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ORIGINAL RESEARCH

Social media disclosure and reputational damage

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Abstract

We provide new evidence on the effects of social media in the context of a financial scandal using a sample of banks that were accused of manipulating the London Interbank Offered Rate (LIBOR). We find that increased bank Twitter activity when the scandal surfaced has a positive moderating effect on equity returns. However, the dissemination of content operated by social media users has a negative counterbalancing effect, thus amplifying the impact of the scandal. In particular, tweets that are unrelated to the scandal and characterized by positive sentiment contribute to exacerbating the reputational damage suffered by banks. We contribute to the emerging literature on the role of social media in capital markets.

Keywords Disclosure · LIBOR scandal · Operational risk · Reputation · Social media · Twitter

JEL Classification G10 · G14 · G21 · M41

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1 Introduction

Social media is arguably the most important development in information technology over the last decades. The use of social media has drastically reshaped the way information is consumed and disclosed. A unique feature of social media is that it allows users to create and disseminate information to a large network with all the "conversations" observable to a growing audience of social media users. Benefiting from a wide reach through the networks, social media provides a powerful platform for disclosing and disseminating corporate information, exchanging news and views, and diverting attention during negative events. The existing literature has overlooked the corporate use of social media and its effects during a corporate crisis and adverse events (Wang et al. 2021). Given the growing impact of social media, it is important to understand whether and how social media is used as a strategic communication channel to manage reputation crises. In this paper, we examine the role of social media disclosure initiated by financial institutions and disseminated by other users during a major industry-wide financial scandal. We aim to shed light on the following questions: First, when banks experience an operational risk event, what is the role of disclosure made through their social media? Does banks' social media activity attenuate or exacerbate the negative market reaction? Second, what is the role of dissemination made by other users in response to banks' social media disclosure?

To answer these questions, we study how Twitter (recently renamed "X") was used by banks during the London Interbank Offered Rate (LIBOR) scandal and whether instant communications made via Twitter had a moderating effect on banks' reputational damage. We focus on Twitter due to its real-time news updates (Russell et al. 2015), popularity for financial and political information (Bartov et al. 2018), its ability to foster extensive interactions and networking effects among users (Lee et al. 2015), and its ability to prompt faster responses to disclosures compared to other platforms, with information reaching more connected investors at a quicker pace (Zhou et al. 2015). This choice is well-suited in a crisis situation where there is increased demand for information amid uncertainty. In this information void, it is important for a firm to convey its intended message ahead of rumors, speculations, or alternative news sources that could exacerbate the situation (Lee et al. 2015). Failing to do so could leave the firm with no opportunity to shape the narrative. Social media communication can bridge this gap by providing additional or alternative information or redirecting public attention to different topics.

On June 27, 2012, Barclays admitted misconduct related to manipulating the setting of the LIBOR and the Euro Interbank Offered Rate (EURIBOR) and agreed to a $453 million fine settlement with regulators in the UK and US. Evidence from the regulators' probe confirmed that the manipulation of LIBOR was not a localized event but part of business-as-usual in the global financial markets. Such a scandal constitutes a negative corporate event bearing serious consequences for the banks involved, such as substantial fines and resulting reputational losses (Fabrizi et al. 2021). An industry-wide banking scandal provides a powerful setting because it not only has direct implications on a bank's market value and reputation, but also enables the observation of differentials in social media communication strategy among banks both directly and indirectly involved. In addition, Scott and Walsham (2005, p. 309) suggest that "*reputation risk is the outcome of a longer historic and ongoing process of defining*" and, as such, a longitudinal analysis of one or several banks may be particularly valuable.

We first ask whether banks' Twitter disclosure has an impact on their reputational damage. We observe that the more a bank interacts through social media (measured as abnormal volume and abnormal length of tweets), the more contained the reputational damage (expressed as negative equity returns) is.[1] This result suggests that banks may have incentives to increase their presence and interaction on social media to ease reputational damage due to the scandal. At the same time, social media entails multi-way engagement (Lee et al. 2015), which allows different users to form their views about the scandal, with the potential of exacerbating banks' reputational damage. We then ask whether users' Twitter activity has an impact on reputational damage. To answer this question, we measure social media activity using retweets and hyperlinks embedded in users' dissemination activity. We find that the more a bank's tweets are disseminated, the more reputational damage is amplified. Whether scandal-related or not, a bank's posts can lend more credibility and consensus to the negative news narrative, which may become prominent in users' retweets. Likewise, users can search for additional information on litigation and the banks' responsibility, disseminating it further, thereby exacerbating the reputational damage to the banks. As a result, any efforts by the banks to be forthcoming via event-period Twitter disclosure are offset by the extent to which other users propagate the conversations, more likely disseminating details and opinions and thus amplifying the accusations against the banks.

While we provide evidence that banks' tweeting partially mitigates the negative market consequences on the event period, determining which tweet type would be prevalent and its effects remains an empirical question. In additional analyses, we turn to the content of banks' tweets and examine their sentiment during the event period. We find that the negative market reaction to the scandal is exacerbated if a bank's tweets are characterized by positive sentiment and disseminate optimistic news involving corporate or societal initiatives but completely unrelated to the LIBOR scandal. In other words, markets efficiently impound the negative information and punish banks' attempts at obfuscating social media communication. We further examine whether nonevent banks' tweeting activity during the event windows affects their indirect exposure to the scandal, and we do not find any significant effect on their equity returns. Finally, we check the robustness of our results by performing out-of-sample falsification tests, accounting for diminishing event effects and confounding events, and using alternative Twitter control windows.

Our study provides the first empirical evidence on the effect of social media on the reputations of financial institutions during operational risk events. We believe that this evidence is timely and relevant for two primary reasons: First, while Twitter has been around since 2006, only since 2011 has it emerged as a popular communication channel among global leaders and a platform for financial news of immediate relevance to investors (Al Guindy et al. 2023). Previous research studying the impact of social media on stock returns looks at interactive social media platforms, with Twitter being the dominant choice for corporate use (Bartov et al. 2018; Chen et al. 2014). Similarly, we focus on Twitter because it has been proven a legitimate source of financial and political information that requires the attention of financial regulators (Sprenger et al. 2014; Bollen et al. 2011). Second, we focus on financial institutions because of the heightened market and regulatory focus on operational risk in financial institutions (Cummins et al. 2006), and the potential of negative market consequences of operational risk events extend beyond the focal institution to

[1] We are not arguing that an abnormal increase in banks' tweets during the event window would necessarily translate into a positive market reaction. Rather, we observe that, on average, banks that exhibit abnormally higher Twitter activity experience less negative market reaction to the scandal.

form systemic risk that could threaten the financial stability (Allen and Saunders 2004) and imply high economic and social costs (Hail et al. 2018).

We make several contributions. First, we contribute to the emerging literature on the role of social media in capital markets. Social media represent an important, new focus within the accounting literature given its widespread use and the potential for individuals to disseminate their content (Miller and Skinner 2015), thus contributing to a democratization of information. Existing research shows that social media have reshaped how investors and other actors obtain company-specific information (e.g., Drake et al. 2023) and that investor opinions expressed on these platforms are relevant in that they predict future stock returns under regular circumstances (Chen et al. 2014). Yet, we know very little about social media use and its effects during a banking scandal. Financial institutions may have a different social media audience with varying layers of sophistication and emphasis on subjective information, which may lead to different outcomes (Blankespoor 2018). We shed light on social media and price formation by investigating how social media provides a channel to aggregate pieces of information and sentiment that affect the response to an industry-wide adverse event. In doing so, we complement previous studies which demonstrate that social media can moderate the stock markets' reaction to corporate events (Lee et al. 2015) and induce price distortions in the presence of speculative information (Jia et al. 2020).

Second, we contribute to the literature on reputation and operational risk. The LIBOR scandal is in effect an operational risk event that affected multiple banks (McConnell 2013), and it represents a unique event, being an industry-wide scandal that channeled reputational contagion across financial institutions (Fabrizi et al. 2021). A broad consensus reached in the literature is that financial institutions are subject to reputational damage following operational loss announcements and accounting restatements (Barakat et al. 2019; Chakravarthy et al. 2014; Fiordelisi et al. 2014; Biell & Muller 2013; Sturm 2013; Gillet et al. 2010; Cummins et al. 2006; Perry & De Fontnouvelle 2005). However, it remains an empirical question whether social media communication activated during operational risk events provides a beneficial or detrimental effect on the reputations of financial institutions involved. To the best of our knowledge, this is the first paper that studies the impact of social media communication and its dissemination on the reputational effects of operational risk events.

Finally, we contribute to the literature on banking scandals and the LIBOR scandal in particular. Extant literature on the LIBOR scandal focuses on submission banks' reporting behavior of the LIBOR rates during the crisis period (Monticini and Thornton 2013), incentives for manipulating LIBOR (Gandhi et al. 2019; Vaughan and Finch 2017), and the differences in market reactions for banks with stronger and weaker incentives to manipulate the rate (Fabrizi et al. 2021). This paper complements these studies by studying the information role of social media in influencing market reactions to the scandal.

The remainder of this paper proceeds as follows: Sect. 2 reviews the literature; Sect. 3 presents our main hypotheses; Sect. 4 describes the data and identification strategy; Sect. 5 presents the main results; Sects. 6 reports additional analysis results; Sect. 7 concludes.

2 Literature review

2.1 The role of social media

Social media enables both firms and individual users to create and exchange information on virtual platforms. Lee et al. (2015) argue that social media platforms enable direct, multi-way engagement between firms and stakeholders, facilitating firm-to-user, user-to-firm, and user-to-user exchanges with the various exchanges readily observable to all. One strand of literature focuses on the general role of social media. Because social media provides a platform to aggregate individual opinions efficiently, information transmitted on social media has the potential to predict future firm performance and improve price formation in the stock market. Chen et al. (2014) provide evidence that views expressed on the investment-related website Seeking Alpha can predict future stock returns and earnings surprises. Bartov et al. (2018) find that the aggregate opinion from individual tweets can predict a firm's future earnings and announcement returns. Finally, Tang (2018) finds that customers' opinions posted on Twitter have the potential to foresee future sales growth.

Despite the many benefits documented by extant research, social media can also pose an informational problem for market participants and firms. Toubia and Stephen (2013) find that social media users are driven by image-related utility and post content to increase their recognition from others, such as the number of followers, likes, and retweets. Similarly, Rennekamp and Witz (2021) show that investors are sensitive to the linguistic characteristics of social media disclosures. While social media is likely a powerful disclosure means that can be used by firms in their interest to anticipate, amend, or obfuscate news and sensitive information, it is also a place where corporate financial information can be easily disseminated due to the wide reach of the interactive platform. Blankespoor et al. (2014) investigate how firms use Twitter to disseminate firm-related news by providing links to press releases in their Twitter feeds. They find that the dissemination of corporate news via social media reduces information asymmetry and increases market liquidity. Jung et al. (2018) show that firms use Twitter to strategically disseminate good news but mute themselves when the news is negative. Jia et al. (2020) document that, in the face of highly speculative financial rumors, social media facilitates their spread and distorts price discovery. Finally, Twitter activity can exacerbate individuals' cognitive biases and have an impact on stock returns. One such bias is limited attention (Da et al. 2011; Barber and Odean 2008). While information surfaces and corporate news is exchanged on social media, it is not clear whether and how these exchanges affect the market reactions to negative corporate events.

2.2 Corporate misconduct and reputational damage

Prior market-based research on corporate misconduct identifies substantial losses in the market value of misconduct firms. The strength of reputational penalties has been examined in different settings, and most of these studies document negative abnormal returns in the selected event period. For example, Karpoff and Lott (1993) examine fraud allegations by public companies and suggest that a small portion of the loss in shareholder wealth is explained by legal sanctions while a substantial portion of the loss is associated with the reputational penalties imposed by the market. Alexander (1999) finds similar reputational effects on shareholder wealth by investigating the reputational losses experienced by public corporations that are accused of federal crimes. Based on a study of enforcement actions for financial misrepresentation by the US Securities and Exchange Commission (SEC), Karpoff et al. (2008) show that around two-thirds of the drop in market value resulting from the announcement of misconduct are attributable to reputational losses.

Another strand of literature focuses on reputational damage emanating from operational loss announcements. Perry and De Fontnouvelle (2005) test the stock market reaction to announcements of major operational loss events and identify a reputational loss when a firm's market value declines by more than the announced amount of loss. Cummins et al. (2006) find similar results by focusing on operational losses by banks and insurance companies. Sturm (2013) examines reputational damage caused by operational losses in European financial firms and suggests that the negative market reaction is more pronounced in response to announcements of settlement than it is to the initial indications of the loss and that reputational damage is more pronounced for highly leveraged banks. Other studies extend the inquiry on this topic to a cross-country setting. Gillet et al. (2010) analyze market reactions to operational loss announcements by financial firms listed in Europe and the US. Compared to US companies, European firms usually present lower market value, indicating higher reputational damage. Fiordelisi et al. (2014) find that reputational losses in the financial industry are higher in Europe than in North America, and fraud generates the greatest reputational damage among all types of operational risk events. Armour et al. (2017) analyze the reputational losses experienced by financial firms that are sanctioned by the UK regulators and find that reputational penalties are average nine times the size of the financial penalties. They also show that the magnitude of the penalties leveled in the UK does not reflect the seriousness of the wrongdoing as perceived by investors and clients; instead, the disclosure of misconduct per se is the primary source of the reputational damage.

3 Hypotheses development

3.1 The effect of banks' twitter activity

The information released by companies on social media is unregulated. Morsing (2006) argues that this type of communication can be employed to improve firm reputation, and thereby, to align the identification of stakeholders with the company itself. However, this type of information might also be subject to opportunistic use by firms to attract investors' attention and readership, and curb their reactions (Jung et al. 2018; Dhaliwal et al. 2011; Highhouse et al. 2009). This use could be prevalent when a financial firm is involved in a scandal. Because a corporate scandal represents a real crisis for the entities involved, they could take an immediate stand and initiate an instant communication flow with the public to minimize the harm and related reputational damage.

To this end, Twitter may be used as an instant disclosure tool to aid the bank in achieving this goal. The nature of social media allows information to be quickly spread to reach a broad audience. In this perspective, if the alleged bank were not forthcoming, it might run the risk of seeing its position worsen due to stakeholders being fed by other sources of information. Alternatively, users may also ignore conversations started from the banks' accounts, in which case social media activities would have no incremental effect on market returns for the involved banks. While the potential to reach out to a large network is somehow guaranteed by the wide reach of social media, there might be an additional cost for alleged banks. After having publicly initiated one or more conversations, more users could associate the bank's profile to the scandal (independent of the content proposed in those tweets) and learn about it, potentially giving more coverage and credibility to the bad news narrative. Alternatively, alleged banks may choose to communicate less than usual through social media platforms (or to remain silent in the extreme case) to avoid attracting additional public attention as a strategy to preserve them longer from public exposure. Overall, our first hypothesis focuses on banks' activism on Twitter (i.e., abnormal Twitter volume and length) and we ask whether communicating more (and more extensively) through social media could help banks to alleviate the negative consequences of the scandal allegation. This effect will be potentially impounded into banks' equity returns, which is consistent with the notion that social media may have a mitigating role in reputational damage when an entity is involved in an industry-wide financial scandal. This leads to our first set of hypotheses, stated in the null form:

Hypothesis 1a (H1a): The abnormal tweet volume of a LIBOR bank during the event window has no moderating effect on the negative market reaction to the allegation of LIBOR manipulation.

Hypothesis 1b (H1b): The abnormal tweet length of a LIBOR bank during the event window has no moderating effect on the negative market reaction to the allegation of LIBOR manipulation.

3.2 The effect of twitter users' dissemination

Social media users are subject to social influence (Lorenz et al. 2011), which makes them eager to post opinions, comments, and reactions as they value recognition from others in the form of shares and retweets. In addition, social media platforms, such as Twitter, allow immediate engagement not only between individual users and companies but also among different users. The fact that a company may be able to communicate first and redirect any subsequent users' response does not fully eliminate the criticism's effect following bad news (Cade 2018). This effect can be exacerbated even more during a financial scandal with the aid of Twitter features such as retweets and hyperlinks. In detail, retweets from other users can provide an indication of the extent to which a bank's tweets have been recirculated within the network, while hyperlinks can direct users to other information sources as they circulate a bank's tweets.

A bank's initial official tweets (whether related to the scandal or not) might trigger a virtual echo with opinions, complaints, and negative sentiment being transmitted to other social media users who are eager to publicly share the story following shared disappointment and negative feelings. Consequently, any tweets posted by an alleged bank when the major event surfaces can be rapidly disseminated on Twitter and used as an anchor to build criticism on the adverse event. The same can happen starting from a hyperlink reported and included in tweets. This negative sentiment can then become magnified and contribute to exacerbating the market reaction to the scandal, undermining a bank's reputation.[2] It is an empirical question whether the propagation effect typical of Twitter will have an incremental impact on bank excess returns when the LIBOR accusation surfaces. Thus, we posit our second hypothesis in its null form as follows:

Hypothesis 2a (H2a): The dissemination operated by other Twitter users in the form of retweets has no moderating effect on the negative market reaction to a bank's allegation of LIBOR manipulation.

[2] Although we do not frame this as a repeated game (our main objective is, in fact, examining the short-term implications of social media disclosure), the very nature of the scandal event involves stalled news and the potential for reputational spillovers.

Hypothesis 2b (H2b): The dissemination operated by other Twitter users starting from hyperlinks has no moderating effect on the negative market reaction to a bank's allegation of LIBOR manipulation.

4 Empirical design

4.1 The setting: LIBOR scandal

On June 27, 2012, Barclays admitted to misconduct related to manipulating the daily setting of the LIBOR and EURIBOR[3] and agreed to a $453 million fine settlement with the UK's Financial Services Authority (FSA), the US Commodity Futures Trading Commission (CFTC), and the US Department of Justice (DoJ). Barclays admitted to three types of manipulation: under-reporting, holding constant, and over-reporting. The motives behind the three types of misrepresentations varied over time and ranged from benefitting derivatives trading positions to avoiding the stigma of appearing weak relative to other banks during the financial crisis.[4] Evidence from the regulators' investigation confirmed that the manipulation of LIBOR was not a localized event but part of business-as-usual in the global financial markets, an unethical and occasionally illegal practice that deliberately and systematically manipulated the benchmark interest rates. Traders made requests to both the internal submitter at the bank and external submitters at third-party banks to influence the LIBOR submissions according to their trading positions in derivatives and the money markets.[5]

4.2 Data and sample

Our sample includes banks that were accused of manipulating the LIBOR during the period between March 2011 and December 2013. Table 1 reports the list of these banks and the currency panel(s) for which they are a rate-submission member. We hand-collected news on the LIBOR scandal from four major media: BBC News, Bloomberg, the Financial Times, and The Wall Street Journal. We chose this set of news providers for the following reasons: First, the LIBOR scandal was discovered and first published in the UK, and BBC News provided full coverage of the scandal. Second, the other three news providers, Bloomberg, the Financial Times, and The Wall Street Journal, specialize in global coverage of financial news. Moreover, The Wall Street Journal was among the first to raise questions about whether banks were manipulating LIBOR during the financial crisis.[6] We identified 39 key event dates when information about the LIBOR investigation was disclosed. For stale news, such as news about market anticipation and information provided by insiders who were familiar with the situation before the settlement date, we took the earliest available date. The description of these events is detailed in Table 13.

[3] EURIBOR is a reference rate overseen by the European Banking Federation. The EUROBOR contributor panel consisted of approximately 42 to 48 banks. Thomson Reuters also acts as an agent for the calculation and publishing of this rate. The administration process of this rate is highly similar to the one of LIBOR. However, only the highest and lowest 15% of all quotes are trimmed in EURIBOR calculation.

[4] See Monticini and Thornton (2013) for the effect of misrepresenting LIBOR rates.

[5] "In the matter of: The Royal Bank of Scotland PLC and RBS Securities Japan Limited". US Commodity Futures Trading Commission. February 6, 2013.

[6] "Study casts doubt on key rate". *The Wall Street Journal*, May 29, 2008.

Table 1 LIBOR Banks

Contributor Bank	Origin	G-SIB	G14	LIBOR	USD	EUR	GBP	JPY	CHF	CAD	AUD	NZD	DKK	SEK
Abbey National (Santander)	ESP			X		X	X							
Bank of America	USA	2	X	X	X									
Bank of New York Mellon	USA	1												
Bank of Nova Scotia	CAN			X						X				
Bank of Tokyo-Mitsubishi UFJ	JPN	2		X	X	X	X	X	X					
Barclays	GBR	3	X	X	X	X	X	X	X	X	X	X	X	X
BBVA	ESP	1												
BNP Paribas	FRA	3	X	X	X		X							
Canadian Imperial Bank of Commerce	CAN			X						X				
Citigroup	USA	3	X	X	X	X	X		X					
Crédit Agricole	FRA	2		X	X		X	X						
Crédit Suisse	CHE	2	X	X	X	X			X					
Deutsche Bank	DEU	3	X	X	X	X	X	X	X	X	X	X	X	X
Goldman Sachs	USA	2	X											
HSBC	GBR	4	X	X	X	X	X	X	X	X	X	X	X	X
ING	NLD	1												
JP Morgan Chase	USA	4	X	X	X	X	X	X	X		X	X	X	X
Lloyds Banking Group	GBR			X	X	X	X	X	X	X	X	X	X	X
Mizuho Bank	JPN	1		X		X	X	X						
Morgan Stanley	USA	2	X											
Nordea Bank	SWE	1												
Royal Bank of Canada	CAN			X	X	X	X			X				
Royal Bank of Scotland	GBR	2	X	X	X	X	X	X	X	X	X	X	X	X
Société Générale	FRA	1	X	X	X	X	X	X	X	X				
Standard Chartered	GBR	1												

Table 1 (continued)

Contributor Bank	Origin	G-SIB	G14	LIBOR	USD	EUR	GBP	JPY	CHF	CAD	AUD	NZD	DKK	SEK
State Street	USA	1												
Sumitomo Mitsui Banking Corporation	JPN	1		X	X			X						
UBS	CHE	2	X	X	X	X	X	X	X					
UniCredit	ITA	1												
Wells Fargo	USA	1	X											

This table presents the interconnection between the three panels: G-SIBs, G14, and LIBOR. We construct a panel that consists of 30 banks from the three panels and name it "LIBOR Banks". G-SIBs stands for Global Systemically Important Banks; The "bucket number" developed by the Financial Stability Board to measure the systemic importance of a bank from 1 (lowest) to 5 (highest). G14 includes the 14 largest derivatives dealers

To construct Twitter activity measures, we collected tweets from banks' official Twitter accounts during the period between October 2010 and December 2013.[7] We developed a Python script to automatically scrape all the tweets posted by the sample banks as well as user replies and retweets. As most sentiment analysis algorithms are designed for English text and later adopted for other languages, prior studies find that sentiment analysis on non-English text translated into English generally performs better than sentiment analysis on text in the original language (Araujo et al. 2016; Mohammad et al. 2016). Thus, we developed a Python script to automatically translate all non-English tweets into English using API provided by Google Translate service. Google Translate service can provide reliable results that are highly correlated with the results based on human translation (Groves and Mundt 2015; Li et al. 2014). Twitter activity data are further aggregated at the bank-day level to accompany the daily stock market data.

4.3 Identification strategy

Our identification strategy relies on four key elements. The first element is based on the variation in banks' exposure to the impact of the LIBOR scandal. Our sample comprises event banks that alleged/admitted rate manipulation on event dates, nonevent LIBOR banks which were not accused of misconduct on the same dates, and control banks that are outside the LIBOR panel. This is in essence a difference-in-differences framework with multiple treatments occurring at different points in time. The second element complements the first element by identifying a group of banks outside the LIBOR panel that are comparable to the LIBOR banks using propensity score matching (PSM).[8] We employ a logit model and perform PSM in a period before the LIBOR scandal (i.e., 2009–2011) based on market capitalization and stock beta for both the overall market and banking industry. We implement the nearest neighbor matching (Rosenbaum and Rubin 1983) by selecting a control bank (without replacement) for each LIBOR bank that has the closest propensity score. The third element is the abnormal measures of Twitter activities that capture any *abnormal* use of Twitter during the scandal period compared to a normal period. The fourth element is the inclusion of a series of fixed effects (FE) to account for various sources of observed and unobserved heterogeneity in stock returns. In our model specifications, we include country, year, country × year, and bank FE in different combinations. Collectively, the identification strategy is intended to minimize omitted variable bias and related endogeneity concerns.

We estimate regression model specifications that are variations of the following form:

$$\begin{aligned} R_{i,t} - Rf_t = & \alpha_0 + \alpha_1 event_{i,t} + \alpha_2 Twitter_{i,t} + \alpha_3 event_{i,t} \times Twitter_{i,t} + \alpha_4 nonevent_{i,t} \\ & + \alpha_5 facebook_{i,t} + \alpha_6 press_{i,t} + \alpha_7 statement_{i,t} + \alpha_8 trend_{i,t} \\ & + \alpha_9 fine_{i,t} + common\_risk_t + FE + \varepsilon \end{aligned} \tag{1}$$

[7] We restricted our sample to banks that are regular Twitter users by removing banks with less than 100 tweets per year during the sample period to rule out the possibility of capturing the effect of inactive Twitter users.

[8] We employ a propensity-score-matched sample rather than using all banks outside the LIBOR panel as a baseline group because different bank characteristics such as bank size (and associated information environment) and stock beta may yield different market reactions.

The dependent variable is daily excess stock returns (*ER*) which is the difference between banks' daily stock return (*R*) and the risk-free rate (*Rf*). *event* is a dummy variable that takes a value of one on the day before,[9] the day of, and the day after the LIBOR scandal event date for alleged banks, and zero otherwise. If an event takes place on a weekend, the event date is adjusted to the next trading day. If two event windows overlap, we merge the two event windows by extending from the day before the first event to the day following the second event. We use a short event window to minimize the potential influence of concurrent releases of other material firm-specific information. Short-horizon event studies offer valuable insights into understanding corporate policy decisions and represent the cleanest evidence on efficiency (Kothari and Warner 2007; Fama 1991). In turn, *nonevent* is a dummy variable that takes a value of one if a bank was a LIBOR bank but was not accused of manipulation when one or more LIBOR banks were accused on the event date.[10] In other words, these nonevent banks' involvement in the scandal was not publicly disclosed when other LIBOR banks were alleged to misconduct.

Twitter includes the following Twitter activity measures calculated over a three-day event window (i.e., [–1, + 1]) and using a three-month control window that starts on October 1, 2010, and ends on December 31, 2010. Twitter activity during the control window captures the normal level of daily Twitter activity on a bank's official account. Following Jia et al. (2020), we deflate the difference in Twitter activity between the event period and the control period by the standard deviation of Twitter activity in the control window to capture any abnormal use of Twitter during the scandal compared to a normal period. Depending on the specification, Twitter activity refers to one of the following measures:

i) Abnormal tweet volume (*volume_ab*), defined as the difference between the average number of daily event-period tweets and the average number of daily control-period tweets, scaled by the standard deviation of the average number of daily control-period tweets;
ii) Abnormal tweet length (*length_ab*), calculated as the difference between the average word count of event-period tweets and the average word count of control-period tweets, scaled by the standard deviation of the average word count of control-period tweets;
iii) Abnormal retweets (*retweet_ab*), calculated as the difference between the percentage of event-period retweets and the percentage of control-period retweets, scaled by the standard deviation of the percentage of control-period retweets;
iv) Abnormal hyperlinks (*hplink_ab*), calculated as the difference between the percentage of event-period tweets containing hyperlinks and the percentage of control-period tweets containing hyperlinks, scaled by the standard deviation of the percentage of control-period tweets containing hyperlinks.

In addition to Twitter activity, it is important to control for alternative and concurrent information coverage (Gao et al. 2020; Peress 2014; Fang and Peress 2009), which includes Facebook disclosure (*facebook*), news dissemination by traditional media press (*press*), LIBOR-related statements published on the corporate website (*statement*), and overall trends of media attention (*trend*). *facebook* captures the number of posts on a bank's official Facebook account during the event window. To construct our *press* variable, we

[9] We include the day before the event to account for the time difference between Europe and North America, and information leakage before the event date.

[10] Once a bank is categorized as an event bank, it cannot be classified as a nonevent bank any longer.

manually searched Factiva for the number of traditional press articles related to the LIBOR scandal for a specific bank based on keyword search during the three-day event window (i.e., $[-1, +1]$).[11] To create the variable *statement*, we verified each bank's corporate website and manually collected all statements published by the banks in their "Investor Relations" section of the website during the period starting with the event date and spanning one year after the scandal was announced. We read each statement and created an indicator variable equal to one if the announcement is categorized as "LIBOR-related",[12] and zero otherwise. *trend* refers to Google Trends index and is calculated based on the search interest in terms of the volume of search queries for each day during the sample period. The index is a normalized integer ranging from 0 to 100. We developed a Python script to automatically scrape the data using Google Trends API. Since the daily data would be provided only when the specified period was shorter than 90 days, we split our data collection into multiple smaller overlapping periods and compiled the data after adjusting the normalized index based on the overlapped date.

Adjusted fine (*fine*) is calculated as fine settlement scaled by the pre-settlement market capitalization. Following Bessler and Kurmann (2014), Bessler et al. (2015), and Fabrizi et al. (2021), we further control for a variety of factors capturing common risk exposures of international banks (*common_risk*): market risk (*mkt*), interest rate risk (*ltb*), credit risk (*corp* and *hy*), sovereign risk (*sov*), real estate risk (*reit*), foreign exchange risk (*forex*), commodity risk (*com*), and political risk (*plt*). Detailed variable definitions are provided in Table 14.

5 Results

5.1 Summary statistics and correlation analysis

Table 2 provides summary statistics for the variables used in our empirical analysis. Bank size (*size*), measured by total capitalization, suggests that some of the largest banks are in our sample, as implied by their membership to the LIBOR committee. Liquidity (*liquid*), measured by share trading volume, indicates that these banks are active in stock markets. The low standard deviation for *size* and *liquid* suggests that sample banks are fairly homogeneous. The differences in the number of observations between Twitter activity measures and common risk factors are mainly due to the availability of Twitter data.[13] Summary statistics for common risk factors are similar to those reported in prior studies (e.g.,Bessler et al. (2015); Bessler and Kurmann (2014)).

Table 3 presents correlation coefficients between variables included in our empirical analysis. Panel A reports correlations between return and media measures. Panel B shows

[11] We searched the following string using the Factiva free text form: Bank name and ("LIBOR" or "scandal" or "LIBOR scandal" or "manipulat*"). For publication sources, we selected "All Sources" to maximize our search results. To reduce potential measurement bias, we excluded article duplicates from our count.

[12] Within the LIBOR-related category we found different types of statements which can be linked to four types of events: settlement with authorities, management changes, board changes, and responsibility statement.

[13] There are two possible reasons for this: First, some banks have no Twitter activity in the event date interval; Second, some banks have no Twitter activity during the control window.

Table 2 Descriptive Statistics

	N	Mean	S.D	Min	Median	Max
ER	2,070	−0.268	1.974	−6.983	−0.336	5.922
volume_ab	2,070	4.051	6.540	−0.181	1.372	26.673
length_ab	2,070	6.000	15.247	−3.419	1.336	69.582
retweet_ab	2,070	2.252	2.450	−0.724	0.895	8.130
hplink_ab	2,070	0.250	3.222	−2.563	−0.091	14.047
facebook	2,070	0.793	1.109	0.000	0.000	10.000
press	2,070	1.877	7.226	0.000	0.000	110.000
statement	2,070	0.000	0.022	0.000	0.000	1.000
trend	2,070	67.811	24.447	0.000	75.000	100.000
size	2,070	23.808	1.072	21.578	24.109	25.791
liquid	2,070	15.173	1.772	12.095	15.677	19.086
fine	2,070	0.001	0.045	0.000	0.000	1.650
mkt	2,070	0.096	0.924	−3.560	0.051	3.414
mkt_bank	2,070	0.070	1.536	−5.292	0.037	5.472
reit	2,070	0.028	1.002	−4.756	0.000	4.163
corp	2,070	0.110	0.301	−0.686	0.088	0.972
hy	2,070	0.054	0.340	−0.696	0.010	1.224
forex	2,070	0.000	0.004	−0.014	0.000	0.013
ltb	2,070	0.000	0.413	−1.281	0.020	1.274
sov	2,070	−0.006	0.107	−0.307	−0.011	0.476
com	2,070	0.049	0.859	−2.418	0.170	2.782
plt	2,070	−0.193	0.906	−2.896	−0.046	3.563

This table presents descriptive statistics of the variables employed in this study. N refers to the number of observations. S.D. is the standard deviation. Min and Max refer to the minimum and maximum values, respectively. Variables are defined in Table 14

correlations between return and other control variables. The correlation statistics do not raise any concerns regarding multicollinearity.

5.2 Main results

To test our first hypothesis, we examine whether the negative market reaction to the LIBOR manipulation accusation is moderated by contemporaneous social media disclosure on part of the banks. We estimate Eq. (1) in Sect. 4.3.[14] *ER* is daily excess stock returns calculated as the difference between banks' daily stock return (*R*) and the risk-free rate (*Rf*). *event* is a dummy variable that takes the value of one on the three-day window around the event date, and zero otherwise. *event* × *volume_ab* and *event* × *length_ab* are the interactions of *event* with the abnormal tweet volume and the abnormal length of a bank's tweets, respectively. We estimate our model using the LIBOR bank sample (models 1–3) and a sample of

[14] To demonstrate that the market reaction to the LIBOR manipulation is negative, we also estimate a baseline model that ignores the effect of social media and document a negative and significant coefficient on the variable *event*.

Table 3 Correlation Matrix

	ER	volume_ab	length_ab	retweet_ab	hplink_ab	facebook	press	statement
Panel A. Correlations Between Returns and Media Measures								
Volume_ab	−0.008	1						
Length_ab	0.001	0.922***	1					
Retweet_ab	−0.040	−0.334***	−0.220***	1				
Hplink_ab	−0.056*	−0.106***	−0.110***	0.392***	1			
Facebook	0.012	0.328***	0.425***	−0.054*	0.191***	1		
Press	0.038	−0.091***	−0.072**	0.050*	−0.006	−0.040	1	
Statement	−0.009	−0.004	−0.001	0.053*	−0.010	−0.016	−0.006	1
Trend	0.016	−0.008	0.030	−0.121***	0.139***	0.030	0.071**	−0.001

	ER	size	liquid	fine	mkt	mkt_bank	reit	corp	hy	forex	ltb	sov	com
Panel B. Correlations Between Returns and Other Control Variables													
Size	−0.043	1											
Liquid	0.073***	0.252***	1										
Fine	−0.015	0.023	0.007	1									
Mkt	0.713***	−0.025	0.005	−0.028	1								
mkt_bank	0.793***	−0.011	0.003	−0.017	0.809***	1							
Reit	0.370***	−0.013	−0.009	−0.009	0.484***	0.416***	1						
Corp	0.312***	−0.006	−0.005	−0.006	0.345***	0.325***	0.233***	1					
hy	0.081***	0.002	−0.003	−0.034	0.186***	0.100***	0.164***	−0.186***	1				
Forex	−0.274***	−0.007	−0.013	0.016	−0.319***	−0.289***	−0.165***	−0.275***	−0.494***	1			
ltb	−0.173***	0.019	0.013	−0.050*	−0.129***	−0.155***	−0.027	−0.054*	0.049*	0.022	1		
sov	−0.433***	−0.014	0.015	−0.010	−0.468***	−0.473***	−0.282***	−0.588***	0.114***	0.267***	0.240***	1	
com	0.341***	−0.021	0.000	0.010	0.462***	0.372***	0.220***	0.334***	0.120***	−0.317***	−0.254***	−0.382***	1
plt	0.127***	−0.011	0.003	0.036	0.207***	0.151***	0.115***	0.204***	0.380***	−0.418***	−0.012	−0.133***	0.320***

This table reports Pearson correlation coefficients between the variables studied. Panel A reports correlations between return and media measures. Panel B shows correlations between return and other control variables. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Table 14

Table 4 The Effect of Banks' Abnormal Tweet Volume

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
Event	−0.271***	−0.258***	−0.250***	−0.204***	−0.206**
	(−4.185)	(−3.876)	(−3.783)	(−2.887)	(−2.744)
Volume_ab	0.044	−0.059	1.602***	0.441*	1.555**
	(0.808)	(−0.139)	(3.812)	(2.072)	(2.483)
Event × volume_ab	0.025***	0.022***	0.018***	0.017**	0.014**
	(5.269)	(3.956)	(3.311)	(2.624)	(2.324)
Nonevent	−0.179	−0.271	−0.292	−0.475**	−0.271
	(−1.062)	(−1.361)	(−1.323)	(−2.105)	(−1.228)
Facebook	−0.046*	−0.056**	−0.027	−0.054	−0.034
	(−1.798)	(−2.575)	(−0.874)	(−1.160)	(−0.771)
Press	0.002	0.001	0.001	0.003	0.002
	(0.309)	(0.298)	(0.244)	(0.538)	(0.440)
Statement	0.431**	0.476***	−0.386	0.320**	−0.096
	(2.825)	(3.241)	(−1.120)	(2.438)	(−0.340)
Trend	−0.002	−0.003	−0.003	−0.002	−0.002
	(−0.863)	(−1.159)	(−1.206)	(−1.188)	(−1.385)
Size	−0.164***	−0.216	−0.187	−0.122	0.077
	(−3.754)	(−1.267)	(−1.014)	(−0.593)	(0.323)
Liquid	0.139	0.311*	−0.223	0.133	−0.255
	(1.736)	(1.883)	(−0.925)	(1.093)	(−0.839)
Fine	−0.072	−0.066	−0.001	−0.122	−0.074
	(−0.281)	(−0.252)	(−0.002)	(−0.503)	(−0.330)
Mkt	0.499	0.503	0.523	0.394	0.411
	(1.245)	(1.258)	(1.292)	(1.208)	(1.242)
Mkt_bank	0.741**	0.739**	0.734**	0.778***	0.774***
	(2.739)	(2.728)	(2.712)	(3.230)	(3.214)
Reit	0.106*	0.105*	0.092*	0.034	0.022
	(1.920)	(1.907)	(1.811)	(0.652)	(0.445)
Corp	0.266*	0.260*	0.272*	0.135	0.156
	(1.972)	(1.964)	(2.088)	(0.942)	(1.093)
Hy	−0.172	−0.170	−0.160	−0.156	−0.144
	(−0.733)	(−0.721)	(−0.685)	(−0.803)	(−0.757)
Forex	−26.880	−26.655	−24.833	−23.996	−21.390
	(−1.145)	(−1.115)	(−1.051)	(−1.196)	(−1.091)
Ltb	−0.318**	−0.316**	−0.301**	−0.232	−0.213
	(−2.538)	(−2.542)	(−2.691)	(−1.659)	(−1.637)
Sov	−0.844	−0.894	−0.907	−0.049	0.010
	(−1.343)	(−1.346)	(−1.370)	(−0.092)	(0.018)
Com	0.015	0.014	0.015	−0.015	−0.010
	(0.287)	(0.269)	(0.278)	(−0.330)	(−0.224)
Plt	−0.042	−0.042	−0.042	−0.047**	−0.047**
	(−1.677)	(−1.697)	(−1.672)	(−2.452)	(−2.424)
Constant	1.148	0.323	6.038	0.410	0.112

Table 4 (continued)

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
	(1.042)	(0.090)	(1.445)	(0.120)	(0.019)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.738	0.738	0.741	0.671	0.677

This table reports test results for Hypothesis 1. *event* × *volume_ab* is the interaction of *event* with abnormal volume of a bank's tweeting activity. Standard errors are adjusted for clustering at the bank level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust *t*-statistics are reported in parentheses. Variables are defined in Table 14

LIBOR banks plus control banks (models 4 and 5). All specifications include one or two of the following: country and year fixed effects, country × year fixed effects, and bank fixed effects. The coefficient on *event* represents the effect of a surfaced LIBOR accusation on the bank's excess returns. The interaction term represents the marginal changes in the *event* coefficient when the bank reports a higher abnormal tweet volume, or posts abnormally longe**r** tweets.

As shown in Table 4 and 5, the coefficient on *event* is negative and significant across all specifications, confirming the banks' reputational damage carried by the negative news (and independent of social media usage). Table 4 reports that coefficients on *event* × *volume_ab* across all model specifications are positive and statistically significant at the 5% level or lower, suggesting that the contemporaneous Twitter activity initiated by the bank during the event window attenuated the negative effect on excess returns.[15] Similarly, as reported in Table 5, coefficients on *event* × *length_ab* across all model specifications are also positive and statistically significant at the 5% level or lower, consistent with abnormally longer bank tweets contributing to divert market attention from the negative event during the event period. Overall, the results suggest that social media can lend banks an instant channel through which they can temporarily ease the reputational damage when the scandal surfaces.

Our second hypothesis turns to the dissemination role of social media because Twitter is a socially interactive platform. To test this hypothesis, we examine whether the negative market reaction to the LIBOR manipulation accusation is moderated by social media activity propagated by Twitter users. We repeat our baseline model and include different interaction terms, *event* × *retweet_ab* and *event* × *hplink_ab*, that capture the marginal changes on the *event* coefficient when Twitter users disseminate posts using retweets (*retweet_ab*) or hyperlink (*hplink_ab*) starting from the banks' original tweets. Table 6 reports that

[15] In terms of the economic significance of our results, we base on the result in column 5 of Table 4 and interpret the finding as one standard deviation increase in the abnormal tweet volume being associated with a reduction in the negative returns due to the event, from –15% to –6%.

Table 5 The effect of banks' abnormal tweet length

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
Event	−0.266***	−0.260***	−0.251***	−0.211***	−0.211***
	(−4.553)	(−4.070)	(−3.968)	(−3.220)	(−3.029)
Length_ab	−0.014	−0.051	1.560***	0.431**	1.513**
	(−0.840)	(−0.126)	(3.818)	(2.116)	(2.489)
Event × length_ab	0.028***	0.027***	0.022***	0.025**	0.020**
	(8.143)	(5.973)	(5.209)	(2.852)	(2.799)
Nonevent	−0.116	−0.275	−0.296	−0.477**	−0.274
	(−0.988)	(−1.403)	(−1.363)	(−2.147)	(−1.261)
Facebook	−0.048*	−0.055**	−0.026	−0.054	−0.034
	(−1.977)	(−2.570)	(−0.863)	(−1.156)	(−0.768)
Press	0.002	0.001	0.001	0.003	0.002
	(0.308)	(0.290)	(0.238)	(0.526)	(0.431)
Statement	0.533***	0.475***	−0.384	0.319**	−0.095
	(3.836)	(3.238)	(−1.114)	(2.432)	(−0.336)
Trend	−0.003	−0.003	−0.003	−0.002	−0.002
	(−1.084)	(−1.158)	(−1.206)	(−1.180)	(−1.379)
Size	−0.184**	−0.214	−0.186	−0.121	0.077
	(−3.030)	(−1.263)	(−1.012)	(−0.590)	(0.323)
Liquid	0.113	0.309*	−0.223	0.132	−0.254
	(1.559)	(1.885)	(−0.923)	(1.092)	(−0.837)
Fine	−0.101	−0.067	−0.002	−0.120	−0.073
	(−0.395)	(−0.258)	(−0.007)	(−0.491)	(−0.321)
Mkt	0.497	0.504	0.524	0.394	0.411
	(1.239)	(1.260)	(1.293)	(1.209)	(1.243)
Mkt_bank	0.742**	0.738**	0.734**	0.778***	0.774***
	(2.738)	(2.728)	(2.712)	(3.230)	(3.214)
Reit	0.106*	0.105*	0.092*	0.034	0.021
	(1.938)	(1.902)	(1.807)	(0.648)	(0.442)
Corp	0.265*	0.259*	0.271*	0.134	0.156
	(1.978)	(1.955)	(2.081)	(0.937)	(1.089)
Hy	−0.175	−0.170	−0.160	−0.156	−0.144
	(−0.745)	(−0.722)	(−0.686)	(−0.801)	(−0.756)
Forex	−27.160	−26.691	−24.862	−23.996	−21.395
	(−1.162)	(−1.115)	(−1.051)	(−1.195)	(−1.091)
Ltb	−0.322**	−0.315**	−0.301**	−0.231	−0.213
	(−2.565)	(−2.539)	(−2.688)	(−1.659)	(−1.637)
Sov	−0.844	−0.894	−0.907	−0.052	0.008
	(−1.328)	(−1.346)	(−1.372)	(−0.096)	(0.015)
Com	0.014	0.014	0.014	−0.016	−0.010
	(0.261)	(0.260)	(0.271)	(−0.335)	(−0.228)
Plt	−0.041	−0.042	−0.042	−0.047**	−0.047**
	(−1.644)	(−1.700)	(−1.674)	(−2.457)	(−2.427)
Constant	1.977	0.303	6.469	0.525	0.543

Table 5 (continued)

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
	(1.295)	(0.083)	(1.516)	(0.153)	(0.089)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.738	0.738	0.741	0.671	0.677

This table reports test results for Hypothesis 1. *Event* × *length_ab* is the interaction of *event* with abnormal length of a bank's tweeting activity. Standard errors are adjusted for clustering at the bank level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust *t*-statistics are reported in parentheses. Variables are defined in Table 14

coefficients on *event* × *retweet_ab* are negative and statistically significant at the 10% level or lower, suggesting that Twitter activities initiated by other users are instantly spread to the social media network and exacerbate the negative market reaction. Similarly, as reported in Table 7, coefficients on *event* × *hplink_ab* are negative and statistically significant at the 10% level or lower, consistent with social media users expressing their concerns and relating them to external sources of information through hyperlinks, thus aggravating the perceived severity of the LIBOR accusation. Overall, these results provide evidence that Twitter activity contributed by users in response to banks' tweets can further damage the banks' reputation and worsen the negative market reaction to the scandal.

6 Additional analyses

6.1 Content and sentiment of tweets

Our main findings suggest that a bank's abnormally higher tweeting activity has the potential to mitigate the negative market consequences. However, we are not explicit about the specific content of banks' tweets. The information disclosed by companies on social media is unregulated, and disclosure quantity is just one of the many disclosure dimensions (Hassan and Marston 2019). Based on reviewing LIBOR banks' tweets during the event period, we identify two communication strategies adopted by these banks. The first strategy banks adopt is to post scandal-related information, namely an admission or more detailed explanations regarding the event and the banks' role in it. The existing finance literature shows that the stock markets react favorably when a firm stands out and recognizes operational risk events and related losses (Gillet et al. 2010). On the other hand, social media disclosure may also be subject to opportunistic use by companies to disperse external impressions and curb investor reactions (Jung et al. 2018; Dhaliwal et al. 2011; Highhouse et al. 2009). Consequently, the second strategy is that banks opt for disclosing information unrelated to the scandal. In this case, a bank could disseminate general good news, characterized by positive sentiment and related to

Table 6 The Effect of Banks' Abnormal Retweets

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
Event	−0.042	−0.059	−0.073	0.054	0.030
	(−0.426)	(−0.583)	(−0.794)	(0.498)	(0.273)
Retweet_ab	−0.114**	−0.023	0.424***	0.115*	0.412**
	(−2.710)	(−0.207)	(3.713)	(2.064)	(2.444)
Event × retweet_ab	−0.058*	−0.054*	−0.049*	−0.076**	−0.071**
	(−2.122)	(−2.104)	(−2.120)	(−2.422)	(−2.277)
Nonevent	−0.221	−0.275	−0.299	−0.479**	−0.279
	(−1.590)	(−1.431)	(−1.403)	(−2.197)	(−1.324)
Facebook	−0.051*	−0.055**	−0.025	−0.053	−0.033
	(−2.035)	(−2.538)	(−0.833)	(−1.141)	(−0.753)
Press	0.002	0.002	0.001	0.003	0.002
	(0.323)	(0.313)	(0.255)	(0.530)	(0.430)
Statement	0.478***	0.476***	−0.380	0.316**	−0.092
	(3.390)	(3.258)	(−1.102)	(2.396)	(−0.327)
Trend	−0.003	−0.003	−0.003	−0.002	−0.002
	(−1.232)	(−1.221)	(−1.268)	(−1.220)	(−1.406)
Size	−0.207***	−0.196	−0.167	−0.104	0.093
	(−4.755)	(−1.174)	(−0.932)	(−0.515)	(0.398)
Liquid	0.013	0.315*	−0.213	0.134	−0.244
	(0.114)	(1.912)	(−0.874)	(1.117)	(−0.801)
Fine	−0.114	−0.108	−0.036	−0.164	−0.110
	(−0.460)	(−0.425)	(−0.142)	(−0.661)	(−0.478)
Mkt	0.498	0.503	0.524	0.394	0.411
	(1.240)	(1.259)	(1.293)	(1.211)	(1.245)
Mkt_bank	0.741**	0.738**	0.734**	0.778***	0.774***
	(2.734)	(2.726)	(2.710)	(3.229)	(3.213)
Reit	0.107*	0.105*	0.092*	0.034	0.022
	(1.933)	(1.902)	(1.807)	(0.650)	(0.445)
Corp	0.261*	0.261*	0.273*	0.135	0.156
	(1.931)	(1.961)	(2.084)	(0.941)	(1.090)
Hy	−0.173	−0.171	−0.160	−0.155	−0.143
	(−0.737)	(−0.723)	(−0.684)	(−0.797)	(−0.751)
Forex	−26.989	−26.579	−24.732	−23.849	−21.240
	(−1.150)	(−1.107)	(−1.042)	(−1.184)	(−1.080)
Ltb	−0.320**	−0.316**	−0.302**	−0.232	−0.214
	(−2.559)	(−2.548)	(−2.696)	(−1.662)	(−1.640)
Sov	−0.862	−0.873	−0.891	−0.043	0.015
	(−1.364)	(−1.317)	(−1.348)	(−0.079)	(0.027)
Com	0.011	0.012	0.013	−0.017	−0.012
	(0.220)	(0.230)	(0.245)	(−0.365)	(−0.255)
Plt	−0.041	−0.042	−0.041	−0.047**	−0.047**
	(−1.624)	(−1.675)	(−1.653)	(−2.440)	(−2.413)
Constant	3.898*	−0.152	5.232	−0.061	−0.634

Table 6 (continued)

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
	(2.128)	(−0.043)	(1.261)	(−0.018)	(−0.108)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.738	0.738	0.741	0.671	0.677

This table reports test results for Hypothesis 1. *event* × *retweet_ab* is the interaction of *event* with abnormal retweets of a bank. Standard errors are adjusted for clustering at the bank level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust *t*-statistics are reported in parentheses. Variables are defined in Table 14

societal or corporate topics, in an attempt to possibly divert the public attention and thus neutralize the adverse impact of the scandal. We report some example tweets representing these two strategies in Table 15. To further check the content of event banks' tweets on event dates, we compute and visualize the frequency of keywords that appeared in the tweets. We follow the standard practices of data preparation and pre-processing in textual analysis to remove potential noise and irrelevant information (Amin et al. 2021; Ferilli et al. 2014; Miner 2012). Specifically, we performed the following tasks: 1) remove stop words that are frequent words without informative content, such as "and", "is", and "this"; 2) normalize the text by converting uppercase letters to lowercase letters; and 3) stem and lemmatize same words of different forms/tenses, such as "thank" and "thanks". Once all the tweets are processed, we visualize the words based on their frequencies. Figure 1 shows the top words used in event banks' tweets on event dates, which indicates that most event banks adopted the second communication strategy on Twitter.

We further consider the sentiment of banks' tweets during the scandal and test the sensitivity of our findings to the content of banks' tweeting activity. We measure sentiment using the open-source Python library TextBlob (Loria et al. 1994).[16] The sentiment analyzer implementation used by TextBlob is based on the Pattern library, which is trained from human-annotated words commonly found in product reviews.[17] Sentiment scores range from –1 to 1. We use residual sentiment (*sentiment_res*) to capture the portion of sentiment that is orthogonal to market risk, calculated as the residuals from regressing daily average sentiment score on daily market return.[18] We replicate our model (Eq. 1) by including our sentiment measure (*sentiment_res*) and the interaction term of *event*

[16] TextBlob has been employed by various studies (e.g., Gauba et al., (2017); Perikos and Hatzilygeroudis, (2016)) and sentiment analysis on Twitters (e.g., Usha and Thampi, (2017); Hawkins et al., (2016)), as a proven sentiment analysis tool.

[17] To check the robustness of our results to the choice of the sentiment dictionary, we re-estimated the baseline model using Linguistic Inquiry and Word Count (LIWC) as an alternative dictionary for sentiment measurement, and the results remain qualitatively similar.

[18] We also develop a more stringent measure for *sentiment_res* by regressing daily average sentiment on a set of common risk factors (i.e., *ltb*, *corp*, *hy*, *sov*, *reit*, *forex*, *com*, and *plt*) that are additional to market risk. Results, unreported for brevity, remain qualitatively the same.

Table 7 The effect of banks' abnormal hyperlinks

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
Event	−0.207**	−0.196**	−0.199**	−0.137*	−0.155*
	(−3.011)	(−2.671)	(−2.811)	(−1.796)	(−1.979)
Hplink_ab	0.010	0.040	−2.328***	−0.657**	−2.270**
	(1.262)	(0.066)	(−3.778)	(−2.168)	(−2.513)
Event × hplink_ab	−0.013**	−0.020**	−0.016*	−0.032***	−0.023**
	(−2.591)	(−2.871)	(−2.105)	(−3.446)	(−2.142)
Nonevent	−0.119	−0.287	−0.309	−0.494**	−0.293
	(−1.038)	(−1.470)	(−1.415)	(−2.250)	(−1.343)
Facebook	−0.048*	−0.055**	−0.025	−0.054	−0.034
	(−1.924)	(−2.485)	(−0.821)	(−1.142)	(−0.754)
Press	0.002	0.002	0.001	0.003	0.002
	(0.350)	(0.324)	(0.267)	(0.550)	(0.453)
Statement	0.546***	0.479***	−0.377	0.320**	−0.090
	(3.902)	(3.295)	(−1.095)	(2.441)	(−0.317)
Trend	−0.003	−0.003	−0.003	−0.002	−0.002
	(−1.212)	(−1.249)	(−1.295)	(−1.261)	(−1.449)
Size	−0.177***	−0.209	−0.180	−0.115	0.080
	(−3.260)	(−1.244)	(−0.993)	(−0.564)	(0.339)
Liquid	0.095	0.299*	−0.227	0.129	−0.258
	(1.336)	(1.830)	(−0.930)	(1.072)	(−0.852)
Fine	−0.134	−0.099	−0.028	−0.157	−0.101
	(−0.559)	(−0.406)	(−0.114)	(−0.676)	(−0.465)
Mkt	0.497	0.504	0.524	0.394	0.411
	(1.236)	(1.260)	(1.294)	(1.211)	(1.243)
Mkt_bank	0.743**	0.739**	0.735**	0.779***	0.774***
	(2.738)	(2.728)	(2.712)	(3.230)	(3.215)
Reit	0.107*	0.105*	0.092*	0.034	0.022
	(1.946)	(1.904)	(1.809)	(0.651)	(0.447)
Corp	0.268*	0.261*	0.273*	0.135	0.156
	(2.009)	(1.977)	(2.105)	(0.944)	(1.096)
Hy	−0.179	−0.175	−0.164	−0.159	−0.146
	(−0.766)	(−0.744)	(−0.702)	(−0.817)	(−0.767)
Forex	−27.389	−26.968	−25.059	−24.188	−21.528
	(−1.175)	(−1.126)	(−1.059)	(−1.204)	(−1.097)
ltb	−0.321**	−0.314**	−0.300**	−0.230	−0.213
	(−2.563)	(−2.524)	(−2.674)	(−1.652)	(−1.632)
Sov	−0.812	−0.864	−0.883	−0.032	0.023
	(−1.288)	(−1.310)	(−1.342)	(−0.059)	(0.042)
Com	0.013	0.013	0.013	−0.017	−0.011
	(0.246)	(0.237)	(0.253)	(−0.359)	(−0.246)
Plt	−0.041	−0.042	−0.042	−0.047**	−0.047**
	(−1.614)	(−1.685)	(−1.660)	(−2.451)	(−2.419)
Constant	2.048	0.318	6.082	0.347	0.232

Table 7 (continued)

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
	(1.421)	(0.088)	(1.442)	(0.101)	(0.039)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.737	0.738	0.741	0.671	0.677

This table reports test results for Hypothesis 1. *event* × *hplink_ab* is the interaction of *event* with a bank's abnormal number of hyperlinks. Standard errors are adjusted for clustering at the bank level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust *t*-statistics are reported in parentheses. Variables are defined in Table 14

Fig. 1 Keywords of Event Banks' Tweets on Event Dates. This figure shows the top words appeared in event banks' tweets on event dates. Larger font size corresponds higher frequency of word usage

with *sentiment_res* (*event* × *sentiment_res*). The results are reported in Table 8. The coefficient on *event* remains negative and significant across all specifications. Coefficients on the interaction term, *event* × *sentiment_res*, are negative and statistically significant at the 10% level or lower. This result confirms that the negative market reaction to the scandal is not attenuated but rather exacerbated if a bank's tweeting activity, around the event day, is characterized by positive sentiment. This reaction is typical for those tweets that put forward good news statements involving corporate or societal initiatives but are not

Table 8 Moderating effect of tweet sentiment

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
Event	−0.212***	−0.199***	−0.191***	−0.157**	−0.156**
	(−4.235)	(−4.112)	(−3.384)	(−2.481)	(−2.254)
Sentiment_res	0.275**	0.281**	0.266*	0.008	−0.022
	(2.314)	(2.198)	(1.991)	(0.062)	(−0.184)
event × sentiment_res	−1.074**	−1.137**	−1.021*	−1.097**	−1.116**
	(−2.217)	(−2.363)	(−1.931)	(−2.402)	(−2.338)
Nonevent	−0.150**	−0.272	−0.347	−0.544***	−0.516*
	(−2.165)	(−1.558)	(−1.702)	(−2.745)	(−2.012)
Facebook	−0.020	−0.020	−0.010	−0.026	−0.017
	(−1.598)	(−1.410)	(−0.596)	(−1.311)	(−0.707)
Press	−0.001	−0.000	−0.001	0.000	0.000
	(−0.308)	(−0.130)	(−0.238)	(0.125)	(0.017)
Statement	0.243	0.275	0.002	0.377***	0.219
	(0.785)	(0.874)	(0.008)	(3.687)	(1.451)
Trend	−0.004	−0.005	−0.005	−0.002*	−0.002*
	(−1.354)	(−1.285)	(−1.300)	(−1.793)	(−1.866)
Size	−0.107***	−0.069	0.015	0.015	0.129
	(−3.245)	(−0.448)	(0.076)	(0.086)	(0.732)
Liquid	0.010	0.224*	−0.212	0.124	−0.080
	(0.396)	(1.940)	(−1.279)	(1.251)	(−0.591)
Fine	0.428	0.456	0.476	0.381	0.380
	(1.125)	(1.123)	(1.178)	(1.031)	(1.000)
Mkt	0.254	0.258	0.245	0.184	0.180
	(1.018)	(1.034)	(1.013)	(1.109)	(1.126)
Mkt_bank	0.907***	0.904***	0.909***	0.874***	0.873***
	(5.315)	(5.295)	(5.466)	(6.654)	(6.846)
Reit	0.070	0.070	0.074	0.001	0.003
	(1.511)	(1.474)	(1.684)	(0.014)	(0.073)
Corp	0.335**	0.342**	0.356**	0.104	0.108
	(2.556)	(2.645)	(2.708)	(0.954)	(0.978)
Hy	−0.068	−0.061	−0.052	−0.045	−0.047
	(−0.489)	(−0.432)	(−0.376)	(−0.426)	(−0.452)
Forex	−15.251	−14.123	−12.040	−5.043	−3.902
	(−1.344)	(−1.205)	(−1.056)	(−0.489)	(−0.391)
Ltb	−0.205*	−0.207*	−0.218**	−0.076	−0.079
	(−1.831)	(−1.864)	(−2.159)	(−0.858)	(−0.947)
Sov	0.231	0.226	0.268	0.628	0.637
	(0.379)	(0.369)	(0.428)	(1.504)	(1.515)
Com	0.070	0.071	0.074	0.032	0.034
	(1.399)	(1.422)	(1.441)	(0.870)	(0.897)
Plt	−0.056**	−0.057**	−0.056**	−0.044**	−0.039**
	(−2.426)	(−2.432)	(−2.293)	(−2.439)	(−2.102)
Constant	1.477	−1.834	3.565	−1.881	−1.102

Table 8 (continued)

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
	(1.494)	(−0.445)	(0.793)	(−0.479)	(−0.252)
Observations	1,509	1,509	1,509	2,947	2,947
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.748	0.747	0.750	0.652	0.657

This table reports test results for the moderating effect of tweet sentiment. *event* × *sentiment_res* is the interaction of *event* with residual sentiment of a bank's tweets. Standard errors are adjusted for clustering at the bank level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust *t*-statistics are reported in parentheses. Variables are defined in Table 14

related to the LIBOR scandal.[19] The evidence is consistent with the markets efficiently impounding the relevant negative news and discounting any attempt of impression management in event banks' social media communication.

6.2 Nonevent banks' twitter activity

So far, we have shed light on the abnormal Twitter activity of event banks and how it affects their excess returns, yet we remain silent on the market reaction to the tweets of nonevent banks. We further explore whether nonevent banks' tweeting activity during the event windows can significantly affect their indirect exposure to the scandal. We rerun our main analyses including a dummy variable for nonevent banks (*nonevent*) and its interaction with nonevent banks' tweet volume (*volume_ab*) and length (*length_ab*). The results are reported in Table 9. While we continue to find a moderating effect of abnormal tweet volume and abnormal length for the event banks, we do not find any significant effect induced by nonevent banks' abnormal Twitter activity (except for column 1 of Panel B, in which country × year and bank fixed effects are absent). We attribute this result to the lesser degree of exposure of nonevent banks compared to the alleged banks throughout the scandal.

6.3 Falsification Tests

It is important to make sure that banks' Twitter activity during the scandal is meaningful and thus different from any tweets otherwise tweeted in normal circumstances. For the

[19] To enhance the validity of the tweet sentiment test, we conducted an additional analysis. We parsed all the scandal-related tweets and identified a set of the most frequently occurring scandal-related keywords (e.g., "LIBOR", "scandal", "manipulation", "settlement", "investigation", "sanction"). Subsequently, we performed textual analysis on the entire subsample of tweets characterized by positive sentiment, searching for these keywords. Any tweets containing at least one of these identified keywords was flagged as scandal related. Out of the 105,352 tweets characterized as having a positive sentiment, only 19 tweets were identified as containing misconduct-related content. This results in a ratio of 0.018%, providing reassurance regarding the nature of the majority of positive tweets as being unrelated to the scandal.

Table 9 Nonevent Banks' twitter activity

	(1)	(2)	(3)	(4)	(5)
	ER	ER	ER	ER	ER
Panel A. Abnormal Tweet Volume					
event	−0.262***	−0.255***	−0.252***	−0.202***	−0.208***
	(−4.238)	(−3.949)	(−3.901)	(−2.990)	(−2.867)
Volume_ab	0.045	−0.043	1.605***	0.441**	1.566**
	(0.909)	(−0.104)	(3.730)	(2.093)	(2.480)
Event × volume_ab	0.021***	0.020***	0.019***	0.016***	0.016***
	(5.107)	(4.083)	(4.170)	(3.629)	(3.441)
Nonevent	−0.126	−0.239	−0.331	−0.458	−0.317
	(−0.632)	(−0.988)	(−1.167)	(−1.603)	(−1.116)
Nonevent × volume_ab	−0.017	−0.009	0.011	−0.005	0.013
	(−1.252)	(−0.600)	(0.539)	(−0.248)	(0.654)
Constant	1.173	0.693	5.914	0.518	0.043
	(1.142)	(0.183)	(1.412)	(0.147)	(0.007)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No
Year FE	Yes	No	Yes	Yes	No
Country × Year	No	Yes	No	No	Yes
Bank FE	No	No	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.738	0.738	0.741	0.671	0.676
Panel B. Abnormal Tweet Length					
event	−0.253***	−0.252***	−0.250***	−0.203***	−0.210***
	(−4.392)	(−4.014)	(−4.020)	(−3.169)	(−3.074)
Length_ab	0.004	0.018	1.567***	0.450**	1.515**
	(0.322)	(0.047)	(3.928)	(2.616)	(2.499)
Event × length_ab	0.022***	0.022***	0.021***	0.020***	0.019***
	(5.158)	(4.643)	(4.919)	(5.338)	(4.580)
Nonevent	−0.075	−0.231	−0.285	−0.428*	−0.266
	(−0.698)	(−1.220)	(−1.255)	(−1.875)	(−1.179)
Nonevent × length_ab	−0.028**	−0.023	−0.006	−0.024	−0.005
	(−2.533)	(−1.169)	(−0.272)	(−0.908)	(−0.210)
Constant	2.005	1.299	6.555	1.043	0.571
	(1.408)	(0.334)	(1.549)	(0.294)	(0.094)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.738	0.738	0.741	0.671	0.676

Table 9 (continued)

This table reports test results for nonevent banks' Twitter activity. Standard errors are adjusted for clustering at the bank level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust *t*-statistics are reported in parentheses. Variables are defined in Table 14

Table 10 Falsification Tests

	Observations	Mean
Panel A. Two−sample t−test Results		
ER_event (2011–2013)	2,228	−1.100
ER_control (2010)	2,228	−0.484
Difference		−0.616***
t−statistic		(−10.615)
df		2227
AR_event (2011–2013)	2,228	−0.098
AR_control (2010)	2,228	0.021
Difference		−0.119***
t−statistic		(−3.823)
df		2227
Panel B. OLS Regression Results		
tweet_volume	−0.002	0.004
	(−0.148)	(0.359)
Constant	−9.736*	−14.818***
	(−1.880)	(−3.780)
Observations	2,181	2,181
Sample	2010	2010
Controls	Yes	Yes
Bank FE	Yes	Yes
Cluster SE	Bank	Bank
Adjusted R^2	0.720	0.047

This table reports falsification test results. Standard errors are adjusted for clustering at the bank level. *df* stands for degrees of freedom. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust *t*-statistics are reported in parentheses. Variables are defined in Table 14

sake of robustness, we run two falsification tests to test whether Twitter activity during the scandal window has an incremental effect. First, for each bank, we match the tweet volume during the 3-day event window with another random 3-day interval outside the event period (i.e., during the out-of-sample period, 2010) that reports identical tweet volume. We conduct standard event studies and examine market reactions during the scandal windows for the two samples. As reported in Panel A of Table 10, compared to the out-of-sample return measures (i.e., *ER_out* and *AR_out*), excess returns (*ER_in*) and abnormal returns (*AR_in*) are significantly different and more negative in the event sample, thus supporting the view that Twitter activity does not have a systemic impact on equity returns of event banks. In addition, we run OLS regressions of excess returns on tweet volume only for the sample of banks with identical tweet volume but at random dates out-of-sample. If social media activity during the scandal period is not significantly different from a bank's normal

Table 11 Diminishing event effects

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
Panel A. Abnormal Tweet Volume					
event	−0.271***	−0.259***	−0.248***	−0.202**	−0.201**
	(−4.141)	(−3.812)	(−3.684)	(−2.831)	(−2.641)
Volume_ab	0.045	−0.015	1.687***	0.442*	1.587**
	(0.812)	(−0.035)	(4.338)	(1.926)	(2.494)
Event × volume_ab	0.025***	0.021***	0.017**	0.017**	0.013*
	(5.095)	(3.701)	(2.987)	(2.423)	(2.060)
Nonevent	−0.182	−0.277	−0.299	−0.487**	−0.278
	(−1.062)	(−1.391)	(−1.365)	(−2.182)	(−1.259)
Constant	1.291	0.985	6.897	0.689	0.376
	(1.118)	(0.261)	(1.612)	(0.195)	(0.061)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.741	0.741	0.745	0.674	0.680
Panel B. Abnormal Tweet Length					
event	−0.266***	−0.261***	−0.250***	−0.210***	−0.208***
	(−4.514)	(−4.003)	(−3.861)	(−3.162)	(−2.914)
Length_ab	−0.015	−0.009	1.642***	0.432*	1.544**
	(−0.878)	(−0.022)	(4.347)	(1.963)	(2.499)
Event × length_ab	0.028***	0.027***	0.021***	0.025**	0.019**
	(8.218)	(5.711)	(4.863)	(2.707)	(2.579)
nonevent	−0.120	−0.281	−0.303	−0.489**	−0.281
	(−0.982)	(−1.432)	(−1.404)	(−2.223)	(−1.290)
Constant	2.171	0.974	7.353	0.805	0.815
	(1.358)	(0.255)	(1.688)	(0.228)	(0.130)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.741	0.741	0.745	0.674	0.680
Panel C. Abnormal Retweets					
event	−0.041	−0.059	−0.075	0.058	0.033
	(−0.403)	(−0.569)	(−0.808)	(0.528)	(0.294)

Table 11 (continued)

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
retweet_ab	−0.119**	−0.012	0.447***	0.114*	0.420**
	(−2.742)	(−0.106)	(4.225)	(1.907)	(2.448)
event × retweet_ab	−0.059*	−0.054*	−0.048*	−0.077**	−0.071**
	(−2.104)	(−2.056)	(−2.075)	(−2.399)	(−2.232)
nonevent	−0.227	−0.281	−0.305	−0.491**	−0.285
	(−1.572)	(−1.459)	(−1.445)	(−2.275)	(−1.353)
Constant	4.134*	0.483	6.088	0.203	−0.389
	(2.200)	(0.130)	(1.432)	(0.058)	(−0.064)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.741	0.741	0.745	0.674	0.680
Panel D. Abnormal Hyperlinks					
event	−0.206**	−0.196**	−0.198**	−0.135*	−0.151*
	(−3.009)	(−2.659)	(−2.782)	(−1.767)	(−1.932)
hplink_ab	0.011	−0.024	−2.452***	−0.659*	−2.318**
	(1.293)	(−0.038)	(−4.309)	(−2.018)	(−2.527)
event × hplink_ab	−0.014**	−0.021**	−0.017*	−0.034***	−0.024**
	(−2.761)	(−2.964)	(−2.147)	(−3.544)	(−2.184)
nonevent	−0.124	−0.294	−0.316	−0.506**	−0.300
	(−1.038)	(−1.504)	(−1.461)	(−2.336)	(−1.378)
Constant	2.227	0.975	6.958	0.620	0.502
	(1.474)	(0.257)	(1.616)	(0.175)	(0.081)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.741	0.741	0.745	0.674	0.680

This table reports results adjusted for diminishing event effects. Models are estimated using a weighted least squares regression. The weight is calculated as $\frac{1}{\ln(eventsequence)}$, which assigns earlier events with higher weights. Standard errors are adjusted for clustering at the bank level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Table 14 tweeting activity, then we should continue to find a significant association between tweet volume and returns also in the period preceding the scandal (2010). We do not find any significant effects of daily tweet volume on excess returns or abnormal returns. Results, reported in Panel B of Table 10, are in line with bank tweeting activity during the scandal period having an incremental effect on equity returns.

6.4 Diminishing event effect

One concern that may affect the robustness of our baseline results is associated with the fact that not all news may be equal, with earlier news being more important than later news. We account for diminishing event effects by using an event-sequence-weighted OLS. The weight is calculated as $\frac{1}{\ln(eventsequence)}$, which assigns earlier events with higher weights. Results are reported in Table 11 and suggest that our results hold even when diminishing event effects are accounted for.

6.5 Confounding Events

We check the robustness of our results to additional confounding events that took place during our sample period. Existing literature suggests that earnings announcements carry information content that is impounded by market participants and can affect both stock prices and trading volume (e.g., Beaver et al. (1979); Ball and Brown (1968); Beaver (1968)). Using the detailed history data from I/B/E/S, we develop the following two variables to further control for the potential effect of confounding earnings announcements on bank excess returns: *eadate* is a dummy variable that takes the value of one when a bank's earnings announcement date overlaps with the 3-day event window, and zero otherwise; *accuracy* is a measure of analyst forecast accuracy, which is the difference between actual earnings and the average of analyst earnings forecast. We include both *eadate* and *accuracy* in all regressions. The results reported in Table 12 confirm that our main inferences are not altered. The coefficients of interest preserve both their magnitude and significance across all specifications.

Another confounding event that may have an impact on our results is heightened merger and acquisition (M&A) activities. We check all the banks in our sample and search for their potential involvement in M&A based on the Securities Data Company's M&A deal data. Among all event dates in our sample, only one date overlaps with the date on which an event bank made an M&A deal announcement. We exclude this date from our sample and repeat the main analysis. Results, unreported for brevity, remain unchanged.

6.6 Alternative twitter control windows

Our main results are based on the use of a three-month control window (i.e., October to December 2010) for Twitter activity. The assumption is that Twitter volume during the control window captures the normal level of daily Twitter activities related to a bank's profile. To check the robustness of our results to the choice of the control window, we re-estimated the baseline model employing alternative control windows that use respectively one month, six months, and nine months before the event date. The results, unreported for brevity, remain qualitatively similar.

Table 12 Confounding effect of earnings announcement

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
Panel A. Abnormal Tweet Volume					
Event	-0.252***	-0.236***	-0.222***	−0.191**	−0.191**
	(−4.055)	(−3.755)	(−3.596)	(−2.795)	(−2.632)
Volume_ab	0.048	0.037	1.632***	0.460**	1.581**
	(0.897)	(0.093)	(3.994)	(2.232)	(2.626)
Event × volume_ab	0.024***	0.021***	0.017***	0.016**	0.013**
	(5.313)	(3.881)	(3.184)	(2.585)	(2.269)
Nonevent	−0.193	−0.291	−0.305	−0.483**	−0.279
	(−1.178)	(−1.494)	(−1.377)	(−2.177)	(−1.263)
Eadate	−0.832	−0.831	−0.822	−0.437	−0.420
	(−1.451)	(−1.445)	(−1.383)	(−1.115)	(−1.048)
Accuracy	0.449	0.463	0.487	0.304	0.319
	(1.596)	(1.645)	(1.651)	(1.009)	(1.038)
Constant	1.253	0.583	5.890	0.309	0.002
	(1.129)	(0.158)	(1.415)	(0.091)	(0.000)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.741	0.742	0.745	0.672	0.678
Panel B. Abnormal Tweet Length					
event	−0.247***	−0.239***	−0.225***	−0.199***	−0.197***
	(−4.499)	(−4.039)	(−3.861)	(−3.150)	(−2.935)
Length_ab	−0.015	0.042	1.589***	0.449**	1.538**
	(−0.897)	(0.110)	(4.001)	(2.281)	(2.632)
Event × length_ab	0.028***	0.026***	0.021***	0.025**	0.020**
	(7.611)	(5.132)	(4.446)	(2.658)	(2.572)
Nonevent	−0.125	−0.295	−0.309	−0.485**	−0.282
	(−1.073)	(−1.538)	(−1.416)	(−2.221)	(−1.295)
Eadate	−0.821	−0.832	−0.823	−0.438	−0.420
	(−1.437)	(−1.445)	(−1.383)	(−1.116)	(−1.049)
Accuracy	0.461	0.464	0.487	0.304	0.319
	(1.636)	(1.647)	(1.652)	(1.010)	(1.038)
Constant	2.133	0.592	6.334	0.431	0.442
	(1.338)	(0.158)	(1.491)	(0.127)	(0.073)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No

Table 12 (continued)

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.741	0.742	0.745	0.672	0.678
Panel C. Abnormal Retweets					
event	−0.008	−0.025	−0.033	0.074	0.054
	(−0.094)	(−0.281)	(−0.404)	(0.745)	(0.514)
Retweet_ab	−0.126**	0.002	0.431***	0.119**	0.418**
	(−2.968)	(0.018)	(3.895)	(2.236)	(2.587)
Event × retweet_ab	−0.063**	−0.058**	−0.054**	−0.079**	−0.074**
	(−2.396)	(−2.393)	(−2.483)	(−2.565)	(−2.437)
Nonevent	−0.241	−0.296	−0.312	−0.487**	−0.287
	(−1.762)	(−1.574)	(−1.463)	(−2.278)	(−1.363)
Eadate	−0.830	−0.833	−0.824	−0.439	−0.421
	(−1.444)	(−1.444)	(−1.382)	(−1.118)	(−1.051)
Accuracy	0.469	0.469	0.491	0.309	0.324
	(1.656)	(1.658)	(1.660)	(1.024)	(1.050)
Constant	4.281**	0.058	5.038	−0.176	−0.768
	(2.402)	(0.016)	(1.217)	(−0.052)	(−0.133)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.742	0.742	0.745	0.672	0.678
Panel D. Abnormal Hyperlinks					
event	−0.185**	−0.172**	−0.169**	−0.123	−0.139*
	(−2.802)	(−2.514)	(−2.556)	(−1.711)	(−1.865)
Hplink_ab	0.011	−0.105	−2.374***	−0.684**	−2.310**
	(1.388)	(−0.184)	(−3.961)	(−2.344)	(−2.661)
Event × hplink_ab	−0.016**	−0.023**	−0.020**	−0.034***	−0.024**
	(−2.612)	(−3.090)	(−2.295)	(−3.656)	(−2.306)
Nonevent	−0.129	−0.309	−0.325	−0.503**	−0.302
	(−1.128)	(−1.628)	(−1.488)	(−2.339)	(−1.388)
Eadate	−0.822	−0.835	−0.826	−0.440	−0.422
	(−1.436)	(−1.448)	(−1.385)	(−1.121)	(−1.053)
Accuracy	0.465	0.467	0.489	0.307	0.321
	(1.651)	(1.661)	(1.662)	(1.020)	(1.046)
Constant	2.215	0.597	5.935	0.247	0.125

Table 12 (continued)

	(1) ER	(2) ER	(3) ER	(4) ER	(5) ER
	(1.472)	(0.161)	(1.411)	(0.073)	(0.021)
Observations	1,248	1,248	1,248	2,070	2,070
Sample	LIBOR	LIBOR	LIBOR	LIBOR + Control	LIBOR + Control
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	No	No	No
Year FE	Yes	Yes	No	Yes	No
Country × Year	No	No	Yes	No	Yes
Bank FE	No	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank
Adjusted R^2	0.741	0.742	0.745	0.672	0.678

This table examines the sensitivity of findings to confounding earnings announcements. Standard errors are adjusted for clustering at the bank level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t−statistics are reported in parentheses. Variables are defined in Table 14

7 Conclusion

We provide the first evidence on the effects of social media activity in the context of a financial scandal using a sample of banks that were accused of manipulating the LIBOR. The LIBOR scandal represents an industry-wide crisis that induced extremely negative market reactions and severe reputational damage. We examine the equity-based reputational effect of social media communications for the involved banks and show how the reputational effect is affected by the concurrent dissemination activity of social media users. We first focus on banks' Twitter activity. Twitter renders banks a strategic communication channel to instantly influence individual perceptions and temporarily lessen the gravity of the scandal. Our results show that banks whose Twitter activity was more pronounced during the scandal window experienced reputational damage to a lesser extent. We next ask whether Twitter users' dissemination on social media affects the reputational damage. In such an industry-wide scandal, Twitter posts initiated by alleged banks might trigger a virtual echo with complaints and negative sentiment rapidly gaining traction and being propagated to a large network of users eager to publicly recall the negative event and share their disappointment. We observe that the more a bank's message is disseminated by users, the more the adverse impact of the event is amplified. Overall, our findings suggest that even though a bank can directly and extensively intervene via its own Twitter account, the negative event can become magnified and exacerbate the market reaction to the scandal.

In additional analyses, we examine the sentiment of banks' tweets on the event days, as a means to better understand its content. We find that bank tweets that are characterized by positive sentiment have a negative moderating effect on the reputational damage. This result implies that markets efficiently impound the negative information and punish banks' attempts of obfuscation in social media communication. We further examine whether nonevent banks' tweeting activity during the event windows affects their indirect exposure to the scandal, and we do not find any significant effect on their equity returns. Finally, we check the robustness of our results by performing out-of-sample falsification tests, accounting for diminishing event effects and confounding events, and using alternative Twitter control windows.

Table 13 List of events

Date	Event
24/03/2011	Barclays emerged as a key focus of the investigation by the US and UK regulators. Bank of America and Citibank also received subpoenas
26/07/2011	UBS confirmed the LIBOR investigation had widened the scope to Yen rates
09/12/2011	Citigroup and UBS faced Tokyo Interbank Offered Rate (TIBOR) penalties
03/02/2012	Swiss authorities launched a probe into 12 banks (Bank of Tokyo−Mitsubishi, Citigroup, Crédit Suisse, Deutsche Bank, HSBC, JP Morgan, Mizuho Corporate Bank, Rabobank, RBS, Société Générale, Sumitomo Mitsui Banking Corporation, and UBS) over claims they have been fixing their interbank lending rates
10/02/2012	Citigroup forced to write off \$50 m after two traders accused of attempting to influence global lending rates left the bank
20/03/2012	Deutsche Bank received data request in LIBOR probe
27/06/2012	Barclays admitted to misconduct. The UK's FSA and the US Department of Justice and the CFTC imposed fines worth \$450 m in total
03/07/2012	Crown Office confirmed investigation into Scottish banking sector (Lloyds Banking Group and RBS)
05/07/2012	RBS withdrawn from TIBOR panel. Moody's and S&P lowered their outlook on Barclays from stable to negative amid the LIBOR scandal
18/07/2012	Investigations focused on Barclays, whose traders were the ringleaders of a circle that included Crédit Agricole, HSBC, Deutsche Bank, and Société Générale
31/07/2012	Deutsche Bank confirmed that a limited number of staff were involved in the LIBOR scandal
05/08/2012*	Crédit Agricole, Deutsche Bank, HSBC, Rabobank, and Société Générale linked to the LIBOR probe
09/08/2012	Bank of Tokyo Mitsubishi became the latest lender to face questions in the widening LIBOR scandal
16/08/2012	Barclays, Citigroup, Deutsche Bank, HSBC, JP Morgan, RBS, and UBS to be questioned in the US for alleged LIBOR rigging
23/08/2012	A former Singapore−based trader at RBS opened a new window into how attempts were allegedly made to manipulate LIBOR
07/09/2012	RBS in talks to settle LIBOR allegations that would cost it £200−300 m
10/09/2012	Trial began of former UBS trader
15/10/2012	A group of US homeowners sued Barclays, Bank of America, JP Morgan, UBS, RBS, Citigroup, Rabobank, Crédit Suisse, Deutsche Bank, HSBC, Lloyds Banking Group, and Royal Bank of Canada, claiming they are liable for their mortgage rates being artificially higher because of illegal LIBOR rigging
26/10/2012	Subpoenas sent to Bank of America, Bank of Tokyo Mitsubishi, Crédit Suisse, Lloyds Banking Group, Rabobank, Royal Bank of Canada, Société Générale, Norinchukin Bank, and WestLB
29/10/2012§	First LIBOR damages trial set to proceed, a case brought by a care home operator against Barclays to go ahead
15/11/2012	Canadian regulators investigated a half−dozen global banks in LIBOR manipulation probe publicly rebuked RBS
03/12/2012	UBS in global talks to reach a settlement of more than \$450 m over the alleged manipulation of LIBOR
11/12/2012	Three men arrested in connection with investigations into the LIBOR rigging. Hayes (UBS; Citigroup) and Two brokers (RP Martin)
13/12/2012	UBS faced \$1bn fine over LIBOR allegation
14/12/2012	UBS staff faced LIBOR probe in the UK
19/12/2012	UBS agreed to pay \$1.5bn to US, UK and Swiss regulators for attempting to manipulate the LIBOR inter−bank lending rate

Table 13 (continued)

Date	Event
20/12/2012	Former UBS trader who faced criminal charges in the probe had been linked to traders at RBS, JP Morgan, Deutsche Bank, and Citigroup
25/01/2013	Ex−Barclays chiefs named in LIBOR case
06/02/2013	RBS fined $610 m by UK and US authorities for its part in the LIBOR scandal. Japanese banks accused of TIBOR fixing
19/03/2013	Freddie Mac sued more than a dozen banks (Bank of America, JP Morgan, UBS, Citigroup, Crédit Suisse, and Deutsche Bank) and the British Bankers' Association. UBS joined exodus from EURIBOR panel
11/04/2013	Yen LIBOR probe focused on RBS
17/06/2013	Former UBS and Citigroup trader Hayes charged by the Serious Fraud Office in connection with its investigation into the LIBOR scandal
18/06/2013	HSBC probed by Hong Kong regulator over Hong Kong Interbank Offered Rates (HIBOR)
18/09/2013*	A Japanese investment banking unit of UBS ordered to pay a $100 m criminal fine after pleading guilty to LIBOR manipulation
23/09/2013	The US credit union regulator filed an anti−trust lawsuit against 13 banks (UBS, RBS, Barclays, Société Générale, Crédit Suisse, JP Morgan, Lloyds Banking Group, WestLB, Raiffeisen Bank, Norinchukin Bank, Bank of Tokyo Mitsubishi, and Royal Bank of Canada) as part of the LIBOR scandal
21/10/2013	Former employees of Rabobank, RBS, Deutsche Bank, UBS, and ICAP were among 22 names that the UK Serious Fraud Office included as alleged co−conspirators on a draft indictment against Hayes, a former trader at both UBS and Citigroup who is facing criminal charges stemming from a probe into alleged LIBOR rigging
31/10/2013	Fannie Mae sued 9 banks for $800 m over LIBOR: Barclays, Deutsche Bank, Citigroup, Bank of America, UBS, RBS, Crédit Suisse, JP Morgan, and Rabobank
08/11/2013	Barclays and Deutsche Bank faced LIBOR claims in civil cases
04/12/2013	The European Commission fined six banks (RBS, Deutsche Bank, Société Générale, JP Morgan, Citigroup, and RP Martin)

* Event day is on a weekend

§ Hurricane Sandy shuts down the stock market in the US

Overall, our paper contributes to the recent debate on the impact of social media in capital markets in general and the growing literature that considers the role of social media in the context of operational risk events in particular. Findings in this paper could be applied to other settings such as political news, economic policy, and public sector information disclosure, which could be subject to negative consequences at both the individual and societal levels due to social media users' dissemination role. Therefore, our paper could also inform policymakers and regulators when analyzing the contents and effects of social media on the economy and society. While we study the information role of social media during the event dates when the LIBOR scandal surfaced and for those banks that were allegedly involved, we are silent on how the scandal may have reshaped their strategic disclosure policy in the aftermath. We acknowledge that this represents an interesting avenue for future research.

Appendix

See Tables 13, 14 and 15

Table 14 Variable definition

Variable	Definition	Source
R	Bank daily stock return	Compustat
Rf	Risk−free rate. 3−month national/regional treasury bill rate	Datastream
ER	Excess return. The difference between R and Rf	
event	Dummy = 1 on the day before, the day of, and the day after the event date (i.e., [−1, + 1]) when a bank was accused of LIBOR manipulation. If an event takes place on a weekend, the event date is adjusted to the next trading day. If two event windows overlap, we merge the two event windows by extending from the day before the first event to the day following the second event	
nonevent	Dummy = 1 when a bank was a LIBOR bank and was not accused of manipulation when one or more LIBOR banks were accused on the event date. In other words, these nonevent LIBOR banks were not yet officially involved in the scandal (i.e., public/press announcements) when other LIBOR banks were accused of being involved	
volume_ab	Abnormal tweet volume. The difference between mean tweet volume in the event window and mean tweet volume in the control window scaled by standard deviation of tweet volume in the control window	Twitter
length_ab	Abnormal tweet length. The difference between mean word count of tweets in the event window and mean word count of tweets in the control window scaled by standard deviation of word count of tweets in the control window	Twitter
retweet_ab	Abnormal retweet. The difference between percentage of retweets in the event window and percentage of retweets in the control window scaled by standard deviation of percentage of retweets in the control window	Twitter
hplink_ab	Abnormal hyper link. The difference between percentage of tweets with hyperlink in the event window and percentage of tweets with hyperlink in the control window scaled by standard deviation of the percentage of tweets with hyperlink in the control window	Twitter
sentiment_res	Residual sentiment. The residual from regressing daily average sentiment on daily return on the overall market (mkt) and the banking industry (mkt_bank). Sentiment is determined using the open−source Python library TextBlob. The sentiment analyzer implementation used by TextBlob is based on the Pattern library, which is trained from human−annotated words commonly found in product reviews. Sentiment scores range from –1 to 1	Twitter
facebook	Facebook disclosure volume. The number of posts on a bank's official Facebook page	Facebook
press	Traditional media press. The number of times a bank is mentioned in Factiva news sources over the event window	Factiva
statement	Dummy = 1 if a bank posts LIBOR−related statements on its official corporate website within the event window	Corporate Website

Table 14 (continued)

Variable	Definition	Source
trend	Overall trends of media attention. Google Trends index is calculated based on the search interest in terms of the volume of search queries, and provided as a normalized integer number between 0 and 100, with 0 being the minimum and 100 the maximum, for each day during the sample period	Google Trends
eadate	Dummy = 1 if a bank's earnings announcement date overlaps with the scandal event window (i.e., [–1, + 1]), and 0 otherwise	I/B/E/S
accuracy	Analyst forecast accuracy. The difference between actual earnings and the average of analyst forecast earnings	I/B/E/S
fine	Adjusted fine. Fine settlement amount as a percentage of pre−settlement market capitalization	
size	Bank size. Natural logarithm of share price times number of shares outstanding	Compustat
liquid	Liquidity. Natural logarithm of trading volume of shares	Compustat
mkt	Market risk. Percentage changes in the market value of the country's stock market portfolios. The factor is provided by MSCI	Datastream
mkt_bank	Market risk (banking sector). Percentage changes in the market value of the country's banking sector stock market portfolios	Datastream
ltb	Interest rate risk. Percentage changes in the market value of long−term assets. The factor is based on market prices of 10−years government bonds	Datastream
corp	(High−grade) credit risk. Changes in the default premium between BBB− and AAA−rated corporate bonds. The factor is based on time series maintained by Merrill Lynch	Datastream
hy	(Low−grade) credit risk. Changes in the default premium between high−yield bonds and corporate bonds. The factor is based on time series maintained by Merrill Lynch	Datastream
sov	Sovereign risk. Changes in the difference of the (mean) of yields on the 7–10 years government bonds (Greece, Portugal, Spain, Italy) and 7–10 years German Government bonds	Datastream
reit	Real estate risk. Percentage changes in the market value of the country's REIT investments. The factor is provided by FTSE/NAREIT	Datastream
forex	Foreign exchange risk. Percentage changes in the trade−weighted currency baskets as provided by the Bank of England. The factor measures the currency value with respect to the currency values of the major trade partners	Bank of England
com	Commodity risk. Percentage changes in the S&P GSCI Total Return Index	Datastream
plt	Political risk. Percentage changes in gold price against US dollars	Bank of England
AR	Abnormal return. The difference between bank daily stock return (R) and daily market return for the banking sector (mkt_bank)	

Table 15 Example Tweets

Date	Bank Name	Tweet	Tone
27/06/2012	Citi	#Citi Zhang "Cities are driving force behind global growth, generate 80% of global GDP" #FTCitiAwards http://bit.ly/Mlftpp	Positive
27/06/2012	Citi	#Citi promotes Jonathan Larsen to Global Head of Re− tail #Banking: http://bloom.bg/KDCsXD	Positive
27/06/2012	Citi	Over 2 K volunteers revitalized playgrounds, schools & sidewalks in #Guatemala in honor of Global Community Day #200YearsCiti	Positive
27/06/2012	Citi	#Citi is transforming the ways in which cities operate and develop thru our #CitiforCities initiative #FTCiti−Awards	Positive
27/06/2012	Bank of America	Proud to partner w/ @VitalVoices in mentoring emerging #women leaders. Learn more about our work in South Africa http://go.bofa.com/4ebs	Positive
27/06/2012	Bank of America	Less than three weeks before the Student Leadership Summit in #DC. Check out some photos from last year: facebook.com/BankofAmerica/É/#SLSummit	Positive
17/07/2012	Deutsche Bank	Deutsche Bank launches the first Matched Giving initiative in Italy http://ow.ly/citwG/#dbcsr	Positive
06/02/2013	RBS	RBS CEO Stephen Hester comments on LIBOR fine http://bit.ly/TJI9MW?	Neutral
06/02/2013	RBS	Stephen Hester "We condemn the behaviour of the individuals who sought to influence some LIBOR currency settings at our bank from 2006–10."	Negative
06/02/2013	RBS	We've just issued a statement on today's LIBOR settlement, you can view the full announcement via this link http://bit.ly/TJI9MW?	Neutral
28/02/2013	RBS	Pre−tax loss of £5.16bn includes past conduct charges of £1.1bn for PPI settlements, £700 m for interest rate swaps and a £381 m LIBOR fine	Negative
25/04/2013	UniCredit	#ijf13 Bergami: Nobody understood exactly what the LIBOR scandal means. The Italian press has covered little and has not explained enough	Negative
04/12/2013	Barclays	Barclays announces antitrust settlement with European Commission over EURIBOR: http://barclays.co/1bHRo9a?	Negative
04/12/2013	Société Générale	EURIBOR: SocGen firmly condemns such inappropriate behavior in contradiction with its internal code of conduct http://bit.ly/1clkjyr?	Negative

On June 27, 2012, Barclays got fined by both the U.K. and U.S. regulators. Other banks were concurrently under investigation but not yet surfaced as involved in LIBOR manipulation at that time. Below are some example tweets that event banks and other large banks (that later admitted to misconduct as the probe went on) tweeted on the same day and other event dates

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Conflict of interest Xing Huan, Antonio Parbonetti, Giulia Redigolo, Zhewei Zhang declare that they have no conflict of interest.

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