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The Impact of Social Media Activities on Stock Price Informativeness

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ABSTRACT

This study investigates the influence of social media activities on stock price informativeness. Using a panel of 49 countries with 231,462 balance-panel firm-year observations from 2010 to 2020, we find that social media activities increase stock price informativeness. Furthermore, social media engagement for political and civil activities reduces information asymmetries that are linked to greater stock price informativeness. We further evidence that the intensity of the impact of social media activities varies between economic development and sectors, which implies that while some of the social media activities proxies are more pronounced in developed countries, others are more pronounced in emerging economies. The same applies to the services and non-services sectors. The result is more pronounced when varying offline political actions are most commonly mobilised on social media. For identification, we employ principal component analysis, difference-in-difference, and propensity score matching.

JEL Classification: G10, G14, G30

1 | Introduction

Earlier studies have shown information plays a significant role in understanding the volatility of asset prices (Grossman and Stiglitz 1980). Firms directly provide a key element of the information through public disclosure. Recent literature documents that firm-level transparency, derived through better financial disclosure and reporting, reduces stock price synchronicity (Jiang et al. 2013; Kim and Shi 2012; Jin and Myers 2006). This is consistent with the view that quality financial disclosure improves the ability of firm-specific information to be incorporated into stock prices. Quality financial reporting and disclosure are self-generated transparency by the firms.

This study broadly examines externally generated new forms of unexpected, timely, less expensive, and ubiquitous firm information through social media. For instance, posts on social media about Netflix's monthly viewing exceeding 1 billion caused Netflix's stock price to increase by over 20%. Under RegFD, firms have the approval of the Security and Exchange Commission (SEC) to communicate and disseminate "essential information" to investors through social media which bypasses the traditional means of disseminating information to investors.

Existing studies have shown how firms' internally generated transparency through disclosure enhances stock price informativeness. Arguably, firms may be reluctant to report fraud and corrupt activities within the company. This leaves a gap in the literature concerning external transparency. We argue that external transparency, generated via social media, can incorporate firm-specific information into stock prices to make them more informative. This study fills the gap left by corporate financial disclosure and reporting. The press and social media serve as a watchdog and monitoring function (Miller 2006) which reduces stock price synchronicity.

Using panel data of 49 countries for the period 2010–2020, we examine whether social media activities have varying impacts on stock price informativeness. We find that social media activities improve stock price informativeness. We interpret this evidence as supportive of our hypothesis that as investors become more informed about a firm's performance via social media, it enhances the ability to incorporate firm-specific information into stock prices. The results are robust to an alternative measure of social media. We perform several tests to alleviate the concern about potential endogeneity as a result of omitted variable bias and reverse causality. Our results are robust to principal component analysis, fixed effects, system GMM, difference-in-differences, placebo test, hierarchical cluster analysis, and heteroscedasticity-fixed difference. We find consistent results showing that social media activities incorporate firm-specific information into stock prices and thus reduce stock price synchronicity.

The purpose of the study is to examine the externallygenerated disclosure explanation for stock price informativeness by conducting several analyses designed to evaluate the effect of social media on stock price informativeness. Our analysis builds on Al Guindy (2021), who investigated corporate Twitter use and the cost of equity capital. The study makes several contributions to the emerging social media literature, stock price informativeness, and externally generated disclosure. First, the study extends the stock price informativeness and the price efficiency literature by identifying the role social media plays in reducing stock price synchronicity. Second, the study is the first to use six measures to proxy for social media engagement following the theories of investor attention. Third, the research contributes to the burgeoning social media literature (Al Guindy and Riordan 2017) and concurrent studies that examine measures that impact stock price informativeness (see Kelly 2014; Fernandes and Ferreira 2009).

The results have several implications. Following RegFD, firms can enhance the informativeness of their stock prices through social media engagement. This will generate external transparency. When information disclosure between investors increases, it will exacerbate information-based trading. Firms may not have the choice of either being subject to lower or greater information asymmetries. For instance, firms in certain industries may be more exposed to information asymmetries. Social media engagement will reduce information asymmetries for smaller firms followed by few analysts, less active shareholders, and small institutional shareholders. Aslan et al. (2011) document that information risk is higher in firms with few shareholders and small turnover. Understanding how social media impacts firm-specific information flow is important to regulators, academics, and investors as it enhances the efficient and optimal allocation of resources that are contingent on the information.

The rest of the paper is organised as follows. Section 2 provides the relevant literature review and hypothesis development. Section 3 describes the variables and data sources. Section 4 provides the empirical analysis. Section 5 concludes the paper.

2 | Related Literature Review

The economic literature shows the key role the media plays in knowledge transmission and transparency. The media exposes corruption, keeps checks on public policy, empowers people with quality information to make better choices, and gives voice to the citizens. Earlier studies document that the media can make the stock market work well by facilitating trade and transmitting ideas (The World Development Report 2002).

Much of the literature implicitly assumes that the media could potentially contribute to economic performance when they satisfy three conditions: media independence, broad coverage, and provision of quality information. The media can increase the accountability and transparency of government and businesses via reputational and monitoring penalties, which help investors to make informed decisions. Dyck et al. (2008) document how the media can exert pressure on corporate managers and directors to behave ethically. Dyck et al. (2008) find from a survey in Malaysia that institutional and individual equity investors consider the frequency and nature of public and press comments to be more important when making investment decisions to invest in publicly listed companies (Tetlock 2007; Tetlock et al. 2008). The media can play an effective role if it is independent, provides quality information, and has a broader reach. Evidence shows that there are wide variations in press freedom across countries.

The recent emergence of social media has improved the information investors can access about companies. The RegFD encourages companies to disseminate information through social media. This reduces the cost associated with the information asymmetries between investors and corporate managers (Myers and Majluf 1984). Social media presents a unique platform for firms to communicate information at a lower cost. A growing literature documents the importance of the media in the financial markets (see Engelberg and Parsons 2011; Fang and Peress 2009). Neuhierl et al. (2013) show that investors react to corporate press releases. Da et al. (2011) document that stock prices are predicted by the Google Search Volume Index (SIV). Chen, Ding et al. (2014) find that stock options on the financial crowd-sourced platform Seeking Alpha predict stock returns.

Recent studies show that investors and corporations gather information dissemination. For instance, Al Guindy (2021) finds that corporate Twitter use reduces the cost of equity capital. Blankespoor et al. (2014) document that firms that use Twitter to communicate information experience a lower bid-ask spread. Jung et al. (2018) find that S&P 1500 firms that experience less press coverage usually use Twitter to disseminate earnings announcements.

Chen et al. (2023) show that personal tweets by CEOs/CFOs increase the investor base and also improve stock liquidity. A recent study by Chawla et al. (2021) documented that disseminating news on Twitter contributes to positive price pressure and reduces bid-ask spreads. Solomon et al. (2014) show that media coverage contributes to investors chasing past returns.

What is missing from the current literature is whether the use of social media platforms for organising offline protests and civil unrest can have implications for the informativeness of stock prices. Social media can exacerbate information asymmetry in financial markets, particularly during periods of unrest. Information asymmetry occurs when one group of market participants has access to information that others do not, leading to an imbalance in decision-making and stock price movements. In the context of social media-organised violence, information asymmetry can arise from the selective dissemination of news, rumours, or misinformation. For instance, if certain investors have access to more accurate or timely information about unrest due to their networks or technological tools, they may be able to make more informed decisions than others. This creates a gap in stock price informativeness, as prices may not fully reflect the underlying risks or opportunities present in the market. Furthermore, the decentralised nature of social media platforms means that rumours and misinformation can spread quickly, leading to irrational market reactions that do not align with the actual economic impact of the unrest (Naeem 2021). In such cases, stock prices may temporarily reflect exaggerated risks or losses, only to correct once more accurate information becomes widely available.

In this study, we provide new evidence that sheds light on social media engagement and stock price informativeness. In recent years, the economic outcomes of social media have emerged as a developing theme in financial literature. Firms use Twitter and Facebook to communicate annual reports. Al Guindy (2021) finds that firms that communicate information through social media experience a lower cost of capital. For instance, social media has emerged as the most important channel for investors and firms to overcome some of the difficulties and challenges in communicating with investors. Blankespoor et al. (2014) show how corporate managers use social networks, news releases, and corporate websites to provide a balanced disclosure.

As investors start to rely on social media to gather financial information, it will enhance the informativeness of stock prices. This is consistent with the view that it will improve firms' external transparency and cheaper information gathering. Other studies show that firms are selective in using social media to communicate information (Jung et al. 2018). The emerging literature on social media can be categorised into three main strands: social media use by corporate managers (Chen et al. 2023), social media use by investors (Bartov et al. 2018; Chawla et al. 2021), and social media use by corporations. This study falls under the stock price informativeness of social media used by firms to communicate information to investors.

The long-term impact of social media-organised offline violence on investor decisions can be profound, particularly in regions or industries that are repeatedly affected by unrest. If investors perceive that a company or geographic region is particularly vulnerable to social unrest, they may reallocate their investments to avoid ongoing risks. This can lead to reduced capital inflows, lower stock valuations, and increased borrowing costs for companies operating in these areas.

Companies that are frequently impacted by social unrest may also face reputational damage, as investors and consumers alike may associate them with instability and risk. This is especially true for industries that have significant physical assets or rely heavily on consumer foot traffic, such as retail or hospitality. In such cases, investors may view these companies as inherently riskier, leading to lower stock price informativeness as prices reflect broader concerns about the company's prospects rather than its underlying financial performance.

2.1 | Theoretical Framework and Hypothesis Development

Investors access financial information through Google and social media. Investors increase their searches on Google and social media, which suggests investors' attention to gathering information from other sources. Prior research has shown that investors depended on financial advisors, financial analysts, the business press, short-sellers, auditors, and credit rating agencies to access value-relevant and timely information to make investment decisions. With the emergence of the internet, investors now rely on Ranging Bull, Yahoo Finance, and Silicon to collect information about firms.

In recent times, the emergence of social media has enhanced the dissemination of corporate information flow to investors. For instance, Twitter allows investors to access instantaneous information about firms' financial performance to make investment decisions. Social media provides an exciting and emerging new source of information to the capital market. Investors can use Twitter to access Wisdom of Crowds where non-expert aggregate information could precisely predict stock outcomes relative to the opinions of financial experts.

Consistent with the view that social media users have a diverse financial background, investors are unlikely to engage in hedging activities which are more prevalent in conventional information intermediaries such as financial analysts. Further, social media portals including investing portals and blogs allow investors to use a central piece of information that is posted on Twitter. The short characteristics format required by Twitter makes it easier for investors to access useful information in a precise manner. Since the social media platforms were launched, several studies have examined their effects on several economic outcomes. Bartov et al. (2018) investigated whether tweets of individual opinions before a firm's earnings announcement can predict announcement and earnings returns.

Recent studies have examined the role social media plays in the stock market. Evidence shows that firms that use social media to communicate financial information to investors increase the information available to investors and have effects on stock price informativeness. For example, firms provide links to corporate press releases and disclosures through social media (Blankespoor et al. 2014). Jung et al. (2018) show that half of S&P 1500 firms have created FaceBook and Twitter accounts and mainly communicate with investors via Twitter. An earlier study by Lee et al. (2015) finds that firms use Twitter to interact with investors to reduce the negative price effects of consumer product recalls.

Another strand of the literature has investigated whether investors can use information from social media to predict stock prices. Bollen et al. (2011) document that investors can predict changes in the Dow Jones Index from the aggregate mood on daily Twitter feeds. This is consistent with the study by Mao et al. (2012) who show that a daily number of tweets that mention S&P 500 stocks substantially relate to the levels, changes, and absolute changes in the S&P 500 index.

The literature also shows that social media influences investors in corporate earnings. For instance, Curtis et al. (2016) show that greater levels of earnings announcement return to earnings surprises, while substantial post-earnings announcement deviation reduces social media activities. Previous studies have examined how investors use platforms such as financial websites, forums, and social media for financial information. Da et al. (2011) find that higher stock prices are predicted by an increase in Google searches. Further, Drake et al. (2012) document that return earnings relate to smaller Google search Volume in the period leading to an earnings announcement. Evidence shows that investment reports in Motley Fool can predict stock returns (Hirschey et al. 2000).

Stock return volatility is positively associated with the volume of messages on Yahoo and Bull message boards (see Antweiler and Frank 2004; Das and Chen 2007). Jame et al. (2016) find that the Estimize platform provides a crowdsourced earnings forecast that offers incremental value –relevant information to the capital market can predict earnings and calibrate the stock market predictions of earnings. Chen, Ding et al. (2014) find that investors can use the information generated from Seeking Alpha to predict long-window stock returns and earnings. This suggests that investors can obtain firm-specific information from social media as it enhances the greater dissemination of information.

Investors who follow firms' social media accounts gain instant access to information through the notification of corporate news. The news can instantly be shared with their followers and friends. Facebook and Twitter users can have an interactive discussion with other users. This enhances the information flow about the firm and rational assessment of information.

Investors need the information to understand stock price movement. In addition to the traditional firm disclosure channel through annual reports, social media increases the amount of information available to determine the informativeness of stock prices at a relatively low cost. Morris and Shin (2002) find that less costly information increases stock price informativeness. When firms tweet, timely information is quickly released, and investors can access the information at a cheaper cost. This is contrary to the long-standing model of communication whereby corporations use press releases to communicate information to institutional investors, analysts, and journalists. Myers and Majluf (1984) show that the cost of managers releasing low-value information could exceed the benefit. How the use of social media—Twitter and Facebook can—enhance the timely release of small information, which can improve the incorporation into stock prices. More importantly, it is less expensive for firms to tweet relative to the preparation of voluntary disclosure.

Social media serves as an early warning system, providing investors with real-time information about the potential for disruptions that could harm company assets, reduce consumer demand, or lead to regulatory consequences. One of the primary ways in which social media-organised offline violence influences investor decisions is through heightened risk perception. Investors, especially those with stakes in companies operating in regions affected by unrest, are likely to reassess their portfolios when the risk of violence increases. Chen, Ding et al. (2014) demonstrated that civil unrest, even when not directly targeting specific companies, can lead to declines in stock prices due to increased perceptions of risk. When investors observe signs of impending unrest or violence on social media, they may pre-emptively adjust their portfolios to mitigate exposure to potential losses. This heightened risk aversion can lead to short-term declines in stock prices, especially for companies with significant operations in affected areas. Further, the uncertainty surrounding the duration and severity of unrest can exacerbate these effects, as investors face difficulties in accurately predicting how long the disruption will last and what the full economic impact will be.

Social media acts as a conduit for information dissemination, and the real-time nature of these platforms allows investors to quickly respond to evolving events. However, this can also lead to overreaction or underreaction, depending on the quality and clarity of the information being shared. For instance, during the George Floyd protests in the United States, there was significant use of social media platforms to organise protests that, in some cases, turned violent. Companies with physical assets in areas affected by the unrest, such as retail stores or warehouses, experienced sharp declines in stock prices as investors reacted to the potential for property damage and disruptions in business operations (Wang and Zuo 2020). Similarly, protests in Hong Kong in 2019, which were widely organised and publicised through social media, led to fluctuations in the Hong Kong stock market as investors weighed the potential long-term impact on the region's economy and business environment (Huo and Wang 2020). These events demonstrate how social media-organised violence can trigger significant market reactions, often resulting in increased stock price volatility. Investors may initially overreact to news of unrest, leading to sharp declines in stock prices, followed by corrections as more information becomes available and the true impact of the events is better understood. This volatility is compounded by the speed and accessibility of social media, which allows both accurate and inaccurate information to spread rapidly, making it difficult for investors to separate fact from speculation. Following the above discussions, we develop the following hypothesis.

H1. *Social media enhances the informativeness of stock prices.*

3 | Data and Variables Descriptions

Our initial sample consisted of 52 countries with a total of 48,856 companies. Following the elimination of the firms with missing stock price data, firms with missing data, firms with incomplete and extreme data, as well as firms whose country-level data are missing, our final data comprised 21,042 covering a period of 11 years from 2010 to 2020 (i.e., resulting in 231,462 balanced-panel firm-year observations within 49 countries). Table 1 provides detailed sample selection procedures.

TABLE 1 | Sample selection procedure.

Panel A: sample selection	Frequency	Percentage
Initial sample	48,856	100.00
Less: firms with missing data	17,523	35.87
Less: firm with incomplete and extreme data	10,291	21.06
Total usable sample	21,042	43.07
Panel B: sector distribution		**Percentage**
Basic materials	2590	12.31
Consumer cyclicals	3828	18.19
Consumer non-cyclicals	1964	9.33
Energy	1353	6.43
Financial services	794	3.77
Health care services	1085	5.16
Industrial	4527	21.51
Real Estate	1595	7.58
Technology	2724	12.95
Utility	582	2.77
Total	21,042	100.00

3.1 | Dependent Variables

Our main dependent variable is stock price informativeness (firm-specific stock return variation also referred to as idiosyncratic risk) for each country. We source our stock price monthly data from the Eikon DataStream for 21-year period from January 2000 to December 2020. In line with Fernandes and Ferreira (2009), we argue that stock return modernisations linked to common factors or market returns are the sources of systematic risk. In this context, we measure these risks based on the regression of equity returns on the market factors. We use the market model, for each firm-year, projection of a stock's excess return on the market using the following model:

$$\mathrm{r}_{j,t} = \alpha_j + \beta_j r_{m,t} + e_{j,t} = \alpha_j + \frac{\delta_{jm}}{\delta_m^2} r_{m,t} + e_{j,t}, \quad (1)$$

With E $(e_{j,t}) = \mathrm{Cov}\ (r_{m,t},\ e_{j,t}) = 0$; where $\mathrm{r}_{j,t}$ is the return of stock j in months above the risk-free rate; $r_{m,t}$ is the value-weighted excess local market return. $r_{m,t} = \sum_j \omega_{j,t} r_{j,t}$ where, $\omega_{j,t}$ is the weight of firm j in month t; $\delta_{jm} = Cov(r_{j,t},\ r_{m.t})$; and $\delta_m^2 = Var(r_{m.t})$. Firm-specific return variation is estimated for each firm-year as

$$\delta_{je}^2 = \delta_j^2 - \frac{\delta_{jm}^2}{\delta_m^2} \quad (2)$$

Following Fernandes and Ferreira (2009), we used the absolute firm-specific return variation δ_{je}^2, to compute the relative firm-specific return variation, that is the ratio of idiosyncratic volatility to total volatility $\frac{\delta_{je}^2}{\delta_j^2}$, which simply $1 - R_j^2$ of Equation (1). See Equation (3).

$$\varphi_j = \log\left(\frac{1 - R_j^2}{R_j^2}\right) = \log\left(\frac{\delta_{je}^2}{\delta_j^2 - \delta_{je}^2}\right) \quad (3)$$

Therefore, our dependent variable φ_j measure firm-specific stock return variation relative to market-wide variation, or lack of synchronicity with the market. We scale firm-specific stock return variation by total variation for comparability with other researchers such as Morck et al. (2000) and Fernandes and Ferreira (2009) who argue that firms in some countries are more subject to economic-wide shocks than others, and therefore firm-specific events can be correspondingly more intense.

3.2 | Key Explanatory Variables

Existing literature such as Sul et al. (2017) and Li et al. (2019) have used dummy variables to proxy for a firm's use of social media to communicate information to stakeholders. This is consistent with the view that there is no data on social media usage. However, social media use by people to engage in other activities including political activities reflects social media engagement. Consistent with theories of investor attention, we argue that social media users are also investors who, while already online, regularly access other financial information. Evidence shows that social media users online access financial blogs (Chen, De et al. 2014) and Google (Drake et al. 2012; Da et al. 2011). This suggests that when people use social media to engage in political activities, they will have access to information communicated by companies and managers. Monitoring the Twitter feeds of companies while using social media to follow interesting videos, news, family members, and political activities reduces the cost of monitoring firms.

Social media continues to fundamentally transform how people communicate, organise, and mobilise for a wide range of activities, including positive engagement. It can also serve as a platform for organising offline protests and civil unrest. The widespread availability of social media platforms allows individuals or groups to coordinate large-scale gatherings that can escalate into violence, leading to economic instability. There have been evident in various global events, from the Arab Spring to recent protests across the United States and other parts of the world. From an investor's perspective, social media-fuelled unrest introduces a new layer of unpredictability into the market. The ability to rapidly mobilise large groups of people can lead to sudden disruptions in business operations, supply chains, and consumer behaviour. Investors are particularly sensitive to these risks, as they can affect company revenues, property damage, and public perceptions of safety in specific regions. Social unrest can also lead to broader economic destabilisation, which can, in turn, affect the stock market and investor confidence.

Prior studies document that investors react swiftly to events that pose significant risks to market stability. For instance, Chen, Ding et al. (2014) demonstrated that civil unrest, even when not directly targeting specific companies, can lead to declines in stock prices due to increased perceptions of risk. When investors observe signs of impending unrest or violence on social media, they may preemptively adjust their portfolios to mitigate exposure to potential losses. This heightened risk aversion can lead to short-term declines in stock prices, especially for companies with significant operations in affected areas. Moreover, the uncertainty surrounding the duration and severity of unrest can further amplify these effects, as investors face difficulties in accurately predicting how long the disruption will last and what the full economic impact will be on market reactions and stock price volatility.

Following the above, we use the following variables to proxy for social media engagement. (1) The extent to which people employ social media to organise offline violence (*SMOOV*). This variable is constructed to capture the extent to which people have used social media to organise offline violence. The variable captures if there have been frequent cases, few cases, or people have never used social media to organise offline violence (see Pemstein et al. 2021). (2) How often do people use social media to organise offline political action of any kind (*SMOOPA*). (3) How often do domestic elites use social media to organise offline political action of any kind (*SMOOPAK*)? This is constructed by converting ordinal responses of whether domestic elites have never, rarely, sometimes, or often used social media to organise offline political action (see Mechkova et al. 2024). (4) Varying offline political action is most mobilised on social media (*VOPAMSM*). (5) The extent to which people consume domestic online media (*PCDOM*). (6) Other types of organisations through social media (*OTOTSM*). The idea for using the variables to proxy for social media engagement is that there is no fuzzy distinction between using social media for other activities. We obtained data from the V-Dem Institute maintained by the University of Gothenburg.

3.3 | Control Variables

We control the effects of several variables on stock price informativeness. We argue that various country-level variables that capture macroeconomic and institutional characteristics of the countries may have an impact on stock price informativeness. Studies such as Li et al. (2017) and Sul et al. (2017) argue that the country's macroeconomic features such as export and import rate, gross domestic product growth rate, stock traded rate, stock turnover rate, interest rate, and inflation rate influence stock price variation. Therefore, in line with Nguyen et al. (2012) and Nofer and Hinz (2015), we argue that the extent to which these features are reported in social media may significantly influence stock price informativeness. We, therefore, control for the sum of imports and exports as a percentage of GDP (*TGDP*), the growth rate of gross domestic product (*GDPG*), the stock traded to total value as a percentage of GDP (*STV*), real interest rate (*RIR*), stocks traded turnover ratio of domestic shares in percentage (*STT*), inflation GDP inflector in percentage (*IGD*) and official exchange rate (*EXR*). We sourced the data from World Bank. We also argue that the extent to which social media activities affect stock price informativeness varies between sectors, as some of the sectors may intensively consider social media for their daily trading activities while others are less likely sensitive to social media activities. We, therefore, control for sector effect in all our regression.

3.4 | Model Specification

Consistent with previous studies on social media activities and stock price informativeness (Nofer and Hinz 2015; Li et al. 2017; Sul et al. 2017), we adopted the annual time-series cross-sectional regression estimation and conducted our multiple regression using the ordinary least squares (OLS) regression technique to test our hypotheses. Our basic regression model is specified as follows:

$$SPI_{it} = \alpha_0 + \beta_i Sm_{it} + \sum_{i=1}^{20} \beta_i Cv_{kit} + \mu_{it} + \varepsilon_{it} \tag{4}$$

where the dependent variable $\boldsymbol{spi_{it}}$ denotes the winsorized[1] stock price informativeness which is the firm-specific return variation. The Sm_{it} refers to the social media activities measured as *VOPAMSM*, *PCDOM*, and *OTOTSM*. Also, for the robustness test, we consider the alternative measure of social media activities such as *SMOOV*, *SMOOPA*, and *SMOOPAK*. The Cv_{kit} is a set of control variables (IQ, GDPP, GDPG, TGDP, IP, ADS, VA, PV, STV, STT, RIR, IGD & EXR)[2], k, for the firm 'i' in year 't,' where $k = 1$ to $n = 21{,}042$. μ_{it} represents country-specific characteristics and ε_{it} represents the unobserved error term clustered in sectors. All models are run with robust standard error. To capture unobservable firm-level and country-level differences (such as firm complexity, and institutional differences), in line with Nguyen et al. (2012), we use fixed effect (FE) panel regressions without instruments and instrumental fixed effect Two Stage Least Square (Fe-2SLS). In line with Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998), we used system-GMM estimation to account for endogeneity, simultaneity, and heterogeneity concerns. Further, we employed principal component analysis, propensity score match, the difference in difference, and pseudo regressions to enhance and inform our finding's robustness. All variables employed in the empirical analysis are fully defined in Appendix A.

4 | Empirical Analysis

4.1 | Descriptive Statistics and Correlation Analysis

Table 2 presents the descriptive statistics for the full sample. The table shows that the stock price informativeness ranges between −104.215% and 6.881, with an average of −10.265, skewed to the left. The table shows that the extent to which other types of organisations through social media evidence higher performance (0.254) relative to the extent to which people consume domestic online (−0.003) and offline political action is commonly mobilised on social media (−0.403). Also, more than 25% of *OTOTSM*.

The correlation analysis results reported in Table 3 show that VOPAMSM, *PCDOM*, and *OTOTSM* are positively associated

TABLE 2 | Descriptive analysis.

Variable	Obs	Mean	Std. Dev.	Min	Max
SPI	231,462	−10.265	15.246	−104.215	6.881
VOPAMSM	231,462	−0.405	1.020	−2.197	2.069
PCDOM	231,462	−0.003	1.191	−2.685	2.210
OTOTSM	231,462	0.249	1.219	−2.398	2.497
IQ	231,462	2.201	0.495	1.167	2.917
GDPG	231,462	3.370	2.284	−1.249	9.551
TGDP	231,462	3.989	0.625	3.262	6.054
IP	231,462	0.830	0.169	0.455	1.000
ADS	231,462	1.818	0.656	1.000	3.000
VA	231,462	0.788	0.178	0.375	1.000
PV	231,462	0.702	0.092	0.473	0.852
STV	231,462	96.619	112.621	0.000	626.704
STT	231,462	79.604	67.850	0.000	262.428
RIR	231,462	2.153	2.814	−2.014	16.903
IGD	231,462	2.241	2.684	−1.895	13.906
EXR	231,462	173.670	935.522	0.000	8770.430

with stock price informativeness, indicating that they are more likely to stabilise the stock price variation, which provides initial support to our hypotheses. The highest VIF reported in Table 2 is 7.86, which is below the threshold of 10, indicating that multicollinearity is not a concern in our data.

4.2 | Social Media Activities and Stock Price Informativeness

This section uses a panel regression estimation to test the relationship between social media activities and stock price informativeness. Table 4 reports panel regression results, together with their robust t-statistics. We show in Model 1 *VOPAMSM* is positively related to stock price informativeness. Consistent with theoretical expectations, social media activities proxied by *VOPAMSM* are positive and statistically significant at the 1% level. The coefficient on *VOPAMSM* is 1.417 *(t-statistics = 25.52)*. In Models 2 and 3, there is a positive relationship between *PCDOM* and *OTOTSM* stock price informativeness, respectively. The coefficient on *PCDOM* and *OTOTSM* is 0.440 *(t-statistics = 9.19)* and 0.965 *(t-statistics = 19.31)*. Therefore, the findings support our first hypothesis (H1), which predicts that social media improves the informativeness of stock prices.

This implies that a one standard deviation increase in social media activities leads to an increase in stock price informativeness 1.445 [(1.417*1.020), *t-statistics = 25.52*, significant at 1%], 0.524 [(0.440*1.191), *t-statistics = 9.19*, significant at 1%], and 1.153 [(0.965*1.195), *t-statistics = 19.31* significant at 1%], for *VOPAMSM, PCDOM*, and *OTOTSM, respectively*. Economically, these results imply that with a one standard deviation change (increase) in using social media activities, the stock price informativeness is stabilised ranging from 68.91% [100(exp(0.524) − 1)] to 362.44% [100(exp(1.531) − 1)]. This implies that of all our social media proxies, the *VOPAMSM* impact on the stock price informativeness plays a significant role in the stabilisation of the market. Thus, managers may rely on social media activities in their investment decision-making with significant confidence; they provide timely information which is very sensitive to how the market reacts.

To capture unobservable firm-level and country-level differences (such as firm complexity, and institutional differences), we use fixed effect (FE) panel regressions and further instrumented the macroeconomic variables with their lagged effect to run instrumented fixed effect two-stage least square (FE-2SLS)[3]. The coefficient on *VOPAMSM, PCDOM*, and *OTOTSM* continues to be statistically significant at the 1% level in both fixed effect and FE-2SLS.

The results are in line with the theoretical argument that social media activities improve the informativeness of stock prices. The results provide reinforcing evidence that varying social media activities across developed and developing countries are strongly and positively associated with international differences in stock price informativeness. An important effective strategy in stock price informativeness is knowledge transmission. Greater social media engagement improves the quality of information available to investors to make better investment choices. Social media reduces natural information asymmetry. Being independent and having broad reach, investors can access quality information. Evidence shows that institutional investors and equity analysts consider the frequency and nature of public and press comments about companies in their decision to invest in publicly listed companies (see Survey done in Malaysia).

TABLE 3 | Correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	VIF
(1) SPI	1.000																
(2) VOPAMSM	0.086	1.000															3.42
(3) PCDOM	0.044	0.616	1.000														3.02
(4) OTOTSM	0.078	0.727	0.480	1.000													3.72
(5) IQ	−0.004	0.355	0.114	0.534	1.000												7.86
(6) GDPG	−0.006	−0.284	0.091	−0.442	−0.483	1.000											2.40
(7) TGDP	0.038	−0.017	0.014	−0.042	0.022	0.034	1.000										2.23
(8) IP	−0.016	0.269	−0.028	0.412	0.852	−0.503	0.132	1.000									7.01
(9) ADS	0.050	0.115	0.480	−0.013	−0.259	0.283	0.347	−0.350	1.000								2.27
(10) VA	0.014	0.140	−0.092	0.423	0.707	−0.444	−0.168	0.539	−0.341	1.000							3.59
(11) PV	0.005	0.412	0.108	0.473	0.624	−0.447	0.195	0.733	−0.211	0.308	1.000						3.25
(12) STV	−0.121	−0.085	−0.024	−0.091	0.183	−0.083	0.479	0.372	0.056	−0.174	0.378	1.000					3.23
(13) STT	−0.116	0.077	0.211	0.010	−0.054	0.098	−0.239	−0.022	−0.012	−0.291	0.153	0.476	1.000				3.54
(14) RIR	−0.078	−0.205	−0.148	−0.246	−0.309	0.107	−0.029	−0.215	−0.105	−0.114	−0.168	−0.027	−0.005	1.000			1.78
(15) IGD	−0.057	−0.231	−0.096	−0.246	−0.448	0.276	−0.027	−0.416	0.040	−0.269	−0.400	−0.084	−0.056	−0.007	1.000		2.24
(16) EXR	−0.011	−0.067	−0.081	−0.027	−0.165	0.081	−0.038	−0.114	0.074	−0.123	−0.101	−0.076	−0.055	0.126	0.073	1.000	1.13

Note: All value (+/−) > 0.004 are significant at 1%.

TABLE 4 | The impact of social media on stock price informativeness (SPI).

	OLS results			Fixed effect results			Fixed effect-2SLS results		
	1	2	3	4	5	6	7	8	9
VOPAMSM	1.417***			0.466***			2.134***		
	(25.52)			(4.76)			(23.15)		
PCDOM		0.440***			0.827***			2.392***	
		(9.19)			(9.58)			(29.49)	
OTOTSM			0.965***			0.996***			2.655***
			(19.31)			(12.83)			(36.03)
IQ	−2.475***	−2.008***	−2.260***	9.031***	9.572***	10.539***	6.206***	6.421***	8.679***
	(−11.93)	(−9.47)	(−10.98)	(13.00)	(13.93)	(14.88)	(8.59)	(9.02)	(12.06)
GDPG	−0.199***	−0.346***	−0.178***	−0.041*	−0.065***	−0.020	0.281***	0.182***	0.323***
	(−8.55)	(−14.60)	(−7.69)	(−1.93)	(−3.05)	(−0.95)	(11.23)	(7.23)	(12.95)
TGDP	2.459***	2.316***	2.072***	2.899***	2.828***	3.117***	2.688***	2.428***	3.142***
	(20.95)	(19.78)	(18.30)	(22.13)	(21.76)	(23.74)	(19.11)	(17.20)	(22.43)
IP	0.810	0.733	0.722	4.251***	4.176***	3.728***	1.817***	2.437***	1.677***
	(1.60)	(1.44)	(1.43)	(8.83)	(8.68)	(7.74)	(3.05)	(4.09)	(2.83)
ADS	0.607***	0.731***	0.855***	−3.102***	−2.836***	−2.942***	0.001	0.279	−0.104
	(6.54)	(7.30)	(9.24)	(−4.05)	(−3.70)	(−3.84)	(0.00)	(0.16)	(−0.06)
VA	2.830***	0.598	−0.087	−14.040***	−14.762***	−14.692***	−13.356***	−16.939***	−17.650***
	(6.56)	(1.38)	(−0.20)	(−8.79)	(−9.28)	(−9.26)	(−7.44)	(−9.40)	(−9.82)
PV	−5.217***	0.073	−2.521***	−13.402***	−13.581***	−11.736***	−15.274***	−15.122***	−11.720***
	(−6.89)	(0.10)	(−3.43)	(−12.84)	(−13.06)	(−11.44)	(−13.07)	(−12.95)	(−10.03)
STV	−0.011***	−0.015***	−0.012***	−0.013***	−0.014***	−0.015***	−0.029***	−0.033***	−0.034***
	(−15.35)	(−21.14)	(−17.10)	(−17.07)	(−18.61)	(−19.85)	(−40.13)	(−46.02)	(−46.84)
STT	0.004***	0.001	0.000	0.010***	0.010***	0.011***	−0.006***	−0.007***	−0.003***
	(3.17)	(1.05)	(0.31)	(7.82)	(7.56)	(8.80)	(−6.54)	(−7.18)	(−3.34)
RIR	−0.107***	−0.155***	−0.111***	−0.301***	−0.307***	−0.315***	−1.245***	−1.240***	−1.262***
	(−5.17)	(−7.48)	(−5.39)	(−15.34)	(−15.71)	(−15.97)	(−69.37)	(−69.15)	(−70.44)
IGD	−0.124***	−0.204***	−0.187***	−0.084***	−0.103***	−0.186***	−1.073***	−1.045***	−1.237***

(Continues)

TABLE 4 | (Continued)

	OLS results			Fixed effect results			Fixed effect-2SLS results		
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
	(−6.05)	(−9.91)	(−9.18)	(−4.26)	(−5.22)	(−8.73)	(−54.82)	(−55.17)	(−60.66)
EXR	0.000*	0.000*	−0.000	−0.000*	−0.000	−0.000	−0.000***	−0.000**	−0.000
	(1.95)	(1.79)	(−1.14)	(−1.89)	(−1.14)	(−0.13)	(−3.85)	(−2.18)	(−0.57)
Constant	−17.007***	−17.827***	−15.851***	−15.085***	−15.586***	−20.020***	−6.807*	−4.758	−13.977***
	(−19.85)	(−20.62)	(−18.25)	(−6.14)	(−6.52)	(−8.31)	(−1.77)	(−1.24)	(−3.63)
Sector effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*No*	*No*	*No*
Year effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*No*	*No*	*No*
Adjusted R^2	0.132	0.129	0.130	0.097	0.098	0.098			
Observations	231,462	231,462	231,462	231,462	231,462	231,462	210,420	210,420	210,420

Note: This table reports regression results examining the influence of social media activities on stock price informativeness. We consider the macroeconomic variables such as IQ, GDPG, TGDP, IP, ADS, VA, PV, STV, STT, RIR, IGD, and EXR endogenous and thus used them with their lagged effect as the instruments to run fixed effect two Stage Least Squares (Fixed-effect-2SLS) regression in models 7–9. All variables are fully defined in Appendix A. For tractable interpretation, all the coefficients are reported as elasticity, and the statistical significance is reported against 10% (*), 5% (**), and 1% (***) significance levels, respectively.

Social media provides cheap, ubiquitous, and timely information to investors, which improves stock price informativeness. For instance, investors can access value-relevant information from Twitter. A recent study by Al Guindy and Riordan (2017) finds that tweeting is positively associated with firm stock price efficiency due to the release of valuation-relevant information. The results confirm Al Guindy (2021), who finds that social media reduces the cost of capital through the informativeness of stock prices, implying greater information flow and lower risk.

4.3 | Robustness Checks

4.3.1 | Sensitivity Analysis

We follow the existing studies such as Morck et al. (2000), Fernandes and Ferreira (2009), and Gul et al. (2011) and compute the relative firm-specific return variation by scaling the firm's specific stock variation by the total market level variation given the fact that firms in some countries are more subject to economic-wide shocks than others, and therefore firm-specific events can be correspondingly more intense. The results reported in models 1–3 in Table 5 continue rendering support for our baseline results. We further consider that social media activities vary and are other alternative proxies. To examine whether our results remain the same after deploying common social media activity proxies, we used the extent to which people employ social media to organise offline violence (*SMOOV*), the extent to which people employ social media to organise offline violence (*SMOOPA*), and how often do domestic elites use social media to organise offline political action of any kind (*SMOOPAK*). We re-ran our regressions and report the results in models 4–6 in Table 5, which support our baseline results.

4.3.2 | Developed and Emerging Countries' Sensitivity Analysis

We further argue that social media activities can be influenced by the level of economic development and, therefore, the extent to which a firm's stock price variations respond may vary. To ascertain the extent to which the firm's stock price informativeness varies between these two economic regions, we truncate our sample into two categories representing developed and emerging countries. The results reported in Table 6 show that apart from *VOPAMSM*, which is negative for developed countries and positive for emerging countries, the rest of the variables depict positive and statistically significant results for both developed and emerging countries, which supports our baseline results. While *PCDOM* is more pronounced in developed countries, *OTOTSM* is more pronounced in emerging countries. The key interpretation for the negative impact of VOPAMSM may imply that the extent to which offline political activities are organised in social media increases the negative impact of the stock price informativeness in developed countries relative to emerging countries.

To further gain an understanding of how *PCDOM* and *OTOTSM* differ in their strength between developed and emerging countries, we run coefficient differences tests to establish whether

TABLE 5 | The impact of social media on stock price informativeness using alternative measures.

Variables	Alternative measures to SPI			Alternative measure to social media activities		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
VOPAMSM	5.431***					
	(23.85)					
PCDOM		1.450***				
		(7.43)				
OTOTSM			3.947***			
			(19.33)			
SMOOV				1.721***		
				(25.28)		
SMOOPA					1.799***	
					(24.11)	
SMOOPAK						1.280***
						(14.87)
IQ	−3.739***	0.973	−0.344	−0.082	0.284	0.111
	(−3.98)	(1.02)	(−0.37)	(−0.37)	(1.28)	(0.49)
GDPG	−1.222***	−1.980***	−1.301***	−0.053**	−0.162***	−0.313***
	(−11.39)	(−17.97)	(−12.20)	(−2.09)	(−6.45)	(−11.60)
TGDP	10.097***	9.233***	8.259***	2.371***	1.955***	2.364***
	(20.22)	(18.69)	(17.38)	(20.56)	(17.41)	(20.63)
IP	1.210	1.333	1.719	0.563	1.133**	−1.425***
	(0.57)	(0.62)	(0.81)	(1.12)	(2.25)	(−2.77)
ADS	2.842***	3.271***	3.351***	0.738***	1.199***	1.298***
	(7.32)	(7.91)	(8.80)	(8.17)	(13.00)	(13.77)
VA	5.052***	−6.157***	−8.469***	−8.927***	−6.886***	−0.862**
	(2.87)	(−3.45)	(−4.72)	(−15.88)	(−13.24)	(−1.97)
PV	−13.905***	9.674***	−1.987	−3.505***	−4.602***	1.498**
	(−4.57)	(3.33)	(−0.67)	(−4.63)	(−5.99)	(2.18)
STV	−0.045***	−0.060***	−0.046***	−0.018***	−0.017***	−0.018***
	(−15.03)	(−19.73)	(−15.33)	(−24.34)	(−22.79)	(−23.91)
STT	0.015***	0.005	−0.000	0.009***	0.008***	0.002*
	(3.10)	(0.92)	(−0.07)	(7.58)	(6.41)	(1.85)
RIR	−0.443***	−0.652***	−0.478***	−0.140***	−0.160***	−0.175***
	(−5.05)	(−7.48)	(−5.53)	(−6.80)	(−7.82)	(−8.50)
IGD	−0.657***	−1.037***	−0.976***	−0.223***	−0.242***	−0.214***
	(−7.33)	(−11.61)	(−11.09)	(−10.37)	(−11.22)	(−9.79)
EXR	0.000**	0.000	−0.000	−0.000***	−0.000***	−0.000***
	(2.06)	(1.45)	(−1.35)	(−7.39)	(−4.54)	(−3.49)
Constant	−62.147***	−66.638***	−57.192***	−13.442***	−13.419***	−20.157***

(Continues)

Variables	Alternative measures to SPI			Alternative measure to social media activities		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	(−17.35)	(−18.45)	(−15.73)	(−14.74)	(−14.25)	(−23.85)
Sector effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adj. R^2	0.098	0.095	0.097	0.134	0.133	0.131
Observations	231,462	231,462	231,462	231,462	231,462	231,462

Note: This table reports regression results examining the influence of social media activities on stock price informativeness. The dependent variable in models 1–3 is an alternative measure of stock price informativeness (SPI2). In models 4–6, the dependent variable is the primary measure of stock price informativeness (SPI), while explanatory variables are replaced with alternative measures of social media activities. For tractable interpretation, all the coefficients are reported as elasticity, and the statistical significance is reported against 10% (*), 5% (**), and 1% (***) significance levels, respectively.

there is any significant difference. The results indicate that the coefficient of *PCDOM* differs significantly by 0.130 at the 5% level with F-statistics = 4.54, indicating a one standard deviation change (increase) in *PCDOM* increases stock price informativeness stability by 0.154 higher in developed countries relative to emerging countries. This is economically significant, indicating a one standard deviation change (increase) results in stabilisation of stock price informativeness by 16.64% [100(exp(0.154) − 1)] higher in developed countries relative to emerging countries.

The *OTOTSM* demonstrates a significant difference at a coefficient of 0.347, significant at the 1% level with F-statistics = 32.02 documenting higher stabilisation in emerging countries relative to developed countries. This is also economically significant and higher by a coefficient of 0.424 [(0.347*1.219)], which indicates a higher in emerging countries by 52.73% [100(exp(0.424) − 1)] relative to developed countries. The different effects evidenced between developed and emerging countries imply that the extent to which *VOPAMSM*, *PCDOM*, and *OTOTSM* influence stock price informativeness between developed and emerging countries statistically and economically differs. This is in line with Lao and Wang (2000) and Baruch and Saar (2009) who argued that variations in technological and economic development levels may affect social media activities.

4.3.3 | Sectoral Sensitivity Analysis

We argue that there are variations and modalities in which different firms in various sectors may respond to social media activities as some may intensively rely on social media activities while some may lightly. This is in line with Guo and Zhou's (2016) views that culture and type of clients differ between the firms, similarly how various firms use or are affected by social media activities differs between sectors. We, therefore, re-truncate our sample into two main categories—service rendering industry and non-service industries to ascertain how the stock price informativeness in these two categories would respond to the social media activities. We report our results in Table 7, which shows that though the extent to which the firms in services industries and non-services industries respond to *VOPAMSM* and *PCDOM* may have no significant difference, the positive impact of *OTOTSM* on stock price informativeness is more pronounced in non-service industries relative to the service rendering sector. The mean different tests for coefficients evidenced a significant difference ($\beta = 0.317$) with F-statistics 14.51 significant at the 1% level. This indicates that a one standard deviation change (increase) in OTOTSM has a positive stabilisation impact on stock price informativeness by 0.386 higher for the non-service sector relative to the service sector. Economically, this implies that the standard deviation change in OTOTSM stabilises the stock price informativeness by 47.18% higher in the non-service sector.

4.3.4 | Addressing Endogeneity Using a Two-Stage System GMM

In line with Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998), we used a two-stage system-GMM estimation with the lagged dependent variable as an internally generated instrument to account for endogeneity, simultaneity, and heterogeneity concerns. In line with Nofer and Hinz (2015), Li et al. (2017), and Sul et al. (2017), we consider the macroeconomic variables such as imports and exports measured as a percentage of GDP (*TGDP*), the growth rate of gross domestic product (*GDPG*), the stock traded to total value as a percentage of GDP (*STV*), real interest rate (*RIR*), stocks traded turnover ratio of domestic shares in percentage (*STT*), inflation GDP inflector in percentage (*IGD*) and official exchange rate (*EXR*) as endogenous, and thus used their lag as the external instruments to run our GMM tests. The two-stage system GMM results reported in Table 8 continue to provide support for the hypotheses of the study (Arellano and Bover 1995; Ullah et al. 2018; Singh et al. 2018).

4.3.5 | Difference-in-Difference Test (DID)

To evaluate the impact of the increased likelihood of social media activities over different points in time, we conduct a difference-in-difference analysis by using the individuals using the Internet (% of the population) as the treatment variable associated with social media activities. If the increased number of individuals using the Internet leads to variables of social media activities undertaken that are positively related to stock price informativeness, we estimate countries with large Internet populations have facilitated the effect of social media activities more than those of countries with small Internet populations.

TABLE 6 | The impact of social media on stock price informativeness using FE.

	Developed countries			Emerging countries		
Variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
VOPAMSM	−0.396**			0.790***		
	(−2.03)			(6.66)		
PCDOM		1.062***			0.692***	
		(7.16)			(6.39)	
OTOTSM			0.661***			1.251***
			(4.70)			(12.73)
IQ	5.108***	7.449***	6.424***	8.623***	6.927***	11.983***
	(5.05)	(7.14)	(6.32)	(8.34)	(6.85)	(11.06)
GDPG	0.106***	0.055	0.061	−0.111***	−0.147***	−0.100***
	(2.73)	(1.41)	(1.57)	(−3.27)	(−4.30)	(−2.96)
TGDP	0.961***	0.586**	1.124***	2.583***	2.688***	3.206***
	(3.63)	(2.14)	(4.41)	(11.19)	(11.45)	(13.84)
IP	1.070	0.545	0.774	4.576***	4.488***	4.905***
	(1.57)	(0.80)	(1.12)	(5.77)	(5.67)	(6.20)
ADS	0.000	0.000	0.000	−3.878***	−3.819***	−3.618***
	(0.00)	(0.00)	(0.00)	(−5.03)	(−4.95)	(−4.70)
VA	8.970	3.952	4.694	−16.269***	−16.269***	−15.698***
	(1.64)	(0.72)	(0.84)	(−9.28)	(−9.36)	(−9.03)
PV	−9.265***	−9.654***	−9.703***	−8.420***	−7.500***	−4.669***
	(−6.26)	(−6.48)	(−6.50)	(−5.09)	(−4.52)	(−2.76)
STV	−0.021***	−0.028***	−0.024***	−0.012***	−0.013***	−0.014***
	(−9.70)	(−12.58)	(−10.81)	(−12.84)	(−13.08)	(−15.10)
STT	0.013***	0.016***	0.014***	0.003	0.004**	0.006***
	(6.70)	(8.15)	(7.27)	(1.41)	(1.99)	(3.42)
RIR	−0.462***	−0.455***	−0.509***	−0.172***	−0.201***	−0.181***
	(−9.88)	(−9.79)	(−10.69)	(−6.03)	(−7.06)	(−6.45)
IGD	−0.125***	−0.091**	−0.159***	−0.102***	−0.111***	−0.197***
	(−2.85)	(−2.09)	(−3.59)	(−2.98)	(−3.25)	(−5.65)
EXR	0.005***	0.005***	0.006***	−0.000***	−0.000**	−0.000
	(6.31)	(6.67)	(6.76)	(−3.50)	(−2.55)	(−1.01)
Constant	−22.726***	−22.489***	−22.819***	−9.677***	−7.806***	−21.705***
	(−4.27)	(−4.25)	(−4.29)	(−3.28)	(−2.69)	(−7.13)
Sector effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adj. R^2	0.082	0.082	0.082	0.132	0.132	0.133
Observations	128,183	128,183	128,183	103,279	103,279	103,279

Note: This table represents the fixed effect estimator (FE) regressions examining the varying influence of social media activities between developed and emerging countries. All variables are fully defined in Appendix A. For tractable interpretation, all the coefficients are reported as elasticity, and the statistical significance is reported against 10% (*), 5% (**), and 1% (***) significance levels, respectively. All models are run with robust standard errors.

TABLE 7 | The impact of social media on stock price informativeness—sector results.

Variables	Non-service sector results			Services sector results		
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
VOPAMSM	0.375**			0.389***		
	(2.51)			(3.43)		
PCDOM		0.979***			0.399***	
		(7.40)			(3.62)	
OTOTSM			1.410***			0.098
			(12.24)			(1.16)
IQ	11.070***	11.880***	14.069***	8.111***	8.055***	7.745***
	(10.60)	(11.42)	(13.19)	(9.32)	(9.40)	(8.89)
GDPG	−0.155***	−0.174***	−0.127***	0.059**	0.053*	0.062**
	(−4.68)	(−5.23)	(−3.80)	(2.05)	(1.85)	(2.18)
TGDP	3.530***	3.516***	3.857***	1.928***	1.916***	1.916***
	(17.38)	(17.52)	(18.98)	(12.54)	(12.50)	(12.38)
IP	6.299***	6.248***	5.510***	1.562**	1.475**	1.549**
	(8.85)	(8.79)	(7.75)	(2.43)	(2.30)	(2.40)
ADS	−4.942***	−4.588***	−4.629***	−0.828	−0.747	−0.889
	(−5.80)	(−5.38)	(−5.44)	(−0.86)	(−0.78)	(−0.92)
VA	−22.961***	−23.345***	−23.417***	−4.506***	−4.962***	−4.917***
	(−9.64)	(−9.86)	(−9.91)	(−2.61)	(−2.88)	(−2.85)
PV	−12.537***	−12.628***	−10.054***	−12.304***	−12.352***	−12.223***
	(−7.91)	(−8.03)	(−6.50)	(−9.35)	(−9.41)	(−9.24)
STV	−0.011***	−0.013***	−0.014***	−0.013***	−0.014***	−0.014***
	(−9.40)	(−11.16)	(−12.11)	(−14.00)	(−14.25)	(−13.70)
STT	0.012***	0.012***	0.014***	0.008***	0.008***	0.008***
	(5.98)	(6.21)	(7.06)	(4.79)	(4.82)	(4.78)
RIR	−0.560***	−0.554***	−0.571***	−0.166***	−0.162***	−0.169***
	(−16.23)	(−16.29)	(−16.68)	(−6.58)	(−6.55)	(−6.70)
IGD	−0.314***	−0.332***	−0.480***	−0.017	−0.011	−0.015
	(−8.34)	(−8.89)	(−12.46)	(−0.59)	(−0.39)	(−0.48)
EXR	−0.000	−0.000	0.000	−0.000***	−0.000**	−0.000**
	(−1.18)	(−0.42)	(0.53)	(−2.62)	(−2.24)	(−2.46)
Constant	−12.224***	−14.433***	−21.661***	−17.948***	−17.593***	−16.777***
	(−3.57)	(−4.40)	(−6.49)	(−5.65)	(−5.64)	(−5.30)
Year effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adj. R^2	0.125	0.126	0.127	0.077	0.077	0.077
Observations	120,395	120,395	120,395	111,067	111,067	111,067

Note: This table represents the FE regressions examining varying influences of social media activities in different sectors grouped into two categories. Non-service sectors comprise basic materials, industrials, and consumer cyclicals, whereas the service sector comprises energy, financial, health care, technology, utilities, real estate, and consumer non-cyclicals. For tractable interpretation, all the coefficients are reported as elasticity, and the statistical significance is reported against 10% (*), 5% (**), and 1% (***) significance levels, respectively. All models are run with robust standard errors.

TABLE 8 | The impact of social media on stock price informativeness using system GMM.

	Main explanatory variables			Alternative explanatory variables		
Variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
VOPAMSM	0.764***					
	(2.89)					
PCDOM		0.629*				
		(1.68)				
OTOTSM			0.363*			
			(1.75)			
SMOOV				1.000***		
				(3.57)		
SMOOPA					0.789***	
					(3.52)	
SMOOPAK						0.999***
						(2.78)
L2.WSPI	0.104***	0.116***	0.104***	0.101***	0.101***	0.101***
	(13.84)	(15.35)	(13.85)	(13.61)	(13.56)	(13.60)
IQ	−2.546***	40.808***	−1.963**	−2.954***	−4.120***	−4.479***
	(−2.76)	(14.42)	(−2.09)	(−3.15)	(−5.33)	(−6.13)
GDPG	−0.540***	−0.596***	−0.670***	−0.490***	−0.543***	−0.595***
	(−5.83)	(−4.00)	(−7.78)	(−6.48)	(−7.86)	(−8.59)
TGDP	−0.002	0.082***	0.003	0.023***	0.021***	0.028***
	(−0.21)	(11.62)	(0.37)	(11.02)	(9.09)	(11.55)
IP	26.454***	32.839***	26.406***	22.789***	25.030***	23.543***
	(12.27)	(9.88)	(12.09)	(10.42)	(12.21)	(10.85)
ADS	0.568***	−6.973***	0.571***	0.090	0.353**	0.443**
	(3.23)	(−9.86)	(3.12)	(0.49)	(2.05)	(2.16)
VA	−1.800	−135.673***	−3.498*	−6.830**	−2.898	0.411
	(−0.93)	(−16.26)	(−1.75)	(−2.31)	(−1.38)	(0.26)
PV	−40.041***	−148.826***	−41.337***	−31.816***	−30.677***	−30.813***
	(−8.66)	(−20.22)	(−7.89)	(−8.32)	(−8.41)	(−8.38)
STV	−0.008	−0.105***	−0.012*	−0.027***	−0.024***	−0.030***
	(−1.28)	(−14.10)	(−1.88)	(−14.21)	(−13.20)	(−13.14)
STT	0.007	0.001	0.013*	0.028***	0.026***	0.029***
	(1.10)	(0.23)	(1.90)	(9.96)	(9.06)	(10.44)
RIR	−0.167***	0.500***	−0.188***	−0.090**	−0.141***	−0.209***
	(−3.80)	(4.19)	(−4.29)	(−1.97)	(−3.80)	(−6.94)
IGD	−0.175***	−1.633***	−0.171**	−0.102**	−0.108**	−0.017
	(−2.93)	(−8.46)	(−2.43)	(−2.33)	(−2.49)	(−0.44)
EXR	0.001*	−0.002*	0.002***	−0.001**	−0.001*	−0.000

(Continues)

TABLE 8 | (Continued)

Variables	Main explanatory variables			Alternative explanatory variables		
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
	(1.88)	(−1.92)	(2.63)	(−2.38)	(−1.73)	(−0.76)
Constant	−240.776***	51.529**	−244.223***	−221.320***	−230.948***	−229.368***
	(−39.86)	(2.35)	(−41.12)	(−27.20)	(−37.49)	(−31.58)
Sector effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Number of observations	189,378	189,378	189,378	189,378	189,378	189,378
No. of instruments	38.000	38.000	38.000	39.000	39.000	39.000
AR1 (*p*)	0.000	0.000	0.000	0.000	0.000	0.000
AR2 (*p*)	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J (*p*)	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J statistics	1742.893	1431.958	1766.934	1722.955	1725.181	1737.103
Sargan (*p*)	0.000	0.000	0.000	0.000	0.000	0.000
Sargan statistics	7474.003	4458.969	7372.896	7749.489	7787.097	7621.842
No. of groups	21,042	21,042	21,042	21,042	21,042	21,042

Note: This table reports the results of the two-stage system GMM regressions with orthogonal deviations. The dependent variable in the rest of the models is SPI. Correlation 1 (AR1) and correlation 2 (AR2) are the first-order and second-order autocorrelations of residuals, respectively. The Sargan and Hansen tests are tests of over-identifying restrictions. For tractable interpretation, all the coefficients are reported as elasticities, and statistical significance at 10% (*), 5% (**), and 1% (***) levels, respectively. All models are run with robust standard errors.

TABLE 9 | Difference-in-difference.

	1	**2**	**3**	**4**	**5**
Year2015	−3.338***				
	(−17.61)				
Year2016		−1.932***			
		(−9.72)			
Year2017			−2.129***		
			(−9.80)		
Year2018				−0.991***	
				(−3.94)	
Year2019					1.861***
					(5.79)
Internet population	0.017***	0.018***	0.013***	0.014***	0.011***
	(9.33)	(10.83)	(8.48)	(9.91)	(7.80)
DID	0.032***	0.025***	0.039***	0.035***	0.035***
	(12.28)	(9.62)	(13.77)	(11.13)	(8.71)
Constant	−10.93***	−11.53***	−11.49***	−11.74***	−11.84***
	(−87.56)	(−99.82)	(−106.31)	(−114.81)	(−121.68)
R-Squared	0.00	0.00	0.00	0.01	0.02
Observations	222,783	222,783	222,783	222,783	222,783

Note: This table reports the results of the Difference in Difference regressions. For tractable interpretation, all the coefficients are reported as elasticity, and statistical significance at 10% (*), 5% (**), and 1% (***) levels, respectively.

Following the difference-in-difference model, we examine individuals using the Internet at different times:

$$SPI_{i,t} = \alpha + \beta_1 Individuals\ using\ the\ Internet_i + \beta_2\ Post_{i,t} + Individuals\ using\ the\ Internet_i \times Post_{i,t} + \varepsilon_{i,t}$$

where $SPI_{i,t}$ is the stock price informativeness; *individuals using the Internet* are an indicator variable for whether the countries where the company is based have a large Internet population; $Post_{i,t}$ is an indicator variable for different periods of network development.

Table 9 presents results from a difference-in-difference test for stock price informativeness. The difference-in-difference (β_2) has the highest value of 3.9% in 2017 and the lowest value of 2.5% in 2016. These results confirm the finding that firms based in countries that have large Internet populations have a higher level of stock price informativeness at a significant level.

4.3.6 | Placebo Regression

We perform a placebo test for our main findings using the social media activities of randomly selected firms in the sample countries. This addresses the concern that a bias is present due to endogeneity. In the placebo regression, we replace each firm *i* with a randomly selected firm from the same data set but with no economic ties to firm *i*'s country. We carry out the exogenous firm measure using the variables of social media activities *VOPAMSM*, *PCDOM*, and *OTOTSM*, respectively, and re-run the regression from Table 5. We then repeat this process of replacing each firm with a randomly selected firm, constructing the measures of *VOPAMSM*, *PCDOM*, and *OTOTSM*, and running the regression 100 times. The social media activities are expected to matter for stock price informativeness if randomly selected firms reveal insignificant effects in the Placebo test.

Table 10 presents the results from a placebo test. We see that based on the randomised treatment of three independent variables, the estimated coefficients on *VOPAMSM*, *PCDOOM*, and *OTOTSM* are statistically insignificant. As expected, our main results survived the placebo test, further suggesting the significant effect of social media activities on stock price informativeness.

Table 8 estimates the impact of social media activities on stock price informativeness by grouping sample countries into developed countries and developing countries. Stock price informativeness of sample companies may be impacted by a similar environment due to the culture, bilateral or political agreements they have in common. Consequently, the economic grouping may not reflect companies in homogeneous countries where the similarity of companies within-group countries is reduced, and the dissimilarity of companies between-group countries is facilitated.

For the robustness purpose, we conduct a hierarchical cluster analysis to identify the distinctive pattern of stock price informativeness of 49 countries in the sample. According to Arbolino et al. (2019), we identify the similarities and dissimilarities between the companies that are based in different countries. We assign control variables, including economic and political observations, into subsets in terms of their similarities. A dendrogram using the average c to examine how clusters are merged (Figure 1).

We first identify sample countries into two clusters based on the dendrogram. As we can see, cluster 2 is a group of comparatively prosperous countries in economic and political development (27 countries), while cluster 1 is a group of developing

TABLE 10 | Placebo test.

	1	2	3
VOPAMSM	0.035		
	(1.12)		
PCPOM		−0.014	
		(−0.53)	
OTOTSM			0.018
			(0.716)
IQ	−0.747***	−0.748***	−0.747***
	(−5.18)	(−5.18)	(−5.180)
TGDP	−0.001***	−0.001***	−0.001***
	(−3.06)	(−3.06)	(−3.055)
IP	−4.076***	−4.075***	−4.076***
	(−10.64)	(−10.64)	(−10.641)
ADS	0.355***	0.355***	0.355***
	(6.41)	(6.41)	(6.413)
VA	−0.104	−0.105	−0.104
	(−0.39)	(−0.40)	(−0.395)
PV	12.882***	12.880***	12.881***
	(27.35)	(27.34)	(27.347)
STT	−0.027***	−0.027***	−0.027***
	(−49.95)	(−49.95)	(−49.945)
RIR	−0.418***	−0.418***	−0.418***
	(−42.24)	(−42.25)	(−42.241)
IGD	−0.478***	−0.478***	−0.478***
	(−46.11)	(−46.11)	(−46.112)
EXR	−0.000***	−0.000***	−0.000***
	(−7.14)	(−7.14)	(−7.140)
Constant	−8.321***	−8.333***	−8.339***
	(−23.10)	(−23.15)	(−23.162)
R-Squared	0.0346	0.0346	0.0346
Observations	231,462	231,462	231,462

Note: This table reports the results of the Placebo effect regressions. For tractable interpretation, all the coefficients are reported as elasticities, and the statistical significance is reported against 10% (*), 5% (**), and 1% (***) significance levels, respectively.

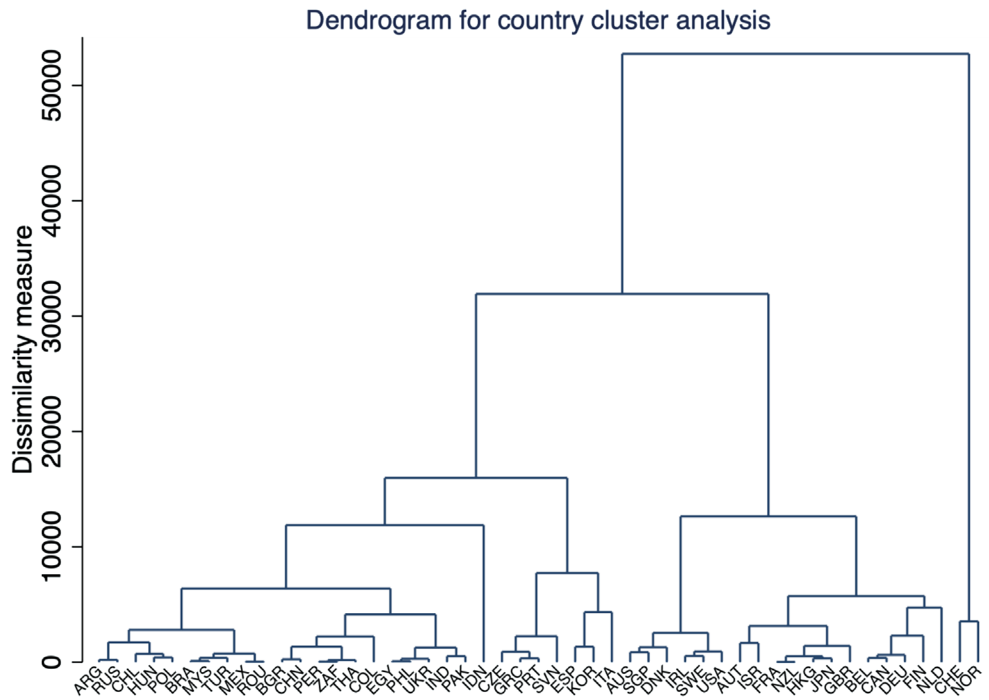

FIGURE 1 | Hierarchical cluster analysis. [Colour figure can be viewed at wileyonlinelibrary.com]

countries (22 countries). We run an OLS regression model to estimate the difference between clusters. As Table 11 presents, the *VOPAMSM*, *PCDOM*, and *OTOTSM* depict positive and statistically significant results for countries in both cluster 1 and cluster 2. The results indicate that apart from *PCPOM*, the economic significance of *VOPAMSM* and *OTOTSM* has increased in cluster 2.

To further identify the distinctive pattern by examining economic and political factors, we further classify sample countries into four clusters (Table 12) and six clusters (Table 13), respectively, based on the dendrogram. The results in Table 12 show that the coefficients of *PCDOM* are negative for countries in cluster 2 and cluster 4; the rest of the social media activity variables are positive at a significant level for countries in all clusters. The findings are consistent with our concern that the impact of social media activities on stock price informativeness may vary due to the culture, bilateral relations, and geopolitics they have in difference. The disparity of the impact of *PCPOM*, *VOPAMSM*, and *OTOTSM* has been relatively enlarged when we have six clusters. Taken together, Table 13 indicates that social media activities have been facilitating stock price informativeness.

4.3.7 | Heteroscedasticity-Fixed Difference and Fixed Effects

We begin our analysis with OLS and fixed effect in Table 4. To address heteroscedasticity, we further conduct additional fixed-effect estimations paired with cluster-robust variance estimation to support the results of the fixed-effect model that are shown in Table 4. The fixed effect robust model *FE_robust* shows the coefficient of fixed effect with cluster robust standard errors. The fixed effect trend model *FE_trend* presents a two-way fixed effect with a time series trend. *LSDV* shows the fixed effect estimation with the Least Square Dummy Variables of countries. These fixed effect estimations may mitigate spurious correlations resulting from macroeconomic and political variables. Standard errors are clustered on dimensions of country-specific and time series. This allows the observation of stock Price informativeness and a specific country to be corrected.

Table 14 shows that the fixed effects of the *FE_trend* are similar to the normal fixed-effect model *FE*. In these fixed effect regressions, social media activities are positively associated with stock price informativeness. The results in Table 14 further support the main findings in Table 4.

4.3.8 | Marginal Effect of Social Media Activities

To determine the level of the political environment at which the effect of social media activities is significantly affected. We estimate the interactive effects of Social Media activities (*VOPAMSM*, *PCPOM*, and *OTOTSM*) and Political Stability and Absence of Violence (*PA*) on stock price informativeness and the interaction effect of Social Media activities (*VOPAMSM*, *PCPOM*, and *OTOTSM*) and Voice &Accountability (*VA*) on stock price informativeness. We then employ the results in Table 14 to draw 3D graphs showing how the marginal effects of *VOPAMSM*, *PCPOM*, and *OTOTSM* change with different levels of political factors.

The results in Figure 2 first present that apart from *PCPOM*, the rest of the social media activities variables have a positive marginal effect on stock price informativeness when PA stays at a lower level. As the level of PA increases, the marginal effect of social media

TABLE 11 | Two-cluster group hierarchical cluster analysis.

	Cluster 1	Cluster 2	Cluster 1	Cluster 2	Cluster 1	Cluster 2
VOPAMSM	0.601***	1.110***				
	(13.55)	(19.46)				
PCPOM			0.586***	0.315***		
			(15.44)	(5.25)		
OTOTSM					0.601***	0.882***
					(13.553)	(14.664)
IQ	−4.744***	1.071***	−4.604***	2.400***	−4.519***	1.232***
	(−21.03)	(3.33)	(−20.34)	(6.49)	(−20.126)	(3.621)
TGDP	0.015***	0.013***	0.024***	0.009***	0.015***	0.011***
	(8.81)	(17.34)	(13.94)	(12.05)	(9.068)	(14.970)
IP	2.128***	−1.901***	1.899***	−4.466***	1.301*	−2.907***
	(3.05)	(−3.27)	(2.77)	(−7.39)	(1.887)	(−5.015)
ADS	1.024***	−0.598***	0.702***	0.096	1.188***	−0.563***
	(12.52)	(−5.38)	(8.14)	(0.79)	(14.444)	(−4.607)
VA	1.609***	3.293***	1.809***	−0.341	1.264***	−1.559***
	(4.20)	(6.11)	(4.71)	(−0.70)	(3.293)	(−3.317)
PV	−1.514**	−5.962***	−1.331**	−3.472***	−2.480***	−4.080***
	(−2.04)	(−7.64)	(−1.98)	(−4.35)	(−3.616)	(−5.372)
STT	−0.020***	−0.017***	−0.022***	−0.015***	−0.022***	−0.016***
	(−29.32)	(−16.75)	(−31.38)	(−14.65)	(−31.051)	(−16.212)
RIR	−0.152***	−0.912***	−0.139***	−0.971***	−0.148***	−0.936***
	(−13.99)	(−25.59)	(−12.80)	(−26.84)	(−13.724)	(−26.315)
IGD	−0.004	−1.457***	0.021	−1.677***	−0.024*	−1.596***
	(−0.24)	(−38.94)	(1.47)	(−48.60)	(−1.670)	(−46.138)
EXR	−0.000***	−0.001***	−0.000***	−0.001***	−0.000***	−0.001***
	(−7.43)	(−4.08)	(−5.60)	(−3.54)	(−9.199)	(−4.109)
Constant	−6.963***	0.253	−7.555***	−0.453	−5.921***	3.262***
	(−11.09)	(0.35)	(−12.95)	(−0.51)	(−9.623)	(3.836)
R-Squared	0.0652	0.0509	0.0655	0.0560	0.0652	0.0568
Observations	90,816	140,646	90,816	140,646	90,816	140,646

Note: Group 1: CZE, IDN, ARG, RUS, EGY, BRA, THA, TUR, CHN, PER, UKR, BGR, POL, SVN, PHL, CHL, GRC, HUN, KOR, MYS, ZAF, ROU, ESP, MEX, IND, COL, PAT, Group 2: ISR, IRL, NLD, FRA, CAN, NOR, BEL, SGP, SWE, DEU, FIIN, ITA, AUT, NZL, DNK, USA, AUS, CHE, BGR, JPN, HKG. This table reports regression results examining the influence of social media activities on stock price informativeness by groups. For tractable interpretation, all the coefficients are reported as elasticity, and the statistical significance is reported against 10% (*), 5% (**), and 1% (***) significance levels, respectively.

activities runs deep. We can see that the impact of *PCPOM* gradually changes from negative to positive when the PA level increases. Figure 2 indicates that *VOPAMSM*, *POPOM*, and *OTOTSM* have a positive marginal effect on stock price informativeness. When the level of VA increases, the marginal effects of *VOPAMSM* and *POPOM* turn negative. For *OTOTSM*, the marginal effect on stock price informativeness is generally positive and the changes do not vary significantly when the level of VA becomes higher.

5 | Conclusions

Information plays a key role in explaining the movement of stock prices. The cost and extent of the information available to investors have important consequences on the informativeness of stock prices. The use of social media to organise offline violence introduces significant risks to both individual companies and broader financial markets. Investors, who are increasingly

TABLE 12 | Four-cluster groups hierarchical cluster analysis.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 1	Cluster 2	Cluster 3	Cluster 4
VOPAMSM	0.685***	−2.568***	0.656***	−4.690								
	(9.04)	(−5.19)	(11.72)	(−1.63)								
PCPOM					0.517***	1.428***	0.110*	2.695***				
					(13.25)	(4.43)	(1.82)	(2.60)				
OTOTSM									0.926***	2.983***	0.786***	2.936**
									(19.170)	(6.586)	(13.028)	(2.504)
IQ	−4.417***	14.083***	3.217***	−9.602**	−4.248***	14.739***	4.648***	−19.940***	−3.451***	8.115***	3.054***	−21.640***
	(−16.72)	(8.75)	(9.41)	(−2.09)	(−16.14)	(8.88)	(12.07)	(−3.10)	(−12.886)	(4.042)	(8.737)	(−2.994)
TGDP	0.008***	0.096***	0.012***	−0.092***	0.019***	0.067***	0.009***	−0.083***	0.007***	0.070***	0.011***	−0.086***
	(4.25)	(8.60)	(15.73)	(−3.98)	(10.08)	(7.22)	(12.05)	(−4.12)	(3.892)	(7.669)	(14.959)	(−3.857)
IP	1.587**	2.145	−3.055***	30.103**	0.905	2.784	−5.154***	43.488***	0.120	1.696	−3.154***	44.716**
	(2.01)	(1.05)	(−5.16)	(2.09)	(1.16)	(1.34)	(−8.44)	(2.64)	(0.154)	(0.853)	(−5.407)	(2.535)
ADS	0.984***	−3.122***	−0.650***	14.570***	0.661***	−7.110***	−0.080	10.775***	1.090***	−6.271***	−0.885***	10.457***
	(11.49)	(−5.17)	(−5.81)	(3.47)	(7.44)	(−12.28)	(−0.66)	(3.59)	(12.609)	(−13.895)	(−7.187)	(3.500)
VA	4.115***	−3.000	1.148**	38.648	3.965***	−2.387	−1.612***	23.473	3.448***	−2.433	−2.515***	6.798
	(10.23)	(−1.24)	(2.10)	(1.17)	(9.81)	(−0.88)	(−3.27)	(0.97)	(8.580)	(−0.876)	(−5.286)	(0.276)
PV	−0.345	−8.418**	−5.718***	65.229**	1.082	−19.084***	−3.785***	44.740*	−0.445	−23.825***	−4.966***	50.494*
	(−0.44)	(−2.48)	(−7.30)	(2.07)	(1.54)	(−5.17)	(−4.69)	(1.87)	(−0.628)	(−6.355)	(−6.481)	(1.739)
STT	−0.016***	−0.036***	−0.014***	0.016	−0.017***	−0.048***	−0.012***	−0.015	−0.018***	−0.054***	−0.014***	−0.019
	(−17.08)	(−9.67)	(−13.75)	(0.69)	(−18.30)	(−12.59)	(−11.72)	(−0.65)	(−18.955)	(−13.935)	(−14.018)	(−0.803)
RIR	−0.161***	−1.087***	−0.777***	−1.059*	−0.152***	−1.008***	−0.798***	0.018	−0.156***	−0.833***	−0.774***	−0.217
	(−14.38)	(−6.83)	(−20.70)	(−1.78)	(−13.57)	(−6.30)	(−20.90)	(0.04)	(−13.909)	(−5.405)	(−20.637)	(−0.516)
IGD	−0.011	−0.179	−1.463***	−0.177	0.023	−0.600***	−1.604***	−0.176	−0.037**	−0.531***	−1.517***	−0.316
	(−0.71)	(−1.05)	(−37.50)	(−0.92)	(1.55)	(−3.60)	(−44.22)	(−1.02)	(−2.416)	(−3.177)	(−41.686)	(−1.542)
EXR	−0.000***	0.000	−0.001***	−0.386**	−0.000**	0.000	−0.001***	−0.449***	−0.000***	0.000	−0.001***	−0.331
	(−4.15)	(0.67)	(−4.67)	(−2.24)	(−2.49)	(0.89)	(−4.42)	(−2.95)	(−5.801)	(0.113)	(−4.902)	(−1.625)
Constant	−9.344***	−26.866***	−0.093	−110.679**	−10.630***	−8.799**	−1.368	−60.142*	−9.343***	5.564	3.325***	−48.482
	(−11.95)	(−7.41)	(−0.13)	(−2.09)	(−14.45)	(−2.10)	(−1.53)	(−1.90)	(−12.741)	(1.062)	(3.889)	(−1.391)
R-Squared	0.0748	0.0650	0.0599	0.0948	0.0755	0.0645	0.0593	0.0957	0.0778	0.0682	0.0600	0.0962
Observations	76,945	13,871	129,635	2332	76,945	13,871	129,635	2332	76,945	13,871	129,635	2332

Note: Cluster1: POL, IND, PER, PAK, MYS, IDN, TUR, RUS, ARG, COL, EGY, CHN, MEX, CHL, BRA, PHL, ZAF, UKR, HUN, ROU, BGR, THA, Cluster2: KOR, ESP, CZE, PRT, GRC, SVN, Cluster3: HKG, CAN, AUS, SWE, SGP, NZL, JPN, DNK, IRL, FRA, USA, NLD, ISR, ITA, FIN, GBR, BEL, DEU, AUT, Cluster4: CHE, NOR. This table reports regression results examining the influence of social media activities on stock price informativeness by groups. For tractable interpretation, all the coefficients are reported as elasticity, and the statistical significance is reported against 10% (*), 5% (**), and 1% (***) significance levels, respectively.

TABLE 13 | Six-cluster hierarchical cluster analysis.

VOPAMSM						
	Cluster1	**Cluster2**	**Cluster3**	**Cluster4**	**Cluster5**	**Cluster6**
VOPAMSM	0.774***	1.268***	−2.568***	1.521***	1.877***	−4.690
	(3.04)	(11.98)	(−5.19)	(5.83)	(19.47)	(−1.63)
IQ	2.402***	−0.926*	14.083***	10.439***	0.165	−9.602**
	(3.47)	(−1.86)	(8.75)	(8.40)	(0.43)	(−2.09)
TGDP	−0.014***	0.032***	0.096***	0.019***	0.014***	−0.092***
	(−2.88)	(9.21)	(8.60)	(11.00)	(13.72)	(−3.98)
IP	9.862***	−6.951***	2.145	11.748***	−4.397***	30.103**
	(8.05)	(−6.25)	(1.05)	(6.99)	(−6.76)	(2.09)
ADS	−2.105***	−0.006	−3.122***	0.866***	1.804***	14.570***
	(−5.71)	(−0.06)	(−5.17)	(3.01)	(6.63)	(3.47)
VA	−7.079***	5.492***	−3.000	11.574***	0.917	38.648
	(−4.54)	(10.42)	(−1.24)	(7.79)	(1.32)	(1.17)
PV	−19.471***	14.010***	−8.418**	−11.817***	−12.739***	65.229**
	(−6.75)	(12.61)	(−2.48)	(−3.36)	(−10.93)	(2.07)
STT	−0.041***	−0.018***	−0.036***	−0.005***	−0.036***	0.016
	(−12.56)	(−14.40)	(−9.67)	(−2.58)	(−25.11)	(0.69)
RIR	−0.059***	−0.569***	−1.087***	−0.246***	−1.395***	−1.059*
	(−4.24)	(−14.01)	(−6.83)	(−3.62)	(−22.91)	(−1.78)
IGD	−0.155***	−0.166***	−0.179	−0.350***	−1.946***	−0.177
	(−6.88)	(−3.97)	(−1.05)	(−3.99)	(−35.33)	(−0.92)
EXR	−0.009***	0.000***	0.000	−0.001**	−0.001***	−0.386**
	(−7.93)	(3.17)	(0.67)	(−2.04)	(−3.17)	(−2.24)
Constant	3.761**	−14.504***	−26.866***	−32.275***	9.927***	−110.679**
	(2.33)	(−10.61)	(−7.41)	(−12.12)	(11.74)	(−2.09)
R-Squared	0.0872	0.0834	0.0650	0.0523	0.0839	0.0948
Observations	18,722	58,223	13,871	54,758	74,877	2332
PCPOM						
	Cluster1	**Cluster2**	**Cluster3**	**Cluster4**	**Cluster5**	**Cluster6**
PCPOM	0.193*	0.807***	1.428***	−0.116	0.697***	2.695***
	(1.89)	(11.99)	(4.43)	(−0.47)	(8.14)	(2.60)
IQ	2.785***	−1.441***	14.739***	12.356***	0.560	−19.940***
	(3.81)	(−2.88)	(8.88)	(10.45)	(1.41)	(−3.10)
TGDP	−0.010*	0.052***	0.067***	0.026***	0.006***	−0.083***
	(−1.96)	(11.14)	(7.22)	(16.38)	(5.72)	(−4.12)
IP	8.637***	−6.015***	2.784	7.612***	−4.960***	43.488***
	(6.82)	(−5.43)	(1.34)	(5.23)	(−7.46)	(2.64)
ADS	−2.051***	−0.398***	−7.110***	1.886***	0.898***	10.775***
	(−5.57)	(−3.40)	(−12.28)	(3.75)	(3.39)	(3.59)
VA	−5.516***	4.687***	−2.387	7.759***	−5.979***	23.473
	(−3.50)	(8.50)	(−0.88)	(6.07)	(−9.78)	(0.97)
PV	−17.491***	13.596***	−19.084***	−16.063***	−5.057***	44.740*

(Continues)

TABLE 13 | (Continued)

PCPOM

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6
	(−6.37)	(12.05)	(−5.17)	(−4.46)	(−4.15)	(1.87)
STT	−0.041***	−0.020***	−0.048***	0.002	−0.032***	−0.015
	(−11.56)	(−15.23)	(−12.59)	(0.76)	(−22.62)	(−0.65)
RIR	−0.060***	−0.539***	−1.008***	−0.384***	−1.478***	0.018
	(−4.28)	(−13.00)	(−6.30)	(−5.23)	(−23.44)	(0.04)
IGD	−0.140***	−0.080*	−0.600***	−0.520***	−2.301***	−0.176
	(−5.91)	(−1.90)	(−3.60)	(−5.98)	(−43.30)	(−1.02)
EXR	−0.009***	0.000***	0.000	−0.001**	−0.001***	−0.449***
	(−7.88)	(4.75)	(0.89)	(−2.26)	(−2.59)	(−2.95)
Constant	0.745	−15.398***	−8.799**	−30.426***	12.037***	−60.142*
	(0.56)	(−11.19)	(−2.10)	(−11.27)	(12.28)	(−1.90)
R-Square	0.0869	0.0833	0.0645	0.0519	0.0781	0.0957
Observations	18,722	58,223	13,871	54,758	74,877	2332

OTOTSM

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6
OTOTSM	0.390***	0.979***	2.983***	1.033***	0.699***	2.936**
	(3.061)	(12.749)	(6.586)	(4.369)	(8.758)	(2.504)
IQ	2.491***	−0.363	8.115***	11.447***	1.246***	−21.640***
	(3.585)	(−0.692)	(4.042)	(9.856)	(3.141)	(−2.994)
TGDP	−0.009*	0.024***	0.070***	0.025***	0.007***	−0.086***
	(−1.697)	(6.932)	(7.669)	(17.299)	(7.430)	(−3.857)
IP	9.759***	−8.055***	1.696	8.365***	−5.479***	44.716**
	(7.988)	(−7.297)	(0.853)	(5.790)	(−8.361)	(2.535)
ADS	−2.000***	0.195*	−6.271***	−0.222	0.579**	10.457***
	(−5.598)	(1.693)	(−13.895)	(−0.432)	(2.278)	(3.500)
VA	−6.879***	4.346***	−2.433	7.787***	−7.914***	6.798
	(−4.487)	(8.089)	(−0.876)	(7.192)	(−12.043)	(0.276)
PV	−17.932***	14.419***	−23.825***	−12.646***	−2.728***	50.494*
	(−6.480)	(12.999)	(−6.355)	(−3.602)	(−2.865)	(1.739)
STT	−0.040***	−0.019***	−0.054***	−0.004*	−0.029***	−0.019
	(−11.622)	(−15.607)	(−13.935)	(−1.906)	(−21.104)	(−0.803)
RIR	−0.066***	−0.465***	−0.833***	−0.225***	−1.377***	−0.217
	(−4.712)	(−10.854)	(−5.405)	(−3.120)	(−22.484)	(−0.516)
IGD	−0.161***	−0.092**	−0.531***	−0.353***	−2.192***	−0.316
	(−7.090)	(−2.250)	(−3.177)	(−3.972)	(−40.223)	(−1.542)
EXR	−0.011***	0.000	0.000	−0.001**	−0.001***	−0.331
	(−7.905)	(0.314)	(0.113)	(−2.157)	(−3.260)	(−1.625)
Constant	1.681	−15.501***	5.564	−27.237***	11.244***	−48.482
	(1.263)	(−11.065)	(1.062)	(−9.697)	(11.632)	(−1.391)
R-Squared	0.0873	0.0837	0.0682	0.0521	0.0780	0.0962
Observations	18,722	58,223	13,871	54,758	74,877	2332

Note: Cluster1: POL, ARG, ROU, RUS, TUR, HUN, CHL, BRA, MEX, MYS, Cluster2: EGY, COL, ZAF, PAK, PER, BGR, UKR, IDN, CHN, THA, PHL, IND, Cluster3: PRT, ESP, CZE, KOR, SVN, GRC, Cluster4: DNK, IRL, AUS, SGP, USA, SWE, Cluster5: CAN, FRA, JPN, ITA, ISR, BEL, FIN, AUT, GBR, NLD, NZL, HKG, Cluster6: NOR, CHE.
This table reports regression results examining the influence of social media activities on stock price informativeness by groups. For tractable interpretation, all the coefficients are reported as elasticity, and the statistical significance is reported against 10% (*), 5% (**), and 1% (***) significance levels, respectively.

TABLE 14 | Heteroscedasticity-fixed difference and fixed effects.

VOPAMSM					
	FE	**FE_robust**	**FE_trend**	**LSDV**	**OLS_VCE**
VOPAMSM	0.466***	2.636***	0.431***	2.618***	1.205***
	(4.76)	(29.79)	(4.38)	(5.56)	(21.75)
IQ	9.031***	6.473***	5.557***	5.755*	−1.149***
	(13.00)	(9.39)	(8.23)	(1.65)	(−5.38)
TGDP	2.899***	0.008***	0.011***	0.007	0.008***
	(22.13)	(8.70)	(12.66)	(0.67)	(10.33)
IP	4.251***	3.164***	4.348***	2.971	0.980**
	(8.83)	(6.46)	(8.85)	(1.10)	(2.14)
ADS	−3.102***	−0.629	−3.323***	−0.023	0.258***
	(−4.05)	(−0.82)	(−4.35)	(−0.03)	(2.64)
VA	−14.040***	−16.139***	−14.313***	−10.647	2.731***
	(−8.79)	(−9.43)	(−8.89)	(−1.25)	(6.49)
PV	−13.402***	−18.626***	−15.171***	−17.222**	−5.006***
	(−12.84)	(−17.53)	(−14.77)	(−2.21)	(−7.76)
STT	−0.013***	−0.027***	−0.005***	−0.027***	−0.007***
	(−17.07)	(−36.31)	(−5.89)	(−3.30)	(−8.39)
RIR	0.010***	−0.967***	−0.272***	−0.962***	−0.209***
	(7.82)	(−41.11)	(−17.32)	(−2.93)	(−13.80)
IGD	−0.301***	−0.852***	−0.114***	−0.849***	−0.135***
	(−15.34)	(−39.91)	(−6.41)	(−3.52)	(−8.22)
EXR	−0.084***	−0.001***	−0.000**	−0.001**	−0.000
	(−4.26)	(−13.28)	(−2.16)	(−2.44)	(−0.02)
Constant	−0.000*	11.983***	6.087***	23.254***	−3.591***
	(−1.89)	(5.19)	(2.58)	(2.64)	(−6.25)
R- squared	−15.085***	0.0158	0.0028	0.1005	0.0400
Number of Observation	(−6.14)	222,783	222,783	222,783	222,783
PCPOM					
	FE	**FE_robust**	**FE_trend**	**LSDV**	**OLS_VCE**
PCPOM	0.440***	1.771***	0.432***	1.725***	0.582***
	(9.19)	(21.23)	(5.08)	(3.92)	(12.74)
IQ	−2.008***	3.927***	5.431***	4.589	−0.788***
	(−9.47)	(5.68)	(8.12)	(1.11)	(−3.70)
TGDP	2.316***	0.003***	0.009***	0.003	0.007***
	(19.78)	(3.30)	(11.10)	(0.24)	(8.43)
IP	0.733	3.150***	4.355***	3.159	1.048**
	(1.44)	(6.40)	(8.87)	(1.08)	(2.27)
ADS	0.731***	−0.355	−3.231***	−0.540	0.119
	(7.30)	(−0.46)	(−4.23)	(−0.63)	(1.12)
VA	0.598	−16.403***	−14.726***	−8.636	2.331***
	(1.38)	(−9.48)	(−9.16)	(−1.01)	(5.52)
PV	0.073	−20.308***	−15.465***	−18.210*	−2.702***

(Continues)

PCPOM					
	FE	**FE_robust**	**FE_trend**	**LSDV**	**OLS_VCE**
	(0.10)	(−19.12)	(−15.05)	(−1.96)	(−4.26)
STT	−0.015***	−0.028***	−0.006***	−0.028***	−0.008***
	(−21.14)	(−37.79)	(−6.58)	(−3.13)	(−10.27)
RIR	0.001	−0.965***	−0.268***	−0.964***	−0.228***
	(1.05)	(−41.79)	(−17.29)	(−2.82)	(−14.66)
IGD	−0.155***	−0.785***	−0.109***	−0.782***	−0.143***
	(−7.48)	(−39.48)	(−6.15)	(−3.69)	(−8.66)
EXR	−0.204***	−0.001***	−0.000*	−0.001**	0.000
	(−9.91)	(−12.23)	(−1.73)	(−2.25)	(0.51)
Constant	0.000*	17.349***	6.600***	26.498***	−5.388***
	(1.79)	(7.58)	(2.88)	(2.84)	(−9.49)
R-square	−17.827***	0.020	0.036	0.070	0.070
Observations	(−20.62)	222,783	222,783	222,783	222,783

OTOTSM					
	FE	**FE_robust**	**FE_trend**	**LSDV**	**OLS_VCE**
OTOTSM	0.976***	1.958***	0.658***	2.036***	1.416***
	(12.83)	(27.850)	(9.265)	(24.064)	(24.905)
IQ	10.539***	6.071***	6.434***	2.642***	−1.624***
	(14.88)	(8.593)	(9.438)	(3.391)	(−6.550)
TGDP	3.117***	0.007***	0.010***	0.007***	0.007***
	(23.74)	(7.779)	(12.495)	(3.552)	(7.722)
IP	3.728***	2.699***	4.145***	1.768***	−3.396***
	(7.74)	(5.488)	(8.424)	(2.743)	(−5.818)
ADS	−2.942***	−1.108	−3.411***	0.372	0.221**
	(−3.84)	(−1.451)	(−4.468)	(1.118)	(2.178)
VA	−14.692***	−16.528***	−14.888***	−5.545***	1.252***
	(−9.26)	(−9.653)	(−9.281)	(−3.579)	(2.662)
PV	−11.736***	−17.150***	−14.349***	−11.742***	2.315***
	(−11.44)	(−16.169)	(−14.183)	(−8.470)	(2.966)
STT	−0.015***	−0.026***	−0.005***	−0.027***	−0.011***
	(−19.85)	(−35.399)	(−6.213)	(−33.143)	(−13.226)
RIR	0.011***	−0.962***	−0.269***	−0.941***	−0.141***
	(8.80)	(−41.771)	(−17.357)	(−34.052)	(−8.491)
IGD	−0.315***	−0.894***	−0.152***	−0.890***	−0.231***
	(−15.97)	(−40.652)	(−8.531)	(−36.011)	(−12.929)
EXR	−0.186***	−0.001***	−0.000*	−0.001***	−0.000**
	(−8.73)	(−12.395)	(−1.666)	(−11.519)	(−2.098)
Constant	−0.000	12.140***	4.179*	18.841***	−2.739***
	(−0.13)	(5.284)	(1.810)	(11.407)	(−3.873)
R-squared	−20.020***	0.0153	0.0011	0.0732	0.0784
Observations	(−8.31)	222,783	222,783	222,783	222,783

Note: This table reports regression results of fixed effects examining the influence of social media activities on stock price informativeness. All variables are fully defined in Appendix A. For tractable interpretation, all the coefficients are reported as elasticity, and the statistical significance is reported against 10% (*), 5% (**), and 1% (***) significance levels, respectively.

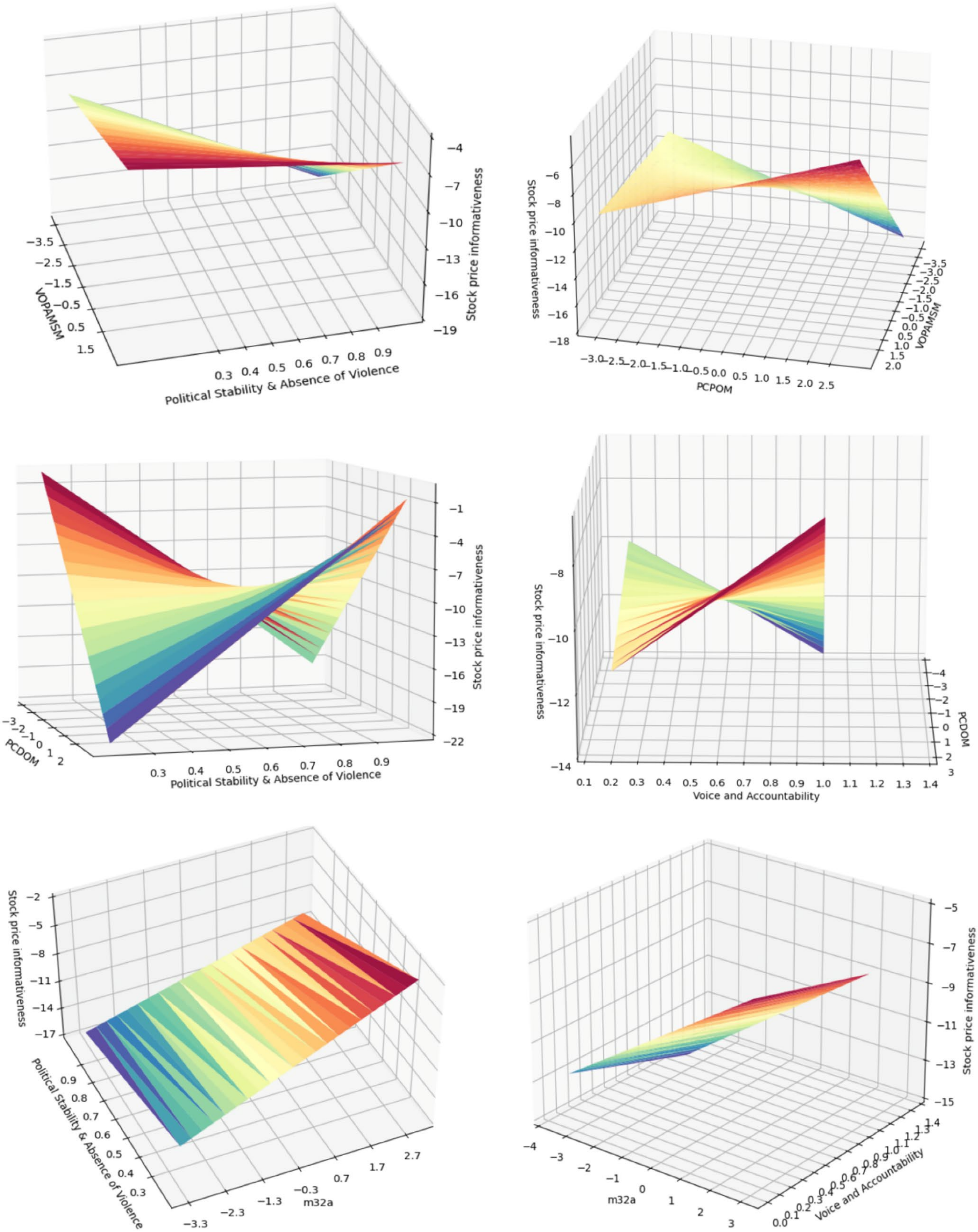

FIGURE 2 | Marginal effect of social media activities and political factors. [Colour figure can be viewed at wileyonlinelibrary.com]

attuned to the role of social media in shaping real-world events, closely monitor platforms for signs of unrest that could disrupt business operations, affect consumer behaviour, or lead to economic instability. Social media-driven violence heightens risk perception, increases market volatility, and exacerbates information asymmetry, all of which influence investor decisions and stock price informativeness. As social media continues to play a central role in organising offline activities, investors will need to adapt their strategies to navigate the unique challenges posed by this digital age of mobilisation and unrest.

This study is the first to use six unique measures to proxy for social media engagement to examine the effects on stock price informativeness. Using panel data from 2010 to 2020, we find that social media increases the informativeness of stock prices. Our results are robust to fixed effects, fixed effect-2SLS, system GMM, difference-in-differences, placebo test, hierarchical cluster analysis, and heteroscedasticity-fixed difference.

Consistent with the theories of investor attention, firms can communicate information via social media channels. This generates external transparency and increases the informativeness of stock prices as Social Media users, including retail investors, monitor the firm's information in real time. Overall, our findings show that social media platforms are an important determinant of the informativeness of stock prices. Our paper partially explains why firms use social media platforms to disseminate information.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] To avoid drawing spurious inferences from extreme values, we winsorize observations in the bottom 1% and top 1% of the individual firm-specific return variation distribution for entire sample.

[2] To avoid drawing spurious inferences from extreme values, we winsorize observations in the bottom 1% and top 1% of the individual country level macroeconomic feature distribution for entire sample.

[3] We run Hausman test, which evidence that fixed effect model is appropriate for our data. Further untabulated results using the instrumented OLS, continue to support our main results.

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Appendix A1

See Table A1.

TABLE A1 | Description of Variables and Data Sources.

Variable	Description and data sources
Panel A: dependent variables—social media activities	
Main dependent variables—used as a proxy for social media activities	
VOPAMSM	Varying offline political action is most commonly mobilised on social media. The performance measure ranges from −2.5 (very poor—poorly engaged) to 2.5 (excellent—highly engaged).
PCDOM	The extent to which people consume domestic online media. The performance measure ranges from −2.5 (very poor—poorly engaged) to 2.5 (excellent—highly engaged).
OTOTSM	Other types of organisations through social media. The performance measure ranges from −2.5 (very poor—poorly engaged) to 2.5 (excellent—highly engaged).
Alternative measure for social media activities	
SMOOV	The extent to which people employ social media to organise offline violence. The performance measure ranges from −2.5 (very poor—poorly engaged) to 2.5 (excellent—highly engaged).
SMOOPA	How often do people use social media to organise offline political action of any kind. The performance measure ranges from −2.5 (very poor—poorly engaged) to 2.5 (excellent—highly engaged).
SMOOPAK	How often do domestic elites use social media to organise offline political action of any kind. The performance measure ranges from −2.5 (very poor—poorly engaged) to 2.5 (excellent—highly engaged).
Panel B: Country-level Control Variables	
IQ	Institutional Quality. The sum of the International Country Risk Guide (ICRG) Political Risk (ICRGP) subcomponents— Voice and Accountability (VA) and Political Stability and Absence of Violence/Terrorism (PV). Voice and Accountability—capturing perceptions of the extent to which a country's citizens can participate in selecting their government, as well as freedom of expression, freedom of association, and free media. Data sourced from the World Governance Indicator (WGI) database. Political Stability and Absence of Violence/Terrorism (PV)—capturing perceptions of the likelihood that the government will be destabilised or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism. Data sourced from the World Governance Indicator (WGI) database.
GDPG	The growth rate of the gross domestic product in US dollars. Data sourced from the World Bank WDI database
TGDP	Trade-to-GDP. The sum of imports and exports as a percentage of GDP. Data sourced from the World Bank WDI database.
IP	
ADS	Administration system. A variable taking a value of one of the types of election is presidential, 2 if the type of election is a parliamentary election, and 3 if the type of election is an assembly-elected president. Data sourced from DPI.
STV	Stocks traded, total value (% of GDP). Data sourced from the World Bank WDI database.
STT	Stocks traded, turnover ratio of domestic shares (%). Data sourced from the World Bank WDI database.
RIR	Real interest rate (%). Data sourced from the World Bank WDI database.
IGD	Inflation, GDP deflator (annual %). Data sourced from the World Bank WDI database.
EXR	Official exchange rate (LCU per US$, period average). Data sourced from the World Bank WDI database.
Internet Population	The extent to which people employ social media to organise offline violence.