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Operational Risk and Reputation in Financial Institutions: Does Media Tone Make a Difference?

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Abstract

Operational risk announcements are unexpected adverse media news that potentially harm the reputation of financial institutions. This paper examines the equity-based and debt-based reputational effects of financial sentiment tones in operational risk announcements and shows how such reputational effects are moderated by alternative sources of public information. Our analysis reveals that the net negative tone and litigious tone have adverse reputational effects, and the uncertainty tone mitigates the adverse reputational impact. Additionally, alternative, simultaneous sources of information neutralize the reputational effects of textual tones. First, third-party information about the event (i.e. regulatory announcements and final settlements) dissolves the favorable (adverse) reputational impact of the uncertainty tone (litigious tone). Second, loss amount disclosure and firm recognition substitute the reputational effects of the net negative tone and uncertainty tone only in Anglo-Saxon countries and market-based economies. Overall, our findings indicate that the reputational effects of the media materialize most when there is lack of certain, quantifiable and regulated public information about the operational risk event.

Keywords: Content Analysis, Financial Sentiment, Media News, Operational Risk, Reputational Risk, Textual Tone

JEL Classifications: D8 Information, Knowledge, and Uncertainty, G1 General Financial Markets, G2 Financial Institutions and Services

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Operational risk announcements are unexpected adverse media news that potentially harm the reputation of financial institutions. This paper examines the equity-based and debt-based reputational effects of financial sentiment tones in operational risk announcements and shows how such reputational effects are moderated by alternative sources of public information. Our analysis reveals that the net negative tone and litigious tone have adverse reputational effects, and the uncertainty tone mitigates the adverse reputational impact. Additionally, alternative, simultaneous sources of information neutralize the reputational effects of textual tones. First, third-party information about the event (i.e. regulatory announcements and final settlements) dissolves the favorable (adverse) reputational impact of the uncertainty tone (litigious tone). Second, loss amount disclosure and firm recognition substitute the reputational effects of the net negative tone and uncertainty tone only in Anglo-Saxon countries and market-based economies. Overall, our findings indicate that the reputational effects of the media materialize most when there is lack of certain, quantifiable and regulated public information about the operational risk event.

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1. INTRODUCTION

Over the last two decades, a number of high-scale operational losses have hit large financial institutions all over the world, leading to severe financial disturbances including the collapse of some institutions. For example, UBS Investment Bank lost $2bn in 2011 when a trader entered false information into the trade booking system in order to hide risky trades without breaching trading thresholds for over three years. This pattern of deception led to the largest unauthorized trading losses in British history, albeit it had followed in the footsteps of similar incidents such as the rogue trading loss of €4.9bn uncovered by Société Générale in 2008. In terms of the business consequences of operational losses, one of the worst examples is the unauthorized speculative trading loss of £827million (approximately $1.3bn) by Nick Lesson to Barings Bank during the period 1992-1995. Although small in comparison to more recent operational risk losses it caused the United Kingdom's then oldest investment bank to collapse due to its inability to absorb such losses. In light of these high-profile scandals, operational risk management and disclosure practices in financial institutions have recently attracted increased attention from academics, professionals, and regulators (e.g. BCBS, 1998, 2001; Helbok and Wagner, 2006; Ford et al., 2009). Moreover, the inception of the Basel II Capital Accord (BCBS, 2006b) required banks to reserve regulatory capital against operational risk[1] exposure in addition to those reserved against exposures of market and credit risk.

Financial firms are subject to reputational risk[2] as a result of the announcements related to these operational risk events, which ultimately encompass elements of 'poor internal controls' as posited by Chava et al. (2017, p. 2) when investigating the effects of misreporting on borrower reputation. The BCBS definition of operational risk (BCBS, 2006b) and the evidence provided by the literature (e.g. Cummins et al., 2006; Chernobai et al., 2011; Wang and Hsu, 2013) show that operational risk event announcements[3] reveal serious problems in internal control systems, behavior of management and employees, and ultimately weak corporate governance mechanisms in financial firms. These problems uncovered in the announcements have important ramifications for investors as they indicate information that could potentially affect their expected return and variance (Markowitz, 1952), whilst allowing for investors to perceive their potential risk exposure to the event itself by taking into consideration the levels of 'controllability' the institution has at its disposal to limit exposure (March and Shapira, 1987; Slovic, 1987; Weber and Milliman, 1997).

[1] Basel Committee on Banking Supervision (Basel Committee on Banking Supervision, 2006, p.144) defines operational risk as *"…the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. This definition includes legal risk, but excludes strategic and reputational risk."*

[2] Detailed review of previous research and regulatory perspectives on reputational risk in financial institutions is provided in Section 2.1.

[3] We use the terms "operational risk event announcements" and "operational risk announcements" interchangeably to refer to online news articles disclosing information on operational risk events incurred by financial institutions.

To the best of our knowledge, no previous paper on operational and reputational risks has examined the market-based effects of narrative contents in operational risk announcements. Operational risk announcements are pieces of adverse news which unexpectedly hit the media headlines revealing new information on deficiencies in corporate governance structures, internal control systems, and risk management practices in financial institutions. Much of the previous research has studied media effects accompanying corporate earnings announcements albeit the empirical evidence documented was mixed. While some studies proved that media coverage and contents drive the financial sentiment (Tetlock, 2007; Tetlock et al., 2008), stock returns (Fang and Peress, 2009; Ahmad et al, 2016), and local trading (Engelberg and Parsons, 2011), other studies have documented the media hype and bias especially towards local firm announcements (Gurun and Butler, 2012). This mixed evidence calls for further investigation into the role of different types of media (e.g. newswire services, TV, internet search engines, social media etc.) in influencing the financial sentiments of investors and driving the reactions of equity, debt, and CDS markets to different types of announcements. In this paper, we examine empirically the market-based reputational effects of financial sentiment tones in operational risk announcements extracted from newswire services.

The recent decision of *'The Independent'* newspaper to discontinue its print edition and continue only as an online service is another early manifestation of a publication trend which is expected to prevail throughout the media news services in the years to come. More focus is being given to online newswire services and less attention is given to hardcopy newspapers (Saperstein, 2014). This attitude is expected to be stronger for financial markets' investors because they can find the required information on business news in a timelier and less costly manner than hardcopy newspapers. Moreover, we argue that this attitude is expected to be amplified around unexpected, adverse news announcements hitting the financial industry as a major pillar in the economic stability of any country. Given the importance and relevance of newswire services, we aim to empirically investigate and document evidence on the reputational contribution of the textual contents in media news on operational risk events recently announced in a global sample of financial institutions.

To achieve the aim of this paper, we utilize a global sample of 305 operational risk event announcements from 90 financial institutions in 18 countries, which hit the public media news following the global financial crisis (2010 - 2014). We then perform a content analysis of textual information disclosed in the first operational risk announcements using the financial sentiment dictionary recently developed by Loughran and McDonald (2011)[4]. More specifically, we measure the financial sentiment tones across four dimensions, which are: negative words, positive words,

[4] We use the most recently updated version of Loughran and McDonald dictionary in 2014: http://www3.nd.edu/~mcdonald/Word_Lists_files/LoughranMcDonald_MasterDictionary_2014.xlsx.

uncertainty words, and litigious words. We include the uncertainty tone and litigious tone due to the high degree of ambiguity and considerable litigation risks known to be associated with operational risk events. On the one hand, ambiguity is usually very high when the exact or estimated operational loss amount is not disclosed, or not mentioned as settled, in the first announcement, or when the operational risk event is neither recognized by the loss firm[5] nor announced by a regulatory body (e.g. the SEC in the USA or FCA in the UK). On the other hand, litigation risks are more significant when operational risk announcements mention on-going or forthcoming legal lawsuits or regulatory sanctions. We argue that this intensive degree of loss severity, ambiguity, and litigation risk represents a unique opportunity to examine how the narrative contents in media news drive the behaviors of different types of investors, thus possibly causing reputational damage to financial institutions.

Our paper adds several original contributions to the extant literature on operational risk, reputational risk, and media coverage. First, this is the first paper to examine the incremental reputational effects of textual information in operational risk announcements. This adds value to the findings of previous relevant papers that have examined only the impact of quantitative information disclosed in operational risk announcements (i.e. absolute loss amount or its ratio to market capitalization). Second, this is the first paper to quantify the reputational effects of textual contents in newswires services in an increasingly out-of-print media world. The paper exploits the unique nature of operational risk announcements well known to cause different degrees of reputational damage to pinpoint the association between online media contents and reputational risk. Third, this is the first paper to study operational risk announcements and relevant reputational risk in an entirely post-GFC setting, thus providing updated evidence in this area. The global financial crisis and recent rapid developments in banking regulations (such as Basel III and its anticipated full implementation in 2018) and insurance regulations (such as Solvency II which has come into full effect in 2016) call for updating the empirical evidence to uncover whether the attitudes of the investing community towards operational and reputational risks have seen any technical or behavioral shifts. Fourth, this is one of the early papers to use the ORIC[6] database (which is actually used by its member institutions to provide external loss event data when calculating their operational risk capital requirements) to extract and examine the market-based consequences of operational risk announcements in financial institutions. Finally, this is the first paper to examine empirically the reactions of both equity and CDS markets to operational risk announcements and draw beneficial inferences on simultaneous behaviors of potential shareholders and creditors. Previous studies have separately examined investor's behavior around operational risk announcements either in 'equity-based' markets (e.g. Perry and de Fontnouvelle, 2005; Cummins et al.,

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[5] We use the term "loss firm" to indicate the loss-making firm, that is, the financial institution which incurred the announced operational risk event.

[6] ORIC stands for Operational Risk International Consortium: https://www.oricinternational.com/.

2006; Gillet et al., 2010; Sturm 2013a) or 'debt-related' markets (e.g. Plunus et al., 2012; Sturm, 2013b) but never together.

We believe that the five contributions mentioned above could inform policymakers, regulators, and market participants as to the importance of developing innovative mechanisms to mitigate the reputational effects of operational risk losses. Given the results presented in this study, the development of media task forces to follow, analyze, and respond to adverse news announcements, which could have disastrous consequences on big financial institutions, or destabilize the whole financial industry should be considered. Moreover, the findings of this paper could advise risk managers, executive officers, and board directors in financial institutions on the importance of establishing and utilizing early warning systems in the form of content analysis software and information processing models (Kremer et al., 2013).

The remainder of this paper is organized as follows: Section 2 presents a review of the literature and develops our research hypotheses. Section 3 provides the details of our research methodology. Section 4 presents and discusses our empirical results and robustness checks. Concluding remarks are mentioned in Section 5.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Reputational Risk in Financial Institutions: Previous Research and Regulatory Framework

The reputation of organizations can offer a significant competitive advantage for them (Gatzert, 2015), as it facilitates raising capital (Fombrun et al., 2000), assists in stakeholder negotiations, alliance building, and contracts (Fombrun and van Riel, 2004; Rhee and Valdez, 2009; Van Den Bogaerd and Aerts, 2015; Eckert, 2017) and is considered a strategic intangible asset (Hall, 1992). These positive benefits of good corporate reputation are linked to the fact that external stakeholders and observers form opinions, beliefs and impressions of an organization (Rindova et al., 2010), that can ultimately affect stakeholder decision making and improve competitiveness (Fombrun and Shanley, 1990; Soana, 2016). However, a good reputation can be associated with a higher reputational risk (i.e. superior abnormal returns in good times such as CEOs receiving a prestigious certification (Wade et al., 2006) and more severe reputational damage in the wake of bad news such as product recalls due to a greater stakeholder disappointment (Rhee and Haunschild, 2006). Hence, in response to the continuously increasing importance of reputational risk in the modern business environment, several international insurance companies have started to offer stand-alone reputational risk insurance policies (Gatzert, Schmit and Kolb, 2016).

The intrinsic link between operational risk events and reputational risk has been highlighted by Sturm (2013a) and the European Banking Authority given that *"most operational risks have a strong* *impact in terms of reputation"* (EBA, 2014, p. 93). This is further accentuated by the ability of social media platforms and the internet to provide quick access to information for stakeholders in a relatively unfiltered manner, whilst allowing them to interact with each other in a way that spreads information further and faster than traditional print media (Aula, 2010; Gatzert, 2015; Heidinger and Gatzert, 2018). It is therefore not surprising that regulators both in the banking and insurance sectors are now paying much closer attention to reputational risk given the importance of trust, and the confidence that it inspires in stakeholders on both sides of the balance sheet within these industries, to ensuring the safety and soundness of financial systems (Fiordelsi et al., 2013; Soana, 2016; Heidinger and Gatzert, 2018). This has been recognized recently in the Solvency II Regulatory Directive (2009/44) governing insurance companies in which reputation risk is defined as:

"the risk of potential loss to an undertaking through deterioration of its reputation or *standing due to a negative perception of the undertaking's image among customers, counterparties, shareholders and/or supervisory authorities. To that extent it may be regarded as less of a separate risk, than one consequent on the overall conduct of an undertaking."* (CEIOPS, 2009, p. 42).

The sentiments of this definition are also reflected in the Basel II capital requirements directive and also the European Banking Authority (2014, p. 100) who highlight that *"By nature, reputational risk is more relevant for large institutions, in particular those with listed equities or debts or those that operate in interbank markets"*. Although neither the Solvency II nor Basel regulations pertaining to capital allocations (e.g. CRD IV) implicitly require institutions to hold capital in relation to their reputational risk exposure directly, they are expected to consider the consequences of a drop in reputation into their scenarios for funding models specific to ILAAP and ICAAP. For example, the Prudential Regulatory Authority (PRA) in the UK expects banks to take account of the detrimental effects reputational risk would have on both capital and liquidity inadequacies when running scenarios to calculate their PRA Capital buffer – an amount of capital banks must hold over and above the requirements of CRD IV pillar 2, to cover losses that may arise under a severe stress scenario (PRA, 2017, p. 36). This in turn has placed a greater onus on boards of directors and senior managers to include the management of reputational risk into their policies and procedures and improve the overall risk management framework of their institution given that it is a consequence of their (poor) internal risk management process (BCBS, 2009).

Previous research within financial services has also found consistent evidence of the adverse reputational effects of large operational risk event announcements in the financial industry as reflected by a drop in the market values of loss firms by more than a one-to-one proportion[7] (Perry and de

[7] For example, suppose the market value of a firm dropped as a result of an announcement of an operational risk event. Then, a drop in the market value of three-to-one means that the magnitude of the market value drop is three times the magnitude of the operational loss.

Fontnouvelle, 2005; Cummins et al., 2006; Gillet et al., 2010; Sturm, 2013a; Fiordelisi et al., 2014). More specifically, Perry and de Fontnouvelle (2005) have studied 115 operational loss announcements in a global banking sample during the period 1974 – 2004 and documented a negative equity-based reputational impact only for internal fraud announcements. In addition, Cummins et al. (2006) have inspected 492 operational loss announcements in a sample of U.S. financial institutions comprising 403 banks and 89 insurers during the period 1978 – 2003 and documented a more negative equity market reaction in the insurance industry (possibly due to less operational risk regulation than in the banking industry) and for firms with higher growth potentials. Moreover, Micocci et al. (2009) have estimated what they call "reputational value-at-risk" by analyzing the negative equity market reactions to 20 fraud announcements exceeding $20 million in U.S. and European financial institutions during the period 2000 – 2006. Furthermore, Fiordelisi et al. (2014) have utilized a comprehensive sample of 430 operational loss announcements in 163 commercial and investment banks in the USA and Europe during the period 1994 – 2008 and documented a more adverse equity-based reputational impact of fraudulent events, events incurred in the 'Payment and Settlement' and 'Trading and Sales' business lines and events announced in Europe.

In their study of 71 operational risk losses in 41 U.S. financial companies between 1994 - 2006, Plunus et al. (2012) have documented the adverse impact of operational risk announcements on the first announcement date and firm recognition date on cumulative abnormal bond returns and interpret their results as 'pure' reputational damage since operational risk losses usually do not deplete shareholders' equity and therefore should not be directly relevant to the behavior of debt investors. In agreement with Gillet et al. (2010) who have investigated the equity-based reputational effects of 152 operational loss announcements in 64 U.S. and 49 European financial institutions between 1994 and 2006, but disagreement with Sturm (2013a) results on the stock returns of 136 operational risk losses in European financial institutions between 2000 - 2009, Plunus et al. (2012) have found that debt markets react favorably to settlement announcements. Sturm (2013b) has inspected the impact of 99 operational risk announcements between 2004 - 2010 in the European banking industry on credit default swap (CDS) markets and found that abnormal CDS spreads increase only around settlement announcements and when the relative operational loss size is higher. These results suggested that some of the characteristics and timings of operational risk announcements can cause an increase in the bank's default risk. We also believe that these results (Sturm, 2013b) confirm the existence of 'pure' debt-based reputational damage caused by operational risk announcements whilst all of the results above confirm the importance of understanding operational risk events in relation to reputation risk for debt and equity markets as outlined by the EBA (2014, p. 100).

Fiordelisi et al. (2013) have studied the firm-specific, event-related, and macro determinants of reputational damage resulting from 215 operational risk announcements in 163 European and U.S.

banks during the period 2003 – 2008. They found that the probability of reputational damage is positively associated with bank's profitability and size, and negatively associated with its capital adequacy and growth potentials. In a relevant research stream, Biell and Muller (2013) have examined the timings and durations of equity market reactions to 279 operational risk announcements in European financial institutions during the period 1974 – 2009 and found that the reputational damage (as measured by the absolute ratio of cumulative abnormal stock returns to the operational loss amount disclosed) starts earlier and accumulates faster for internal fraud events when compared to External Fraud (EF) and Clients, Products, and Business Practices events (CPBP)[8]. They have also shown that reputational damage occurs later when the firm suffering the loss has a higher credit rating and that the extent of reputational damage is positively associated with the duration of market's overreactions to the announcements.

Overall, there is no conclusive evidence in the literature on the exact determinants of reputational risk around operational risk announcements in the financial industry. Hence, we posit a new factor that can be considered in this context which is media tones and their interactions with alternative sources of public information addressing the operational risk event.

2.2. Hypothesis Development

In this section, we develop our research hypotheses regarding the equity-based and debt-based reputational effects of media tones in operational risk event announcements and how these effects are moderated by alternative sources of public information.

2.2.1. The Net Negative Tone

Previous studies have documented that stock returns are negatively associated with the negative tone in media news (Tetlock, 2007; Ahmad et al., 2016), 10-k filings (Loughran and McDonald, 2011), earnings announcements (Demers and Vega, 2014), and analyst reports (Huang et al., 2014). However, several studies (e.g. Tetlock, 2007; Engelberg, 2008; Loughran and McDonald, 2015) have shown that the positive tone is not priced in equity markets, possibly because equity investors view positive words as merely 'cheap talk'.

As the number of negative words is expected to largely exceed positive words in 'adverse' operational risk announcements, we decided to focus our investigations on the net negative tone (i.e. negative words minus positive words standardized by the total number of financial sentimental words) in these announcements. Journalists, news agents and media experts (we group them together as 'media channels') get access to both public and private sources of information which they are willing to disclose

[8] As defined by the Basel II loss event categories.

to their different audiences (obviously including investors) through newswire services. Therefore, we expect that media channels will tend to reveal the current or expected severity of the operational risk event through the net negative tone used in the first news announcement. To the extent that the markets are efficient, the media transmission channels are free from noise, and the investors are willing to believe the media. Therefore, we expect investors to interpret the net negative tone as an indicator of the unexpected adverse impact of the operational risk event on future cash flows and default risk of the loss firm causing an abnormal drop in stock prices and an abnormal boost in CDS spreads following the operational risk announcements. Therefore, we formulate our first research hypothesis as follows:

H_1: The net negative tone in operational risk event announcements is negatively associated with loss-adjusted abnormal stock returns and positively associated with abnormal CDS spreads following the announcements.

2.2.2. The Uncertainty Tone

Previous papers have found that the uncertainty tone in different types of business communication is negatively associated with stock returns and positively associated with stock return volatility (Demers and Vega, 2014; Loughran and McDonald, 2011). These findings indicate that uncertainty words are interpreted by investors as revealing a higher degree of distrust in the firm-specific distributions of future cash flows and earnings, which ultimately manifests itself in higher discount rates and greater volatilities.

However, we argue here that media channels are expected to reveal the degree of ambiguity they know to be associated with the operational risk event through the uncertainty tone in the first news announcement. Ambiguity associated with the operational risk event on its announcement date could come from several sources; i.e. the operational loss amount is unknown either exactly or approximately, the firm has not yet recognized an internal fraud (e.g. embezzlement) or external fraud (hacking damage), there is no simultaneous regulatory announcement which clarifies more detailed information on the event from an independent government agency, or there is no final in-court or out-of-court settlement announced. The reputational impact of ambiguity/uncertainty tone on markets could have one of two potential consequences (apart from the 'Cheap Talk' theory which posits that, under certain circumstances, investors fully discount media news and consider it as merely hype thus supporting the status-quo bias (Samuelson and Zeckhauser, 1988)). The first consequence is that higher ambiguity reflected in an amplified uncertainty tone would reduce investors' trust in the reliability of future cash flows and increase their downside suspicions about the long-term default risk of the loss firm. This outcome has been supported by empirical evidence in previous studies (Demers and Vega, 2014; Loughran and McDonald, 2011). The second potential consequence is that investors could give the loss firms the benefit of the doubt in the case of high uncertainty and therefore could be conditionally optimistic that the consequences of the operational risk event might not be as bad as initially suggested by the first news announcement as the institution begins to implement 'controllability' of the exposure. This latter outcome could be more suitable for the nature of operational risk announcements; i.e. investors interpret uncertain bad news as good news. Therefore, we formulate our second research hypothesis using the second suggested consequence as follows:

H_2: The uncertainty tone in operational risk event announcements is positively associated with loss-adjusted abnormal stock returns and negatively associated with abnormal CDS spreads following the announcements.

2.2.3. The Litigious Tone

The litigious tone in operational risk announcements is likely to be utilized by media channels in disclosing the level of litigation risk they believe to be associated with the operational risk event. In the case of first news announcements on operational risk events, litigation risk could imply both upside and downside potentials. For example, when an employee or group of employees are suing a bank over allegations of employer malpractice, it might not be that clear on the first announcement date whether the bank will lose or win this forthcoming legal case. Hence, the litigious tone could reveal either upside or downside litigation risk and the net impact on investors' behavior could therefore be indeterminable. However, since previous empirical evidence mostly links the litigious tone to an increase in trading volume and stock return volatility (Loughran and McDonald, 2011), we formulate our third research hypothesis to reflect the downside, letting our empirical evidence challenge the following null hypothesis:

H_3: The litigious tone in operational risk event announcements is negatively associated with loss-adjusted abnormal stock returns and positively associated with abnormal CDS spreads following the announcements.

2.2.4. Interactions with Loss Amount Disclosure

The operational loss amount (whether exact or estimated) is an objective measure of the operational risk event's financial severity. Since the net negative tone (i.e. bad news) in the operational risk announcement could be seen as a qualitative assessment reflecting the subjective beliefs of media channels about the severity of the operational risk event, it would be expected that the net negative tone and operational loss amount disclosed in the media channels are interpreted by investors as substitute sources of information. In contrast, disclosing the operational loss amount, as a quantifiable, reliable measure of severity, is expected to neutralize the adverse impact of the narrative bad news (i.e. the net negative tone) on the loss firm's reputation. Albeit the work of Fischoff (1995, p. 139) has highlighted that although managers may 'hand over the numbers', the suspicious recipients of such raw information (investors) may re-adjust these estimates to accommodate their perception that they have been calculated under likely biases internally.

We also argue that the disclosure of an exact amount or best estimate of the operational loss would partially reduce the uncertainty around the operational risk event's severity but may not remove the uncertainty associated with the causes and consequences of the operational risk event (for example, the uncertainty concerning the underlying Internal Control Weaknesses (ICWs)[9] or any possible future effects on the business model, corporate governance[10], and customer satisfaction of the loss firm). Hence, to the extent that the underlying uncertainty has been reduced by the loss amount disclosure, we expect the calming effect of the uncertainty tone on the equity and debt markets to be counteracted. Similarly, we argue that when the operational loss amount is disclosed, the degree of underlying litigation risk (whether upside or downside) will shrink because investors will know, or at least can more accurately estimate, the maximum legal reserve which needs to accumulated by the loss firm in relation to the announced operational risk event. Hence, the information conveyed by narratives on litigation risk (i.e. the litigious tone) in the first news announcement could become less influential to investors. Therefore, we formulate our fourth hypothesis as follows:

H_4: The associations *of the textual tones in operational risk event announcements with loss-adjusted abnormal stock returns and abnormal CDS spreads following the announcements become weaker when the exact amount or best estimate of the loss is disclosed.*

2.2.5. Interactions with Firm Recognition

Gillet et al. (2010) have shown that equity markets react favorably when the loss firm recognizes the operational risk event and/or loss. Hence, such a corporate confession may calm turbulent market reactions and alleviate the adverse impact of the net negative tone whereas a lack of confession as investigated by Kothari et al. (2009) can increase the cost of equity for the offending organization. However, such a confession could also give more credibility and attention to the narrative bad news, thus magnifying its adverse market consequences. We also attribute the Gillet et al. (2010) finding to the higher degree of certainty implied by firm recognition which the markets seem to appreciate. Hence,

[9] Chernobai et al. (2011) have found that ICWs are associated with higher frequency of operational risk events incurred by U.S. financial institutions, whilst Cosetllo and Wittenberg-Moerman (2011) highlight that ICWs affect the contractual terms of borrowing from lenders based on the severity of the ICW.

[10] Barakat (2014) has shown that U.S. financial institutions respond to large operational risk announcements by making significant changes in their corporate governance structures and that equity markets react (either favorably or unfavorably) to such changes.

we expect the decreased underlying uncertainty caused by simultaneous firm recognition to mitigate the impact of the uncertainty tone in the first news announcement since investors become less uncertain and hence are less vulnerable to the sentimental effects of media news. However, firm recognition could have mixed effects on the underlying litigation risk. On the one hand, confession by the loss firm could indicate that it is in a weak legal position and hence likely to be exposed to a more severe court decision or regulatory sanction (i.e. downside litigation risk). In this case, investors might search for more litigation-related information in the first news announcement, thus amplifying the adverse impact of the litigious tone. On the other hand, it might imply that the loss firm is able to resolve the legal situation in a less hostile manner since it has already admitted the underlying fault (whether intentional or not). In this latter case, investors might become less concerned about searching for, or interpreting litigation-related narratives, thus causing the litigious tone to be of less adverse impact. Therefore, we formulate our fifth hypothesis using the latter proposition and let our empirical evidence challenge it:

H_5: The associations *of the textual tones in operational risk event announcements with loss-adjusted abnormal stock returns and abnormal CDS spreads following the announcements become weaker when the loss firm recognizes the event.*

2.2.6. Interactions with Regulatory Announcement

Many operational risk announcements are associated with regulatory sanctions (which are related to underlying operational risk drivers) or regulatory announcements on emerging cases (i.e. on-going investigations or prosecutions). For example, the U.S. Department of Justice might announce that it is going to prosecute a certain bank for alleged wrong-doing or breach of fiduciary duties. Accompanying operational risk announcements in the media might include brief allusions or, in rare cases, actual contents of simultaneous regulatory announcements and additional information clarifying the relevant underlying facts and expected consequences of such a regulatory process. Hence, regulatory announcements can be seen by investors as alternative sources of information, thus reducing investors' reliance on narrative bad media news to make their investment decisions. Obviously, regulatory announcements inject more credible information into the markets and are likely to reduce the degree of underlying uncertainty associated with the operational risk event. For example, Fiordelisi et al. (2014) found that reputational damage is only caused by 'pure' operational losses which are neither regulatory sanctions nor legal cases. We argue here that more 'simultaneous' 'trustable' sources of information and a lower degree of underlying uncertainty are likely to dissolve the favorable reputational impact of the uncertainty tone on investors' behavior. In addition, litigation risk emerges mostly from either a legal (e.g. class action lawsuits) or regulatory (e.g. fines by regulators or supervisors) source; hence the importance of interacting the litigious tone with the regulatory announcement to extract any marginal effects due to differences in investors' attitudes toward legal-related and regulatory-induced litigation risks. If investors view regulatory-induced litigation risks to be more (less) severe than legal-related litigation risks, we then expect investors to be more (less) interested in searching for and processing litigious information when the operational risk event is (not) simultaneously announced by a regulatory body. Therefore, we formulate our sixth hypothesis as follows:

H_6: The associations *of the textual tones in operational risk event announcements with loss-adjusted abnormal stock returns and abnormal CDS spreads following the announcements become weaker when the event is simultaneously announced by a regulatory body.*

2.2.7. Interactions with Settlement

Gillet et al. (2010) have documented clear positive equity market reactions to settlement announcements on operational risk events, and Plunus et al. (2012) have documented similar reactions in debt markets. The settlement means that an in-court or out-of-court agreement has been reached or a final regulatory fine or sanction has been decided which the firm agrees with. It is noteworthy here to mention that settlement and firm recognition are not identical as the loss firm could recognize the event but would not accept a pending settlement or would decide to go through an appeal process. In very rare cases (only two events in our sample), the loss firm might accept the final settlement but does not admit any wrong-doing or fault within its internal control system or risk management function. Some might view settlement as an implicit recognition by the firm and therefore consider settlement as a sub-division or special case of firm recognition. Although on first appearance it may seem that the final settlement obviously removes all of the uncertainty underlying the operational risk event, it is still possible that there is an element of unresolved ambiguity regarding the vulnerability of the loss firm to similar events or litigation processes in the future (possibly due to inherent ICWs, corporate governance problems, or risk management deficiencies). This is of particular importance within the UK as the FCA incentivize early settlement for operational risk breaches by reducing financial penalties by up to 30%. Hence, we expect settlements (if explicitly mentioned in the first news announcement) to remove, if not reverse, the favorable impact of the uncertainty tone on investors' behavior. Similarly, final settlements should indicate no further 'current' litigation risk but it could still pinpoint to future litigation risk associated with similar events or other events caused by the same underlying factors of the current event. Hence, we again posit that the sentimental effects of the litigious tone would become weaker when a final settlement is mentioned in the first news announcement on the operational risk event. Therefore, we formulate our seventh research hypothesis as follows:

H_7: The associations *of the textual tones in operational risk event announcements with loss-adjusted abnormal stock returns and abnormal CDS spreads following the announcements become weaker when the event is settled.*

3. RESEARCH METHODOLOGY

3.1. Sample Selection and Composition

Table 1 details our sample selection procedures. We begin with all 16110 public announcements in the commercial database ORIC[11] which spans the period 1921 – 2015 (data extracted in March 2015). Since ORIC announcements are only regularly collected from 2010, our sample period covers the post global financial crisis (post-GFC) years (2010 – 2014). We exclude the following from the dataset: announcements before 2010 and after 2014, announcements in non-financial firms because the nature of operational risk is clearly different from that in financial institutions, announcements in loss firms not headquartered in USA, Europe, Canada, and Australia to coincide with previous operational risk studies which focused mainly on U.S. & European firms, announcements which have no clear operational risk classification (event type or business line), announcements whose dates are not confirmed or full-text news articles not found (we have cross-checked and downloaded available full-texts of operational risk announcements from LexisNexis news database), announcements in privately held financial firms, and announcements with outliers in reputational returns (i.e. less than -10% or more than 10%) or abnormal CDS relative spread changes (i.e. less than -50% or more than 50%).[12]

[Insert Table 1 here]

Hence, we end up with a final sample of 305 operational risk announcements from 90 financial institutions in 18 countries (Table 2, Panel A) which hit the public media news during the years 2010 - 2014. We believe that our final sample is of a good size as it exceeds, in terms of yearly average, the sample sizes in most of previous studies on operational and reputational risks such as 115 events (1974 – 2004) in Perry and de Fontnouvelle (2005), 492 events (1978 – 2003) in Cummins et al. (2006); 152 events (1994 – 2006) in Gillet et al. (2010), 71 events (1994 – 2006) in Plunus et al. (2012), 136 events (2000 – 2009) in Sturm (2013a); 99 events (2004 – 2010) in Sturm (2013b); and 430 events (1994 – 2008) in Fiordelisi et al. (2014).

Table 2 (Panel B) presents the composition of our final sample by industry type. Our final sample is diversified as it encompasses 16 different industry types of financial institutions (according to Bloomberg classification), with most of the sample coming from banking-related activities (218/71%) and the remaining events coming mainly from brokerage-related activities (26/9%), wealth management-related activities (21/7%), and insurance-related activities (21/7%).

[Insert Table 2 here]

[11] More detailed information about the ORIC database is provided in Appendix A.
[12] Our results remain qualitatively similar if outliers are not removed from the sample.

3.2. Variables Tested and Data Sources

Our empirical analysis is performed in the event window (-10,+10) around operational risk event announcements in our final sample. Our event window is clean of any other news disclosed or published about our sample firms. We have not extended our research beyond a two-week trading period before and after our announcement dates to make sure that our results are not contaminated by other material firm-specific information contemporaneously released to the markets such as earnings announcements, credit rating updates and corporate governance changes. To provide a clearer picture of market reactions to media tones, we split our overall event window (-10,+10) into four smaller event windows which are: i) pre-announcement window (-10,-1), ii) announcement day (0,0), iii) post-announcement – first week (+1,+5) and iv) post-announcement – second week (+6,+10). Examining pre-announcement windows would reveal whether the leakage of private information has caused any anomalous effects (e.g. bias in the media tones) and post-announcement windows would capture the market reactions to the public information disclosed in the media news.

3.2.1. Equity-based Reputational Impact

Following the literature on operational risk announcements (De Fontnouvelle and Perry, 2005; Gillet et al., 2010; Sturm, 2013a; Fiordelisi et al., 2013; Fiordelisi et al., 2014), we measure the informational impact of textual information in operational risk announcements using the Cumulative Abnormal Stock Returns *(CAR)* which is computed utilizing the single-index market model with the estimation period being a window of 250 trading days ending one calendar month before the announcement date. We collect data on stock prices and local stock market indices from DataStream.

Also, following the literature on reputational risk (Gillet et al., 2010; Fiordelisi et al., 2013; Fiordelisi et al., 2014), we measure the equity-based reputational impact using the loss-adjusted CAR which we call the reputational return or $RCAR$ and compute according to the following formula for an event i:

$$RCAR(x,z)_i = CAR(x,z)_i + \left| \frac{Operational\ Loss\ Amount_i}{Market\ Capiltalisation_i} \right|$$

We measure the market capitalization eleven trading days before the announcement date to exclude any impact on the firm’s market value caused by leakage of information in the two trading weeks preceding the announcement date. We follow a conservative approach and assume the operational loss amount to be zero if no exact figure or best estimate has been disclosed in the relevant event window[13]. In this way, we relax the strong assumption posited by Gillet et al. (2010) that the market is able to accurately estimate the settlement amount on the first announcement date even if it is not actually

[13] We cross-checked the data downloaded from ORIC with the announcements extracted from LexisNexis to confirm whether the loss amount had been disclosed.

disclosed. Since our whole event window (-10,+10) is clean of any other announcements, we believe that $RCAR$ can accurately measure the 'pure' reputational impact (i.e. non-mechanical market reaction to the information disclosed in the operational risk announcement).

3.2.2. Debt-based Reputational Impact

Following (Sturm, 2013b), we use Cumulative Abnormal CDS Spread Changes ($CASC$) as a measure of debt-based reputational damage. To the extent that losses are covered by shareholders' equity, operational risk events should be of no relevance to creditors. Therefore, any positive impact on abnormal CDS spread changes would indicate both an increase in the implied default risk of the loss firm and a pure reputational loss.

We have chosen to employ CDS spreads rather than bond returns to measure the debt-based impact of operational risk announcements (i.e. which we consider as a proxy for both the pure reputational impact and change in implied default risk around the operational risk announcement). There are three reasons for our choice. Firstly, Ericsson, Jacobs, & Oviedo (2009) found that CDS spreads are superior to stock returns and bond returns in measuring the default risk of the business entity. Second, Mengle (2007) documented a boost in CDS market liquidity due to the increased contribution of hedge funds in more recent years. Third, Blanco et al. (2005) showed that the causality relationship flows from CDS spreads (the cause) to bond spreads (the effect) and not vice versa.

We collect data on five year modified modified structure CDS spreads in Euro from DataStream and data on the iTraxx index from Bloomberg.

We compute cumulative abnormal CDS spread change (*CASC*) for firm *i* on day *t* as follows:

$$ASC_{it} = (CDS_{it} - CDS_{it-1}) - (iTraxx_t - iTraxx_{t-1})$$

$$CASC(t_1, t_2) \quad = \sum_{\boldsymbol{t=t_1}}^{\boldsymbol{t_2}} ASC_t$$

3.2.3. Financial Sentiment Tones

These are the main explanatory variables of interest in our empirical analysis. Here, we use financial sentiment tones proposed by Loughran and McDonald (2011) from their comprehensive research into 10-K filings of U.S. firms. We focus on four types of financial sentiment words which are positive words, negative words, uncertainty words, and litigious words. We then construct the following three proxies of textual tone in operational risk announcements:

$$Net\ Negative\ Tone = \left(\frac{Negative\ Words - Positive\ Words}{Total\ Financial\ Sentiment\ Words}\right) * 100$$

$$Uncertainty\ Tone = \left(\frac{Uncertainty\ Words}{Total\ Financial\ Sentiment\ Words}\right) * 100$$

$$Litigous\ Tone = \left(\frac{Litigious\ Words}{Total\ Financial\ Sentiment\ Words}\right) * 100$$

Where:

$$\begin{aligned} Total\ Financial\ Sentiment\ Words \\ &= Negative\ Words + Positive\ Words + Uncertainty\ Words \\ &+ Litigous\ Words \end{aligned}$$

We compute these three financial sentiment tones for the longest news article disclosing the operational risk event and published on day (0).[14]

3.2.4. Operational Risk Event Features and Announcement Characteristics

Since the reputational impact of operational risk announcements could also be caused by the features of the operational risk event *per se* or characteristics of the announcement, we control for such factors in our multivariate regressions. Firstly, we employ a dummy variable to capture whether the operational loss amount is disclosed in the first announcement. In addition, we control for whether the operational risk event has been recognized by the loss firm itself. This does not necessarily mean that the loss firm has issued a press release but this recognition could simply be mentioned in the first announcement (for example, a representative of the loss firm has made a short comment affirming the event but challenging the relevant fine imposed by a regulatory body or court of law). Moreover, we include a dummy to indicate whether a simultaneous regulatory announcement concerning the operational risk event has been released. Almost always, operational risk announcements come out on the same day as the relevant regulatory announcement.

Furthermore, a dummy is included to indicate whether the first announcement includes a final settlement. Since our sample is recent, many of our operational risk announcements have not yet been settled with only 22% settlement announcements included in our final sample. It is to be noted that no settlement does not mechanically imply no firm recognition as we relax our definition of settlement to include cases when the settlement is accepted by only one party to the legal or regulatory conflict. Following this logic, we find that approximately 20% of our no-settlement announcements have already been recognized by the loss firm. Furthermore, we control for the location of the operational risk event itself (not the announcement) and whether it has taken place outside the incorporation's country.

Additionally, we consider whether the operational risk event has included top corporate figures (i.e. C-suite officers or board directors of the loss firm). Moreover, we control for the fraudulent nature of

[14] We choose the longest news article because we expect that equity and debt investors are looking for the most comprehensive and most detailed source of information on the operational risk event. We get qualitatively similar results when we use the averages of financial sentiment tones for all news articles published on day (0).

the event by including a dummy to capture whether the operational risk event is classified as internal fraud or external fraud event type. We collect data on these dummies by cross-checking the relevant news articles in LexisNexis. Finally, since ORIC employs some additional non-Basel II business lines such as life insurance, general insurance and insurance broking, we include a dummy variable to control for the Basel II business lines which are: corporate finance, trading and sales, retail banking, commercial banking, payment and settlement, agency services, asset management and retail brokerage.

Finally, we gauge the extent of media coverage using two variables. First, we control for the international media attention using a dummy capturing whether the operational risk event has been featured in *The Financial Times* (FT) or *The Wall Street Journal* (WSJ). Second, we count the number of online news articles covering the operational risk event on day (0). We collect data on these two variables from LexisNexis.

3.2.5. Control Variables

To properly identify our multivariate regression models, we include some common control variables. Firstly, we control for the size, profitability, leverage, and growth of the loss firm using the natural logarithm of total assets, ROA, long-term debt to shareholders' equity ratio, and market-to-book ratio, respectively. In addition to accounting-based proxies, we also control for the riskiness of the loss firm using market-based measures which are the annualized standard deviation of daily stock returns and monthly betas. Moreover, we consider the share's floatation by including the percentage of outstanding shares available to ordinary shareholders one week before the announcement date. In addition, we control for trading volume by including the natural logarithm of the number of shares traded for the stock (in thousands) one week before the announcement date. We collect accounting and market data from DataStream. Since we conduct a multi-country analysis, we control for the GDP per capita whose data is collected from the World Bank's website.

Further, to account for any leakage of private information before the first operational risk event announcement date, we include lagged measures of the informational and reputational impact over the trading week preceding the first announcement date. For example, in the multivariate regressions modelling the equity-based reputational impact, we use $CAR(-10,-1)$ as a proxy for any leakage of information before the first announcement date. By definition, $CAR(-10,-1)$ is not added as a control variable in the pre-announcement regressions since it has already been included in the computation of the dependent variable $RCAR(-10,-1)$.

Finally, to consider the information environment of the loss firm before the announcement date, we employ the number of analysts estimating the firm's EPS in the month preceding the announcement. We collect data on analyst coverage from Bloomberg. Additionally, we control for the creditworthiness of the loss firm by including S&P long-term local issuer credit rating in the form of a cardinal scale which ranges from AAA=1 to D or SD = 22. We collect credit rating data from Bloomberg.

3.2.6. Descriptive Statistics

Table 3 presents descriptive information on all our variables. The average reputational return *(RCAR)* decreases from 0.44% and 0.31% in the event windows (-10,-1) and (0,0), respectively, to -0.29% and -0.10% in the post-announcement windows (+1,+5) and (+6,+10), respectively. Together with the wide range and material heterogeneity in *CASC* in all pre-announcement and post-announcement windows, these statistics do not clearly indicate whether operational risk announcements would always cause an equity-based or debt-based reputational damage, thus calling for a more in-depth univariate and multivariate analyses of the determinants of the reputational effects of these announcements.

Since operational risk announcements typically reveal bad news on the loss firm, the net negative tone is expectedly dominating the financial sentiment of the announcements with 54% on average, compared with averages of only 8% for the uncertainty tone and 26% for the litigious tone. It is also as expected that the litigious tone dominate the uncertainty tone as most operational risk announcements include detailed legal or regulatory information. These financial sentiment statistics give credibility to the Loughran and McDonald (2011) dictionary as appropriately classifying the textual tones in our sample of operational risk announcements.

Additionally, there is a clear heterogeneity in the announcement characteristics and event features, which enable us to test their main and marginal reputational effects. For example, 68% of the announcements disclose the exact loss amount or its best estimate, while 36% and 58% of operational risk announcements are recognized by the loss firm itself and simultaneously announced by a regulatory body, respectively. Moreover, only 22% of the first announcements include final settlements which reduces the possibility of private information leaking prior to the first announcement. Furthermore, only 8% of events involve top executives or board directors, and 26% of events took place in a different country. Finally, most of the announcements relate to events of non-fraudulent nature (88%) and occurred in one of the eight Basel II business lines (79%).

Our sample events receive substantial international attention since 48% of them have been featured in FT or WSJ. In addition, our sample reflects a considerable media exposure as there are, on average, 15 news articles covering each operational risk event.[15]

Finally, the wide range of accounting-based proxies, market-based measures, and information environment factors all confirm the diversity of our sample as it includes big corporations (maximum

[15] Our results remain qualitatively similar if operational risk events covered by only one news article on day (0) are removed from our sample.

total assets of $2,867,353 million USD) and small firms (minimum total assets of $644 million USD), profitable (maximum ROA of 7.20%) and non-profitable firms (minimum ROA of -3.28%), high-risk (maximum beta of 4.46) and low-risk firms (minimum beta of 0.44), and highly visible (37 analysts) and least visible firms (only one analyst)[16]. On the macroeconomic level, our sample covers both developing economies (minimum GDP per capita of $10,646 USD) and highly advanced economies (maximum GDP per capita of $100,575 USD).

[Insert Table 3 here]

3.2.7. Correlation Analysis

In the interests of brevity, Pearson correlation coefficients are not reported[17]. However, It is noteworthy that the medium negative correlations between the three financial sentiment tones (-0.45 between *Uncertainty Tone* and *Litigious Tone*, -0.30 between *Uncertainty Tone* and *Net Negative Tone*, and -0.25 between *Litigious Tone* and *Net Negative Tone*) reflect an overlap between the three textual tones (i.e. words classified under two or more of these tones) and show that these textual tones could partially substitute each other (Loughran & McDonald, 2015). This has two implications for the design of our empirical study. Firstly, we run a separate baseline regression and four interaction regressions for each of the textual tones. Secondly, the interaction terms could reflect the marginal effects of overlapping words (e.g. the interaction term *Settlement Dum * Uncertainty Tone* could reflect the marginal effects of uncertain bad news once a final settlement is announced and the underlying certainty is fully resolved). Finally, untabulated correlation coefficients do not reveal any serious multicollinearity concerns. In addition, it is noteworthy that Variance Inflation Factor (VIF) scores do not reflect any material biases in variable coefficients for our multivariate regression models.

3.3. Multivariate Regression Models

In this subsection, we identify our equity-based and debt-based multivariate regression models (both baseline and interactions) that will be utilized to test our research hypotheses.

3.3.1. Equity-based Reputational Impact Regressions

First, we test the following OLS model to extract the equity-based reputational impact of financial sentiment tones in the first media news announcement of operational risk event i incurred by the loss firm j incorporated in country k during the event window (x, z):

[16] Our results remain qualitatively similar if firms followed by only one equity analyst are removed from our sample.

[17] Full results on Pearson correlation coefficients among all our variables are available upon request.

$$
\begin{aligned}
RCAR_{ijk}(x,z) = \alpha_{ijk} &+ \beta_1 Net\ Negative\ Tone_i\ or\ \beta_1 Uncertainty\ Tone_i\ or\ \beta_1 Litigious\ Tone_i \\
&+ \beta_2 Loss\ Disclosure\ Dum_i + \beta_3 Firm\ Recognition\ Dum_i \\
&+ \beta_4 Regulatory\ Announcement\ Dum_i + \beta_5 Settlement\ Dum_i \\
&+ \beta_6 Different\ Country\ Dum_i + \beta_7 Top\ Figures\ Dum_i \\
&+ \beta_8 Fraud\ Dum_i + \beta_9 Basel\ Business\ Line\ Dum_i + \beta_{10} FT\ \&\ WSJ\ Dum_i \\
&+ \beta_{11} Number\ of\ News\ Articles_i + \beta_{12} Analyst\ Coverage_j + \beta_{13} StDev\ Ret_j \\
&+ \beta_{14} Beta_j + \beta_{15} Float\%_j + \beta_{16} Ln(Volume)_j + \beta_{17} Ln(Total\ Assets)_j \\
&+ \beta_{18} ROA_j + \beta_{19} Leverage_j + \beta_{20} Market\ to\ Book\ Ratio_j \\
&+ \beta_{21} GDP\ Per\ Capita_k + \beta_{22} CAR_{ijk}(-10,-1) + \epsilon_{ijk}
\end{aligned}
$$

3.3.2. Debt-based Reputational Impact Regressions

To test the debt-based reputational impact caused by financial sentiment tones in the first media news announcement of operational risk event i incurred by the loss firm j incorporated in country k during the event window (x, z), we test the following OLS models:

$$
\begin{aligned}
CASC_{ijk}(x,z) = \kappa_{ijk} &+ \delta_1 Net\ Negative\ Tone_i\ or\ \delta_1 Uncertainty\ Tone_i\ or\ \delta_1 Litigious\ Tone_i \\
&+ \delta_2 Loss\ Disclosure\ Dum_i + \delta_3 Firm\ Recognition\ Dum_i \\
&+ \delta_4 Regulatory\ Announcement\ Dum_i + \delta_5 Settlement\ Dum_i \\
&+ \delta_6 Different\ Country\ Dum_i + \delta_7 Top\ Figures\ Dum_i \\
&+ \delta_8 Fraud\ Dum_i + \delta_9 Basel\ Business\ Line\ Dum_i + \delta_{10} FT\ \&\ WSJ\ Dum_i \\
&+ \delta_{11} Number\ of\ News\ Articles_i + \delta_{12} Analyst\ Coverage_j \\
&+ \delta_{13} Credit\ Rating_i + \delta_{14} StDev\ Ret_j + \delta_{15} Beta_j + \delta_{16} Ln(Total\ Assets)_j \\
&+ \delta_{17} ROA_j + \delta_{18} Leverage_j + \delta_{19} Market\ to\ Book\ Ratio_j \\
&+ \delta_{20} GDP\ Per\ Capita_k + \delta_{21} CASC_{ijk}(-10,-1) + \nu_{ijk}
\end{aligned}
$$

3.3.3. Interaction Regressions

To examine whether the reputational effects could be partially driven by the operational risk announcement characteristics, we interact each of the four variables measuring the nature of disclosure in operational risk announcements (i.e. loss amount disclosure, firm recognition, regulatory announcement, final settlement) with the three textual tones (net negative tone, uncertainty tone, litigious tone). To alleviate collinearity concerns, we separately interact each disclosure characteristic with each of our textual tones. Heteroscedasticity-robust standard errors are used to infer the significance of the coefficients estimated in all our baseline and interaction regressions.

4. EMPIRICAL RESULTS

4.1. Univariate Analysis

In this subsection, we present and analyze the results of the event studies conducted on our measures of equity-based and debt-based reputational damage. The results in this section provide an indication of the reputational effects of our sample events in general, and the inspected media tones more specifically.

4.1.1. Event Study on the Equity-based Reputational Effects of Operational Risk Event Announcements

Table 4 reports the average reputational returns *(RCARs)* for different event windows and various subsamples of media tones. Top25% and Bottom75% subsamples include the events in the upper quartile and lowest three quartiles of the relevant media tone's distribution, respectively. Following Fiordelisi et al. (2013 & 2014) who performed equity-based event studies on operational risk event announcements in an international context, we assess the statistical significance of *RCARs* in our main and subsamples by running the parametric test presented by Boehmer, Musumeci, and Poulsen (1991) which adjusts for any event-induced increase in return volatility[18,19].

In Table 4, the equity-based reputational damage materializes most in the post-announcement period, with a mean *RCAR* amounting to -0.29% and -0.10% in the event windows (+1,+5) and (+6,+10), respectively. However, mean comparisons of various media tone subsamples reveal some clear trends. First, the event window (-10,-1) does not show any significant differences in the mean *RCARs* for the different media tone subsamples, thus initially indicating that media tones are not driven by any pre-announcement leakage of private information. Second, the biggest and most significant differences in subsample means occur in the event window (+1,+5) with qualitatively similar but less significant results in the event windows (0,0) and (+6,+10). Third, in the event window (+1,+5), the Top-25% subsamples of the net negative, uncertainty and litigious tones have mean *RCARs* that are significantly lower by 0.77%, higher by 1.75% and lower by 0.85% than their respective Bottom-75% subsamples. Taken together, the results in Table 4 support our hypotheses H_1, H_2 and H_3.

[Insert Table 4 here]

---

[18] In unreported robustness checks, we follow Fiordelisi et al. (2013 & 2014) and assess the statistical significance of *RCARs* using two other parametric tests which are: i) the normally distributed test presented by Campbell, Lo, and Mackinley (1997) and ii) the variance-adjusted test applied by Borenstein and Zimmerman (1988) and Campbell, Lo, and MacKinlay (1997). We also apply the non-parametric Sign Test (Peterson, 1989; Campbell, Lo, and MacKinlay, 1997) which relaxes the normal distribution assumption of abnormal returns. Overall, our univariate results and inferences on *RCARs* remain qualitatively unchanged for all parametric and non-parametric tests performed. Full results of robustness checks are available upon request.

[19] For detailed information on the estimation procedures and hypothesis tests of parametric and non-parametric statistics applied in event studies on international samples of operational risk event announcements, review Fiordelisi et al. (2014).

4.1.2. Event Study on the Debt-based Reputational Effects of Operational Risk Event Announcements

Table 5 reports the average cumulative abnormal CDS spread changes *(CASCs)* for different event windows and various subsamples of media tones around operational risk event announcements. Top25% and Bottom75% subsamples are constructed as mentioned in the previous section 4.1.1. Following Sturm (2013b) who performed a debt-based event study on operational risk event announcements in a European context, we test the statistical significance of *CASCs* using the cross-sectional t-test[20].

The debt-based results in Table 5 are mostly consistent with the equity-based inferences drawn from Table 4. There is a debt-based reputational damage suffered in all post-announcement windows with the most severe one being a significant increase of 2.4 basis points (bps) in the event window (+1,+5). Additionally, the event window (-1,-10) does not show any significant differences in the mean *CASCs* of various media tone subsamples. This confirms the initial indication given above that media tones are not affected by any pre-announcement leakage of private information. Moreover, in the event window (+1,+5), the Top-25% subsamples of the net negative, uncertainty and litigious tones have mean *CASCs* that are significantly higher by 1.21bps, lower by 2.21bps and higher by 1.63bps than their respective Bottom-75% subsamples. Overall, the results in Table 5 also support our hypotheses H_1, H_2 and H_3.

[Insert Table 5 here]

4.2. Multivariate Analysis

Since univariate results need to be interpreted with caution due to unobserved heterogeneity, we expand on the initial inferences drawn in the previous subsection by running a comprehensive set of baseline and interaction regressions. Hence, in this subsection, our multivariate results are discussed and utilized to test our research hypotheses.

4.2.1. Baseline Regressions

In Table 6, we inspect the equity-based (Panel A) and debt-based (Panel B) reputational effects of media tones in operational risk event announcements. As discussed in the following paragraphs, the results consistently show an adverse reputational impact of the net negative and litigious tones and a favorable reputational impact of the uncertainty tone.

In Table 6 (Panel A), the coefficients of the three media tones enter insignificant in the pre-announcement window (-10,-1). This indicates that media tones on Day 0 are not driven by any pre-announcement leakage of private information. This result is consistent in all our baseline regressions.

[20] In unreported robustness checks, we follow Sturm (2013b) and perform the non-parametric Wilcoxon sign-ranked test and get qualitatively similar univariate results and inferences on *CASCs*. Full results of robustness checks are available upon request.

However, it is interesting to note that *Number of News Articles* enters significantly negative in the reputational return regression, thus indicating that more severe pre-announcement reputational damage would increase the extent of media coverage on Day 0. Surprisingly, *FT & WSJ Dum* enters significantly positive in the post-announcement windows, thus indicating that international media attention is associated with less severe equity-based reputational damage. One possible interpretation is that international media such as *The Financial Times* or *The Wall Street Journal* are more likely to feature operational risk event announcements in reputable firms that are more resilient and likely to safely weather the storm. It is though noteworthy that there is a very short adverse debt-based reputational impact of international media coverage on Day 0 (Table 6, Panel B) where *FT & WSJ Dum* increases *CASC* by around 1.1bps. However, this impact does not persist beyond the first announcement day.

Returning to our first three research hypotheses, we find that the strongest impact of media tones occurs in the event window (+1,+5) followed by (+6,+10) and (0,0). This is expected due to the five-day length of the two post-announcement windows compared with the short one-day reaction captured in the event window (0,0). Since our results are consistent across all post-announcement windows, we focus all our coming discussions in this subsection on the event window (+1,+5) where the strongest and most significant coefficients of media tones are reported.

In Table 6 (Panel A), a one standard deviation increase in the net negative tone (i.e. 14%) and litigious tone (i.e. 12%) would decrease *RCAR(+1,+5)* by 0.54% and 0.51%, respectively, whereas a one standard deviation increase in the uncertainty tone (i.e. 7.5%) would increase *RCAR(+1,+5)* by 0.47%. Similar economically powerful and statistically significant results occur in the debt-based baseline regressions (Table 6, Panel B). A one standard deviation increase in the net negative tone and litigious tone would increase *CASC(+1,+5)* by 0.69bps and 0.74bps, respectively. On the contrary, a one standard deviation increase in the uncertainty tone would decrease *CASC(+1,+5)* by 0.69bps.

Overall, the results in Table 6 coincide with the event study results reported in Tables 4 & 5 and, hence, strongly support our research hypotheses H_1, H_2, and H_3.

[Insert Table 6 here]

4.2.2. Interactions with Loss Amount Disclosure

In Table 7, we examine whether the equity-based and debt-based reputational effects of media tones are moderated by the disclosure of the exact amount or best estimate of the operational risk loss. As discussed in the following paragraphs, the results show that only the uncertainty tone is moderated by operational loss amount disclosure.

In Table 7 (Model i), the interaction term *Loss Amount Disclosure Dum * Uncertainty Tone* enters significantly negative in the event window (+1,+5). For example, a one standard deviation increase in the uncertainty tone would be associated with a 0.59% less favorable impact on *RCAR(+1,+5)* if the operational loss amount is disclosed. The debt-based results in Table 7 (Model ii) confirm the equity-based results. For example, a one standard deviation increase in the uncertainty tone would be associated with a marginal increase of 3.04bps in *CASC(+1,+5)* if the operational loss amount is disclosed.

However, the interaction terms *Loss Amount Disclosure Dum * Net Negative Tone* and *Loss Amount Disclosure Dum * Litigious Tone* enter with the expected signs but insignificant in the post-announcement windows. Overall, the results in Table 7 show that the loss amount disclosure dissolves the calming effect of the uncertainty tone in operational risk event announcements. Hence, our research hypothesis H_4 is supported only for the uncertainty tone.

[Insert Table 7 here]

4.2.3. Interactions with Firm Recognition

In Table 8, we examine whether the equity-based and debt-based reputational effects of media tones are moderated by the loss firm admitting the occurrence or extent of the operational risk event. As discussed in the following paragraphs, the results show that only the uncertainty tone is moderated by firm recognition.

In Table 8 (Model i), the interaction term *Firm Recognition Dum * Uncertainty Tone* enters significantly negative in all post-announcement windows with the strongest moderation impact incurred in the event window (+1,+5). For example, a one standard deviation increase in the uncertainty tone would be associated with a 0.49% less favorable impact on *RCAR(+1,+5)* if the event is recognized by the loss firm. The debt-based results in Table 8 (Model ii) confirm the equity-based results. For example, a one standard deviation increase in the uncertainty tone would be associated with a marginal increase of 1.61bps in *CASC(+1,+5)* if the loss firm recognizes the event.

However, the interaction terms *Firm Recognition Dum * Net Negative Tone* and *Firm Recognition Dum * Litigious Tone* enter with the expected signs but insignificant in the post-announcement windows. Overall, the results in Table 8 indicate that firm recognition reduces the ambiguity surrounding the operational risk event and hence reinforces the adverse financial sentiment of equity and debt investors who become more certain about the scope of the bad news that have unexpectedly hit the markets. Hence, our research hypothesis H_5 is supported only for the uncertainty tone.

[Insert Table 8 here]

4.2.4. Interactions with Regulatory Announcement

In Table 9, we examine whether the equity-based and debt-based reputational effects of media tones are moderated by simultaneous announcements made by regulatory bodies such as banking supervisors or stock exchange watchdogs. As discussed in the following paragraphs, the results show that the financial sentiment effects of the uncertainty and litigious tones in the media news are reversed and become much weaker once a regulatory announcement regarding the operational risk event has been made.

In Table 9 (Model i), the interaction term *Regulatory Announcement Dum * Uncertainty Tone* enters significantly negative in post-announcement windows with the strongest moderation impact incurred in the event window (+1,+5). For example, a one standard deviation increase in the uncertainty tone would be associated with a 0.94% less favorable impact on *RCAR(+1,+5)* if a regulatory body makes a relevant announcement. When it comes to the uncertainty tone, it is interesting to note that the dissolving effect of regulatory announcements is much stronger than that of firm recognition, thus pinpointing the higher credibility of third-party regulated information disclosed around operational risk event announcements.

Additionally, in Table 9 (Model i), the interaction term *Regulatory Announcement Dum * Litigious Tone* enters significantly positive in all post-announcement windows with the strongest moderation impact incurred in the event window (+1,+5). For example, a one standard deviation increase in the litigious tone would be associated with a 1.16 % more favorable impact on *RCAR(+1,+5)* if a regulatory body makes a relevant announcement.

The debt-based results in Table 9 (Model ii) confirm the equity-based results. For example, a one standard deviation increase in the uncertainty tone would be associated with a marginal increase of 1.62bps in *CASC(+1,+5)* if a simultaneous regulatory announcement is made. On the contrary, a one standard deviation increase in the litigious tone would be associated with a marginal decrease of 1.78bps in *CASC(+1,+5)* if there is a relevant announcement by a regulatory body.

However, the interaction term *Regulatory Announcement Dum * Net Negative Tone* enters with the expected sign but insignificant in the post-announcement windows. Overall, the results in Table 9 show that regulatory announcements reduce the level of uncertainty and substitute the litigation risk related information reflected in the media news on operational risk events. Hence, our research hypothesis H_6 is supported only for the uncertainty and litigious tones.

[Insert Table 9 here]

4.2.5. Interactions with Settlement

In Table 10, we examine whether the equity-based and debt-based reputational effects of media tones are moderated by final settlements which usually involve a court decision or regulatory fine to which the loss firm consents and hence no further action by any relevant party is expected. As discussed in the following paragraphs, the results show that final settlements would dissolve the ambiguity and litigation risk associated with operational risk events and hence tend to cancel out the reputational effects of the uncertainty and litigious tones.

In Table 10 (Model i), the interaction term *Settlement Dum * Uncertainty Tone* enters significantly negative in post-announcement windows with the strongest moderation impact incurred in the event window (+1,+5). For example, a one standard deviation increase in the uncertainty tone would be associated with a 1.14% less favorable impact on *RCAR(+1,+5)* if a final settlement is announced. Additionally, the interaction term *Settlement Dum * Litigious Tone* enters significantly positive in the post-announcement windows with the strongest moderation impact incurred in the event window (+1,+5). For example, a one standard deviation increase in the litigious tone would be associated with a 2.84% more favorable impact on *RCAR(+1,+5)* if a final settlement is announced.

The debt-based results in Table 10 (Model ii) confirm the equity-based results. For example, a one standard deviation increase in the uncertainty tone would be associated with a marginal increase of 2.86bps in *CASC(+1,+5)* if a settlement announcement is made. On the contrary, a one standard deviation increase in the litigious tone would be associated with a marginal decrease of 1.98bps in *CASC(+1,+5)* if a settlement is announced.

However, the interaction term *Settlement Dum * Net Negative Tone* enters with the expected sign but insignificant in the post-announcement windows. Overall, the results in Table 10 show that the financial sentiment effects of the uncertainty and litigious tones become much weaker and are even reversed if the operational risk event announcement involves a final settlement. These moderation effects are stronger than those of regulatory announcements not involving a final settlement (e.g. when the regulatory body announces a fine which the loss firm will appeal). Hence, our research hypothesis H_7 is supported only for the uncertainty and litigious tones.

[Insert Table 10 here]

4.3. Robustness Checks

In this subsection, we run a number of robustness checks to examine the generalizability of our main multivariate results in different cultural and economic contexts and their persistence under various model identification strategies.

4.3.1. Subsamples by Linguistic Communication

Since we collect full-texts of operational risk event announcements only in English, we want to examine whether our main baseline and interaction results are driven by the cultural impact of linguistic communication when the loss firms are listed in stock exchanges dominated in non-English speaking countries. Although the majority of our sample firms are multi-national institutions which are listed on big stock exchanges in terms of market capitalization, we still find that it is crucial to split our final sample into an Anglo-Saxon subsample (233 events) and a non-Anglo-Saxon subsample (72 events) to isolate the cultural effects due to language differences (See Table 2, Panel A for a list of the countries in each subsample). We define an Anglo-Saxon country as an English-speaking country. Since our strongest and most significant main results come in the event window (+1,+5), we report the results of our robustness checks only for *RCAR(+1,+5)* and *CASC(+1,+5)*[21].

The baseline and interaction results for the subsamples by linguistic communication are reported in Table 11. For baseline regressions, although all coefficients of media tones enter with the expected signs, they are much bigger (by a factor ranging from 3.5 to 6 times) and more significant in Anglo-Saxon countries. For example, a one standard deviation increase in the uncertainty tone would increase *RCAR(+1,+5)* by 1.09% in an Anglo-Saxon country but only by 0.30% in a non-Anglo-Saxon country. Moreover, a one standard deviation increase in the uncertainty tone would decrease *CASC(+1,+5)* by 1.61bps in an Anglo-Saxon country but only by 0.36bps in a non-Anglo-Saxon country. However, the net negative tone and litigious tone enter insignificant in non-Anglo-Saxon countries. This result indicates that our English-dominated media tones are better able to predict the equity-based and debt-based reputational effects of operational risk event announcements in Anglo-Saxon countries.

For the interaction coefficients reported in Table 11, the results are qualitatively similar to our main interaction results reported in Tables 7 – 10. Similar to the baseline regressions, the direct and interaction terms are much bigger and more significant in the Anglo-Saxon subsample. However, there are two main differences from our main interaction results. Both interaction terms *Loss Amount Disclosure Dum * Net Negative Tone* and *Firm Recognition Dum * Net Negative Tone* enter significantly positive in the reputational return regression and significantly negative in the CDS spread regression only for Anglo-Saxon countries. This result indicates that the operational risk severity captured by the loss amount substitutes the event's adversity reflected in the narrative media news and that firm recognition alleviates the reputational effects of adverse media news about the operational risk event. Though, both results do not extend to non-Anglo-Saxon countries possibly because our English-dominated net negative tone does not capture the full event's adversity reflected in the net negative tone dominated in the domestic language.

[Insert Table 11 here]

4.3.2. Subsamples by Financial Structure

Efficient market hypothesis (EMH) asserts that more efficient capital markets tend to react faster and incorporate newly released information into asset prices more accurately (Fama, 1970). However, EMH is more applicable in market-based economies where there is stronger competition and less information asymmetry in the capital markets than bank-based economies. Therefore, we want to examine whether our main baseline and interaction results are different across the two main types of financial structure. Hence, we follow Beck, Demirgüç-Kunt and Levine (2009) and measure the degree

[21] Our robustness checks results are qualitatively similar to our main results for the other event windows (-10,-1), (0,0) and (+6,+10).

of the economy's market orientation using the *Structure-Activity* indicator which equals stock market value traded to GDP divided by bank credit to GDP (higher values of Structure-Activity indicate a more market-based financial structure)[22]. More specifically, we consider an economy to be market-based if it has a Structure-Activity indicator of at least 1[23]. Applying these criteria, the market-based and bank-based subsamples comprise 230 events and 75 events, respectively (See Table 2, Panel A for a list of the countries in each subsample)[24].

The baseline and interaction results in the event window (+1,+5) for the subsamples by financial structure are reported in Table 12. For baseline regressions, although all coefficients of media tones enter with the expected signs, they are much bigger and more significant in market-based economies. However, the differences in the magnitude and significance across the financial structure subsamples are smaller than those across the linguistic communication subsamples. For example, a one standard deviation increase in the litigious tone would decrease *RCAR(+1,+5)* by 0.90% in a market-based economy but only by 0.39% in a bank-based economy. Moreover, a one standard deviation increase in the litigious tone would increase *CASC(+1,+5)* by 1.24bps in a market-based economy but only by 0.51bps (insignificant at the 10% level) in a bank-based economy. However, the net negative tone is always insignificant at the 10% level in bank-based economies. This result coincides with market-based economies having more efficient capital markets that are more promptly responsive to the information contents and sentiments in operational risk event announcements.

For the interaction coefficients reported in Table 12, the results are qualitatively similar to our main interaction results reported in Tables 7 – 10. Similar to the baseline regressions, the direct and interaction terms are much bigger and more significant in the market-based sample. However, there are two main differences from our main interaction results. Both interaction terms *Loss Amount Disclosure Dum * Uncertainty Tone* and *Firm Recognition Dum * Uncertainty Tone* are significant in the market-based sample only. This result indicates that less efficient capital markets in bank-based economies do not fully incorporate the additional information revealed by the operational loss amount and firm recognition as a substitute that dissolves the favorable reputational effects of the uncertainty tone in narrative media news.

[Insert Table 12 here]

[22] Our results remain qualitatively similar when we use other indicators of financial structure such as the *Structure-Size* indictor which equals stock market capitalization to GDP divided by bank credit to GDP (Beck, Demirgüç-Kunt and Levine, 2009).

[23] Our results remain qualitatively unchanged when we use different thresholds to determine our subsamples by financial structure such as the median *Structure-Activity* indictor.

[24] Although there is a considerable overlap between our Anglo-Saxon and market-based subsamples that amounts to 86.5% (i.e. for events incurred in US and UK firms), we still believe that running separate robustness checks for the effects of linguistic communication and financial structure is crucial to examining the consistency of our main results in different cultural and economic environments.

4.3.3. Additional Robustness Checks

We have performed several additional robustness checks to make sure that our main results hold under different assumptions[25]. First, we address the endogeneity concerns arising from the assumption that the *actual media tones* (i.e. the average net negative, litigious and uncertainty tones on Day 0) are a natural response to the operational risk event characteristics (i.e. the actual media tones are endogenous variables in our estimation models) by utilizing the *lagged media tones* (i.e. the average net negative, litigious and uncertainty tones in all media articles featuring the firm name in their headlines during the year ending one month before the announcement date).We believe that these lagged media tones are valid as instrumental variables in a two-stage least squares (2SLS) regression model given that they measure the *ex ante* overall attitude of the media towards the loss firm and hence correlate with the actual media tones on Day 0. In other words, these lagged media tones drive the reputational effects of operational risk event announcements exclusively through their impact on the actual media tones around these announcements. Running this 2SLS regression, the results for all our variables of interest remain qualitatively similar.

Additionally, we rerun all our regressions for different post-announcement windows ranging from (0,+1) to (+9,+10) where the media tones are once measured on Day 0 (i.e. as used in our main regressions) and once measured on a one-day-lagged basis (e.g. for the analysis in the (+1,+5) event window, we use the average media tones in the event window (0,+4), and so forth). For different combinations of media tones and event windows, we find that Day-0 media tones and one-day-lagged average media tones are highly correlated and almost equally able to predict the reputational effects of operational risk event announcements during the two post-announcement trading weeks.

Furthermore, we split our final sample into a North American (NA) subsample comprising USA and Canada (124 events) and a non-NA subsample comprising Europe and Australia (181 events) and rerun all our empirical analyses for each of the two subsamples, separately. We find that the reputational effects of media tones are stronger and more significant in the NA subsample (possibly because the NA subsample is 100% Anglo-Saxon, whereas the non-NA subsample is only 60% Anglo-Saxon).

Moreover, we distinguish between news articles published in the online versions of printed newspapers, such as *FT* and *WSJ*, and those published in digital format only via websites and newsfeeds, such as *Bloomberg* and *Reuters*. We found no consistent differences in the reputational effects of media tones across the two subsamples, indicating that the printed media version of the news does not make a difference in investor reactions to online media content around operational risk event announcements.

Finally, we rerun all our empirical analyses utilizing a logit model of the odds of reputational damage (i.e. having a negative *RCAR*) to capture the equity-based reputational effects and an OLS model of cumulative abnormal CDS relative spread changes (i.e. as computed in Sturm, 2013b) to capture the

[25] In the interests of brevity, our additional robustness checks are not reported but their full results are available upon request.

debt-based reputational effects. Again, the inferences drawn from our main results are confirmed by the alternative measures of reputational effects.

Overall, in all additional robustness checks, our main baseline and interaction results hold qualitatively similar, thus confirming our main conjecture that media tones have an incremental explanatory power for the reputational effects of operational risk event announcements in financial institutions.

5. CONCLUSIONS

We utilized the financial sentiment dictionary introduced by Loughran and McDonald (2011) to assess the reputational effects of the net negative tone, uncertainty tone, and litigious tone in a global sample of 305 operational risk event announcements in financial institutions extracted from the Operational Risk International Consortium (ORIC) database during the post-crisis period (2010 – 2014). In particular, we examine the main and marginal effects of these tones on the loss-adjusted abnormal stock returns (i.e. reputational returns) and abnormal CDS spread changes (i.e. also used as a direct measure of the loss firm's implied default risk) following operational risk event announcements.

Our empirical analysis revealed a number of original findings. First, we found strong evidence that the net negative tone and litigious tone have adverse reputational effects and that the uncertainty tone has a favorable reputational impact following operational risk event announcements. On one side, capital market participants (i.e. investors in equity and debt markets) penalize loss firms for the adverse content and litigation risk related information in operational risk event announcements. On the other side, investors give loss firms the benefit of the doubt (as proxied by the uncertainty tone in media news) following operational risk event announcements. Second, third-party information about the operational risk event (i.e. regulatory announcements and final settlements) dissolves the favorable reputational impact of the uncertainty tone and mitigates the adverse reputational impact of the litigious tone. Third, the reputational effects of media tones are much stronger in Anglo-Saxon countries (i.e. due to the cultural effects of linguistic communication) and market-based economies (i.e. due to more efficient capital markets). Fourth, loss amount disclosure and firm recognition substitute the reputational effects of the net negative tone and uncertainty tone only in Anglo-Saxon countries and market-based economies. Fifth, the reputational effects of online media content do not differ regardless of the availability of its printed version. Finally, the reputational effects of media tones following operational risk event announcements are most pronounced in the first post-announcement trading week and almost entirely fade away beyond the second post-announcement trading week.

Our results provide robust evidence on how narratives in unexpected adverse media news can drive the financial sentiment of equity and debt investors. Hence, our results could inform market participants about developing more effective trading strategies that incorporate content analysis of online media news. In addition, policymakers and regulators could consider establishing media task forces that analyze the contents and effects of adverse media news in the financial industry, and recommend further actions, including follow-up regulatory statements. Furthermore, financial institutions need to respond promptly to operational risk event announcements if they are to mitigate the reputational effects of media tone and help calm any investor concerns. This reinforces the need for careful media monitoring and objectivity when responding to loss event announcements. More specifically, our results suggest that, internal to financial institutions, risk managers should at least be much more involved and careful in the coordination of messages to the market when detailing the specifics of operational risk events within them.

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Table 1: Sample Selection Procedures

This table reports the selection criteria and procedure of our final sample comprising operational risk event announcements in publicly listed financial institutions incorporated in USA, Europe, Canada, and Australia during the post-global financial crisis (post-GFC) period (2010 – 2014).

Selection Procedure	**Observations**
Complete ORIC Database (March 2015)	16110
(-) Announcements before 1st January 2010	(804)
(-) Announcements after 31st December 2014	(99)
(-) Announcements in non-financial Firms	(2190)
(-) Announcements in loss firms not headquartered in USA, Europe, Canada, and Australia	(3653)
(-) Announcements which have no clear operational risk classification (event type or business line)	(5044)
(-) Announcements whose dates are not confirmed or full-text press articles not found	(3291)
(-) Announcements in privately held financial firms	(696)
(-) Announcements with outliers in reputational returns (i.e. less than -10% or more than 10%) or abnormal CDS relative spread changes (i.e. less than -50% or more than 50%) in the event window (-10,+10)	(28)
Final Sample	305

Table 2: Composition of the Final Sample

This table reports the composition of our final sample comprising operational risk event announcements in publicly listed financial institutions incorporated in USA, Europe, Canada, and Australia during the post-global financial crisis (post-GFC) period (2010 – 2014). An Anglo-Saxon country is an English-speaking country. A Market-based economy has a Structure-Activity indicator of at least 1. According to (Beck, Demirgüç-Kunt and Levine, 2009), Structure-Activity indicator equals stock market value traded to GDP divided by bank credit to GDP (higher values of Structure-Activity indicate a more market-based financial structure).

Panel A: By Country

Country	Number of Events	Percent (%)	Anglo-Saxon?	Structure-Activity Indicator	Market-based or Bank-based?
Australia	13	4.26	YES	0.9	Bank-based
Austria	3	0.98	NO	0.18	Bank-based
Belgium	2	0.66	NO	0.46	Bank-based
Canada	11	3.61	YES	0.62	Bank-based
France	4	1.31	NO	0.97	Bank-based
Germany	17	5.57	NO	0.7	Bank-based
Hungary	3	0.98	NO	0.44	Bank-based
Ireland	10	3.28	YES	0.17	Bank-based
Italy	4	1.31	NO	0.64	Bank-based
Netherlands	3	0.98	NO	0.85	Bank-based
Norway	1	0.33	NO	0.79	Bank-based
Russian Federation	2	0.66	NO	1.15	Market-based
Spain	4	1.31	NO	0.89	Bank-based
Sweden	2	0.66	NO	1.37	Market-based
Switzerland	21	6.89	NO	1.73	Market-based
Turkey	6	1.97	NO	1.52	Market-based
United Kingdom	86	28.20	YES	1.25	Market-based
United States	113	37.05	YES	1.45	Market-based
Total	305	100			

Table 2: Composition of the Final Sample

This table reports the composition of our final sample comprising operational risk event announcements in publicly listed financial institutions incorporated in USA, Europe, Canada, and Australia during the post-global financial crisis (post-GFC) period (2010 – 2014).

Panel B: By Industry Type

Industry Type	**Number of Events**	**Percent (%)**
Banks	47	15.41
Consumer Finance	6	1.97
Corporate Banking	3	0.98
Diversified Banks	150	49.18
Institutional Brokerage	20	6.56
Institutional Trust, Fiduciary and Custody	5	1.64
Insurance Brokers	6	1.97
Investment Income - Life Insurance	7	2.30
Investment Management	3	0.98
Life Insurance	9	2.95
Managed Care	2	0.66
Mortgage Finance	2	0.66
Other Financial Services	4	1.31
Property and Casualty Insurance	5	1.64
Retail Banking	18	5.90
Wealth Management	18	5.90
Total	305	100

Table 3: Descriptive Statistics

This table reports the descriptive statistics for the variables tested. Variables description is reported in Appendix B.

	Obs	Min	25%	Median	Mean	StDev	75%	Max
1) Equity-based Reputation Variables:								
RCAR(-10,-1)	305	-14.5018	-0.5955	0.4008	0.4369	2.0816	1.4607	8.8959
RCAR(0,0)	305	-8.2222	-0.6759	0.1979	0.3087	1.8944	1.3136	7.2937
RCAR(+1,+5)	305	-8.5050	-1.3486	-0.6481	-0.2858	2.3878	-0.0183	10.4541
RCAR(+6,+10)	305	-4.7691	-1.9024	-0.7019	-0.1018	1.5486	1.3175	5.3876
2) Debt-based Reputation Variables:								
CASC(-10,-1)	166	-3.0405	-0.1762	0.0160	0.2076	0.7724	0.2673	2.6794
CASC(0,0)	166	-9.4620	-1.0630	0.2800	0.5825	3.4361	3.4150	11.1710
CASC(+1,+5)	166	-137.9418	-38.3815	-5.6617	2.4040	52.3157	34.5607	183.4670
CASC(+6,+10)	166	-64.8695	-4.3423	-0.0070	1.5589	15.8348	8.4196	53.7892
3) Media Tone Variables:								
Net Negative Tone	305	0	45	54.8387	53.6645	14.0570	62.8571	90
Uncertainty Tone	305	0	3.0769	7.5472	8.4136	7.5169	10.7143	41.1765
Litigious Tone	305	0	19.6429	26.3158	26.0702	12.1593	33.3333	60
4) Other Information Variables:								
Loss Amount Disclosure Dum	305	0	0	1	0.682	0.4665	1	1
Firm Recognition Dum	305	0	0	0	0.3607	0.481	1	1
Regulatory Announcement Dum	305	0	0	1	0.577	0.4948	1	1
Settlement Dum	305	0	0	0	0.2197	0.4147	0	1
5) Control Variables:								
Different Country Dum	305	0	0	0	0.2557	0.437	1	1
Top Figures Dum	305	0	0	0	0.0754	0.2645	0	1
Fraud Dum	305	0	0	0	0.1246	0.3308	0	1
Basel Business Line Dum	305	0	1	1	0.7869	0.4102	1	1
FT & WSJ Dum	305	0	0	0	0.482	0.5005	1	1
Number of News Articles	305	1	1	6	14.8525	21.4437	19	98
Analyst Coverage	305	1	18	24	22.7934	8.0467	29	37
Credit Rating	166	3	6	7	6.8554	1.7898	7	12
StDev Ret	305	0.0084	0.0147	0.0205	0.0227	0.0104	0.0281	0.0766
Beta	305	0.4387	1.2780	1.7454	1.8054	0.6965	2.27	4.4556
Float%	305	0	61	92	77.7869	28.4356	100	100
Ln(Volume)	305	-0.6931	8.3336	9.3957	9.0127	2.0156	10.2034	12.7171
Ln(Total Assets)	305	6.4677	12.7863	14.1065	13.4791	1.5228	14.5596	14.8689
ROA	305	-3.2781	-0.0121	0.3733	0.3768	0.9935	0.8012	7.1995
Leverage	305	0	0.8425	1.3475	1.5928	0.9847	2.3037	5.4624
Market to Book Ratio	305	0.26	0.61	0.84	1.0169	0.6694	1.19	4.79
GDP Per Capita	305	10.646	42.295	49.781	48.976	13.519	52.828	100.575

Table 4: Event Study on the Equity-based Reputational Effects of Operational Risk Event Announcements

This panel reports the average reputational returns *(RCARs)* for different event windows and various subsamples around operational risk event announcements. *RCARs* are reported as a percentage (%). Full Sample is composed of 305 events (Top25% subsample is composed of 77 events and Bottom75% sample is composed of 228 events). Top25% and Bottom75% subsamples include the events in the upper quartile and lowest three quartiles of the relevant media tone's distribution, respectively. The Boehmer, Musumeci, and Poulsen (1991) parametric test is used to test the statistical significance of the mean *RCARs* of the full, Top25% and Bottom75% samples (+, ++ and +++ indicate significance of the Z-statistic at the 10%, 5% and 1% levels, respectively). The cross-sectional parametric t-test is used to test the statistical significance of the differences in mean *RCARs* of the Top25% and Bottom75% subsamples (*, ** and *** indicate significance of the t-statistic at the 10%, 5% and 1% levels, respectively). Variables description is reported in Appendix B.

	Mean RCARs (%)			
	(-10,-1)	**(0,0)**	**(+1,+5)**	**(+6,+10)**
Full Sample	0.4369++	0.3087+	-0.2858++	-0.1018
Net Negative Tone (Top25%)	0.2656+	-0.0913	-0.8627+++	-0.5425+++
Net Negative Tone (Bottom75%)	0.4948++	0.4438++	-0.0909	0.0471
Difference (Top25% - Bottom75%)	-0.2292	-0.5351	-0.7718*	-0.5896
Uncertainty Tone (Top25%)	0.5627+++	0.8043+++	1.0252+++	0.8321+++
Uncertainty Tone (Bottom75%)	0.3944++	0.1413	-0.7286+++	-0.4173++
Difference (Top25% - Bottom75%)	0.1683	0.6630*	1.7538***	1.2494***
Litigious Tone (Top25%)	0.5018+++	-0.0877	-0.9200+++	-0.6576+++
Litigious Tone (Bottom75%)	0.4150++	0.4426++	-0.0716	0.0859
Difference (Top25% - Bottom75%)	0.0868	-0.5303	-0.8484**	-0.7435*

Table 5: Event Study on the Debt-based Reputational Effects of Operational Risk Event Announcements

This panel reports the average cumulative abnormal CDS spread changes *(CASCs)* for different event windows and various subsamples around operational risk event announcements. *CASCs* are reported in basis points (bps). Full Sample is composed of 166 events (Top25% subsample is composed of 42 events and Bottom75% sample is composed of 124 events). Top25% and Bottom75% subsamples include the events in the upper quartile and lowest three quartiles of the relevant media tone's distribution, respectively. The cross-sectional parametric t-test is used to test the statistical significance of the mean *CASCs* of the full, Top25% and Bottom75% samples and to test the statistical significance of the differences in mean *CASCs* of the Top25% and Bottom75% subsamples. *, ** and *** indicate significance of the t-statistic at the 10%, 5% and 1% levels, respectively. Variables description is reported in Appendix B.

	Mean CASCs (bps)			
	(-10,-1)	**(0,0)**	**(+1,+5)**	**(+6,+10)**
Full Sample	0.2076	0.5825**	2.4040***	1.5589***
Net Negative Tone (Top25%)	0.4073	1.0721***	3.3053***	2.0786***
Net Negative Tone (Bottom75%)	0.1400	0.4167	2.0987***	1.3829***
Difference (Top25% - Bottom75%)	0.2673	0.6554	1.2066*	0.6957
Uncertainty Tone (Top25%)	0.1267	-0.3582	0.7496**	0.3173
Uncertainty Tone (Bottom75%)	0.2350	0.9011**	2.9643***	1.9794***
Difference (Top25% - Bottom75%)	-0.1083	-1.2593*	-2.2147***	-1.6621**
Litigious Tone (Top25%)	0.4296	1.1684***	3.6200***	2.4162***
Litigious Tone (Bottom75%)	0.1324	0.3841	1.9922***	1.2685***
Difference (Top25% - Bottom75%)	0.2972	0.7843	1.6278**	1.1477*

Table 6: Baseline Regressions, Panel A: Reputational Returns

This table reports the results of the OLS regression model estimating the equity-based reputational returns *(RCARs)* around operational risk event announcements for different event windows. Variables description is reported in Appendix B. t-statistics based on heteroscedasticity-robust standard errors are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	RCAR(-10,-1)			*RCAR(0,0)*			*RCAR(+1,+5)*			*RCAR(+6,+10)*		
Net Negative Tone	-0.0083			-0.0194			-0.0385			-0.0227		
	(0.48)			(1.77)*			(3.05)***			(1.89)*		
Uncertainty Tone		0.0048			0.0283			0.0624			0.0427	
		(0.35)			(2.01)**			(4.40)***			(2.86)***	
Litigious Tone			0.0038			-0.0230			-0.0423			-0.0333
			(0.19)			(2.26)**			(3.23)***			(2.65)***
Loss Amount Disclosure Dum	-0.3401	-0.2791	-0.2918	0.2729	0.2909	0.2992	0.1529	0.1402	0.1414	0.3579	0.3030	0.3071
	(1.04)	(0.87)	(0.90)	(0.98)	(1.04)	(1.08)	(0.45)	(0.42)	(0.42)	(0.94)	(0.79)	(0.80)
Firm Recognition Dum	-0.1553	-0.2714	-0.2169	-0.0273	-0.0515	-0.1213	-0.0939	-0.1149	-0.1245	-0.1239	-0.0768	-0.1124
	(0.23)	(0.39)	(0.31)	(0.08)	(0.16)	(0.37)	(0.24)	(0.29)	(0.31)	(0.30)	(0.18)	(0.26)
Regulatory Announcement Dum	0.1595	-0.0171	-0.0876	-0.3759	-0.4354	-0.5048	-0.1922	-0.1176	-0.1464	-0.5093	-0.3035	-0.2848
	(0.33)	(0.04)	(0.20)	(1.41)	(1.67)*	(1.94)*	(0.56)	(0.37)	(0.46)	(1.35)	(0.86)	(0.80)
Settlement Dum	1.0593	1.0964	1.1374	0.3283	0.3408	0.3802	0.5623	0.5461	0.5609	0.2457	0.2022	0.1959
	(1.37)	(1.41)	(1.43)	(0.93)	(0.96)	(1.07)	(1.16)	(1.14)	(1.17)	(0.50)	(0.42)	(0.40)
Different Country Dum	-0.8800	-0.9550	-0.9579	-0.2259	-0.2482	-0.2584	-0.2550	-0.2369	-0.2391	-0.0374	0.0326	0.0295
	(2.20)**	(2.41)**	(2.42)**	(0.74)	(0.82)	(0.85)	(0.64)	(0.60)	(0.60)	(0.08)	(0.07)	(0.07)
Top Figures Dum	-1.5201	-1.4779	-1.4493	-0.0745	-0.0592	-0.0189	-0.6688	-0.6910	-0.6749	-0.3106	-0.3657	-0.3749
	(1.47)	(1.44)	(1.40)	(0.17)	(0.13)	(0.04)	(1.29)	(1.34)	(1.31)	(0.54)	(0.65)	(0.65)
Fraud Dum	-0.8174	-0.8398	-0.9659	0.1032	0.0833	0.0572	0.0648	0.1327	0.1082	0.0942	0.1933	0.2385
	(1.11)	(1.09)	(1.28)	(0.29)	(0.23)	(0.16)	(0.13)	(0.26)	(0.21)	(0.17)	(0.35)	(0.44)
Basel Business Line Dum	-0.1270	-0.0838	-0.1093	0.0955	0.1033	0.1390	-0.1698	-0.1561	-0.1507	0.1899	0.1797	0.1963
	(0.23)	(0.15)	(0.20)	(0.31)	(0.33)	(0.46)	(0.48)	(0.44)	(0.42)	(0.48)	(0.45)	(0.49)
FT & WSJ Dum	-0.0936	-0.0484	0.0339	0.3531	0.3777	0.3773	0.8895	0.8266	0.8388	1.1732	1.0654	1.0309
	(0.18)	(0.10)	(0.07)	(1.38)	(1.51)	(1.49)	(2.75)***	(2.57)**	(2.58)**	(3.21)***	(2.93)***	(2.82)***
Number of News Articles	-0.0323	-0.0343	-0.0344	-0.0084	-0.0089	-0.0099	-0.0125	-0.0123	-0.0126	-0.0092	-0.0077	-0.0079
	(1.90)*	(1.93)*	(1.93)*	(1.44)	(1.51)	(1.63)	(1.70)*	(1.66)*	(1.67)*	(1.10)	(0.91)	(0.92)
Analyst Coverage	0.0324	0.0364	0.0311	0.0158	0.0165	0.0154	-0.0062	-0.0046	-0.0057	0.0003	-0.0002	0.0019
	(0.79)	(0.88)	(0.75)	(0.65)	(0.68)	(0.63)	(0.19)	(0.14)	(0.17)	(0.01)	(0.01)	(0.05)
StDev Ret	0.2883	0.2749	0.2772	0.3365	0.3319	0.3366	0.2164	0.2222	0.2234	0.1426	0.1584	0.1591
	(1.08)	(1.01)	(1.02)	(1.76)*	(1.74)*	(1.77)*	(1.14)	(1.17)	(1.18)	(0.72)	(0.79)	(0.79)
Beta	0.9794	1.0583	1.0760	-0.1557	-0.1328	-0.0955	0.2589	0.2422	0.2531	0.0639	-0.0067	-0.0040
	(2.06)**	(2.15)**	(2.19)**	(0.62)	(0.54)	(0.38)	(0.76)	(0.71)	(0.75)	(0.18)	(0.02)	(0.01)
Float%	-0.0088	-0.0079	-0.0074	-0.0117	-0.0114	-0.0109	-0.0096	-0.0101	-0.0098	-0.0072	-0.0083	-0.0084
	(1.18)	(1.05)	(0.99)	(2.04)**	(2.00)**	(1.93)*	(1.34)	(1.41)	(1.40)	(0.86)	(0.99)	(1.01)
Ln(Volume)	-0.0174	-0.0454	-0.0441	-0.0371	-0.0448	-0.0570	-0.1912	-0.1874	-0.1903	-0.1821	-0.1596	-0.1623
	(0.17)	(0.46)	(0.45)	(0.59)	(0.71)	(0.87)	(2.18)**	(2.11)**	(2.12)**	(2.05)**	(1.74)*	(1.77)*
Ln(Total Assets)	0.0838	0.0978	0.0913	0.1799	0.1836	0.1801	0.4001	0.3991	0.3970	0.3956	0.3855	0.3882
	(0.53)	(0.62)	(0.58)	(1.11)	(1.12)	(1.11)	(1.93)*	(1.92)*	(1.91)*	(1.87)*	(1.80)*	(1.82)*
ROA	0.1380	0.1306	0.1139	0.3919	0.3867	0.3941	0.4641	0.4799	0.4790	0.6843	0.7088	0.7177
	(0.55)	(0.51)	(0.45)	(1.66)*	(1.63)	(1.66)*	(1.47)	(1.52)	(1.53)	(2.26)**	(2.35)**	(2.39)**
Leverage	-0.3745	-0.4053	-0.3967	-0.0815	-0.0889	-0.1005	-0.1757	-0.1769	-0.1782	-0.1388	-0.1209	-0.1277
	(1.25)	(1.31)	(1.30)	(0.52)	(0.57)	(0.64)	(0.94)	(0.94)	(0.94)	(0.69)	(0.59)	(0.62)
Market to Book Ratio	-0.0268	0.0198	0.0555	-0.3767	-0.3578	-0.3546	-0.1133	-0.1479	-0.1417	-0.1025	-0.1754	-0.1898
	(0.08)	(0.05)	(0.15)	(1.60)	(1.49)	(1.49)	(0.35)	(0.46)	(0.44)	(0.33)	(0.54)	(0.58)
GDP Per Capita	0.0033	0.0041	0.0042	0.0017	0.0024	0.0031	0.0086	0.0082	0.0084	0.0089	0.0083	0.0087
	(0.19)	(0.27)	(0.30)	(0.16)	(0.20)	(0.34)	(0.63)	(0.63)	(0.64)	(0.59)	(0.53)	(0.53)
CAR(-10,-1)				0.0488	0.0499	0.0509	0.0021	-0.0024	-0.0010	0.0452	0.0392	0.0361
				(0.91)	(0.93)	(0.96)	(0.04)	(0.04)	(0.02)	(0.69)	(0.57)	(0.54)
Constant	-0.1680	-1.8276	-1.2594	-1.1689	-1.6474	-1.2102	-4.0654	-3.7434	-3.5418	-5.6488	-4.1925	-4.3667
	(0.06)	(0.63)	(0.41)	(0.55)	(0.75)	(0.54)	(1.58)	(1.40)	(1.32)	(2.18)**	(1.61)	(1.66)*
R^2	0.17	0.17	0.16	0.12	0.12	0.12	0.10	0.10	0.10	0.13	0.12	0.12
N	305	305	305	305	305	305	305	305	305	305	305	305

Table 6: Baseline Regressions, Panel B: Abnormal CDS Spread Changes

This table reports the results of the OLS regression model estimating the cumulative abnormal CDS spread changes *(CASCs)* around operational risk event announcements for different event windows. Variables description is reported in Appendix B. t-statistics based on heteroscedasticity-robust standard errors are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	CASC(-10,-1)			*CASC(0,0)*			*CASC(+1,+5)*			*CASC(+6,+10)*		
Net Negative Tone	0.0115			0.0248			0.0492			0.0283		
	(0.73)			(1.29)			(2.45)**			(1.61)		
Uncertainty Tone		-0.0077			-0.0597			-0.0921			-0.0710	
		(0.60)			(2.98)***			(4.27)***			(3.72)***	
Litigious Tone			0.0138			0.0378			0.0613			0.0469
			(0.53)			(1.69)*			(2.85)***			(2.29)**
Loss Amount Disclosure Dum	-0.5416	-0.6571	-0.6519	-0.3589	-0.4135	-0.4201	-0.0125	0.0198	0.0208	-0.4342	-0.4199	-0.4173
	(0.29)	(0.36)	(0.35)	(0.57)	(0.67)	(0.68)	(0.01)	(0.02)	(0.02)	(0.39)	(0.37)	(0.37)
Firm Recognition Dum	-0.8391	-1.0084	-1.0097	-1.1381	-0.9686	-0.8290	-3.2134	-3.2533	-3.3011	-2.4382	-2.4982	-2.5520
	(0.36)	(0.43)	(0.42)	(1.12)	(0.98)	(0.80)	(2.58)**	(2.64)***	(2.58)**	(1.38)	(1.42)	(1.39)
Regulatory Announcement Dum	1.0824	1.7247	1.2949	-0.8387	-0.6675	-0.3702	0.1096	-0.0218	-0.0755	0.2537	0.2166	0.0996
	(0.56)	(0.86)	(0.68)	(1.20)	(0.96)	(0.52)	(0.12)	(0.02)	(0.09)	(0.21)	(0.18)	(0.08)
Settlement Dum	1.2519	0.7384	1.1673	0.8083	0.6238	0.2977	1.6962	1.8159	1.8818	0.9586	1.0042	1.1322
	(0.46)	(0.29)	(0.43)	(0.68)	(0.54)	(0.26)	(1.13)	(1.24)	(1.24)	(0.48)	(0.52)	(0.57)
Different Country Dum	-0.7672	-0.4458	-0.6722	-0.6514	-0.7470	-0.6990	-0.9056	-0.9068	-0.8998	-0.2132	-0.1733	-0.1930
	(0.42)	(0.24)	(0.36)	(0.87)	(1.01)	(0.95)	(0.85)	(0.83)	(0.85)	(0.15)	(0.13)	(0.14)
Top Figures Dum	1.7812	1.5942	1.8156	-1.3267	-1.2439	-1.3260	0.8837	0.8736	0.8798	0.8815	0.8497	0.8825
	(0.53)	(0.48)	(0.55)	(1.20)	(1.15)	(1.21)	(0.72)	(0.70)	(0.70)	(0.58)	(0.55)	(0.57)
Fraud Dum	-2.4684	-1.6903	-2.0280	1.1684	1.1934	1.2689	0.9538	0.8619	0.8698	1.1538	1.1670	1.1363
	(0.90)	(0.67)	(0.78)	(1.38)	(1.45)	(1.50)	(0.86)	(0.81)	(0.80)	(0.83)	(0.86)	(0.82)
Basel Business Line Dum	1.1102	1.1885	1.1716	0.8175	0.7431	0.7005	-0.7887	-0.7723	-0.7550	-0.0979	-0.0713	-0.0550
	(0.46)	(0.50)	(0.51)	(1.30)	(1.17)	(1.13)	(0.86)	(0.84)	(0.81)	(0.07)	(0.05)	(0.04)
FT & WSJ Dum	-2.0471	-2.2863	-2.2702	1.1888	1.1183	1.1186	-0.1799	-0.1270	-0.1311	-0.4094	-0.3938	-0.3938
	(1.16)	(1.24)	(1.22)	(1.82)*	(1.71)*	(1.73)*	(0.20)	(0.14)	(0.15)	(0.35)	(0.34)	(0.34)
Number of News Articles	-0.0222	-0.0238	-0.0241	0.0051	0.0080	0.0102	0.0314	0.0306	0.0298	-0.0289	-0.0299	-0.0308
	(0.50)	(0.54)	(0.52)	(0.41)	(0.65)	(0.81)	(2.03)**	(1.99)**	(1.89)*	(1.13)	(1.14)	(1.13)
Analyst Coverage	-0.3312	-0.3290	-0.3276	0.1239	0.1306	0.1306	0.0888	0.0866	0.0861	-0.0504	-0.0526	-0.0525
	(1.54)	(1.52)	(1.50)	(1.46)	(1.56)	(1.57)	(0.72)	(0.69)	(0.69)	(0.34)	(0.36)	(0.36)
Credit Rating	3.0761	2.8959	2.9376	-0.1356	-0.0925	-0.0356	0.2184	0.2203	0.1998	0.2264	0.2081	0.1862
	(2.64)***	(2.49)**	(2.62)***	(0.28)	(0.19)	(0.07)	(0.31)	(0.32)	(0.28)	(0.25)	(0.23)	(0.20)
StDev Ret	0.6912	0.8582	0.7581	-0.5200	-0.5111	-0.4616	0.6686	0.6464	0.6411	-0.1718	-0.1698	-0.1895
	(0.48)	(0.59)	(0.53)	(1.48)	(1.47)	(1.35)	(1.14)	(1.10)	(1.08)	(0.24)	(0.23)	(0.26)
Beta	-4.4566	-4.2909	-4.2661	0.6022	0.5580	0.4386	1.5374	1.5388	1.5720	0.8819	0.8998	0.9463
	(2.52)**	(2.42)**	(2.34)**	(0.80)	(0.76)	(0.58)	(1.75)*	(1.76)*	(1.73)*	(0.75)	(0.76)	(0.76)
Ln(Total Assets)	-6.4550	-6.2739	-6.4997	0.0799	0.0764	0.1813	1.7148	1.7021	1.6840	0.1449	0.1496	0.1082
	(3.32)***	(3.18)***	(3.44)***	(0.13)	(0.12)	(0.30)	(2.19)**	(2.17)**	(2.13)**	(0.13)	(0.14)	(0.10)
ROA	-0.6174	-0.6404	-0.7711	0.3778	0.4280	0.5725	2.2509	2.2365	2.2008	1.5487	1.5317	1.4753
	(0.22)	(0.23)	(0.28)	(0.50)	(0.58)	(0.74)	(1.99)**	(1.98)**	(1.88)*	(1.05)	(1.03)	(0.94)
Leverage	-2.6980	-2.6034	-2.6961	-0.1847	-0.1919	-0.1581	-0.0192	-0.0246	-0.0289	-1.2128	-1.2084	-1.2218
	(1.64)	(1.59)	(1.64)	(0.52)	(0.53)	(0.44)	(0.04)	(0.05)	(0.06)	(1.66)*	(1.64)	(1.67)*
Market to Book Ratio	-4.5824	-4.6987	-4.7367	1.5420	1.5838	1.6456	1.6296	1.6320	1.6105	-0.0274	-0.0453	-0.0692
	(1.70)*	(1.77)*	(1.76)*	(1.65)	(1.69)*	(1.79)*	(1.35)	(1.36)	(1.32)	(0.02)	(0.03)	(0.04)
GDP Per Capita	0.0769	0.0842	0.0871	0.0320	0.0298	0.0237	0.0731	0.0734	0.0751	0.0808	0.0810	0.0842
	(0.63)	(0.70)	(0.69)	(1.39)	(1.26)	(0.94)	(1.93)*	(1.95)*	(1.97)*	(1.42)	(1.44)	(1.45)
CASC(-10,-1)				0.0345	0.0403	0.0376	0.0083	0.0072	0.0071	-0.0750	-0.0771	-0.0760
				(0.95)	(1.14)	(1.09)	(0.19)	(0.16)	(0.16)	(1.33)	(1.37)	(1.35)
Constant	91.5018	89.9698	95.8239	-7.8997	-6.3179	-9.5231	-35.5646	-36.0342	-35.4738	-3.3373	-3.8717	-2.6093
	(2.70)***	(2.66)***	(3.03)***	(0.64)	(0.51)	(0.81)	(2.20)**	(2.26)**	(2.16)**	(0.16)	(0.19)	(0.13)
R^2	0.61	0.61	0.61	0.34	0.35	0.34	0.25	0.25	0.25	0.14	0.14	0.14
N	166	166	166	166	166	166	166	166	166	166	166	166

Table 7: Interactions with Loss Amount Disclosure

This table reports the results of the interactions with loss amount disclosure *(Loss Amount Disclosure Dum)* for: i) the OLS regression model estimating the equity-based reputational returns *(RCARs)* and ii) the OLS regression model estimating the cumulative abnormal CDS spread changes *(CASCs)* around operational risk event announcements for different event windows. In the interests of brevity, the constant term and all other variables are not reported. Variables description is reported in Appendix B. t-statistics based on heteroscedasticity-robust standard errors are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

i) Reputational Returns:	***RCAR(-10,-1)***			***RCAR(0,0)***			***RCAR(+1,+5)***			***RCAR(+6,+10)***		
Net Negative Tone	-0.0129			-0.0295			-0.0415			-0.0345		
	(0.42)			(1.05)			(1.46)			(1.14)		
*Loss Amount Disclosure Dum * Net Negative Tone*	0.0058			0.0126			0.0038			0.0148		
	(0.16)			(0.41)			(0.17)			(0.43)		
Uncertainty Tone		0.0054			0.0496			0.1144			0.0702	
		(0.17)			(1.38)			(3.17)***			(1.90)*	
*Loss Amount Disclosure Dum * Uncertainty Tone*		-0.0009			-0.0324			-0.0789			-0.0418	
		(0.04)			(0.76)			(1.79)*			(0.91)	
Litigious Tone			0.0076			-0.0306			-0.0688			-0.0420
			(0.23)			(1.26)			(2.78)***			(1.71)*
*Loss Amount Disclosure Dum * Litigious Tone*			-0.0053			0.0105			0.0367			0.0120
			(0.15)			(0.42)			(1.34)			(0.45)
Loss Amount Disclosure Dum	-0.6636	-0.2719	-0.1525	-0.4291	0.5495	0.0204	-0.0606	0.7699	-0.8326	-0.4641	0.6366	-0.0119
	(0.33)	(0.18)	(0.21)	(0.27)	(1.29)	(0.08)	(0.05)	(1.85)*	(0.98)	(0.36)	(1.38)	(0.03)
R^2	0.17	0.18	0.18	0.13	0.13	0.14	0.11	0.11	0.12	0.13	0.12	0.12
N	305	305	305	305	305	305	305	305	305	305	305	305
ii) Abnormal CDS Spread Changes:	***CASC(-10,-1)***			***CASC(0,0)***			***CASC(+1,+5)***			***CASC(+6,+10)***		
Net Negative Tone	0.0119			0.0325			0.0761			0.0421		
	(0.20)			(0.65)			(1.47)			(0.76)		
*Loss Amount Disclosure Dum * Net Negative Tone*	-0.0005			-0.0101			-0.0352			-0.0179		
	(0.03)			(0.15)			(0.44)			(0.19)		
Uncertainty Tone		-0.0088			-0.1625			-0.3822			-0.2517	
		(0.13)			(2.19)**			(5.04)***			(3.31)***	
*Loss Amount Disclosure Dum * Uncertainty Tone*		0.0015			0.1436			0.4052			0.2525	
		(0.02)			(0.81)			(2.27)**			(1.36)	
Litigious Tone			0.0158			0.0487			0.0946			0.0669
			(0.31)			(1.09)			(2.08)**			(1.40)
*Loss Amount Disclosure Dum * Litigious Tone*			-0.0031			-0.0164			-0.0502			-0.0302
			(0.05)			(0.13)			(0.39)			(0.17)
Loss Amount Disclosure Dum	-0.5130	-0.6697	-0.5753	0.1880	-1.5877	-0.0093	1.8956	-3.2928	1.2742	0.5394	-2.4841	0.3375
	(0.04)	(0.71)	(0.28)	(0.07)	(1.78)*	(0.01)	(0.51)	(3.25)***	(0.33)	(0.18)	(2.74)***	(0.10)
R^2	0.61	0.61	0.61	0.34	0.35	0.34	0.26	0.25	0.26	0.14	0.15	0.14
N	166	166	166	166	166	166	166	166	166	166	166	166

Table 8: Interactions with Firm Recognition

This table reports the results of the interactions with firm recognition *(Firm Recognition Dum)* for: i) the OLS regression model estimating the equity-based reputational returns *(RCARs)* and ii) the OLS regression model estimating the cumulative abnormal CDS spread changes *(CASCs)* around operational risk event announcements for different event windows. In the interests of brevity, the constant term and all other variables are not reported. Variables description is reported in Appendix B. t-statistics based on heteroscedasticity-robust standard errors are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

i) Reputational Returns:	***RCAR(-10,-1)***			***RCAR(0,0)***			***RCAR(+1,+5)***			***RCAR(+6,+10)***		
Net Negative Tone	-0.0101			-0.0274			-0.0558			-0.0363		
	(0.51)			(1.38)			(2.71)***			(1.76)*		
*Firm Recognition Dum * Net Negative Tone*	0.0036			0.0166			0.0359			0.0283		
	(0.12)			(0.61)			(1.42)			(1.07)		
Uncertainty Tone		0.0055			0.0414			0.0957			0.0685	
		(0.26)			(1.96)**			(4.45)***			(3.18)***	
*Firm Recognition Dum * Uncertainty Tone*		-0.0014			-0.0254			-0.0647			-0.0501	
		(0.07)			(0.92)			(2.40)**			(1.88)*	
Litigious Tone			0.0047			-0.0327			-0.0532			-0.0499
			(0.29)			(2.23)**			(3.62)***			(2.96)***
*Firm Recognition Dum * Litigious Tone*			-0.0021			0.0227			0.0255			0.0385
			(0.09)			(0.86)			(0.95)			(1.37)
Firm Recognition Dum	-0.3449	-0.2590	-0.1651	-0.8952	0.1742	-0.6856	-1.9684	0.4601	-0.7583	-1.5988	0.3682	-1.0717
	(0.27)	(0.31)	(0.15)	(0.62)	(0.39)	(0.58)	(1.41)	(1.16)	(0.62)	(1.23)	(0.92)	(0.87)
R^2	0.17	0.17	0.16	0.13	0.12	0.12	0.12	0.10	0.10	0.14	0.12	0.12
N	305	305	305	305	305	305	305	305	305	305	305	305
ii) Abnormal CDS Spread Changes:	***CASC(-10,-1)***			***CASC(0,0)***			***CASC(+1,+5)***			***CASC(+6,+10)***		
Net Negative Tone	0.0121			0.0343			0.0827			0.0524		
	(0.14)			(0.33)			(0.79)			(0.45)		
*Firm Recognition Dum * Net Negative Tone*	-0.0013			-0.0223			-0.0784			-0.0563		
	(0.03)			(0.38)			(1.41)			(1.05)		
Uncertainty Tone		-0.0086			-0.0999			-0.1825			-0.1344	
		(0.23)			(2.46)**			(4.04)***			(2.93)***	
*Firm Recognition Dum * Uncertainty Tone*		0.0021			0.0955			0.2146			0.1507	
		(0.05)			(1.76)*			(3.82)***			(2.65)***	
Litigious Tone			0.0135			0.0418			0.0872			0.0642
			(0.44)			(1.32)			(2.78)***			(1.97)**
*Firm Recognition Dum * Litigious Tone*			0.0010			-0.0126			-0.0814			-0.0544
			(0.01)			(0.15)			(1.08)			(0.70)
Firm Recognition Dum	-0.7708	-1.0277	-1.0309	0.0462	-1.8394	-0.5460	0.9428	-5.2097	-1.4769	0.5476	-3.8727	-1.3313
	(0.06)	(1.01)	(0.36)	(0.03)	(1.88)*	(0.19)	(0.12)	(4.77)***	(0.45)	(0.08)	(3.42)***	(0.45)
R^2	0.61	0.61	0.61	0.34	0.35	0.35	0.26	0.25	0.25	0.14	0.15	0.14
N	166	166	166	166	166	166	166	166	166	166	166	166

Table 9: Interactions with Regulatory Announcement

This table reports the results of the interactions with regulatory announcement *(Regulatory Announcement Dum)* for: i) the OLS regression model estimating the equity-based reputational returns *(RCARs)* and ii) the OLS regression model estimating the cumulative abnormal CDS spread changes *(CASCs)* around operational risk event announcements for different event windows. In the interests of brevity, the constant term and all other variables are not reported. Variables description is reported in Appendix B. t-statistics based on heteroscedasticity-robust standard errors are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

i) Reputational Returns:	***RCAR(-10,-1)***			***RCAR(0,0)***			***RCAR(+1,+5)***			***RCAR(+6,+10)***		
Net Negative Tone	-0.0083			-0.0216			-0.0466			-0.0291		
	(0.77)			(1.98)**			(3.82)***			(2.51)**		
*Regulatory Announcement Dum * Net Negative Tone*	-0.0001			0.0059			0.0215			0.0171		
	(0.02)			(0.31)			(1.32)			(1.02)		
Uncertainty Tone		0.0055			0.0478			0.1147			0.0798	
		(0.21)			(1.60)			(3.13)***			(2.22)**	
*Regulatory Announcement Dum * Uncertainty Tone*		-0.0017			-0.0466			-0.1249			-0.0886	
		(0.03)			(1.00)			(2.38)**			(1.70)*	
Litigious Tone			0.0034			-0.0390			-0.0818			-0.0614
			(0.19)			(2.39)**			(4.11)***			(3.34)***
*Regulatory Announcement Dum * Litigious Tone*			0.0009			0.0391			0.0963			0.0685
			(0.07)			(1.94)*			(3.47)***			(2.73)***
Regulatory Announcement Dum	0.1662	-0.0032	-0.1108	-0.6918	-0.0529	-1.5379	-1.3414	0.9067	-2.6921	-1.4219	0.4235	-2.0951
	(0.12)	(0.03)	(0.17)	(0.76)	(0.15)	(2.62)***	(1.48)	(1.68)*	(3.57)***	(1.58)	(0.79)	(3.06)***
R^2	0.17	0.18	0.16	0.14	0.12	0.12	0.11	0.11	0.10	0.13	0.13	0.12
N	305	305	305	305	305	305	305	305	305	305	305	305
ii) Abnormal CDS Spread Changes:	***CASC(-10,-1)***			***CASC(0,0)***			***CASC(+1,+5)***			***CASC(+6,+10)***		
Net Negative Tone	0.0109			0.0284			0.0679			0.0414		
	(0.14)			(0.25)			(0.74)			(0.35)		
*Regulatory Announcement Dum * Net Negative Tone*	0.0015			-0.0086			-0.0446			-0.0310		
	(0.03)			(0.05)			(0.38)			(0.20)		
Uncertainty Tone		-0.0091			-0.0848			-0.1811			-0.1342	
		(0.22)			(1.82)*			(3.50)***			(2.44)**	
*Regulatory Announcement Dum * Uncertainty Tone*		0.0033			0.0610			0.2165			0.1541	
		(0.05)			(0.88)			(2.86)***			(2.05)**	
Litigious Tone			0.0152			0.0602			0.1242			0.0917
			(0.61)			(1.95)*			(3.20)***			(2.54)**
*Regulatory Announcement Dum * Litigious Tone*			-0.0035			-0.0529			-0.1485			-0.1060
			(0.04)			(0.65)			(1.80)*			(1.29)
Regulatory Announcement Dum	1.0042	1.6993	1.3838	-0.3758	-1.1306	0.9741	2.4987	-1.6648	3.6972	1.9159	-0.9527	2.7939
	(0.11)	(0.95)	(0.26)	(0.28)	(0.40)	(0.19)	(0.53)	(0.67)	(0.85)	(0.29)	(0.35)	(0.54)
R^2	0.61	0.62	0.61	0.34	0.35	0.34	0.26	0.25	0.26	0.14	0.14	0.14
N	166	166	166	166	166	166	166	166	166	166	166	166

Table 10: Interactions with Settlement

This table reports the results of the interactions with settlement *(Settlement Dum)* for: i) the OLS regression model estimating the equity-based reputational returns *(RCARs)* and ii) the OLS regression model estimating the cumulative abnormal CDS spread changes *(CASCs)* around operational risk event announcements for different event windows. In the interests of brevity, the constant term and all other variables are not reported. Variables description is reported in Appendix B. t-statistics based on heteroscedasticity-robust standard errors are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

i) Reputational Returns:	***RCAR(-10,-1)***			***RCAR(0,0)***			***RCAR(+1,+5)***			***RCAR(+6,+10)***		
Net Negative Tone	-0.0090			-0.0243			-0.0476			-0.0328		
	(0.45)			(1.32)			(2.53)**			(1.70)*		
*Settlement Dum * Net Negative Tone*	0.0027			0.0186			0.0346			0.0383		
	(0.11)			(0.59)			(1.21)			(1.32)		
Uncertainty Tone		0.0046			0.0440			0.1147			0.0726	
		(0.16)			(1.39)			(3.27)***			(2.08)**	
*Settlement Dum * Uncertainty Tone*		0.0004			-0.0455			-0.1515			-0.0866	
		(0.01)			(1.54)			(4.39)***			(2.81)***	
Litigious Tone			0.0044			-0.0364			-0.0882			-0.0628
			(0.24)			(2.20)**			(4.55)***			(3.31)***
*Settlement Dum * Litigious Tone*			-0.0029			0.0689			0.2363			0.1511
			(0.08)			(1.98)**			(5.67)***			(3.46)***
Settlement Dum	0.9168	1.0920	1.1990	-0.6369	0.8144	-1.1032	-1.2308	2.1233	-4.5249	-1.7355	1.1035	-3.0567
	(0.74)	(1.23)	(0.95)	(0.46)	(0.92)	(0.84)	(0.89)	(2.33)**	(2.66)***	(1.26)	(1.20)	(1.84)*
R^2	0.18	0.17	0.17	0.12	0.12	0.12	0.11	0.10	0.10	0.13	0.12	0.12
N	305	305	305	305	305	305	305	305	305	305	305	305
ii) Abnormal CDS Spread Changes:	***CASC(-10,-1)***			***CASC(0,0)***			***CASC(+1,+5)***			***CASC(+6,+10)***		
Net Negative Tone	0.0139			0.0351			0.0735			0.0507		
	(0.18)			(0.38)			(0.80)			(0.49)		
*Settlement Dum * Net Negative Tone*	-0.0103			-0.0431			-0.1017			-0.0932		
	(0.13)			(0.50)			(1.19)			(1.04)		
Uncertainty Tone		-0.0091			-0.1072			-0.2067			-0.1469	
		(0.14)			(1.79)*			(3.18)***			(2.41)**	
*Settlement Dum * Uncertainty Tone*		0.0048			0.1576			0.3807			0.2526	
		(0.06)			(2.08)**			(5.23)***			(3.94)***	
Litigious Tone			0.0141			0.0404			0.0827			0.0689
			(0.56)			(1.66)*			(3.03)***			(2.39)**
*Settlement Dum * Litigious Tone*			-0.0029			-0.0202			-0.1648			-0.1701
			(0.04)			(0.21)			(1.90)*			(2.04)**
Settlement Dum	1.7582	0.6925	1.2419	2.9251	-0.8980	0.8063	6.6969	-1.8593	6.0354	5.5399	-1.4344	5.4179
	(0.71)	(0.23)	(0.27)	(1.20)	(0.67)	(0.18)	(2.89)***	(1.45)	(1.19)	(2.32)**	(0.99)	(1.02)
R^2	0.61	0.61	0.61	0.34	0.36	0.34	0.27	0.26	0.25	0.14	0.14	0.14
N	166	166	166	166	166	166	166	166	166	166	166	166

Table 11: Robustness Checks: Linguistic Communication

This table reports the results of the OLS regression models estimating the equity-based reputational returns *(RCARs)* and cumulative abnormal CDS spread changes *(CASCs)* around operational risk event announcements in the event window (+1,+5) for the Anglo-Saxon and non-Anglo-Saxon countries (See Table 2, Panel A for a list of countries and their classifications). In the interests of brevity, the constant term and all other variables are not reported. Variables description is reported in Appendix B. t-statistics based on heteroscedasticity-robust standard errors are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	RCAR(+1,+5)						***CASC(+1,+5)***					
	Anglo-Saxon			**Non-Anglo-Saxon**			**Anglo-Saxon**			**Non-Anglo-Saxon**		
i) Baseline Regressions:												
Net Negative Tone	-0.0804			-0.0209			0.1089			0.0179		
	(5.32)***			(0.96)			(3.06)***			(0.63)		
Uncertainty Tone		0.1452			0.0399			-0.2150			-0.0482	
		(5.76)***			(1.72)*			(5.23)***			(1.82)*	
Litigious Tone			-0.0948			-0.0268			0.1324			0.0340
			(5.51)***			(1.38)			(3.69)***			(1.08)
ii) Interactions with Loss Amount Disclosure:												
Net Negative Tone	-0.1731			-0.0333			0.1997			0.0296		
	(5.98)***			(1.31)			(1.99)**			(0.35)		
*Loss Amount Disclosure Dum * Net Negative Tone*	0.1181			0.0140			-0.1214			-0.0143		
	(2.54)**			(0.50)			(1.68)*			(0.30)		
Uncertainty Tone		0.3216			0.0794			-0.3796			-0.0847	
		(4.92)***			(2.18)**			(1.87)*			(0.57)	
*Loss Amount Disclosure Dum * Uncertainty Tone*		-0.2840			-0.0440			0.2359			0.0391	
		(5.54)***			(1.04)			(1.66)*			(0.35)	
Litigious Tone			-0.1147			-0.0438			0.2129			0.0506
			(3.90)***			(1.70)*			(2.16)**			(0.50)
*Loss Amount Disclosure Dum * Litigious Tone*			0.0284			0.0222			-0.1163			-0.0232
			(0.92)			(0.80)			(1.38)			0.29
Loss Amount Disclosure Dum	-6.2623	2.7065	-0.5877	-0.5976	0.4587	-0.3067	7.1693	-1.6559	3.2945	-0.0447	-0.7548	0.0667
	(4.88)***	(4.29)***	(0.79)	(0.45)	(0.69)	(0.41)	(1.17)	(0.54)	(1.36)	(0.02)	(0.27)	(0.05)
iii) Interactions with Firm Recognition:												
Net Negative Tone	-0.1378			-0.0323			0.2030			0.0323		
	(4.27)***			(1.71)*			(3.61)***			(0.63)		
*Firm Recognition Dum * Net Negative Tone*	0.1123			0.0310			-0.1968			-0.0676		
	(2.53)**			(0.87)			(2.97)***			(1.04)		
Uncertainty Tone		0.2672			0.0743			-0.4154			-0.0831	
		(4.14)***			(1.32)			(4.69)***			(0.88)	
*Firm Recognition Dum * Uncertainty Tone*		-0.2325			-0.0651			0.4781			0.0791	
		(3.40)***			(1.51)			(2.13)**			(0.54)	
Litigious Tone			-0.1060			-0.0561			0.1861			0.0522
			(3.15)***			(1.76)*			(2.38)**			(0.60)
*Firm Recognition Dum * Litigious Tone*			0.0259			0.0812			-0.1685			-0.0592
			(0.37)			(0.84)			(1.13)			(0.36)
Firm Recognition Dum	-5.5607	2.5636	-0.3785	-3.0093	-1.2169	-4.1052	6.1966	-9.0981	-0.4475	1.4692	-2.0334	0.2313
	(3.29)***	(3.80)***	(0.26)	(1.72)*	(1.11)	(2.47)**	(1.52)	(4.18)***	(0.29)	(0.37)	(0.96)	(0.08)
N	233	233	233	72	72	72	126	126	126	40	40	40

Table 11: Robustness Checks: Linguistic Communication (Continued)

This table reports the results of the OLS regression models estimating the equity-based reputational returns *(RCARs)* and cumulative abnormal CDS spread changes *(CASCs)* around operational risk event announcements in the event window (+1,+5) for the Anglo-Saxon and Non-Anglo-Saxon countries (See Table 2, Panel A for a list of countries and their classifications). In the interests of brevity, the constant term and all other variables are not reported. Variables description is reported in Appendix B. t-statistics based on heteroscedasticity-robust standard errors are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	RCAR(+1,+5)						***CASC(+1,+5)***					
	Anglo-Saxon			**Non-Anglo-Saxon**			**Anglo-Saxon**			**Non-Anglo-Saxon**		
iv) Interactions with Regulatory Announcement:												
Net Negative Tone	-0.0927			-0.0285			0.1878			0.0304		
	(4.24)***			(1.58)			(2.78)***			(0.71)		
*Regulatory Announcement Dum * Net Negative Tone*	0.0380			0.0133			-0.2020			-0.0704		
	(1.31)			(0.47)			(0.91)			(0.28)		
Uncertainty Tone		0.2324			0.0984			-0.4569			-0.1979	
		(5.78)***			(1.98)**			(5.45)***			(2.40)**	
*Regulatory Announcement Dum * Uncertainty Tone*		-0.2351			-0.0897			0.7345			0.2536	
		(4.85)***			(1.89)*			(5.14)***			(1.74)	
Litigious Tone			-0.1460			-0.0563			0.3081			0.0835
			(4.52)***			(1.70)*			(5.24)***			(1.69)*
*Regulatory Announcement Dum * Litigious Tone*			0.1299			0.0641			-0.4262			-0.1436
			(3.62)***			(1.89)*			(4.22)***			(1.76)*
Regulatory Announcement Dum	-2.3431	1.8187	-3.6271	-0.8018	0.7272	-2.0003	12.0754	-4.9756	11.4475	1.8464	-3.5798	2.2955
	(1.63)	(2.04)**	(1.82)*	(0.58)	(0.80)	(1.08)	(0.99)	(2.36)**	(2.42)**	(0.17)	(1.70)*	(0.51)
v) Interactions with Settlement:												
Net Negative Tone	-0.0967			-0.0277			0.1364			0.0217		
	(3.38)***			(0.98)			(3.44)***			(0.51)		
*Settlement Dum * Net Negative Tone*	0.0578			0.0290			-0.1040			-0.0941		
	(1.46)			(0.69)			(1.16)			(1.14)		
Uncertainty Tone		0.3423			0.1074			-0.4983			-0.1730	
		(5.77)***			(1.84)*			(5.98)***			(2.35)**	
*Settlement Dum * Uncertainty Tone*		-0.5768			-0.1328			1.1061			0.2811	
		(7.85)***			(3.85)***			(6.70)***			(1.96)**	
Litigious Tone			-0.1376			-0.0508			0.1868			0.0695
			(4.17)***			(2.22)**			(4.06)***			(1.73)*
*Settlement Dum * Litigious Tone*			0.2107			0.1337			-0.4508			-0.1960
			(4.15)***			(3.27)***			(4.59)***			(1.69)*
Settlement Dum	-2.2669	6.6523	-3.8403	-1.6032	0.8188	-3.0215	7.2562	-8.9299	13.4465	6.0540	0.0406	7.3786
	(1.86)*	(5.86)***	(3.01)***	(1.27)	(1.20)	(2.47)**	(1.62)	(3.67)***	(4.55)***	(1.48)	(0.01)	(2.48)**
N	233	233	233	72	72	72	126	126	126	40	40	40

Table 12: Robustness Checks: Financial Structure

This table reports the results of the OLS regression models estimating the equity-based reputational returns *(RCARs)* and cumulative abnormal CDS spread changes *(CASCs)* around operational risk event announcements in the event window (+1,+5) for the market-based and bank-based economies (See Table 2, Panel A for a list of countries and their classifications). In the interests of brevity, the constant term and all other variables are not reported. Variables description is reported in Appendix B. t-statistics based on heteroscedasticity-robust standard errors are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	RCAR(+1,+5)						***CASC(+1,+5)***					
	Market-based			**Bank-based**			**Market-based**			**Bank-based**		
i) Baseline Regressions:												
Net Negative Tone	-0.0635			-0.0105			0.0816			0.0480		
	(4.22)***			(0.73)			(2.35)**			(1.41)		
Uncertainty Tone		0.1113			0.0420			-0.1643			0.0698	
		(5.05)***			(2.10)**			(5.14)**			(2.61)***	
Litigious Tone			-0.0748			-0.0323			0.1032			0.0424
			(4.43)***			(1.71)*			(2.70)***			(1.22)
ii) Interactions with Loss Amount Disclosure:												
Net Negative Tone	-0.1421			-0.0161			0.2092			0.0854		
	(5.61)***			(0.79)			(2.13)**			(0.83)		
*Loss Amount Disclosure Dum * Net Negative Tone*	0.0988			0.0064			-0.1663			-0.0425		
	(1.98)**			(0.17)			(1.89)*			(0.50)		
Uncertainty Tone		0.2630			0.0709			-0.4182			-0.1837	
		(2.73)***			(0.77)			(2.15)**			(0.91)	
*Loss Amount Disclosure Dum * Uncertainty Tone*		-0.2547			-0.0327			0.3604			0.2850	
		(5.29)***			(0.83)			(1.75)*			(1.36)	
Litigious Tone			-0.0936			-0.0470			0.1853			0.0702
			(3.16)***			(1.60)			(2.01)**			(0.77)
*Loss Amount Disclosure Dum * Litigious Tone*			0.0256			0.0198			-0.1176			-0.0540
			(0.79)			(0.67)			(0.58)			(0.24)
Loss Amount Disclosure Dum	-4.9745	2.6632	-0.0709	-0.2523	0.2628	-0.5240	9.4173	-3.0113	3.0902	2.3212	-0.8801	1.6695
	(4.07)***	(4.58)***	(0.08)	(0.19)	(0.48)	(0.40)	(1.46)	(0.99)	(0.65)	(0.33)	(0.25)	(0.38)
iii) Interactions with Firm Recognition:												
Net Negative Tone	-0.1262			-0.0143			0.1581			0.0691		
	(3.70)***			(0.41)			(3.12)***			(1.41)		
*Firm Recognition Dum * Net Negative Tone*	0.1345			0.0074			-0.1691			-0.0892		
	(2.68)***			(0.17)			(2.62)***			(1.36)		
Uncertainty Tone		0.2854			0.0640			-0.3399			-0.1390	
		(4.51)***			(1.24)			(4.05)***			(1.68)*	
*Firm Recognition Dum * Uncertainty Tone*		-0.3713			-0.0299			0.4710			0.4182	
		(4.26)***			(0.42)			(1.78)*			(1.51)	
Litigious Tone			-0.0970			-0.0459			0.1315			0.0724
			(2.72)***			(1.31)			(2.77)***			(1.57)
*Firm Recognition Dum * Litigious Tone*			0.0572			0.0237			-0.0951			-0.0872
			(1.11)			(0.43)			(1.26)			(1.13)
Firm Recognition Dum	-6.9447	3.4643	-1.2425	-1.4004	-1.1100	-2.0818	4.8077	-9.0999	-2.0916	1.3728	-5.5466	-0.3965
	(4.71)***	(5.12)***	(0.78)	(0.96)	(1.18)	(1.35)	(0.56)	(4.27)***	(0.96)	(0.26)	(2.55)**	(0.17)
N	230	230	230	75	75	75	117	117	117	49	49	49

Table 12: Robustness Checks: Financial Structure (Continued)

This table reports the results of the OLS regression models estimating the equity-based reputational returns *(RCARs)* and cumulative abnormal CDS spread changes *(CASCs)* around operational risk event announcements in the event window (+1,+5) for the market-based and bank-based economies (See Table 2, Panel A for a list of countries and their classifications). In the interests of brevity, the constant term and all other variables are not reported. Variables description is reported in Appendix B. t-statistics based on heteroscedasticity-robust standard errors are reported in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

	RCAR(+1,+5)						***CASC(+1,+5)***					
	Market-based			**Bank-based**			**Market-based**			**Bank-based**		
iv) Interactions with Regulatory Announcement:												
Net Negative Tone	-0.0770			-0.0161			0.1250			0.0679		
	(3.60)***			(0.92)			(1.69)*			(0.95)		
*Regulatory Announcement Dum * Net Negative Tone*	0.0385			0.0129			-0.1060			-0.0990		
	(1.41)			(0.49)			(0.66)			(0.58)		
Uncertainty Tone		0.1811			0.0725			-0.3522			-0.1687	
		(5.41)***			(3.37)***			(4.40)***			(2.24)**	
*Regulatory Announcement Dum * Uncertainty Tone*		-0.1597			-0.0937			0.5653			0.3387	
		(3.14)***			(1.96)**			(3.86)***			(2.37)**	
Litigious Tone			-0.1173			-0.0528			0.1992			0.0887
			(4.08)***			(1.90)*			(3.53)***			(2.02)**
*Regulatory Announcement Dum * Litigious Tone*			0.1019			0.0664			-0.2460			-0.1310
			(3.11)***			(2.06)**			(2.96)***			(1.67)*
Regulatory Announcement Dum	-1.9654	1.3271	-2.5191	-1.0621	0.6120	-2.1963	6.7163	-3.5145	6.9901	3.0010	-4.5996	1.1426
	(1.34)	(2.35)**	(2.89)***	(0.74)	(1.15)	(2.52)**	(1.62)	(2.28)**	(3.16)***	(0.71)	(2.76)***	(0.57)
v) Interactions with Settlement:												
Net Negative Tone	-0.0683			-0.0135			0.1314			0.0631		
	(2.31)**			(0.47)			(3.26)***			(1.55)		
*Settlement Dum * Net Negative Tone*	0.0186			0.0126			-0.1954			-0.2438		
	(0.49)			(0.36)			(1.00)			(1.18)		
Uncertainty Tone		0.2654			0.0925			-0.4329			-0.1765	
		(5.08)***			(2.47)**			(5.63)***			(2.63)***	
*Settlement Dum * Uncertainty Tone*		-0.4548			-0.1182			1.2052			0.4848	
		(6.93)***			(2.88)***			(7.18)***			(3.35)***	
Litigious Tone			-0.0943			-0.0536			0.1925			0.1095
			(3.24)***			(1.89)*			(4.58)***			(2.67)***
*Settlement Dum * Litigious Tone*			0.1041			0.1010			-0.7848			-0.6910
			(2.60)***			(2.49)**			(5.56)***			(4.65)***
Settlement Dum	-0.5630	4.7603	-1.9099	0.9955	3.1709	-0.6085	11.7576	-9.4657	22.3567	12.9357	-1.4859	19.1802
	(0.19)	(5.04)***	(1.45)	(0.54)	(3.69)***	(0.48)	(2.76)***	(3.16)***	(5.04)***	(2.83)***	(0.58)	(4.04)***
N	230	230	230	75	75	75	117	117	117	49	49	49

Appendix A: ORIC Database

ORIC International Newsflash Service is a database of over 26,000 risk events sourced from the public domain and transposed into ORIC's Operational Risk Information System (ORIS). The database contains both qualitative and quantitative information on each risk event and includes information on the reported loss amount, the name of the organisation and its industry type, as well as a description of the event, including the category of operational risk (See Figure 1 for an example of how an operational risk event is reported in the ORIC database).

The public data on ORIS is populated by human media reviewers and automated web-trawlers that are programmed to look for operational risk stories and events from around the world. Institutional members of the ORIC International private database service may also include loss events that they have found. The database is updated daily. As is the case with all information in the public domain the information that is collected is only as good as what has been released or discovered, but in most cases a loss amount is provided, along with the organisation and its industry sector.

Compared with other operational loss databases used in the literature, the ORIC data is very similar to the ALGO OpData™ (De Fontnouvelle and Perry, 2005; Cummins et al., 2006; Micocci et al., 2009; Fiordelisi et al., 2013; Fiordelisi et al., 2014) and the ALGO First™ database (De Fontnouvelle and Perry, 2005; Gillet et al., 2010) used by much of the past research on operational and reputational risks, but offers a more comprehensive dataset (as of March 2018, ORIC has over 26,000 risk events and ALGO First™, now owned by IBM, has over 15,000 risk loss events[26]). In addition, the ÖffSchOR database provided by the Association of German Public Sector Banks (Bundesverband offentlicher Banken, VOB) used by Sturm (2013 a & b) contains around 2,000 risk loss events[27]. Hence, ORIC has enabled us to extract the largest sample size possible for the study period 2010 – 2014.

One limitation of the ORIC database is that it covers very few operational risk events before 2010, thus not allowing to inspect market reactions to operational risk announcements before and during the global financial crisis. Another limitation (although it is shared with some other proprietary operational risk databases) is that ORIC only collects media news in English.

[26] IBM Algo FIRST: https://www.ibm.com/uk-en/marketplace/ibm-algo-first [Accessed 31/03/2018].
[27] Öffentliche Schadenfälle Oprisk (ÖffSchOR): https://www.voeb-service.de/informationsdienste/oeffschor/ [Accessed 31/03/2018].

Figure 1: An Example of an Operational Risk Event as Reported in the ORIC Database

Event Details			
Title	Knight bruised as analyst estimates $170 million loss		
Description	The latest black eye for U.S. equity markets is proving a body blow for Knight Capital Group Inc. Shares of the Jersey City, New Jersey-based firm plunged 33 percent, the most ever, in record volume yesterday as investors speculated on how much a breakdown that whipsawed owners of 140 stocks will cost the company. Its loss may be as much as $170 million, according to analysts at JPMorgan Chase & Co. Loss Totals The decline is justified because Knight's "potential hit to revenue" may total $170 million, according to analysts Kenneth B. Worthington and Paul Lanks at JPMorgan. They based their projections on a comparison of where the 140 stocks that were affected traded in the morning with levels after they recovered, according to a note to clients. "The market is accurately evaluating the situation with the potential downside of losses and hit to Knight's market-making reputation," they wrote. "We don't see the dip as a buying opportunity." 45 Minutes NYSE Euronext (NYX) reviewed trading between 9:30 a.m. and 10:15 a.m. New York time in the affected securities listed on the New York Stock Exchange and NYSE MKT, the former American Stock Exchange, including Bank of America Corp. and Caterpillar Inc. In a decision that it said isn't subject to appeal, NYSE canceled trades in six securities where prices swung at least 30 percent in the first 45 minutes, according to a statement on its website. As stock swings mounted yesterday, Knight told some clients of its market-making business that a "technical issue" was affecting its systems and advised them to route orders elsewhere, according to e-mails from spokeswoman Kara Fitzsimmons yesterday. The issue was confined to that unit and its other operations were unaffected, she said. One issue Knight may face with regulators is explaining why trading was disrupted for up to 45 minutes and why the problem wasn't caught soon enough to stem the fluctuations, Lee said. Knight shareholders may want to know whether the market maker is still holding the positions it acquired yesterday or unwound the trades and took a loss, he said. Fitzsimmons didn't provide a comment beyond the statement. Joyce, who had knee surgery on July 31 and came to work yesterday, was unavailable, the spokeswoman said. The U.S. Securities and Exchange Commission is monitoring the situation, spokesman Kevin Callahan said in an e-mail. Nasdaq OMX Group Inc. (NDAQ) spokesman Robert Madden declined to comment. The errors were caused by a malfunction in a trading algorithm, according to a person at Knight who asked to remain anonymous because the matter hasn't been publicized. Technicians are reviewing the possibility the error was generated by faulty software, the person said.		
Event date	8/2/2012	**Source**	Bloomberg (www.bloomberg.com)
Source article URL	http://www.bloomberg.com/news/2012-08-02/knight-bruised-as-analyst-estimates-170-million-loss.html		
Country	United States of America	**Amount**	440,000,000.00 USD
Involved entities	Knight Capital Group		
Industry type	Banking	**Business line**	Trading and Sales
Risk category	Business Disruption and System Failures / Infrastructure and Systems Failures / Internal Application Failures / Application Failures and Errors – Model Error		
Business function	Execution / Instruction Management		
Business risk component	No	**Credit risk component**	No
Environment risk component	No	**Insurance risk component**	No
Liquidity risk component	No	**Market risk component**	No
Strategic risk component	No		
Tags	Model Errors; System Errors; Trading Losses		
Related Newsflashes	10/16/2013 Knight Capital reaches $12m SEC settlement over IT meltdown 11/15/2012 SEC expands probe into Knight Capital 9/21/2012 Humbled Knight seeks new CTO and operational risk manager 8/23/2012 HFT in the dock as another trading error hits exchanges 8/14/2012 SEC was looking at Knight in midst of errant trade 8/13/2012 Australia bids to curb rogue algos 8/3/2012 SEC examining risk controls at Knight Capital 8/3/2012 The $5bn trading error that may cause a firm to collapse		

Appendix B: Variables Description

Variable Name	Definition	Data Source(s)
CAR (x,z)	Cumulative abnormal stock return in the event window (x,z) = $\sum_{i=x}^{z} Abnormal\ Stock\ Return_i$, where $Abnormal\ Stock\ Return_i = Firm\ Stock\ Return_i - Normal\ Stock\ Return_i$ Estimation window of the normal stock return is 250 trading days ending one calendar month before the announcement date. Estimation model is single-factor market model. Original stock prices are measured in U.S. dollar. The variable is measured as a percentage (%).	DataStream
RCAR (x,z)	Reputational return in the event window (x,z) = Cumulative abnormal stock return + |(Disclosed operational loss amount / Market value of the loss firm two calendar weeks before the announcement date)|. The variable is measured as a percentage (%).	- DataStream - ORIC - LexisNexis
CASC (x,z)	Cumulative abnormal CDS spread change in the event window (x,z) = $\sum_{i=x}^{z} Abnormal\ CDS\ Spread\ Change_i$, where $Abnormal\ CDS\ Spread\ Change_i = (Firm\ CDS\ Spread_i - Firm\ CDS\ Spread_{i-1}) - (iTraxx\ Spread_i - iTraxx\ Spread_{i-1})$. The variable is measured in basis points (bps) for a five-year duration (modified modified structure).	DataStream
Net Negative Tone	((Negative Words – Positive Words) / Total Financial Sentiment Words) * 100	- Loughran and McDonald (2011) - ORIC - LexisNexis
Uncertainty Tone	(Uncertainty Words / Total Financial Sentiment Words) * 100	- Loughran and McDonald (2011) - ORIC - LexisNexis
Litigious Tone	(Litigious Words / Total Financial Sentiment Words) * 100	- Loughran and McDonald (2011) - ORIC - LexisNexis
Loss Amount Disclosure Dum	1 if the operational loss amount is disclosed; 0 otherwise	- ORIC - LexisNexis
Firm Recognition Dum	1 if the operational risk event is recognized by the loss firm; 0 otherwise	- ORIC - LexisNexis
Regulatory Announcement Dum	1 if the operational risk event is announced by a regulatory body; 0 otherwise	- ORIC - LexisNexis
Settlement Dum	1 if the operational risk event is settled; 0 otherwise	- ORIC - LexisNexis
Different Country Dum	1 is the operational risk event takes place in a country different from the loss firm headquarters' country; 0 otherwise	- ORIC - LexisNexis
Top Figures Dum	1 if the operational risk event directly involves one or more of the board directors or chief executives; 0 otherwise	- ORIC - LexisNexis

Fraud Dum	1 if the operational risk event is classified as internal fraud or external fraud; 0 otherwise	- ORIC - LexisNexis
Basel Business Line Dum	1 if the operational risk event is classified under one of the eight Basel II business lines: Corporate Finance, Trading and Sales, Retail Banking, Commercial Banking, Payment and Settlement, Agency Services, Asset Management, Retail Brokerage; 0 otherwise	- ORIC - LexisNexis
FT & WSJ Dum	1 if the operational risk event is featured in The Financial Times or The Wall Street Journal; 0 otherwise	LexisNexis
Number of News Articles	Number of news articles that feature the operational risk event	LexisNexis
Analyst Coverage	Number of equity analysts following the firm (i.e. issuing EPS estimates)	Bloomberg
Credit Rating	S&P long-term local issuer credit rating. It is measured in an ascending numerical scale ranging from AAA=1 to D or SD = 22	Bloomberg
StDev Ret	Standard deviation of daily stock returns for one trading year ending one calendar month before the announcement date (Decimals)	DataStream
Beta	Monthly stock's Beta (measured at the end of calendar month preceding the announcement date)	DataStream
Float%	The percentage of outstanding shares available to ordinary shareholders two calendar weeks before the announcement date	DataStream
Ln(Volume)	The natural logarithm of the number of shares traded for the stock (in thousands) two calendar weeks before the announcement date	DataStream
Ln(Total Assets)	Natural logarithm of total assets (in millions of U.S. dollar) measured at the end of calendar quarter preceding the announcement date	DataStream
ROA	Return on assets (%)	DataStream
Leverage	Long-term debt / Shareholders' equity (Decimals)	DataStream
Market to Book Ratio	Market value of equity / Book value of equity (Decimals)	DataStream
GDP Per Capita	GDP per capita (in thousand U.S. dollar)	World Bank