |
| Turnover$_{t-30,t-7}$ | 0.001*** | 0.001*** | -0.000 | 0.001 |
| | (6.76) | (6.90) | (-1.28) | (0.61) |
| Realized Volatility$_{t-30,t-7}$ | 0.004** | 0.001*** | -0.004* | -0.010 |
| | (2.29) | (3.63) | (-1.76) | (-1.38) |
| Earnings Announcement$_t$ | 1.463*** | 0.462*** | 0.006 | -0.141 |
| | (5.98) | (7.61) | (0.02) | (-0.27) |
| Dependent Variable$_{t-1}$ | 0.279*** | 0.393*** | 0.170** | 0.104 |
| | (10.11) | (14.32) | (2.37) | (1.69) |
| Dependent Variable$_{t-2}$ | 0.115*** | 0.090*** | 0.053 | 0.074 |
| | (10.80) | (10.63) | (1.02) | (0.95) |
| Dependent Variable$_{t-3}$ | 0.082*** | 0.083*** | 0.012 | 0.022 |
| | (6.84) | (10.37) | (0.35) | (0.27) |
| Dependent Variable$_{t-4}$ | 0.060*** | 0.059*** | 0.055* | 0.151 |
| | (6.93) | (7.07) | (2.01) | (1.36) |
| Dependent Variable$_{t-5}$ | 0.068*** | 0.061*** | -0.034 | -0.267*** |
| | (8.58) | (7.92) | (-1.03) | (-2.93) |
| Firm FEs | Yes | Yes | Yes | Yes |
| Week FEs | Yes | Yes | Yes | Yes |
| Day-of-week FEs | Yes | Yes | Yes | Yes |
| Observations | 87,341 | 87,333 | 4,582 | 422 |
| R-squared | 0.592 | 0.965 | 0.097 | 0.299 |

# Appendix – Data Collection and Methodology

## A1. Instagram Data

We use the web-crawling method to build the dataset of Instagram. We first identify the mega influencers from Trackalytics.com. We set the benchmark as all the accounts with more than one million followers in June 2021 and use the web-crawling method to download all the accounts' names. Then, we upload the names of accounts to the Supermetrics API (Application Programming Interface) by Google data studio to download all the posts of the mega accounts from March 2011 to December 2022. An example of an Instagram post is shown in Figure A1. For each post, the downloaded data include the account's name, the number of likes and comments, the date of the post, the content of the post, the hashtags contained in the post (as explained in the next paragraph), and the URL (Uniform Resource Locator) of the post. After downloading, to simplify and improve the accuracy of the sentiment detection, we filter the accounts with the main language used (the target firms are U.S. listed). We use the "langdetect" package from Python to detect the main language of each post and tag the influencers with the language used. We keep only the mainly English-speaking influencers. We, therefore, end up collecting 16,156,419 posts from 5,743 mega influencers.

[Figure A1]

We use the hashtags contained in the content to determine whether the post is related to a firm.[34] If a string starts with "#", it will be automatically transformed into a hashtag and a link to the specific topic webpage by Instagram. Hence, we allocate all the hashtags contained in every post by searching the strings that start with "#". If there are many hashtags contained in one post, all the mentioned firms will be linked to the post. If there are many hashtags for the same firm, then they will be counted only once. For each firm there could be more than one hashtag. For

[34] It is worth noting that we do not use the "@" feature to capture the potential firm(s) associated to a given post. The "@" is a feature that enables users to tag another Instagram account (either an influencer's or a firm's account). Although the "@" feature seems to be the most immediate way to identify firms, using it would limit our sample size. Indeed, by using the hashtags, we can broaden our sample to include all influencer posts that are related to a specific firm (and not just those that simply bear the firm's tag), thus to gather a wider and more accurate idea of firms' *sentiment*.

instance, Unilever has 'unilever', 'unileverusa', 'unileveruk', etc. Hence, we fuzzy match the hashtags with the firms and all the firm' subsidiaries' names from the 10-K and the Exhibit 21 files to allocate all the possible hashtags. The matching is based on the separated word of the names and on the different combinations of two and three words of the subsidiaries' and firms' names. After matching, we manually clean the hashtag bank to make sure the hashtags are linked correctly.

Many other methods are used to improve data accuracy. First, we delete all the obscure hashtags. For instance, the webpage of the 'innocent' brand topic (searched by "#innocent"), which is owned by Coca-Cola, contains many innocent faces of babies and animals. This page is excluded from the sample. Furthermore, we manually check the ambiguous hashtags and drop them if there are too many irrelevant posts. Second, we manually check the most used hashtags to find if they are actually related to firms, to reduce the mismatches. Third, we manually check the related brands of identified firms to find if there are more related hashtags. Then, we drop the hashtags that have been used less than five times from 2011 to 2022 to reduce noise in the sample. After applying the aforementioned filters, the sample contains 368,677 posts from 4,763 mega influencers related to 546 listed firms.

### A2. VADER Method for Analyzing the Sentiment of Influencers' Posts

We use the Hutto and Gilbert (2014) VADER (for Valence Aware Dictionary for sEntiment Reasoning) lexicon (which has been used by Costa et al., 2019; Tumasjan et al., 2021; Shapiro et al., 2022) to analyze the sentiment of influencers' posts. We choose the VADER method after comparing it with the commonly used dictionaries that include LM (Loughran and McDonald, 2011), HL (Hu and Liu, 2004), and GI (Stone et al., 1966). Shapiro et al. (2022) state that domain specificity is vital for sentiment detection accuracy. Compared with the aforementioned dictionaries, the VADER method is a tailor-made lexicon for social media posts. It is an open-sourced Python package for sentence-based textual sentiment detection. The VADER method combines formerly established dictionaries with informal social media words and emoji sentiments. Compared with the traditional Bag of Words method, the VADER can also detect the punctuation and capitalization sentiment. For example, "The food here is GREAT!!!" gets a higher positive score than "The food here is great!!!" whose score is higher than "The food here is great." It gives a possible solution to the noise that slang, emojis and other unique expressions may cause in social media textual analysis, as noted by Loughran and McDonald (2016). By employing this lexicon, we can detect social media sentiment more precisely. Also, compared with the machine learning method, the VADER method has a listed dictionary and algorithm which can be accessed online rather than being "hidden within a black box".

The VADER method gives an open-source lexicon online.[35] Hutto and Gilbert (2014) hired ten independent English-speaking people to rate the sentiment score for every word from –4 (extremely negative) to 4 (extremely positive).[36] They kept the words with non-neutral mean scores and dropped the ones with more than 2.5 standard deviations to minimize the impact of ambiguous words. Also, they transformed the commonly used emojis and emoticons into a list of words, which can be obtained from their Github.com page, and for which a sentiment score is available.[37] Based on these lexicons, the VADER model assigns to each sentence a sentiment score and the associated confidence. For each sentence, the model calculates both of these metrics by aggregating and standardizing the sentiment scores of the individual words of the sentence. The aggregate sentiment score, which is referred to as sentiment polarity, can take two possible values; –1 or 1, which correspond to negative and positive sentiment, respectively. Confidence can take values between 0 and 1 and indicates the intensity of a sentence's sentiment. The more positive the tone of a sentence (e.g., the higher the percentage of positive words in the sentence or the higher the scores for the positive words), the higher will be the confidence value. We calculate the sentiment polarity and the associated confidence for each post by treating all the content of the post as a single sentence.

[35] https://github.com/cjhutto/vaderSentiment
[36] https://github.com/cjhutto/vaderSentiment/blob/master/vaderSentiment/vader_lexicon.txt
[37] https://github.com/cjhutto/vaderSentiment/blob/master/vaderSentiment/emoji_utf8_lexicon.txt

The aggregate sentiment score for all posts by an influencer about a specific company on a particular day is calculated by following the Twitter Bloomberg sentiment score illustrated by Gu and Kurov (2020). Different from their equal-weighted method, we use the number of likes to represent the impact power of each post. Therefore, our adapted formula for calculating the daily aggregate sentiment score of an influencer's posts about a specific firm is:

$$Sentiment_{i,t,z} = \frac{\sum_{k \in P(i,t,z)} S_i^k C_i^k \times \#\ of\ Likes_i^k}{\sum_{k \in P(i,t,z)} \#\ of\ Likes_i^k} \qquad (1)$$

where $Sentiment_{i,t,z}$ is the sentiment score of all posts by influencer $z$ about firm $i$ on day $t$, $k$ is the post $k$, $P(i, t, z)$ is the set of influencer's $z$ posts about firm $i$ on day $t$, $S_i^k$ is the sentiment polarity of post $k$ about firm $i$, $C_i^k$ is the confidence of post $k$ about firm $i$, $\#\ of\ Likes_i^k$ is the number of likes of post $k$ about firm $i$. The influencer-firm-day sentiment values range from -1 to 1, with -1 corresponding to the most negative sentiment and 1 corresponding to the most positive sentiment. We then calculate the abnormal sentiment score as the difference between the sentiment on day $t$ and the average sentiment of an influencer's posts uploaded from the time of the influencer's initial posting until day $t$–1. The formula is as follows:

$$Abnormal\ Sentiment_{i,t,z} = Sentiment_{i,t,z} - Average\ Sentiment\ of\ Influencer_{t,z} \qquad (2)$$

If a firm is being advertised/discussed by more than one influencer on a given day, then our "*Abnormal Sentiment*" variable will be calculated as the average abnormal sentiment of all influencers who posted about the firm on that day.

We use the change in sentiment – that we label as "Abnormal Sentiment" – as one of our main independent variables. This is to capture investors changing their expectation of brands' reputation based on the sentiment changing.

## A3. VADER Method for Analyzing the Sentiment of Influencers' Posts – Construct Validity

We assess the construct validity of the sentiment measure by examining its variation across the calendar year, particularly during the peak shopping season when we expect influencer posts to have higher sentiment scores.

Figure A2 illustrates the average sentiment for each month of the year throughout the sample period. The month-of-year influencer sentiment (IS) is hence calculated by assigning equal weight to each post on day *d* (results are similar when we assign weights based on the number of likes each post receives), and then by equally weighting the mean value of each day in each month of the year throughout the sample period.

$$\text{Daily IS} = \Sigma \text{Post Sentiment}_p \ / \ \text{Total Number of Posts}_d \tag{3}$$

$$\text{Month-of-year IS}_m = \Sigma \text{Daily IS} \ / \ \text{Total number of days in each month of the year } (m \in [1,12]) \text{ across the sample period} \tag{4}$$

Figure A2 provides evidence that our sentiment measure reflects the intended construct. First, the sentiment score of posts remains, on average, above zero, indicating that the influencers' posts usually have positive tones. This is consistent with the notion that influencers maintain a positive and pleasant tone in their communication to attract and maintain followers. Second, the sentiment score of posts rises sharply towards the end of the year. This likely reflects the strategy of influencers to step up their campaigns with the aim of generating excitement about products and driving sales up, allowing their firm-clients to capitalize on the holiday season. This season covers the end of the year and is regarded as the peak shopping season, including holiday shopping and top shopping events such as Cyber Monday and Black Friday.

[Figure A2]

## A4. Instagram Dataset - Overview

Table A1 presents summary statistics of the dataset obtained from Instagram, containing 368,677 firm-related posts from 4,763 mega influencers related to 546 listed firms. Panel A contains data pertaining to all posts. Panel B contains data for a subsample including sponsored posts, wherein influencers are paid by firms to advertise their products and services. These are the posts containing typical hashtags used by influencers to indicate that a post is sponsored, including "ad", "adv", "sponsor", "sponsored", "paidpartnership", "supplied", "suppliedby", "paidfor", "gift", "gifted" or a specific hashtag with the sponsor's name followed by the term "partner," for example, #nikepartner.[38] Panel C contains another subsample including all posts with a negative sentiment, namely those with a sentiment score lower than –0.05, which account for almost 8% of total posts. Arguably, many of these posts will criticize firms. Panel D contains data for the total posts but grouped across influencers.

[Table A1]

Considering total posts in Panel A, a post receives, on average, 31,236 likes and 325 comments. The median values being substantially lower than the mean values indicate the presence of positive outliers in the distribution of comments and likes. This likely reflects posts by top influencers with many millions of followers, receiving extreme numbers of likes and comments. This pattern is sustained in both groups of sponsored and negative sentiment posts. The mean and median of sentiment are larger than 0, indicating that influencers maintain a positive tone, on average, in their firm-related posts. Finally, on average, each post mentions only one firm. Considering that the

[38] Influencers employ various comprehensive methods to indicate if a post is sponsored. The primary approach involves placing a "Paid Partnership" or "Sponsored" tag at the top of the post, positioned just below their profile name. Alternatively, influencers may use one or more of the aforementioned hashtags. Unfortunately, the extraction of tags like "Paid Partnership" or "Sponsored" proved unattainable through web-crawling. Consequently, this data is not accessible to us. As an alternative, we resorted to the next best method, which involved identifying all posts containing the aforementioned hashtags. Considering that, when utilizing tags, there is no obligation for influencers to include any of the specified hashtags, we suspect that by relying exclusively on hashtags to identify post sponsorship, a substantial portion of sponsored posts might be overlooked. However, the number of sponsored posts we managed to identify remains high, despite representing a small portion of the total posts. Thus, we conjecture that the summary statistics of these posts will be representative of the total population of sponsored posts.

75th percentile value is also 1, it suggests that the majority of posts mention only one firm. This pattern holds for sponsored and negative sentiment posts too.

Comparing Panel B to Panel A, we observe that sponsored posts receive, on average, more likes and comments than non-sponsored posts. These posts also exhibit a higher sentiment, likely reflecting the influencers' efforts to promote the products and services they advertise. Comparing Panel C to Panel A, we observe that negative sentiment posts receive, on average, more likes and comments, although the difference is not large. Panel D shows that, on average, an influencer has published 77 posts during the sample period. The substantially lower median value indicates the presence of extreme positive outliers. This likely reflects a group of influencers who are extremely active and/or have been on Instagram for a longer period. Finally, an influencer has posted, on average, about 8 firms during the sample period.

The summary statistics reveal that among mega influencers there is a number of top influencers who manage to attract more attention from followers as manifested through the extreme number of comments and likes on their posts. To gain a sense of the types of individuals who are top influencers, Table A2 reports a number of characteristics of the top 5 influencers, as ranked by the average number of comments received on firm-related posts since they started posting on Instagram. We provide their usernames, real names, careers, the average number of comments and likes and the average sentiment score of their firm-related posts. The nature of these top influencers adds sense as to why they manage to attract more attention and generate more engagement with their posts.

[Table A2]

Finally, we have used hashtags to identify the content of the posts, excluding paid advertisements, in an attempt to gauge what influencers talk about in their posts. According to the 50 most frequently used hashtags in the posts of our dataset, influencers talk mostly about human relationships, travelling, food, fashion, fitness, animals, art, beauty, sports, events, and nature. There are also numerous posts focused on feel-good and motivational content, encompassing cheerful and uplifting messages, motivational messages, personal growth, and self-improvement content. Lastly, a broad category of posts focus on lifestyle, covering various aspects of everyday life, moments of reflection, personal achievements, challenges, and experiences shared with others.

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**Figure A1: Example of an Instagram Influencer Post**

This figure shows one of the mega influencer's posts on Instagram (https://www.instagram.com/p/Btr3QGmHS_B). The following information is obtained from the page: the influencer's account name (piawurtzbach), the content of the post, the hashtag (#Olay28daychallenge), the number of likes (88,118 likes), the date of the post (February 10, 2019), while the number of comments can be retrieved from the API.

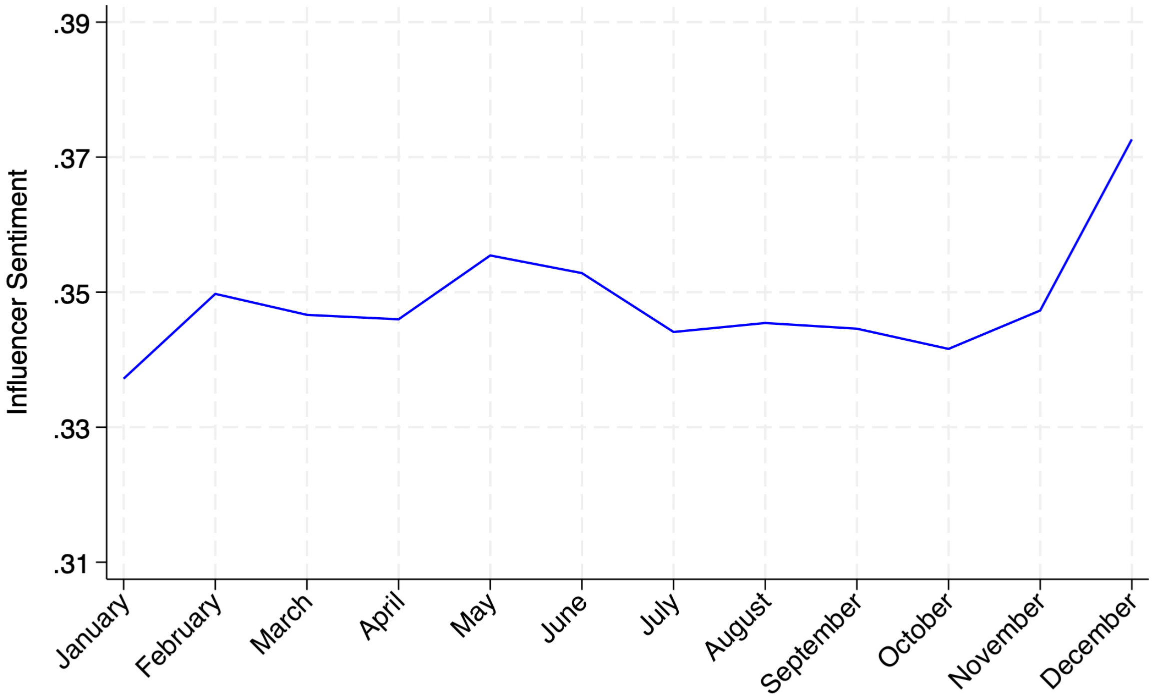


**Figure A2: Influencer Sentiment by Month-of-Year**

This figure illustrates the month-of-year sentiment of the influencers' posts from 2011 to 2022. The values are obtained by averaging the daily (mean value of) sentiment of the posts, across the sample period, according to the month of the year they were posted.

## Table A1: Summary Statistics

This table presents summary statistics of the dataset obtained from Instagram, containing 368,677 firm-related posts from 4,763 mega influencers related to 546 listed firms during March 2011 to December 2022. Panel A reports data on all posts. Panel B reports sponsored posts as identified by typical hashtags used by influencers to indicate that a post is sponsored, including "ad", "adv", "sponsor", "sponsored", "paidpartnership", "supplied", "suppliedby", "paidfor", "gift", "gifted" or a specific hashtag with the sponsor's name followed by the term "partner," for example, #nikepartner. Panel C includes all posts with a negative sentiment score, namely those with a sentiment score lower than -0.05 to be consistent with Hutto and Gilbert (2014). Panel D contains data for the total posts but grouped across influencers.

| | N | Mean | Std. Dev. | p25 | Median | p75 |
|---|---|---|---|---|---|---|
| Panel A: Total Posts | | | | | | |
| Likes | 368,677 | 31,235.717 | 116,642.619 | 2,590.000 | 8,489.000 | 25,789.000 |
| Comments | 368,677 | 325.008 | 6758.628 | 20.000 | 60.000 | 186.250 |
| Sentiment | 368,677 | 0.407 | 0.441 | 0.000 | 0.488 | 0.799 |
| Firms | 368,677 | 1.105 | 0.380 | 1.000 | 1.000 | 1.000 |
| Panel B: Sponsored Posts | | | | | | |
| Likes | 4,676 | 67,073.726 | 242,549.397 | 6,624.000 | 16,742.000 | 45,199.000 |
| Comments | 4,676 | 511.855 | 1791.203 | 49.000 | 133.000 | 324.000 |
| Sentiment | 4,676 | 0.669 | 0.382 | 0.526 | 0.835 | 0.942 |
| Firms | 4,676 | 1.113 | 0.376 | 1.000 | 1.000 | 1.000 |
| Panel C: Negative-Sentiment Posts | | | | | | |
| Likes | 30,295 | 32,680.579 | 104,298.332 | 2,903.000 | 9,035.000 | 28,102.000 |
| Comments | 30,295 | 381.321 | 1736.266 | 23.000 | 70.000 | 225.000 |
| Sentiment | 30,295 | -0.452 | 0.236 | -0.624 | -0.402 | -0.273 |
| Firms | 30,295 | 1.057 | 0.271 | 1.000 | 1.000 | 1.000 |
| Panel D: Influencers | | | | | | |
| Posts | 4,763 | 77.113 | 374.361 | 4.000 | 12.000 | 38.000 |
| Firms | 4,763 | 8.454 | 9.904 | 2.000 | 5.000 | 11.000 |

## Table A2: Top Influencers

This table reports the top 5 influencers, as ranked by the average number of comments received on firm-related posts since they started posting on Instagram. We provide their usernames, real names, careers, the average number of comments and likes and the average sentiment score of their firm-related posts.

| Username | Real Name | Main Career | Comments | Likes | Sentiment |
|---|---|---|---|---|---|
| realdonaldtrump | Donald Trump | President of the USA | 129,659.903 | 104,401.290 | 0.349 |
| hilaryduff | Hilary Duff | Actress | 93,137.000 | 1,225,656.333 | 0.278 |
| kyliejenner | Kylie Jenner | Social Media Personality | 76,604.500 | 733,480.000 | 0.369 |
| eminem | Eminem | Singer | 53,411.000 | 3,871,827.000 | 0.647 |
| kendalljenner | Kendall Jenner | Social Media Personality | 50,647.500 | 994,786.000 | 0.291 |