Research Article

Corporate Use of Social Media and Earnings Management of Thai Listed Companies: Evidence from Twitter Platform*

Dr.Jomsurang Ruangprapun

Lecturer of Department of Accountancy, Chulalongkorn Business School, Accounting Analytics for Insight and Prediction Research Group, Chulalongkorn University

Received: *December 26, 2021*
Revised: *February 12, 2022*
Accepted: *March 4, 2022*

ABSTRACT

Using Twitter as a proxy for social media platforms, I examine whether the corporate adoption of social media is associated with earnings management. I also identify and examine the determinants of firms' adoption of social media and their posting activity on social media. Due to scant research on social media and earnings management in emerging markets, I scrape public Twitter data of the Stock Exchange of Thailand 50 companies (SET50) between 2015 and 2019 to provide additional empirical evidence. Cross-sectional analyses suggest that firms with presence on Twitter more likely engage in earnings management than firms that are not on Twitter. Firm-specific characteristics, such as size, growth opportunities, leverage, profitability, and financial health, are the main determinants of firms' adoption of Twitter. In addition to general firm characteristics, I find that the number of firm followers and number of hashtags per tweet are the determinants of firms' Twitter posting activity. Results have practical implications for capital market stakeholders and contribute to the voluntary disclosure via social media and earnings management literature.

Keywords: Social Media, Corporate Use of Social Media, Earnings Management, Twitter, Facebook, Voluntary Disclosure, Emerging Markets, Thai Listed Companies

* This work was supported by the Accounting Analytics for Insight and Prediction Research Group under the Special Task Force for Activating Research (STAR) of Chulalongkorn University.

บทความวิจัย

การใช้สื่อสังคมออนไลน์และการบริหารกำไรของบริษัทในตลาดหลักทรัพย์แห่งประเทศไทย : หลักฐานจากทวิตเตอร์*

ดร.จอมสุรางค์ เรืองประพันธ์
อาจารย์ประจำภาควิชาการบัญชี คณะพาณิชยศาสตร์และการบัญชี
กลุ่มวิจัยการวิเคราะห์ทางการบัญชีเพื่อความเข้าใจเชิงลึกและการคาดการณ์
จุฬาลงกรณ์มหาวิทยาลัย

วันที่ได้รับต้นฉบับบทความ : *26 ธันวาคม 2564*
วันที่แก้ไขปรับปรุงบทความ : *12 กุมภาพันธ์ 2565*
วันที่ตอบรับตีพิมพ์บทความ : *4 มีนาคม 2565*

บทคัดย่อ

บทความวิจัยฉบับนี้จัดทำขึ้นเพื่อศึกษาความสัมพันธ์ระหว่างการใช้สื่อสังคมออนไลน์และการบริหารกำไร โดยใช้ทวิตเตอร์เป็นตัวแทนของสื่อสังคมออนไลน์ นอกจากนี้ยังได้มีการระบุและศึกษาปัจจัยที่ส่งผลต่อการเลือกใช้สื่อสังคมออนไลน์และการสื่อสารข้อมูลบริษัทผ่านสื่อสังคมออนไลน์ เนื่องจากงานวิจัยทางด้านสื่อสังคมออนไลน์และการบริหารกำไรโดยใช้ข้อมูลในตลาดเศรษฐกิจเกิดใหม่ยังมีจำนวนค่อนข้างจำกัด ผู้วิจัยจึงได้ทำการรวบรวมข้อมูลสาธารณะจากทวิตเตอร์ของ 50 บริษัทหลักในตลาดหลักทรัพย์แห่งประเทศไทยระหว่างปี พ.ศ. 2558-2562 มาวิเคราะห์เพื่อเพิ่มหลักฐานเชิงประจักษ์ ผลการวิเคราะห์ทางสถิติพบว่า บริษัทที่เลือกใช้ทวิตเตอร์มีแนวโน้มที่จะบริหารกำไรมากกว่าบริษัทที่ไม่ใช้ทวิตเตอร์ ในด้านของคุณลักษณะของบริษัทพบว่า ขนาดของบริษัท โอกาสในการเติบโตทางธุรกิจ การใช้เงินกู้ดำเนินธุรกิจ ความสามารถในการทำกำไร และสุขภาพทางการเงิน เป็นปัจจัยหลักที่ทำให้บริษัทเลือกใช้ทวิตเตอร์ นอกจากนี้จำนวนผู้ติดตามในทวิตเตอร์ และจำนวนแฮชแท็กที่ใช้ในข้อความ เป็นปัจจัยที่ส่งผลต่อระดับการสื่อสารข้อมูลผ่านทวิตเตอร์ของบริษัท งานวิจัยนี้มีประโยชน์ในทางปฏิบัติต่อผู้มีส่วนได้เสียในตลาดทุนและเพิ่มองค์ความรู้ให้กับวรรณกรรมทางด้านการเปิดเผยข้อมูลโดยสมัครใจผ่านสื่อสังคมออนไลน์และการบริหารกำไร

คำสำคัญ: สื่อสังคมออนไลน์ การใช้สื่อสังคมออนไลน์ของบริษัท การบริหารกำไร ทวิตเตอร์ เฟซบุ๊ก การเปิดเผยข้อมูลตามความสมัครใจ ตลาดเกิดใหม่ บริษัทในตลาดหลักทรัพย์แห่งประเทศไทย

* งานวิจัยฉบับนี้ได้รับการสนับสนุนจากกลุ่มวิจัยการวิเคราะห์ทางการบัญชีเพื่อความเข้าใจเชิงลึกและการคาดการณ์ภายใต้กลุ่มขับเคลื่อนการวิจัย จุฬาลงกรณ์มหาวิทยาลัย

1. Introduction

Traditional media, such as business press, plays an important role as information intermediaries in capital markets. A survey of 462 financial journalists by Call, Emett, Maksymov, and Sharp (2021) finds that journalists believe monitoring companies to hold them accountable is one of the most important objectives for financial journalism and thus are likely to produce more accurate and timely articles. Recent research examines the role of social media in capital markets. Similarly, corporate information disseminated via social media is associated with reduced information asymmetry (Blankespoor, Miller, & White, 2014). Nevertheless, voluntary disclosure literature suggests that firms use social media strategically to disseminate financial information and adopt various self-presentational disclosure techniques to emphasize positive news (Jung, Naughton, Tahoun, & Wang, 2018; Yang & Liu 2017). Evidence also proves that social media coverage is positively associated with earnings management, as management is pressured to meet additional expectations set by their followers (Meng, 2020; Zhang, Li, Urquhart, & Wang, 2021). Given that these latter studies examine social media coverage by individual users, whether the corporate use of social media also contributes to earnings management remains unclear. Taken together, whether social media platforms act as information intermediaries or used for impression management purposes is still inconclusive.

To answer calls for further research on social media and earnings management (Meng, 2020), I address three research questions in this study. First, I ask whether firms' adoption of social media is associated with earnings management. Second, building on the first question, I identify and examine the determinants of firms' adoption of social media.[1] Third, I investigate further the determinants of firms' social media posting activity to provide complete analyses. Capital market participants use several social media platforms to communicate financial and nonfinancial information about firms. Prominent examples include Twitter, Facebook, LinkedIn, YouTube, and Instagram. Zhou, Lei, Wang, Fan, and Wang (2015) examine the firm usage of two popular social media platforms (Twitter and Facebook) in corporate disclosures. Among corporate disclosures made by firms on both platforms, financial disclosures increase the fastest on Twitter. Specifically, financial disclosures account for 16.8 percent and 30.24 percent of all corporate disclosures released on Facebook and Twitter, respectively (Zhou et al., 2015). These results suggest that firms prefer Twitter to Facebook when releasing financial information. Therefore, I select Twitter as the main social media platform in this study.

[1] In this paper, I use the term "corporate adoption of social media" when I discuss firms with presence on social media platforms or the first time that firms adopt social media. I use the term "corporate use of social media" when I discuss the firm usage of social media, such as firm disclosures via social media and firms' posting activity.

Using Twitter data and financial variables between 2015 and 2019, I observe that firms' adoption of Twitter is positively associated with earnings management via accruals and cash flows. This finding suggests that firms with social media presence likely engage in earnings management activities. Given that these firms adopt Twitter as another communication channel, firms are more visible to their followers in capital markets than firms without Twitter. In addition, firms are likely to strategically disclose more favorable news via Twitter than traditional firm disclosures. Firm disclosures via social media thus serve as an additional benchmark that incentivizes firms to engage in earnings management strategies to meet or beat market expectations.

Next, I find that firm size, growth opportunities, leverage, profitability, and financial health are the main determinants of corporate adoption of Twitter. These findings are consistent with extant literature, which documents these firm characteristics as determinants of firms' voluntary disclosure via traditional or social media. Using a subset of firms with Twitter accounts, I find that the number of firm followers, number of hashtags per tweet, firm size, firm growth opportunities, and firm leverage are the determinants of firms' Twitter posting activity. I perform several robustness tests to validate the main results, including scraping data from Facebook. Facebook results are qualitatively similar but slightly weaker than Twitter results.

This study contributes to accounting and finance literature with respect to voluntary disclosure, corporate use of social media, and earnings management. Due to limited data availability, I scrape public data from Twitter and Facebook to form one proprietary social media database of the SET50 firms that can be used to examine the corporate use of social media platforms and related attributes. Furthermore, my findings have practical implications for investors, regulators, and managers. First, investors make informed decisions, as they understand which firm characteristics likely adopt social media platforms, and whether firms' presence on social media contributes to earnings management. Second, regulators can better monitor and govern firms that adopt social media platforms to disseminate more complete and neutral financial information to investors. Last, managers are incentivized to reduce the use of social media for impression management purposes to avoid potential negative market reactions.

The rest of this paper is organized as follows: Section 2 discusses literature review and develops hypotheses. Section 3 describes sample selection and research methodology. Section 4 explains the empirical results and data analyses. Section 5 provides the conclusions.

2. Literature Review and Hypothesis Development

2.1 The Role of Traditional Media in Capital Markets

Prior literature suggested that traditional media plays an important role as information intermediaries in capital markets. As discussed in Bushee, Core, Guay, and Hamm (2010), information intermediary is defined as an agent that provides new and useful information to other parties because it has not been publicly released or widely disseminated. In addition, business press is viewed as the most widely disseminated of all information intermediaries to capital market participants. Specifically, Fang and Peress (2009) and Bushee et al. (2010) find that great press coverage reduces information asymmetry around earnings announcements. Similarly, Peress (2014) and Guest (2021) demonstrate that the media contributes to the efficiency of stock markets by improving the dissemination of information among investors and its incorporation into stock prices.

Media also plays a monitoring role in detecting and/or deterring irregularities and management opportunism. Dai, Parwada, and Zhang (2015) show that media plays a role in corporate governance by disseminating news and reducing insider trading profits. Miller (2006) investigates the media role as a watchdog for accounting fraud and finds that the press rebroadcasts information from other information intermediaries and thus lowers the cost to identify and investigate accounting fraud. Dyck, Morse, and Zingales (2010) reveal that media can help detect corporate fraud, as journalists have incentives to reveal fraud in their articles to build career and reputation. As discussed in Kothari, Li, and Short (2009), empirical evidence suggests that investors consider business press articles to be a more credible source of information than firm disclosures. While business press disseminates good and bad news about firms they cover, firms tend to disclose more favorable news via their social media platforms. Therefore, the role of social media may have different implications to capital markets compared with the role of traditional media, as discussed in the following section.

2.2 The Role of Social Media in Capital Markets

Academic literature has recently extended research interests from examining the role of traditional media to the use of social media in disseminating news. Prominent examples of social media platforms include Twitter and Facebook, which were created and launched in 2004 and 2006, respectively. As important sources of information to capital market participants, these two social media platforms are therefore still relatively new compared with traditional media, such as business press. Investors also increasingly rely on information from social media when making investing decisions. Nonetheless, Bartov, Faurel, and Mohanram (2018) note that information from social media, such as Twitter, may be uninformative or intentionally misleading because Twitter is an unregulated platform with anonymous users.

Several studies examine the role of corporate use of social media in developed markets. For example, Blankespoor, Miller, and White (2014) find that firm-initiated news via Twitter in addition to traditional disclosures are associated with low abnormal returns, consistent with the role of social media in reducing information asymmetry. Lee, Hutton, and Shu (2015) document that firms with any social media platforms experience less negative market reactions than firms without any social media accounts. Using S&P 1500 firms, Jung, Naughton, Tahoun, and Wang (2018) examine whether firms use social media to strategically disseminate financial information. The authors show that firms less likely disseminate when news is bad. Furthermore, Yang and Liu (2017) analyze Financial Times Stock Exchange 100 firms and find that firms minimize negative earnings-related news but adopt various self-presentational patterns and disclosure techniques through Twitter to emphasize positive news. Recent studies also analyze firms' posting activity on social media. For example, Hasan and Cready (2019) find that firms' Facebook posting activity increases around earnings announcements, especially for posts containing earnings news. This finding reflects the fact that engaging in posting activity during announcement periods draws attention to the contents of earnings announcements. As for emerging markets, an international case study of Nestle's Twitter accounts in Indonesia by Naibaho, Naibaho, and Davianti (2019) provides contrasting evidence that Nestle uses Twitter to disclose various kinds of information related to environmental, branding, health, gender, and education. Nonetheless, the corporate use of Twitter in emerging markets to disclose either financial or nonfinancial information is rather limited in Indonesia compared with the corporate use of social media in the United States.

2.3 Earnings Management Literature

As discussed in Healy and Wahlen (1999), earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to mislead stakeholders about firm performance or to obtain contractual benefits from reported accounting numbers. Regulators and investors have raised concerns that certain management incentives, such as stock-based compensation, can induce managers to increase short-term stock prices through earnings management (Cheng & Warfield, 2005). Studies document these managerial incentives to manipulate reported earnings. For example, Bergstresser and Philippon (2006) provide evidence that the use of discretionary accruals to manipulate reported earnings is high for firms with high levels of chief executive officer stock-based compensation. Similarly, Cheng and Warfield (2005) show that managers with high equity incentives are motivated to engage in earnings management to increase the values of shares they sell in subsequent periods. Capital market pressures also incentivize managers to engage in earnings management. Graham, Harvey, and Rajgopal (2005) survey and interview more than 400 executives to determine factors that drive reported earnings and disclosure decisions. Chief financial officers express that that their two most important earnings benchmarks are quarterly earnings for the same quarter last year and the analyst consensus estimate. Therefore, meeting or beating these two benchmarks to influence stock prices is considered important to executives. In addition, the survey results suggest that 78 percent of the sample admit to sacrificing long-term value to smooth earnings.

According to Sloan (1996), earnings are the sum of accruals and operating cash flows, and investors do not fully adjust their earnings expectations for information in accruals and cash flows. Therefore, management can manipulate accruals and/or cash flow components of total earnings as mechanisms to meet or beat earnings benchmarks (Xu, Taylor & Dugan, 2007). As discussed by Gunny (2010), earnings management can be classified into two categories: accrual-based earnings management and real activities manipulation. Accrual-based earnings management occurs when managers manipulate reported earnings through discretionary accrual choices that are allowed under Generally Accepted Accounting Principles (Kim & Sohn, 2013). Examples include premature revenue recognition, delayed expense recognition, and big bath restructuring charges (Gunny, 2010; Xu et al., 2007). Real activities manipulation is defined as departures from normal operational practices to meet or beat certain earnings benchmarks (Roychowdhury, 2006). For example, management can use discretion to cut research and development expenses or offer price discounts. To further shed light on whether managers use real earnings management and accrual management as substitutes in managing earnings, Zang (2012) examines this issue and finds that managers trade-off the two earnings management methods based on their relative costs. Extant literature also documents a shift from accrual earnings management to real earnings management during the post-Sarbanes–Oxley Act period (Cohen, Dey, & Lys, 2008; Mason & Morton, 2020). Taken together, prior literature suggested the importance of examining accrual-based and real earnings management, as both strategies may have different implications to firms.

2.4 Social Media and Earnings Management Literature

This section reviews a specific research area that examines the association between different types of media and earnings management. Chen, Cheng, Li, and Zhao (2020) show that traditional media coverage is negatively associated with accrual-based and real earnings management, suggesting the role of media as an external monitor to constrain managerial opportunistic earnings management. While extant literature focuses on examining the effect of traditional media coverage on earnings management, only a few studies examine the role of social media on earnings management (Meng, 2020). However, note that relative to traditional media, social media can help provide timely information about firms and effectively promote two-way communication among individual investors and between individual investors and companies. On the one hand, social media attention may play a monitoring role in curbing earnings management consistent with the role of traditional media. On the other hand, social media coverage may incentivize managers to meet or exceed expectations transmitted through social media platforms by individual users. For example, Meng (2020) examines the effect of media attention on real earnings management. The author uses a sample of listed companies of the Shenzhen Stock Exchange and media data from the financial news database and Chinese social media database. In contrast to the findings of the monitoring role of traditional media in Chen et al. (2020), Meng (2020) finds a positive correlation between media attention and real earnings management. That is, the higher the media attention, the more the management can engage in real activities manipulation to manipulate reported earnings. Zhang, Li, Urquhart, and Wang (2021) examine the effect of social media on financial reporting quality by using data from the Internet stock message board in China. Consistent with findings in Meng (2020), Zhang et al. (2021) provide evidence that individual investors' postings on the stock message board (a proxy for social media platform) can promote earnings management. That is, a positive association exists between social media coverage and earnings management, as management is pressured to meet the irrational expectations of these individual but less sophisticated investors.

2.5 Hypothesis Development

As discussed in the literature review, several studies document the role of corporate use of social media platforms in disseminating news to capital markets. However, these studies do not examine the association between social media and earnings management directly. Therefore, I draw on recent studies that address this research question, such as Meng (2020) and Zhang et al. (2021). Specifically, these studies find that capital market participants' use of social media contributes to high earnings management. This finding suggests that the corporate use of social media may also be associated with an increase in earnings management for two reasons. First, the adoption of social media as another disclosure channel makes companies more visible to the scrutiny by capital markets than usual. Second, impression management literature suggests that firms have an incentive to manage impressions of their organizational image and reputation by presenting a favorable view of their performance (Yang & Liu, 2017). Firms with presence on social media tend to engage in impression management by strategically disclosing more favorable information via these platforms than firms without social media accounts. Firm disclosures via social media platforms thus become an additional benchmark that firms are pressured to meet or beat market expectations in addition to other earnings benchmarks, such as analyst consensus forecasts. These market pressures on firm performance may incentivize firms to engage in high earnings management to meet or beat market expectations, leading to my first directional hypothesis:

Hypothesis 1 (H1): Firms' adoption of social media is positively associated with earnings management.

Despite an increasing use and reliance on information disclosed through various social media platforms in business, the economic benefits of the presence of companies on social media platforms is not well documented in literature. Ravaonorohanta and Sayumwe (2020) reveal that companies that are on Twitter outperform companies that are not on Twitter for their stock performance. This finding suggests that differential economic consequences exist between firms that use versus firms that do not use social media platforms. Nonetheless, a few studies explore the determinants of firms' use of social media platforms in accounting and finance literature. Therefore, in addition to examining the association between firms' adoption of social media and earnings management, shedding light further on which firm characteristics likely have presence on social media platforms is also important. Drawn on related voluntary disclosure literature, I identify and examine five firm characteristics. First, prior literature suggested that disclosure activity increases with firm size (Ettredge, Richardson & Scholz, 2002; Lang & Lundholm, 1993). Second, growing companies, as measured by market-to-book (MTB) ratios, also tend to have considerable information to disclose (Hasan & Cready, 2019). Third, firms with high levels of leverage are subject to high monitoring costs and thus are likely to disclose considerable information voluntarily (Elfeky, 2017). Fourth, higher profit firms tend to disclose more voluntary information to satisfy the needs of stakeholders and justify their higher profits (Elfeky, 2017). Fifth, Jankensgard (2015) shows that voluntary disclosure increases with a firm's financial status, as measured by Altman's Z-score. Taken together, extant literature documents these five firm characteristics as determinants of voluntary disclosure, as such firms have many resources to devote to disclosure-related activities. Therefore, I examine whether these factors incentivize firms to adopt social media platforms to disseminate voluntary disclosure, leading to my second hypothesis:

Hypothesis 2 (H2): Firm-specific characteristics (firm size, growth opportunities, leverage, profitability, financial health) are positively associated with firms' adoption of social media.

After examining the differential effects of firms with and without presence on social media platforms, I investigate factors that influence firm posting activity on social media for firms that adopt social media platforms. This research question is considered important, given that little is known about the determinants of firms' voluntary disclosure via social media. Certain common features exist among various social media platforms, such as Twitter and Facebook that are worth examining. The number of followers of corporate social media accounts may indicate firms' tendency to engage in posting activity to communicate with their followers. Most social media platforms allow users to click the like button to show an interest in each post made by firms. Research on tags and tagging indicates that users prefer to use their own vocabulary to convey certain meanings (Chang & Iyer, 2012). Hashtags used in social media platforms are created and included in each post by users to reference to certain topics or keywords. A search for each hashtag returns all posts that have been tagged with that hashtag, which can be helpful for research and communication purposes. Another interesting property of social media platforms is the character length of each post. While Facebook allows 63,206 characters per post, Twitter has increased its character limit from 140 to 280 characters per tweet since 2017 (Hasan & Cready, 2019). These factors suggest the importance of posting length, as companies can include additional detailed information to reach their followers. Considering that whether these social media characteristics are associated with social media posting activity by firms and in which direction is unclear ex ante in literature, I set the third hypothesis as null.

Hypothesis 3a (H3a): Social media characteristics (number of firm followers, number of likes, number of hashtags, posting length) are not associated with firms' posting activity on a social media platform.

I draw on related voluntary disclosure literature to identify three common firm characteristics as additional determinants. Jung et al. (2018) provide evidence that S&P 1500 firms with Twitter accounts tend to be larger and more valuable (growth opportunities) than other firms. Firm leverage is also found to be associated with voluntary disclosure (Boshnak, 2021; Zamil, Ramakrishnan, Jamal, Hatif & Khatib, 2021), leading to another directional hypothesis:

Hypothesis 3b (H3b): Firm-specific characteristics (firm size, growth opportunities, leverage) are positively associated with firms' posting activity on a social media platform.

3. Sample Selection and Research Methodology

3.1 Twitter Data and Sample Selection

Prior literature suggested that Twitter and Facebook are the two most frequently adopted social media platforms for corporations and academic research (Jung et al., 2018; Yang & Liu, 2017). I select Twitter as the main social media platform to test my hypotheses, as extant literature indicates the importance and prevalence of this platform. Specifically, Barnes, Lescault, and Wright (2013) reveal that

77 percent of Fortune 500 companies are active on Twitter; Balasubramanian, Fang, and Yang (2021) find similar patterns for S&P 500 firms. Furthermore, anecdotal evidence shows that Twitter has the most diverse set of users among social media platforms (Bartov et al., 2018). I also discuss Facebook data collection as part of robustness tests. Given that most prior studies focused on examining the corporate use of social media in developed countries, such as the United States and Canada, research in emerging markets is scant and limited to data from China, a unique setting that is different from other developing countries. Therefore, I intend to fill the literature gap by collecting and investigating social media data in Thailand, which is considered an important emerging market in the Southeast Asia region (Sayari & Marcum, 2018).

First, I identify the list of the Stock Exchange of Thailand 50 firms as of December 2019 (SET50 firms) from the SET website. Second, I identify whether each of the SET50 firms has a Twitter account by visiting their corporate website for links to official social media sites. Third, I use Twitter application programming interface (API) to scrape data for the Twitter posts (tweets) of SET50 firms that adopt Twitter during my sample period from 2015 to 2019. Raw scraped data for each post include posting date, full text of each tweet, number of likes, number of retweets, and hashtags used in each tweet. Following Jung et al. (2018), I collect data of each firm's followers as of a specific date and include this measure as a static or time-invariant variable because historical data for the daily number of firm followers are not publicly available. Social media adoption and usage of Twitter by SET50 firms are summarized by industry in Table 1. My sample period spans for five years beginning in 2015 and ending in 2019 to provide recent data analyses without the confounding effect of the COVID-19 pandemic. Overall, 24 firms in the SET50 market have presence on Twitter with available data in any year during the sample period. I obtain financial variables from the SETSMART database. Overall, the full sample for testing H1 and H2 comprises 665 firm-quarter observations (38 unique firms), excluding firms in the financial industry and observations with missing financial variables. After removing observations without Twitter and financial variables, the final subsample consists of 222 firm-quarter observations (15 unique firms) for testing H3a and H3b. Table 2 summarizes the sample selection process.

Table 1 SET50 Social Media Adoption and Usage by Industry during the 2015–2019 Period

Industry	Number of SET50 Firms	Twitter Adoption		Twitter Usage				
		n	%	Number of Firm Followers	Average Tweets Per Quarter	Average Retweets Per Quarter	Average Likes Per Quarter	Average Hashtags Per Quarter
Agro & Food	5	1	4.2%	26,686	12	34,268	35,516	26
Financial	10	6	25.0%	1,318,437	3,060	31,396	24,047	2,219
Industrial	2	1	4.2%	1,026	3	6	12	5
Property & Construction	6	4	16.7%	980,987	200	7,267	3,928	191
Resources	12	2	8.3%	259	4	3	5	3
Services	10	7	29.2%	3,452,841	763	40,716	12,631	381
Technology	5	3	12.5%	1,045,606	3,094	120,325	117,626	703
Total	**50**	**24**	**100%**					

Notes to Table 1: This table presents SET50 Twitter adoption and usage by industry during the sample period 2015–2019.

Table 2 Sample Selection

Step 1:	
Number of firms listed in the SET50 market for hand-collected data (List of 50 firms as of December 2019)	50
Less: Number of firms without Twitter data between 2015 and 2019	(26)
Remaining firms for hand-collected data	24
Step 2:	
Firm-quarter observations with financial variables obtained from the SETSMART database between 2015 and 2019 for full sample analyses (38 unique firms)	665
Less: Firm-quarter observations without Twitter and financial variables between 2015 and 2019	(443)
Firm-quarter observations for subsample analyses (15 unique firms)	222

Notes to Table 2: The sample comprises firm-quarter observations during the 2015–2019 period.

3.2 Measurement of Earnings Management

Prior literature suggested that earnings are the sum of cash flows and accruals and that firms can manage earnings via accruals and/or cash flows (Gunny, 2010; Sloan, 1996). Therefore, I use two main proxies for earnings management via accruals and cash flows. For the first main proxy of earnings management via accruals, I follow the well-known modified Jones Model, as discussed in Zang (2012), to estimate abnormal accruals (*ABACC1*). Specifically, I estimate the expected level of accruals for each industry-year by using available firm-quarter observations in that year for all Thai listed companies between 2015 and 2019 that meet the required minimum number of 15 observations. Following the approach for quarterly models in Matsumoto (2002), I include the fourth-quarter indicator variable because fourth-quarter accruals may be different from other quarters. *ABACC1* is the difference between the reported accruals and the normal accruals estimated from the model. Consistent with abnormal accruals definition, I use abnormal operating cash flows (*ABCFO*) as a proxy for earnings management via cash flows. Expected operating cash flows are estimated as a function of current period sales and change in sales. *ABCFO* is the difference between the reported and expected operating cash flows, following Dechow, Kothari, and Watts (1998), Roychowdhury (2006), and Lee (2012). In addition, I use the lagged model of Dechow, Richardson, and Tuna (2003) to estimate abnormal accruals (*ABACC2*) as an alternative measure of accrual management because this model has a higher explanatory power than the well-known modified Jones Model. Last, I include two proxies of abnormal discretionary expenses (*ABDISEXP*) and abnormal production costs (*ABPROD*) as alternative measures of real earnings management, following Roychowdhury (2006). All variables are defined in the Appendix.

3.3 Measurement of Twitter Adoption and Twitter Characteristics

As for the measurement of Twitter adoption (*TWDUMMY*), I use an indicator variable that is equal to one (zero) for each of the SET50 firms with (without) presence on the Twitter platform during the sample period. For social media posting activity, I follow Hasan and Cready (2019) and measure Twitter posting activity (*TWEET*) as the logarithm of the average number of tweets per day made by each firm *i* in quarter *q*. I also include four Twitter characteristics. Firm followers (*FOLLOWER*) are measured as the logarithm of the total number of followers as of a specific date, following Jung et al. (2018). Three other potential determinants of Twitter posting activity are number of likes, number of hashtags, and posting length. I measure these variables per each post because they are obtained directly from each post. *LIKEPERPOST* is measured as the logarithm of the average number of likes per each post of firm *i* in quarter *q*. *HTAGPERPOST* is measured as the logarithm of the average number of hashtags per each post of firm *i* in quarter *q*. *LENPERPOST* is measured as the logarithm of the average number of character length per each post of firm *i* in quarter *q*.

3.4 Empirical Models

To test H1, I use the following linear regression model to examine whether firms' adoption of Twitter is associated with earnings management, as shown in Eq. (1).

$$\begin{aligned} ABACC1_{i,q}(ABCFO_{i,q}) \;=\; & \alpha_0 + \alpha_1 TWDUMMY_{i,q} + \alpha_2 SIZE_{i,q-1} + \alpha_3 MTB_{i,q-1} + \alpha_4 LEV_{i,q-1} \\ & + \alpha_5 ZSCORE_{i,q-1} + Industry\ and\ YearQuarter\ Fixed\ Effects + \varepsilon_{i,q} \qquad \text{Eq. (1)} \end{aligned}$$

The main dependent variable in Eq. (1) is *ABACC1*, which is measured as the absolute value of abnormal accruals estimated from the modified Jones Model. An alternative dependent variable is *ABCFO*, which is measured as the absolute value of abnormal cash flows, following Dechow et al. (1998). The main test variable is *TWDUMMY*, which is an indicator variable that is equal to one (zero) for firms with (without) presence on Twitter for each firm *i* in quarter *q*. Other control variables are included, following prior literature, as they are found to be associated with earnings management (Agrawal & Chatterjee, 2015; Roychowdhury, 2006; Zang, 2012). All control variables are in the lagged period. *SIZE* and *MTB* control for firm size and growth opportunities, respectively. *SIZE* is measured as the logarithm of the total assets. *MTB* is measured as the ratio of market value of equity to book value of equity. *LEV* is calculated as total debts divided by total assets and is included to control for risks from financial leverage. Return on assets (*ROA*) is the calculated net income divided by total assets and is included to control for firm performance. Altman's Z-Score or *ZSCORE* is included to control for financial health.

To test H2, I use the following logistic regression model to examine the determinants of firms' adoption of Twitter, as presented in Eq. (2).

$$\begin{aligned} TWDUMMY_{i,q} \;=\; & \gamma_0 + \gamma_1 SIZE_{i,q-1} + \gamma_2 MTB_{i,q-1} + \gamma_3 LEV_{i,q-1} + \gamma_4 ROA_{i,q-1} + \gamma_5 ZSCORE_{i,q-1} \\ & + Industry\ and\ YearQuarter\ Fixed\ Effects + \varepsilon_{i,q} \qquad \text{Eq.(2)} \end{aligned}$$

The main dependent variable in Eq. (2) is *TWDUMMY*, an indicator variable equals to one (zero) for firms with (without) presence on Twitter for firm *i* in quarter *q*. Drawn on voluntary disclosure literature, five firm characteristics are included as the potential determinants of firms' adoption of Twitter: *SIZE*, *MTB*, *LEV*, *ROA*, and *ZSCORE*, which are defined earlier. Note that the same set of control variables from Eq. (1) is also identified as the determinants of social media voluntary disclosure. The reason is that these variables are general firm characteristics that are found to be associated with most activities performed by firms, as discussed in accounting literature.

To test H3a and H3b, I use the following linear regression model to examine the determinants of Twitter posting activity levels made by firms, as shown in Eq. (3).

$$\begin{aligned} TWEET_{i,q} = {} & \delta_0 + \delta_1 FOLLOWER_{i,q} + \delta_2 LIKEPERPOST_{i,q-1} + \delta_3 HTAGPERPOST_{i,q-1} \\ & + \delta_4 LENPERPOST_{i,q-1} + \delta_5 SIZE_{i,q-1} + \delta_6 MTB_{i,q-1} + \delta_7 LEV_{i,q-1} \\ & + Industry\ and\ YearQuarter\ Fixed\ Effects + \varepsilon_{i,q} \end{aligned} \qquad \text{Eq. (3)}$$

The main dependent variable in Eq. (3) is *TWEET*, defined as the logarithm of the average number of tweets per day made by each firm i in quarter q. *FOLLOWER* is defined as the logarithm of the number of firm followers as of a specific date. *LIKEPERPOST*, *HTAGPERPOST*, and *LENPERPOST* are defined as the logarithm of the average number of likes, number of hashtags, and character length of each post. Drawn on voluntary disclosure literature, three firm characteristics are included as the potential determinants of social media posting activity: *SIZE*, *MTB*, and *LEV*. I use lagged variables for all independent variables, except for the number of firm followers that is a static time-invariant variable. For all empirical models in Eqs. (1)–(3), continuous variables are winsorized at the top and bottom 1 percent to minimize outlier issues. Industry and year-quarter fixed effects are included to control for unobserved heterogeneity.

4. Empirical Results and Analyses

4.1 Descriptive Statistics and Univariate Analyses

Table 3 Panel A (Panel C) provides descriptive statistics for all variables included in the empirical models for full sample (subsample) analyses. To ensure that results are not driven by a particular subgroup, I perform t-test of the differences in the mean value of each variable for firms with and without Twitter. Untabulated results suggest that the mean values of most variables from the two groups are statistically different at the 0.05 level, except for *ABDISEXP* and *ABPROD*. Table 3 Panel B (Panel D) presents the correlation coefficients of all variables for full sample (subsample) analyses. Examining the correlations in Panel B of Table 3 (full sample) reveals that firms' adoption of Twitter (*TWDUMMY*) is positively associated with the earnings management variables (*ABACC1* or *ABCFO*). This result suggests that firms with presence on Twitter more likely engage in earnings management than firms without Twitter accounts. As for the determinants of firms' adoption of Twitter, the univariate analyses indicate that firms' adoption of Facebook is positively associated with their presence on Twitter.

In addition, larger firms (*SIZE*), higher MTB ratio firms (*MTB*), and highly leveraged firms (*LEV*) more likely adopt the Twitter platform. As for the subsample analyses in Panel D of Table 3, the correlation results reveal that firm characteristics (*SIZE*, *MTB*, *LEV*) are positively associated with Twitter posting activity (*TWEET*). Furthermore, Twitter characteristics (*FOLLOWER*, *LIKEPERPOST*, *HTAGPERPOST*) are shown to be associated with *TWEET*. To address the potential multicollinearity issue among variables, I examine each correlation coefficient and find that the highest positive (negative) coefficient in Table 3 is at 0.77 (–0.57). Therefore, multicollinearity is not an issue for subsequent multivariate analyses.

Table 3 Summary Statistics

Panel A: Full Sample Descriptive Statistics (n = 665)

Variable	Mean	P25	Median	P75	Minimum	Maximum	Standard Deviation (SD)
TWDUMMY	0.36						0.48
ABACC1	0.03	0.01	0.02	0.03	0.00	0.15	0.03
ABACC2	0.02	0.01	0.01	0.03	0.00	0.10	0.02
ABCFO	0.04	0.01	0.03	0.05	0.00	0.18	0.04
ABDISEXP	0.03	0.01	0.02	0.04	0.00	0.14	0.03
ABPROD	0.01	0.00	0.01	0.02	0.00	0.10	0.02
SIZE_LAG	18.70	17.87	18.65	19.46	16.16	21.53	1.12
MTB_LAG	4.14	1.53	2.57	5.75	0.78	14.23	3.37
LEV_LAG	0.30	0.20	0.31	0.41	0.01	0.63	0.15
ROA_LAG	0.05	0.02	0.04	0.06	–0.01	0.22	0.04
ZSCORE_LAG	3.65	1.53	2.53	4.24	0.22	18.89	3.45
FBDUMMY	0.55						0.50

Table 3 Summary Statistics (Cont.)

Panel B: Full Sample Pearson Correlations (n = 665)

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	*TWDUMMY*	1											
2	*ABACC1*	0.11*	1										
3	*ABACC2*	0.10*	0.77*	1									
4	*ABCFO*	0.21*	0.51*	0.37*	1								
5	*ABDISEXP*	0.06	0.07	0.07	0.03	1							
6	*ABPROD*	−0.03	0.03	0.05	0.01	−0.02	1						
7	*SIZE_LAG*	0.09*	−0.11*	−0.14*	−0.18*	−0.23*	0.13*	1					
8	*MTB_LAG*	0.23*	0.05	0.02	0.35*	0.23*	−0.11*	−0.42*	1				
9	*LEV_LAG*	0.10*	−0.04	−0.08*	−0.12*	−0.16*	0.01	0.40*	0.10*	1			
10	*ROA_LAG*	−0.03	0.04	0.11*	0.34*	0.10*	0.02	−0.36*	0.44*	−0.34*	1		
11	*ZSCORE_LAG*	0.04	−0.04	−0.02	0.33*	0.13*	−0.07	−0.55*	0.45*	−0.57*	0.64*	1	
12	*FBDUMMY*	0.55*	0.10*	0.14*	0.27*	0.18*	−0.19*	−0.08*	0.42*	−0.06	0.16*	0.22*	1

Panel C: Twitter Subsample Descriptive Statistics (n = 222)

Variable	Mean	P25	Median	P75	Minimum	Maximum	SD
TWEET	0.95	0.09	0.63	1.60	0.01	3.65	0.99
FOLLOWER	10.66	9.17	10.19	12.74	4.72	14.73	2.79
LIKEPERPOST_LAG	2.01	0.68	1.67	2.94	0.00	8.40	1.72
HTAGPERPOST_LAG	0.39	0.02	0.18	0.65	0.00	1.77	0.48
LENPERPOST_LAG	4.85	4.61	4.76	5.11	3.99	5.55	0.36
SIZE_LAG	18.85	18.47	18.90	19.46	16.83	20.26	0.80
MTB_LAG	5.21	2.11	4.59	7.10	1.17	14.06	3.65
LEV_LAG	0.32	0.25	0.32	0.39	0.09	0.62	0.13
ABACC1_LAG	0.03	0.01	0.02	0.04	0.00	0.18	0.04
ABACC2_LAG	0.02	0.01	0.01	0.03	0.00	0.11	0.03
ABCFO_LAG	0.05	0.02	0.04	0.07	0.00	0.17	0.04
ABDISEXP_LAG	0.03	0.01	0.03	0.04	0.00	0.12	0.03
ABPROD_LAG	0.01	0.00	0.01	0.01	0.00	0.09	0.02

Table 3 Summary Statistics (Cont.)

Panel D: Twitter Subsample Pearson Correlations (n = 222)

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	*TWEET*	1												
2	*FOLLOWER*	0.47*	1											
3	*LIKEPERPOST_LAG*	0.09*	0.41*	1										
4	*HTAGPERPOST_LAG*	−0.22*	−0.17*	0.34*	1									
5	*LENPERPOST_LAG*	0.04	0.05*	0.32*	0.48*	1								
6	*SIZE_LAG*	0.34*	−0.16*	0.10*	−0.04	−0.02	1							
7	*MTB_LAG*	0.30*	0.12*	−0.16*	−0.05*	−0.05*	−0.19*	1						
8	*LEV_LAG*	0.50*	0.08*	−0.13*	−0.10*	−0.13*	0.50*	0.36*	1					
9	*ABACC1_LAG*	0.33*	0.36*	0.14*	−0.05*	−0.03	−0.11*	−0.17*	0.02	1				
10	*ABACC2_LAG*	0.31*	0.36*	0.16*	−0.10*	0.02	−0.09*	−0.18*	0.04	0.74*	1			
11	*ABCFO_LAG*	0.31*	0.39*	0.15*	−0.05*	−0.03	−0.25*	0.17*	−0.02	0.57*	0.41*	1		
12	*ABDISEXP_LAG*	0.06*	−0.05*	−0.01	0.02	0.01	−0.00	0.31*	0.10*	0.08*	0.08*	−0.05*	1	
13	*ABPROD_LAG*	−0.05*	−0.40*	−0.24*	−0.11*	−0.13*	0.07*	−0.11*	−0.05*	0.05*	0.04	−0.04	0.07*	1

Notes to Table 3:
See Appendix for variable definitions. All continuous variables are winsorized at the top and bottom 1^{st} and 99^{th} percentiles. * represents Pearson correlation coefficients that are statistically significant at the 0.05 level.

4.2 Multivariate Analyses

Table 4 presents the cross-sectional regression results of Eq. (1), which examines whether firms' adoption of Twitter is associated with earnings management via accruals and cash flows. A coefficient on *TWDUMMY* is positive and statistically significant at the 0.01 level in Models 1 and 3. The results of the alternative measures of earnings management are qualitatively similar, as shown in Models 2 and 5. Therefore, the overall results suggest that relative to firms without Twitter accounts, firms that adopt Twitter more likely engage in earnings management, thereby confirming H1. SET50 firms with presence on Twitter have another disclosure channel that is more visible and interactive to capital market participants. These firms also tend to engage in impression management by disclosing more favorable information via this platform than firms without Twitter accounts. Firm disclosures via Twitter and market pressure from firm followers therefore serve as additional benchmarks that motivate firms to engage in high earnings management, relative to firms without Twitter. As for control variables, I find that firms with higher growth opportunities (*MTB*), better financial performance (*ROA*), and better financial health (*ZSCORE*) more likely engage in real earnings management than in accrual management. Differential results for these firm characteristics are expected due to the trade-off between the two earnings management strategies, as discussed in Zang (2012).

Table 4 Test of Twitter Adoption and Earnings Management (H1)

Variable	Predicted Sign	Eq. (1) Accrual Management				Eq. (1) Real Earnings Management					
		Model 1 DV = *ABACC1*		Model 2 DV = *ABACC2*		Model 3 DV = *ABCFO*		Model 4 DV = *ABDISEXP*		Model 5 DV = *ABPROD*	
		Coefficient	*t*	Coefficient	*t*	Coefficient	*t*	Coefficient	*t*	Coefficient	*t*
Main Test Variable											
TWDUMMY	+	0.009***	3.93	0.007***	3.80	0.011***	3.94	−0.003	−1.52	0.005***	2.74
Control Variable											
SIZE_LAG		−0.005***	−4.22	−0.005***	−5.50	0.001	0.80	−0.001	−0.99	0.001*	1.95
MTB_LAG		0.000	0.50	−0.001	−1.39	0.001**	2.27	0.003***	5.19	0.000	0.37
LEV_LAG		−0.026**	−2.44	−0.015*	−1.83	0.001	0.07	−0.049***	−4.16	−0.020***	−3.44
ROA_LAG		−0.000	−0.01	0.044	1.04	0.129**	2.11	−0.073**	−2.01	0.052***	2.67
ZSCORE_LAG		−0.002***	−4.36	−0.001***	−4.18	0.002***	3.71	−0.002***	−4.12	−0.001***	−2.77
Constant		0.124***	6.11	0.117***	7.11	−0.032	−1.38	0.093***	4.60	−0.020*	−1.78
Industry Fixed Effects		Included		Included		Included		Included		Included	
Year-Quarter Fixed Effects		Included		Included		Included		Included		Included	
Number of Observations		665		665		665		665		665	
R-squared		0.209		0.184		0.435		0.365		0.369	

Notes to Table 4:

This table presents the ordinary least squares (OLS) regression results of Eq. (1).

$$ABACC1_{i,q}(ABCFO_{i,q}) = \alpha_0 + \alpha_1 TWDUMMY_{i,q} + \alpha_2 SIZE_{i,q-1} + \alpha_3 MTB_{i,q-1} + \alpha_4 LEV_{i,q-1} + \alpha_5 ROA_{i,q-1} + \alpha_5 ZSCORE_{i,q-1} + Industry\ and\ YearQuarter\ Fixed\ Effects + \varepsilon_{i,q} \quad \text{Eq. (1)}$$

Fixed industry and year-quarter effects are included, and p-values are based on robust standard errors. *, **, ***: significant at 10%, 5%, 1% two-sided p-values, respectively. All continuous variables are winsorized at the top and bottom 1^{st} and 99^{th} percentiles. All variables are defined in the Appendix.

Table 5 presents the logistic regression results of Eq. (2), which examines the determinants of firms' adoption of Twitter (H2). The overall results confirm H2, except for *ROA*. That is, firms with larger size (*SIZE*), higher growth opportunities (*MTB*), higher financial leverage (*LEV*), and better financial health (*ZSCORE*) more likely adopt Twitter. These findings are consistent with prior literature, which documented these firm characteristics to be associated with firms' voluntary disclosure via traditional or social media platforms. However, a coefficient on *ROA* is negative, suggesting that firms with low *ROA* in the prior-period likely adopt Twitter in the current period. That is, firms with poor performance

Table 5 Test of Firm Characteristics and Twitter Adoption (H2)

Eq. (2) DV = *TWDUMMY*					
Variable	Predicted Sign	Model 1		Model 2	
		Coefficient	*z*	Coefficient	*z*
SIZE_LAG	+	0.605***	6.12	0.485***	4.14
MTB_LAG	+	0.112**	2.29	−0.019	−0.41
LEV_LAG	+	3.631***	3.29	4.383***	3.92
ROA_LAG	+	−17.278***	−4.02	−16.436***	−3.75
ZSCORE_LAG	+	0.177***	3.82	0.178***	3.49
FBDUMMY	+			2.715***	7.89
Constant		−14.855***	−7.60	−14.388***	−5.66
Industry Fixed Effect		Included		Included	
Year-Quarter Fixed Effect		Included		Included	
Number of Observations		665		665	
Pseudo-R^2		0.287		0.404	

Notes to Table 5:
This table presents the logistic regression results of Eq. (2).

$$TWDUMMY_{i,q} = \gamma_0 + \gamma_1 SIZE_{i,q-1} + \gamma_2 MTB_{i,q-1} + \gamma_3 LEV_{i,q-1} + \gamma_4 ROA_{i,q-1} + \gamma_5 ZSCORE_{i,q-1} + Industry\ and\ YearQuarter\ Fixed\ Effects + \varepsilon_{i,q} \quad \text{Eq. (2)}$$

Fixed industry and year-quarter effects are included, and p-values are based on robust standard errors. *, **, ***: significant at 10%, 5%, 1% two-sided p-values, respectively. All continuous variables are winsorized at the top and bottom 1^{st} and 99^{th} percentiles. All variables are defined in the Appendix.

may be incentivized to use social media for impression management purposes. In addition, I identify firm presence on Facebook, which is another frequently adopted social platform, as a potential determinant. I include this variable in Model 2. The results suggest that firms with presence on Facebook (*FBDUMMY*) also likely adopt Twitter (*TWDUMMY*). Given that Facebook was available a few years prior to the creation of Twitter, firms that already have official Facebook accounts likely adopt Twitter as another alternative platform.

To test H3a and H3b, I use a subsample of firms that adopt Twitter during the sample period and report results in Table 6. Specifically, Table 6 presents the cross-sectional regression results of Eq. (3), which examines the determinants of firms' Twitter posting activity (*TWEET*). Model 1 includes all firm and Twitter characteristics, whereas Model 2 (Model 3) includes accrual management (cash flow management) as an additional determinant. The results suggest that larger firms (*SIZE*), growing firms (MTB), and higher leverage firms (*LEV*) likely post more daily tweets in each quarter. Findings of these firm characteristics as determinants of firms' posting activity are consistent with the determinants of corporate adoption of Twitter, as discussed for the test of H2. As for Twitter characteristics, the number of firm followers (*FOLLOWER*) is positively associated with the number of daily tweets. This finding implies that firms with larger audiences likely use more tweets to disseminate information to their followers in a timely manner. A coefficient on *HTAGPERPOST* is negative and statistically significant in all models, suggesting that the more hashtags used in each post, the lower the number of tweets per day. This case is possible, given that the use of multiple hashtags per post can help spread the news broadly and quickly; thus, firms do not necessarily need to post additional tweets each day. However, I do not find results for *LIKEPERPOST* and *LENPERPOST*, indicating that the number of likes per post and character length per post is not associated with daily tweets. Furthermore, I notice that firms engaged in prior-period earnings management tend to post more daily tweets in the current period. For all empirical results in Tables 4–6, I use variance inflation factor (VIF) as a check for multicollinearity issue. A VIF value greater than 10 indicates a case of multicollinearity. Nevertheless, the computed VIF in all models are less than 4. Therefore, I validate that no multicollinearity issue exists in this study.

Table 6 Test of Firm Characteristics and Twitter Posting Activity by Firms (H3a & H3b)

Eq. (3) DV = Log of Average Number of Tweets Per Day (*TWEET*)							
Variable	Predicted Sign	Model 1		Model 2		Model 3	
		Coefficient	t	Coefficient	t	Coefficient	t
FOLLOWER	?	0.059***	3.20	0.048**	2.53	0.051***	2.78
LIKEPERPOST_LAG	?	0.020	0.87	0.011	0.48	0.004	0.17
HTAGPERPOST_LAG	?	−0.290***	−3.68	−0.296***	−3.74	−0.273***	−3.44
LENPERPOST_LAG	?	0.196	1.31	0.139	0.95	0.187	1.29
SIZE_LAG	+	0.242***	4.14	0.297***	5.57	0.278***	5.08
MTB_LAG	+	0.064***	5.68	0.075***	6.85	0.055***	4.66
LEV_LAG	+	0.653**	2.03	0.424	1.35	0.768**	2.43
ABACC1_LAG	?			3.526***	3.14		
ABCFO_LAG	?					2.589**	2.61
Constant		−6.594***	−5.53	−7.362***	−6.81	−7.246***	−6.32
Industry Fixed Effect		Included		Included		Included	
Year-Quarter Fixed Effect		Included		Included		Included	
Number of Observations		222		222		222	
R-squared		0.863		0.873		0.868	

Notes to Table 6:

This table presents the OLS regression results of Eq. (3).

$$TWEET_{i,q} = \delta_0 + \delta_1 FOLLOWER_{i,q} + \delta_2 LIKEPERPOST_{i,q-1} + \delta_3 HTAGPERPOST_{i,q-1} + \delta_4 LENPERPOST_{i,q-1} + \delta_5 SIZE_{i,q-1} + \delta_6 MTB_{i,q-1} + \delta_7 LEV_{i,q-1} + Industry\ and\ YearQuarter\ Fixed\ Effects + \varepsilon_{i,q} \quad \text{Eq. (3)}$$

Fixed industry and year-quarter effects are included, and p-values are based on robust standard errors. *, **, ***: significant at 10%, 5%, 1% two-sided p-values, respectively. All continuous variables are winsorized at the top and bottom 1^{st} and 99^{th} percentiles. All variables are defined in the Appendix.

4.3 Robustness Tests

In addition to the use of alternative proxies for accrual and real earnings management discussed earlier, I perform three robustness tests to validate the main results in Section 4.2. First, I collect the same sets of data for the Facebook platform and test the three hypotheses. Overall, 300 firm-quarter observations of 20 unique firms that adopt Facebook and have available Facebook data are recorded for the 2015–2019 period. Untabulated results are qualitatively similar to Twitter results in Table 4 (H1). That is, firm presence on Facebook also contributes to accrual and real earnings management. Consistent with Table 5 results, I find that similar firm characteristics (*SIZE*, *MTB*, *ROA*) lead to firms' adoption of Facebook (H2). For H3a and H3b, some similarities and differences are observed in the results between Facebook and Twitter data. For example, firm size and the number of firm followers are positively associated with the average numbers of daily Twitter and Facebook posts. While a negative association is found between the number of hashtags per post and number of daily tweets, opposite results are obtained for Facebook data. That is, the number of hashtags used for each post leads to a high number of daily Facebook posts. By contrast, Dewan and Kumaraguru (2014) discuss that on average, Twitter produces 16.28 times the number of hashtags as Facebook. Therefore, assuming that the Twitter results with respect to hashtags may be more relevant than the Facebook results is reasonable, with a caution that conflicting results may occur due to different social media platforms, sample sizes, and sample periods. Another difference is that length for each Facebook post is positively associated with the number of posts each day.

Second, using Twitter and Facebook adoption data, I examine whether the number of social media platforms adopted by each firm in each quarter is associated with earnings management. Untabulated results suggest that the number of social media platforms used is positively associated with earnings management via accruals and cash flows, consistent with the main results in Table 4. Third, although the focus of this study is on the corporate use of social media platforms, examining how Twitter users disseminate information from firms' posting activity are important. As discussed in Jung et al. (2018), social media platforms, such as Twitter, enable not only firms to directly tweet information to their followers but also enable firm followers to share or retweet the information to their followers. On the basis of voluntary disclosure, I examine the determinants of Twitter users to share each post made by firms as part of a robustness test. Similar to the test of H3a and H3b, I use the following linear regression model to examine the determinants of Twitter posting activity by Twitter users, as shown in Eq. (4).

$$
\begin{aligned}
RETWEET_{i,q} = {} & \lambda_0 + \lambda_1 FOLLOWER_{i,q} + \lambda_2 LIKEPERPOST_{i,q} + \lambda_3 HTAGPERPOST_{i,q} \\
& + \lambda_4 LENPERPOST_{i,q} + \lambda_5 SIZE_{i,q-1} + \lambda_6 MTB_{i,q-1} + \lambda_7 LEV_{i,q-1} \\
& + \textit{Industry and Quarter Fixed Effects} + \varepsilon_{i,q} \qquad \text{Eq. (4)}
\end{aligned}
$$

The main dependent variable in Eq. (4) is *RETWEET*, defined as the logarithm of the average number of retweets per day for each firm i in quarter q. Other variables are defined earlier. For this model, I use the current period data for all four Twitter variables because they usually precede or predict followers' activity to retweet posts. Table 7 presents the OLS regression results of Eq. (4), which examines the determinants of users' Twitter posting activity (*RETWEET*). Consistent with Table 6 results, firm size, growth opportunities, and the number of hashtags per post are associated with the number of retweets per day. Similar to Table 6 results, no association is found between *LENPERPOST* and *RETWEET*. Number of likes per post (*LIKEPERPOST*) is positively associated with number of retweets per day (*RETWEET*). This finding is expected because followers show an interest by liking tweets and thus likely retweet the same messages. Last, the results for LEV variable are not statistically significant across all models.

Table 7 Test of Firm Characteristics and Twitter Posting Activity by Twitter Users

Eq. (4) DV = Log of Average Number of Retweets Per Day (*RETWEET*)							
Variable	Predicted Sign	Model 1		Model 2		Model 3	
		Coefficient	*t*	Coefficient	*t*	Coefficient	*t*
FOLLOWER	?	0.097**	2.00	0.064	1.38	0.075	1.57
LIKEPERPOST	?	1.129***	17.42	1.126***	17.99	1.105***	17.17
HTAGPERPOST	?	−0.617***	−3.53	−0.650***	−3.73	−0.565***	−3.28
LENPERPOST	?	−0.202	−0.54	−0.242	−0.65	−0.263	−0.72
SIZE_LAG	+	0.805***	5.43	0.915***	6.00	0.886***	6.07
MTB_LAG	+	0.071***	2.65	0.096***	3.38	0.051*	1.93
LEV_LAG	+	−0.082	−0.09	−0.517	−0.60	0.205	0.24
ABACC1_LAG	?			7.610***	3.68		
ABCFO_LAG	?					5.945***	2.84
Constant		−17.410***	−5.96	−19.309***	−6.39	−18.722***	−6.37
Industry Fixed Effect		Included		Included		Included	
Year-Quarter Fixed Effect		Included		Included		Included	
Number of Observations		222		222		222	
R-squared		0.857		0.866		0.862	

Notes to Table 7:
This table presents the OLS regression results of Eq. (4).

$$RETWEET_{i,q} = \lambda_0 + \lambda_1 FOLLOWER_{i,q} + \lambda_2 LIKEPERPOST_{i,q} + \lambda_3 HTAGPERPOST_{i,q} + \lambda_4 LENPERPOST_{i,q} + \lambda_5 SIZE_{i,q-1} + \lambda_6 MTBi,q-1 + \lambda_7 LEV_{i,q-1} + Industry\ and\ Quarter\ Fixed\ Effects + \varepsilon_{i,q} \quad \text{Eq. (4)}$$

Fixed industry and year-quarter effects are included, and p-values are based on robust standard errors. *, **, ***: significant at 10%, 5%, 1% two-sided p-values, respectively. All continuous variables are winsorized at the top and bottom 1^{st} and 99^{th} percentiles. All variables are defined in the Appendix.

5. Conclusion

Prior literature documented the role of social media usage by firms and individual users as information intermediaries to reduce information asymmetry. However, only a few studies have examined the relationship between social media and earnings management. Whether firms' adoption of social media contributes to earnings management remains unclear, and research in this area is scarce. Therefore, this study adds to voluntary disclosure and earnings management literature by providing evidence of the relationship among firm presence on social media and earnings management, the determinants of firms' adoption of social media, and the determinants of firms' posting activity. Specifically, firms with presence on Twitter more likely engage in earnings management than firms that are not on Twitter. Firm size, growth opportunities, leverage, profitability, and financial health are the main determinants of firms' adoption of Twitter. For a subset of firms with Twitter accounts, I find that firm size, growth opportunities, leverage, number of firm followers, and number of hashtags per tweet are the determinants of firms' Twitter posting activity. The results have practical implications for capital market participants, such as investors, regulators, and managers. Despite the prevalence of social media studies in developed markets, research on social media in accounting literature is rather limited in Thailand and other developing countries. The reason is that social media data are originated and stored on their platforms, but none of these data are readily available or directly linked to financial variables in typical financial and accounting databases. Therefore, I had to scrape original data from Twitter using Twitter API for each of the SET50 firms to form an integrated database. Given that this study includes only the SET50 firms between 2015 and 2019, the sample size for full sample and subsample analyses is relatively small compared with studies in the United States. Therefore, future research may consider extending the sample size to cover public companies more broadly or span for longer periods. It may also consider examining other social media platforms, attributes, and usage by individual investors. Finally, further studies on the textual analysis of social media content and financial attributes can uncover accounting irregularities or provide more accurate predictions of firm performance.

REFERENCES

Agrawal, K., & Chatterjee, C. (2015). Earnings management and financial distress: Evidence from India. *Global Business Review, 16 (5_suppl)*, 140S–154S.

Balasubramanian, S. K., Fang, Y., & Yang, Z. (2021). Twitter presence and experience improve corporate social responsibility outcomes. *Journal of Business Ethics, 173*(4), 737–757.

Barnes, N. G., Lescault, A. M., & Wright, S. (2013). Instagram, foursquare and Pinterest. *Fortune*. Retrieved from http://www.umassd.edu/cmr. University of Massachusetts – Dartmouth Center for Marketing Research 500 are bullish on social media: Big companies get excited about Google+.

Bartov, E., Faurel, L., & Mohanram, P. S. (2018). Can Twitter help predict firm-level earnings and stock returns.? *The Accounting Review, 93*(3), 25–57.

Bergstresser, D., & Philippon, T. (2006). CEO incentives and earnings management. *Journal of Financial Economics, 80*(3), 511–529.

Blankespoor, E., Miller, G. S., & White, H. D. (2014). The role of dissemination in market liquidity: Evidence from firms' use of Twitter™. *The Accounting Review, 89*(1), 79–112.

Boshnak, H. A. (2021). Determinants of corporate social and environmental voluntary disclosure in Saudi listed firms. *Journal of Financial Reporting and Accounting, ahead-of (ahead-of)*. DOI:10.1108/JFRA-05-2020-0129

Bushee, B. J., Core, J. E., Guay, W., & Hamm, S. J. W. (2010). The role of the business press as an information intermediary. *Journal of Accounting Research, 48*(1), 1–19.

Call, A. C., Emett, S. A., Maksymov, E., & Sharp, N. Y. (2021). Meet the press: Survey evidence on financial journalists as information intermediaries. Working Paper.

Chang, H., & Iyer, H. (2012). Trends in Twitter hashtag applications: Design features for value-added dimensions to future library catalogues. *Library Trends, 61*(1), 248–258.

Chen, Y., Cheng, C. S. A., Li, S., & Zhao, J. (2020). The monitoring role of the media: Evidence from earnings management. *Journal of Business Finance and Accounting, 48*(3–4), 533–563.

Cheng, Q., & Warfield, T. D. (2005). Equity incentives and earnings management. *The Accounting Review, 80*(2), 441–476.

Cohen, D. A., Dey, A., & Lys, T. Z. (2008). Real and accrual-based earnings management in the pre- and post-Sarbanes-Oxley periods. *The Accounting Review, 83*(3), 757–787.

Dai, L., Parwada, J. T., & Zhang, B. (2015). The governance effect of the media's news dissemination role: Evidence from insider trading. *Journal of Accounting Research, 53*(2), 331–366.

Dechow, P. M., Kothari, S. P., & Watts, R. L. (1998). The relation between earnings and cash flows. *Journal of Accounting and Economics, 25*(2), 133–168.

Dechow, P. M., Richardson, S. A., & Tuna, I. (2003). Why are earnings kinky? An examination of the earnings management explanation. *Review of Accounting Studies, 8*(2–3), 355–384.

Dewan, P., & Kumaraguru, P. (2014). It doesn't break just on Twitter. Characterizing Facebook content during real world events. *Arxiv, Admin/1405.4820*.

Dyck, A., Morse, A., & Zingales, L. (2010). Who blows the whistle on corporate fraud? *The Journal of Finance, 65*(6), 2213–2253.

Elfeky, M. I. (2017). The extent of voluntary disclosure and its determinants in emerging markets: Evidence from Egypt. *Journal of Finance and Data Science, 3*(1–4), 45–59.

Ettredge, M., Richardson, V. J., & Scholz, S. (2002). Dissemination of information for investors at corporate Web sites. *Journal of Accounting and Public Policy, 21*(4–5), 357–369.

Fang, L., & Peress, J. (2009). Media coverage and the cross-section of stock returns. *The Journal of Finance, 64*(5), 2023–2052.

Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economics implication of corporate financial reporting. *Journal of Accounting and Economics, 40*(1–3), 3–73.

Guest, N. M. (2021). The information role of the media in earnings news. *Journal of Accounting Research, 59*(3), 1021–1076.

Gunny, K. A. (2010). The relation between earnings management using real activities manipulation and future performance: Evidence from meeting earnings benchmarks. *Contemporary Accounting Research, 27*(3), 855–888.

Hasan, R., & Cready, W. M. (2019). Facebook posting activity and the selective amplification of earnings disclosures. *China Journal of Accounting Research, 12*(2), 135–155.

Healy, P. M., & Wahlen, J. M. (1999). A review of the earnings management literature and its implications for standard setting. *Accounting Horizons, 13*(4), 365–383.

Jankensgård, H. (2015). The relationship between voluntary disclosure, external financing and financial status. *Journal of Business Finance and Accounting, 42*(7–8), 860–884.

Jung, M. J., Naughton, J. P., Tahoun, A., & Wang, C. (2018). Do firms strategically disseminate? Evidence from corporate use of social media. *The Accounting Review, 93*(4), 225–252.

Kim, J., & Sohn, B. C. (2013). Real earnings management and cost of capital. *Journal of Accounting and Public Policy, 32*(6), 518–543.

Kothari, S. P., Li, X., & Short, J. E. (2009). The effects of disclosures by management, analysts, and business press on cost of capital, return volatility, and analyst forecasts: A study using content analysis. *The Accounting Review, 84*(5), 1639–1670.

Lang, M., & Lundholm, R. (1993). Cross-sectional determinants of analyst ratings of corporate disclosures. *Journal of Accounting Research, 31*(2), 246–271.

Lee, L. F. (2012). Incentives to inflate reported cash from operations using classification and timing. *The Accounting Review, 87*(1), 1–33.

Lee, L. F., Hutton, A. P., & Shu, S. (2015). The role of social media in the capital market: Evidence from consumer product recalls. *Journal of Accounting Research, 53*(2), 367–404.

Mason, T. W., & Morton, R. M. (2020). The economic effects of earnings management pre- and post-SOX. *Accounting and the Public Interest, 20*(1), 76–103.

Matsumoto, D. A. (2002). Management's incentives to avoid negative earnings surprises. *The Accounting Review, 77*(3), 483–514.

Meng, Y. (2020). An empirical study on the influence of media attention on real earnings management. *Advances in Social Science, Education and Humanities Research, 435*, 228–233. DOI:10.2991/assehr.k.200428.050.

Miller, G. S. (2006). The press as a watchdog for accounting fraud. *Journal of Accounting Research, 44*(5), 1001–1033.

Naibaho, C. V. D. P., Naibaho, C. V. D. P., & Davianti, A. (2020). Social media phenomena in corporate disclosures practice (A case study of Nestle). *Indonesian Management and Accounting Research, 19*(1), 51–70.

Peress, J. (2014). The media and the diffusion of information in financial markets: Evidence from newspaper strikes. *The Journal of Finance, 69*(5), 2007–2043.

Ravaonorohanta, N., & Sayumwe, M. (2020). Social media presence and organizational performance: An empirical study on companies' presence on Twitter. *Contemporary Management Research, 16*(2), 123–144.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics, 42*(3), 335–370.

Sayari, N., & Marcum, B. (2018). Reducing risk in the emerging markets: Does enhancing corporate governance work? *BRQ Business Research Quarterly, 21*(2), 124–139.

Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review, 71*(3), 289–315.

Xu, R. Z., Taylor, G. K., & Dugan, M. T. (2007). Review of real earnings management literature. *Journal of Accounting Literature, 26*, 195–228.

Yang, J. H., & Liu, S. (2017). Accounting narratives and impression management on social media. *Accounting and Business Research, 47*(6), 673–694.

Zamil, I. A., Ramakrishnan, S., Jamal, N. M., Hatif, M. A., & Khatib, S. F. A. (2021). Drivers of corporate voluntary disclosure: A systematic review. *Journal of Financial Reporting and Accounting, ahead-of (ahead-of)*. DOI:10.1108/JFRA-04-2021-0110.

Zang, A. Y. (2012). Evidence on the trade-off between real-activities manipulation and accrual-based earnings management. *The Accounting Review, 87*(2), 675–703.

Zhang, W., Li, Y., Urquhart, A., & Wang, P. (2021). How does social media influence earnings management? Working Paper. *SSRN Electronic Journal*.

Zhou, M., Lei, L., Wang, J., Fan, W., & Wang, A. G. (2015). Social media adoption and corporate disclosure. *Journal of Information Systems, 29*(2), 23–50. DOI:10.2308/isys-50961.

Appendix: Variable Definitions

Variable	Definition
ABACC1	Abnormal accrual is the absolute value of the difference between the reported accrual and the normal level of accrual, as estimated by the modified Jones Model in Zang (2012) for quarterly data. $ACC/LagTA = \alpha_0 + \alpha_1(1/LagTA) + \alpha_2(\Delta SALE/LagTA) + \alpha_3(PPE/LagTA) + \alpha_4 Q4 + \varepsilon$, where ACC = accruals, measured as the difference between EBITDA and operating cash flows, LagTA = lagged total assets, SALE = total sales, PPE = property, plant and equipment, Q4 = fourth quarter indicator variable.
ABACC2	Abnormal accrual is the absolute value of the difference between the reported accrual and the normal level of accrual, as estimated by the lagged modified Jones Model in Dechow et al. (2003) for quarterly data. $ACC = \alpha_0 + \alpha_1((1{+}K)\,\Delta SALE - \Delta REC) + \alpha_2 PPE + \alpha_3 LagACC + \alpha_4 Q4 + \varepsilon$, where ACC = accruals, measured as the difference between EBITDA and operating cash flows, REC = receivables, SALE = total sales, PPE = property, plant and equipment, LagACC = lagged total accruals,Q4 = fourth quarter indicator variable. All variables are scaled by average total assets.
ABCFO	Abnormal operating cash flow is the absolute value of the difference between the actual operating cash flows and the normal level of operating cash flows, as estimated using the Dechow et al. (1998) model for quarterly data. $CFO/LagTA = \alpha_0 + \alpha_1(1/LagTA) + \alpha_2(SALE/LagTA) + \alpha_3(\Delta SALE/LagTA) + \alpha_4 Q4 + \varepsilon$, where CFO = Operating cash flows, SALE = total sales, LagTA = lagged total assets, Q4 = fourth quarter indicator variable.
ABDISEXP	Abnormal discretionary expense is the absolute value of the difference between the actual discretionary expenses and the normal level of discretionary expenses, as estimated using Roychowdhury's (2006) model for quarterly data. $DISEXP/LagTA = \alpha_0 + \alpha_1(1/LagTA) + \alpha_2(LagSALE/LagTA) + \alpha_3 Q4 + \varepsilon$, where DISEXP = discretionary expenses, LagSALE = lagged total sales, LagTA = lagged total assets, Q4 = fourth quarter indicator variable.
ABPROD	Abnormal production cost is the absolute value of the difference between the actual production costs and the normal level of production costs, as estimated using Roychowdhury's (2006) model for quarterly data. $PROD/LagTA = \alpha_0 + \alpha_1(1/LagTA) + \alpha_2(SALE_t/LagTA) + \alpha_3(\Delta SALE_t/LagTA)$ $+ \alpha_4(\Delta SALE_{t-1}/LagTA) + \alpha_5 Q4 + \varepsilon$, where PROD = production costs (sum of normal COGS and inventory growth), SALE = total sales, LagTA = lagged total assets, Q4 = fourth quarter indicator variable.

Variable	Definition
FBDUMMY	An indicator variable that is equal to one (zero) for firms with (without) presence on Facebook for firm *i* in quarter *q*.
FOLLOWER	Firm followers are defined as the logarithm of the number of firm followers as of a specific date (a static time-invariant variable).
HTAGPERPOST	Hashtags per post are defined as the logarithm of the average number of hashtags used in each tweet.
LENPERPOST	Length per post is defined as the logarithm of the average number of character length used in each tweet.
LEV	Leverage is defined as total liabilities scaled by total assets.
LIKEPERPOST	Likes per post are defined as the logarithm of the average number of likes for each tweet.
MTB	Market-to-book ratio is measured as the ratio of market value of equity to book value of equity.
RETWEET	Logarithm of the average number of retweets per day made by followers for each firm i in quarter q.
ROA	Return on assets is calculated as EBITDA divided by total assets.
SIZE	Firm size is calculated as the natural logarithm of the total assets.
TWDUMMY	An indicator variable that is equal to one (zero) for firms with (without) presence on Twitter for firm i in quarter q.
TWEET	Logarithm of the average number of tweets per day made by each firm *i* in quarter *q*.
ZSCORE	Altman's Z-Score = 1.2 (Net working capital)/Total assets + 1.4 (RE)/Total assets + 3.3 (EBIT)/Total assets + 0.6 (Market value of equity)/Book value of liabilities + 1.0 (Sale)/ Total assets