The Impact of Terrorist Attacks and Mass Shootings on Earnings Management [*]

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ABSTRACT: This study investigates the role of salient events on accrual-based and real earnings management activities. For people using availability heuristics, the salience of an event may temporarily increase perceived risk even though the actual risk does not change, and individuals making decisions by availability heuristics are subsequently more likely to assign a higher probability to unrelated negative future events. I use terrorist attacks and mass shootings as salient events and conjecture that the negative effects of terrorist attacks and mass shootings spill over and lead to pessimistic risk assessments of financial reporting choices. The findings show a decrease in accrual-based and real earnings management for firms located in the impacted regions. The documented effects are driven by firms with high information asymmetry levels and pessimistic annual reports. Additional analysis reveals that affected firms decrease the readability of their annual reports, suggesting affected firms engage in a more complex narrative disclosure. The findings of this paper support the argument that managers exhibit a cognitive bias which affects their financial reporting choices.

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1. INTRODUCTION

How do managers make decisions? The decision-making process is a cognitive process of evaluation and selection inside of a set of options to satisfy different aims (e.g., economic, moral, political). The classical economic theories about decision-making suggest managers to be rational beings who thoroughly evaluate the different options, using all available information (Verónica, 2018). However, prior research in psychology finds that individuals could not possibly analyze all available information and many decisions could be carried out under cognitive bias, such as heuristics (i.e., mental shortcuts) (Tversky & Kahneman, 1973, 1974). In doing so, they save time and effort, even though their decision-making ignores some available information. This paper asks whether firm managers, who are more likely to resort to heuristics in their decision-making, overestimate the costs of their financial reporting, i.e., the costs of earnings management.[1]

Examining this question requires the identification of an event increasing the likelihood of resorting to heuristics over rational decision-making. I address this issue by exploiting terrorist attacks and mass shootings (terrorist attacks, hereafter)[2] across the United States (U.S.). First, the occurrence of these events is exogenous to firm and manager characteristics, which would mitigate any concerns about reverse causality. Second, for these events to trigger the use of availability heuristics among managers, they must be perceived as salient events, and must have substantial psychological effects. Traumatic events raise questions about the burden and nature of post-event psychopathology. Neria, Nandi and Galea (2008) argue that the mental health consequences of traumatic events among those indirectly exposed to trauma may well exceed the mental health

[1] This paper examines both accrual-based and real earnings management. I refer to them as earnings management for brevity.

[2] The remainder of the paper refers to terrorist attacks and mass shootings as terrorist attacks. Terrorist attacks are committed in expression of and commitment to a political or religious ideology; whereas, mass shootings are associated with personal feelings of having been wronged by an individual or group (National Institute of Justice (NIJ), 2017). Distinguishing between these two types of events is beyond the scope of this paper.

consequences among those who were directly exposed to it. For instance, researchers show a link between indirect exposure and post-traumatic stress disorder using the Oklahoma City bombing as a shock (Pfefferbaum et al., 1999).

Terrorist attacks may cause a similar mental burden on those directly or indirectly exposed to these events. Healthcare research documents serious psychological consequences of terrorist attacks, such as potential subsequent spikes in the suicide rate (Lubin et al., 2010), and an impact on psychiatric disorders like depression and post-traumatic stress disorder (Lowe & Galea, 2017). While firm managers may not be directly exposed to the trauma of terrorist attacks, by virtue of being located in the affected regions, they may experience the loss of family members, friends, or colleagues, and they may be exposed to these events through the media. In short, managers in affected regions will perceive terrorist attacks as salient events because they are likely to suffer a mental burden.

I explore two explanations for a link between terrorist attacks, and earnings management. The first link derives from the prospect theory introduced by Kahneman and Tversky (2012). The basic idea of their model was individuals making decisions by heuristics; a kind of shortcut, intuitive judgments based in partial knowledge, rather than conducting cost–benefit analyses. There are three general heuristics: availability, representativeness, and anchoring. This paper focuses on availability heuristics.

Availability heuristics refer to the ease with which concrete occurrences of a salient event come to mind (Tversky & Kahneman, 1973, 1974). Prior research suggests that past experience is an important factor influencing people's perception of events (Weinstein, 1989).[3] The salience of an

[3] Past experience with earthquakes influenced the adoption of precautions (Jackson, 1981), and the experience of flood damage was the most important factor that led to the purchase of insurance (Baumann & Sims, 1978; Zaleskiewicz et al., 2002).

event is affected by emotional affect, novelty, time proximity, or media coverage (Dessaint & Matray, 2017). For people using availability heuristics, the salience of an event may temporarily increase perceived risk even though the actual risk does not change, and individuals making decisions by availability heuristics are subsequently more likely to assign a higher probability to unrelated negative future events (Johnson & Tversky, 1983). Thus, they tend to overestimate the frequency of salient events until there is another type of salient event. If firm managers (a subset of the general population) use availability heuristics, they may overreact to salient events because their perceived risk has temporarily increased even though the real risk does not change. Further, the psychology literature suggests that any cognitive bias in subjective expectations can spill over and affect many economic outcomes (Dickinson & Oxoby, 2011).

Following the psychology literature, I conjecture that the negative effects of salient events (i.e., terrorist attacks) spill over and lead to pessimistic risk assessments of financial reporting choices. Specifically, I expect managers to overestimate the risks and costs of earnings management. Accrual-based and real earnings management can lead to distortions in resource allocation, inefficient investment decisions, reduced firm financial statement quality, increased regulatory risks and decreased future opportunity wages for managers (Healy & Wahlen, 1999). For instance, aggressive accrual-based earnings management practices may cross legal and regulatory boundaries, leading to potential legal consequences (Beneish, 1999; Cohen et al., 2008). Regulators and authorities may investigate and penalize companies and managers engaged in fraudulent or misleading financial reporting practices, which can result in reputational damage, fines, and legal liabilities. In some cases, manipulating earnings through real activities can distort resource allocation decisions (Roychowdhury, 2006). For example, real earnings management may boost reported earnings in the short-term but may not be in the long-term interest of the firm.

This can result in inefficient allocation of resources, reduced productivity, and missed investment opportunities. If managers have the perception that costs and risks associated with earnings management are heightened, they will have incentives to avoid these activities. The availability heuristics hypothesis predicts that firms near terrorist attacks will experience a decrease in earnings management compared to non-affected firms.

The second link I explore is based on the rent-extraction argument. It is possible that rent-extracting managers may act rationally and not allow pessimism induced by terrorist attacks to affect their judgments. During significant events, information dissemination and investor attention may be convoluted. To the extent that these events create investor distraction, managers of affected firms may have more incentives to engage in rent-extracting activities. A large body of empirical research in accounting has provided evidence that managers take unobservable actions to manage reported accounting earnings to meet various objectives. For example, self-serving managers have obvious incentives to engage in earnings management if their bonuses are based on reported accounting earnings. Rent-seeking managers may receive big rewards for superior performance and substantial penalties (including a real threat of dismissal) for poor performance. Thus, the rent-extraction hypothesis predicts that firms near terrorist attacks will experience an increase in income-increasing earnings management compared to non-affected firms.

I gather data (e.g., number of victims) on terrorist attacks and collapse this information into yearly measures for the sample period between 2000 and 2020. These metrics are then combined with firm characteristics. I use discretionary abnormal accruals as my main proxy for accrual-based earnings management, and measure real earnings management using abnormal discretionary expenses, abnormal production costs, and abnormal operating cash flow. I find a significantly negative association between the number of victims and earnings management metrics. The overall analyses indicate a decrease in the earnings management activities of firms near terrorist attacks (i.e., headquartered within 100 miles of attacks). These findings support the availability heuristics hypothesis. Pessimism induced by these events increases the perceived risk associated with earnings management activities, which reduces incentives to engage in these activities. I do not find any evidence supporting the rent-extraction argument.

The second part of my paper examines the primary channels that may explain my results: (1) information asymmetry and (2) annual report sentiment. Analytical models have demonstrated the existence of information asymmetry for the practice of earnings management (Dye, 1988; Trueman & Titman, 1988). When information asymmetry is high, stakeholders do not have the necessary information to "see through" the managed earnings. Therefore, my primary results will be more pronounced for firms with low levels of information asymmetry because firms with high levels of information asymmetry may not have incentives to decrease earnings management. On the other hand, managers in firms with greater information asymmetry levels may have greater incentives to reduce earnings management activities because costs associated with earnings management may be greater for those firms. Firms with greater information asymmetry exhibit more accounting irregularities, including restatements (Elayan et al., 2008), which are linked to higher cost of capital and investors' required rate of return (Hribar & Jenkins, 2004). Additionally, higher information asymmetry is associated with elevated audit fees (Frino et al., 2022). Thus, firms characterized by higher information asymmetry levels are likely to experience a more significant decline in earnings management following terrorist attacks. This is due to the managers of such firms having a more stringent evaluation of the risks connected to earnings management activities.

Next, I focus on annual report sentiment (i.e., 10-K). During periods of high firm sentiment, managers have more incentives and opportunities to portray the firm in a manner that maximizes its appeal to investors. Hence, during periods of high firm sentiment, managers will boost earnings to meet investors' optimistic expectations of future firm performance. During low-sentiment periods, managers may report conservatively to mitigate the higher disclosure costs arising from increased scrutiny. Further, terrorist attacks can also have an influence on the sentiment expressed in the annual reports. If the observed shift in earnings management activities among firms affected by terrorist attacks is driven by a cognitive bias, it is plausible to expect that firms with pessimistic sentiment in their annual reports are more likely to exhibit this bias. This discussion leads me to conjecture that the decrease in the magnitude of earnings management around terrorist attacks is more pronounced in firms exhibiting pessimistic sentiment in their annual reports.

Following the accounting and finance literatures, I use bid-ask spread as a proxy of information asymmetry (e.g., Flannery et al., 2004) and the number of Loughran-McDonald financial negative and positive words as my proxies of pessimism and optimism in annual reports (Loughran & McDonald, 2011). Using a split-sample analysis, I report that my main results are mainly driven by firms with high information asymmetry and those that exhibit pessimism in their annual reports. These findings suggest that the use of heuristics around terrorist attacks is exacerbated by information asymmetry and manager pessimism.

I examine various alternative explanations that may drive my results: (1) future profitability, (2) overinvestment, and (3) managers' opportunistic behavior. It is plausible that any decrease in earnings management could be explained by future profitability. Terrorist attacks may create opportunities for firms to increase their revenues. For instance, anecdotal evidence suggests that in the aftermath of terrorist attacks, sales of self-defense products rise, which leads to higher profits. Future profitability would reduce managers' incentives to manipulate earnings upward. If my results can be explained by firms' profitability, I expect my results to disappear, after I control for future profitability. These expectations receive no support from my empirical tests, and I conclude that future profitability does not explain my main findings.

Next, I examine the role of overinvestment in explaining my results. Contracting theory suggests that firms with more investment opportunities and greater access to positive net present value projects are more difficult to observe and monitor, because as the proportion of firm value represented by investment opportunities increases, the observability of managerial actions decreases (Gaver & Gaver, 1993; Smith & Watts, 1992). Thus, managers in firms with more investment opportunities are more likely to engage in opportunistic behavior (Skinner, 1993). On the other hand, with increasing investment opportunities firms may feel the need to engage in earnings manipulation less. Even after controlling for overinvestment, I find qualitatively similar results to my main findings and rule out the existence of investment opportunities as an alternate explanation. Finally, I create two indicator variables to capture firm-years just meeting or beating key earnings benchmarks to control for managers' incentives to engage in earnings management. Even after including these indicator variables, my main results do not change.

In addition, I analyze whether reported results may be observed in other financial reporting decisions. I document that affected firms decrease readability (i.e., Gunning Fox Index, Automated Readability Index) of their annual reports. A decrease in readability suggests that affected firms obfuscate their pessimistic assessments by creating a more complex narrative disclosure. My overall results are robust to sub-sample tests, matched sample analysis, and alternative dependent variable definitions. Specifically, my interpretations of my main findings are unchanged even if I control for the inverse relationship between earnings management types, limit my sample to the post-2010 period, conduct matched sample analysis, and use the reporting of negative special items as a binary dependent variable.

My paper makes at least three contributions. First, I extend the literature that analyzes the economic implications of terrorist attacks. Previous studies examine both the microeconomic and macroeconomic implications of terrorist attacks. For instance, Dai et al. (2020) suggest that chief executive officers employed by firms located near terrorist attacks receive a terrorist attack premium. Wang and Young (2020) find that find that aggregate investor risk aversion inversely relates to terrorist activity in the U.S. and show a fear-induced increase in aggregate risk aversion. Cuculiza et al. (2021) show that analysts who are local to terrorist attacks issue forecasts that are relatively more pessimistic than the consensus forecast. Chen et al. (2021) show that firms located in the metropolitan areas attacked issue more negatively biased earnings forecasts. I provide evidence of another channel affecting financial markets through its impact on managers' sentiment and, subsequently, earnings management activities. My evidence suggests that sentimental disruptions (i.e., terrorist attacks) to firms' operating activities create incentives to decrease earnings management activities. The prior literature extensively shows how managers manage earnings to maximize their compensation.[4] My findings offer some contrast. This study indicates that cognitive bias may act as a mediating factor and decrease incentives to engage in value-maximizing behavior (i.e., earnings management). To the best of my knowledge, I am the first to document an association between terrorist attacks and earnings management.

Second, my evidence offers a unique insight by showing that the documented effect is mainly driven by information asymmetry and annual report sentiment. Last, this paper extends consideration of cognitive bias effects to the earnings management literature. The central role of feelings in decision-making has only partially been incorporated into behavioral finance and accounting (Hirshleifer, 2015). Hirshleifer (2015) calls for more theoretical and empirical research

[4] Please see Healy and Wahlen (1999) for a discussion on how compensation contracts affect managers' earnings management incentives.

on how feelings affect financial decisions and the implications of such effects for real outcomes. Further, he emphasizes the importance of analyzing particular psychological biases. My research answers this call by documenting a link between a specific type of cognitive bias (i.e., availability heuristics) and earnings management. I contribute to the strand of behavioral finance and accounting literatures that studies the effects of managers' behavioral biases (Bourveau & Law, 2021; Chen et al., 2021; Cuculiza et al., 2021; Dessaint & Matray, 2017).

Section 2 discusses the background information and presents testable hypotheses. Section 3 describes the research design and empirical models. Section 4 presents my main results, cross-sectional and robustness tests. Finally, Section 5 delivers my concluding remarks.

2. BACKGROUND AND HYPOTHESES

2.1. Terrorist Attacks and Post-Traumatic Stress Disorder

My argument that terrorist attacks affect market participants relies on two underlying assumptions: (i) terrorist attacks affect communities and lead to psychological effects; and (ii) the psychological effects are observed over a long-term period. Both these assumptions are supported by the findings in the psychology, sociology, and accounting literatures, which I discuss in detail below.

Extensive psychology and sociology research shows that terrorist attacks not only impact those who were present for the event (primary victims) but also the communities in which the incident occurred and beyond (secondary and tertiary victims) (Cowan et al., 2020). These events can lead to secondary traumatic stress disorder among journalists, educators, social workers, and members of the affected communities (e.g., Cowan et al., 2020; Lowe & Galea, 2017). The affected community has been described as a "co-victim" of this type of violence, as many organizations, schools, and businesses are impacted by terrorist attacks (Rowhani-Rahbar et al., 2019). Those who are located closer to these types of events may experience a period of stress, anxiety, fatigue, and hopelessness. They may experience these feelings during or after the event. Particularly those who believed their lives or those of their loved ones were in danger or who lack social support experience ongoing mental health problems, including post-traumatic stress disorder (PTSD), depression, anxiety, and substance abuse (e.g., Cowan et al., 2020). The National Center for PTSD estimates that 28 percent of people who have witnessed a terrorist attack develop PTSD and about a third develop acute stress disorder (U.S. Department of Veteran Affairs, 2022). In addition, the incessant media coverage of terrorist attacks has been found to put individuals in every community across the U.S. at higher risk for secondary traumatization (Substance Abuse and Mental Health Services Administration (SAMHSA), 2017). Thus, there is enough scholarly evidence to support my first assumption that terrorist attacks create significant psychological effects among secondary and tertiary victims in affected communities.

My second assumption is about the long-lasting impact of these events. To predict a reaction to these events, one needs to assume the psychological effects are not temporary or short-lived. Symptoms of PTSD usually begin within three months of the traumatic incident, but they sometimes emerge later. To meet the criteria for PTSD, symptoms must last longer than 1 month, and they must be severe enough to interfere with aspects of daily life (American Psychiatric Association, 2013). While some people recover within six months (e.g., Evans & Heiberger, 2016), for some, these symptoms can persist for a prolonged period (i.e., longer than one year) and can lead to long-term health issues (National Institute of Mental Health, 2020). Some medical professionals argue that the symptoms of PTSD may never go away because there has been a profound psychological and physiological reaction to something traumatic (Ball, 2019; Brain & Behavior Research Foundation, 2013). Most people with long-standing PTSD find that the symptoms are not steady in their severity. For some people, PTSD symptoms gradually fade over time. Other people find that symptoms may increase when they encounter reminders of their traumatic events. Anniversaries of the event, for example, are commonly difficult times. Not surprisingly, one factor that predicts how well terrorist attacks survivors will fare long-term is their proximity to the incident. Wilson (2014) examines PTSD symptoms among more than 8,000 participants and shows that the individuals who were most directly exposed to the shooting, including those who were physically injured, witnessed someone being shot, or lost a friend or loved one, as well as those who perceived their own lives were in danger, were at a significantly higher risk for experiencing long-term PTSD symptoms. Overall, even though the duration of PTSD symptoms may vary, it is not uncommon to observe long-lasting effects.

The above discussion indicates that direct exposure to trauma is not a necessary condition for PTSD, and even indirect exposure may result in post-exposure psychopathology (e.g., Neria et al., 2008). Therefore, managers of firms located in affected communities may suffer psychological consequences associated with terrorist attacks.

The underlying assumptions are well-supported by the existing literature, which shows that terrorist attacks affect market participants in various ways. Cuculiza, Antoniou, Kumar and Maligkris (2021) provide evidence that analysts who are local to terrorist attacks issue forecasts that are relatively more pessimistic than the consensus forecast. Chen, Wu and Zhang (2021) find that firms located in the metropolitan areas experiencing terrorist attacks issue more negatively biased earnings forecasts.

2.2. Hypotheses

My paper examines the impact of terrorist attacks on firms' earnings management activities. The directional association between terrorist attacks and earnings management depends on the economic perspective one takes. In this section, I consider two perspectives based on theories of availability heuristics and rent-extraction.

The availability heuristics perspective is motivated by the work of Tversky and Kahneman (1973, 1974). Their work argues that people simplify the task of assessing probabilities by using a heuristic which they call availability. The availability heuristic derives from the experience that "frequent events are much easier to recall or imagine than infrequent ones" (Tversky & Kahneman, 1973). Therefore, when judging the probability of an event, most people assess how easy it is to imagine an example of a situation in which this event actually occurred (e.g., one may evaluate the probability of a motorcycle accident by recalling examples of such occurrences among one's acquaintances). The heuristic availability may also be affected by the salience of the event and/or the event's proximity. This, in turn, can generate a discrepancy between the perceived and actual risk.

The psychology literature shows that people experiencing negative emotional shocks tend to overweight the possibility of unrelated negative outcomes (Lerner et al., 2003; Lerner & Keltner, 2001) and that unlikely events are overweighted when the associated outcome is salient and underweighted otherwise (Bordalo et al., 2012, 2013). Johnson and Tversky (1983) show that reading sad newspaper articles is positively associated with assigning a higher probability to unrelated negative future events. Slovic, Finucane, Peters and MacGregor (2007) suggest that salient events not only have negative effects on people's sentiments but can also spill over and lead to pessimistic assessments of risks in unrelated domains.

When a terrorist attack has been recently observed (increasing its salience), the availability of these events is high and their probability is overestimated. When the salience increases, we may observe a shift in managers' risk assessments of their reporting choices. For instance, Dessaint and

Matray (2017) find that the sudden shock to the perceived liquidity risk leads managers to increase corporate cash holdings and to express more concern about hurricane risk in 10-Ks/10-Qs, even though the actual risk remains unchanged. Their findings support the notion of a shift in risk assessments of managers in the aftermath of traumatic events.

I consider whether managers relying on the availability heuristic to assess the risk of terrorist attacks overestimate the costs of earnings management activities. Accrual-based and real earnings management practices can damage the company's reputation and erode trust among stakeholders, including investors, employees, and customers (Ashbaugh-Skaife et al., 2006). This loss of trust can have long-lasting effects on relationships, partnerships, and the overall brand image of the company. Managers who engage in accrual-based or real earnings management strategies may also face private costs, including a decrease in their future opportunity wages. This refers to the potential negative impact on their professional reputation and career prospects, as engaging in earnings management practices may be viewed unfavorably by potential employers and stakeholders.

Prior research demonstrates that income-increasing discretionary accruals exhibit greater expected litigation costs than income-decreasing discretionary accruals (Heninger, 2001; Palmrose et al., 2004; Palmrose & Scholz, 2004; Simunic & Stein, 1996) and may lead to auditor resignations due to earnings management risk (Krishnan et al., 2013). Real earnings management may involve decisions that prioritize short-term earnings goals at the expense of long-term value creation. This can result in suboptimal allocation of resources, missed investment opportunities, and lower overall performance (Roychowdhury, 2006).

If the salient risk of terrorist attacks spills over to other domains and leads to the pessimistic assessment of earnings management risk, then incentives to engage in earnings management should decrease in response to the salience of these events. The above discussion yields the following hypothesis:

> **[H1] Hypothesis 1 – Availability Heuristic:** Terrorist attacks lead to a <u>decrease</u> in accrual-based and real earnings management for affected firms (i.e., headquartered within 100 miles of these events).

On the other hand, under the rent-extraction perspective, rational managers have strong incentives to engage in rent-extracting activities for their private benefits. Large-scale events have the potential to shift attention away from firm-specific and global news. For example, Luca, Malhotra, and Poliquin (2020) find that terrorist attacks evoke large policy responses. A single mass shooting leads to a 15% increase in the number of firearm bills introduced within a state in the year after the mass shooting and the focus of the media shifts to gun-related shootings after these events. To the extent that these events distract market participants, managers will have greater leeway to maximize their private benefits by engaging in rent-extracting efforts.

There are reasons to expect rent-extracting managers to engage in more earnings management. Rent-extracting managers will try to maximize their compensation, and compensation provides managers an incentive to increase earnings management (Shleifer & Vishny, 1989). Bonus- or equity-based incentives that depend on firm performance provide executives the incentive to manipulate reported earnings to increase pay (Bergstresser & Philippon, 2006; Ibrahim & Lloyd, 2011). Salary also provides an incentive for earnings manipulation, because salary is positively associated with past performance and poor performance is associated with higher executive termination (Dikolli et al., 2014). Because repeatedly underperforming expectations is likely to undermine the rent-extraction efforts (e.g., maximizing compensation), one expects rent-extracting managers to use income-increasing earnings management to avoid the adverse consequences of missing market expectations. Therefore, I posit that managers may act rationally and not allow pessimism induced by the salience of terrorist attacks to distract their rent-extraction efforts. The above discussion yields the following hypothesis:

> **[H2] Hypothesis 2 – Rent Extraction:** Terrorist attacks lead to an increase in accrual-based and real earnings management for affected firms (i.e., headquartered within 100 miles of these events).

Finally, it is plausible that even though managers act rationally and do not let the salience of terrorist attacks affect their decision-making, this may not lead to an increase in earnings management activities. Cuculiza et al. (2021) find that analysts who are local to terrorist attacks issue more pessimistic forecasts and Chen et al. (2021) show that firms located in the metropolitan areas by terrorist attacks issue more negatively biased earnings forecasts. Thus, managers may not even need to manage earnings upward because earnings expectations may have been lowered.

3. RESEARCH DESIGN

3.1. Data Sources

I collect information on terrorist attacks that happened in the U.S. I obtain terrorist attacks data from the Global Terrorism Database (GTD),[5] an open-source database at the University of Maryland that contains comprehensive data on global terrorism. I obtain mass shootings data from the database created by Follman, Aronsen, and Pan (2022) and released by the American magazine Mother Jones.[6] From these two databases, I collect the location of the event and the number of fatalities and injured victims. Following the prior literature using similar events (e.g., Chen et al.,

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[5] Available at: https://www.start.umd.edu/research-projects/global-terrorism-database-gtd.

[6] Follman et al. (2022) define mass shootings as indiscriminate rampages in public places resulting in four or more victims being killed by the attacker. They exclude shootings stemming from more conventionally motivated crimes such as armed robbery or gang violence. They also exclude shootings in which the perpetrators have not been identified.

2021; Kuang et al., 2022; Wang & Young, 2020), I exclude the September 11 attacks from my sample because they have nationwide implications.

Table 1 reports the descriptive statistics of terrorist attacks. The dataset includes 716 events between 2000 and 2020. Forty-six U.S. states were affected by at least one terrorist attack. The average number of total victims is six, while the average number of fatalities is two. The maximum number of fatalities in an event included in my sample is 60.

Next, I use Compustat, EDGAR, Audit Analytics and the Center for Research in Security Prices (CRSP) to gather firm-level information. I obtain firm-level accounting information and firm location from Compustat. Compustat provides each firm's headquarters' zip code, county, and state. In the Compustat database, a firm's headquarters' state is the current record. This means once a firm relocates (or updates its state of incorporate), all historical observations are updated and no longer record historical state information. I collect the historical headquarters location from the header section of 10-K/Qs (and all variants) filed on EDGAR.[7] I exclude firms without headquarters information from the analysis. I collect information on current auditors from Audit Analytics. The stock prices are obtained from the CRSP. Last, I collect each U.S. state's annual unemployment rate and GDP from the Federal Reserve Bank of St. Louis website.[8]

3.2. Accrual-Based Earnings Management

I rely on a cross-sectional model of discretionary abnormal accruals as my main proxy for accrual-based earnings management (Dechow et al., 2010; DeFond, 2010). Jones, Krishnan, and Melendrez (2008) compare ten measures of earnings management to assess whether these models detect actual cases of fraudulent earnings. They find that estimation errors from the Dechow and

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[7] https://sraf.nd.edu/data/augmented-10-x-header-data/
[8] https://fred.stlouisfed.org/

Dichev (2002) and related McNichols (2002) models consistently exhibit the largest association with both the existence and the magnitude of the fraud, making abnormal accrual models a suitable proxy for earnings management metrics.[9]

Jones (1991) models accruals as a function of fundamental firm attributes, measured by sales growth and gross property, plant, and equipment (PP&E). To increase the test power of the Jones model, Dechow, Sloan, and Sweeney (1995) modify it by adjusting for growth in credit sales, because credit sales are frequently manipulated. I use the Modified Jones model (Dechow et al., 1995) and estimate the following model for each year and each industry, requiring at least ten observations per industry.[10]

$$TAC_{i,t} = \beta_0 + \beta_1\left(1/AT_{i,t-1}\right) + \beta_2\left(\Delta REV_{i,t} - \Delta RECT_{i,t}\right)/AT_{i,t-1} + \frac{\beta_3 PPE_{i,t}}{AT_{i,t-1}} + \mu_{i,t} \tag{a}$$

TAC is the total accruals scaled by lagged total assets, and total accruals are calculated as the net income minus cash flow from operations, scaled by lagged total assets. AT is the total assets; ΔREV is the change in net revenues scaled by lagged total assets; ΔRECT is the change in accounts receivable scaled by lagged total assets; and PPE is property, plant, and equipment, scaled by lagged total assets. The subscripts *i* and *t* indicate firm *i* in year *t*. For each industry in each year, I conduct regression (a) and obtain the residuals, which are measures for discretionary abnormal accruals. *DA_JONES* is the signed discretionary abnormal accruals obtained from this regression.

[9] These measures also perform comparatively well in measuring financial reporting quality. A higher level of earnings management would indicate lower financial reporting quality.
[10] My results are robust to alternative discretionary accrual measures.

3.3. Real Earnings Management

I measure real earnings management using abnormal discretionary expenses, abnormal production costs, and abnormal operating cash flow (Cohen & Zarowin, 2010; Garel et al., 2021; Roychowdhury, 2006). I conceptualize real earnings management in three steps.

First, I estimate abnormal discretionary expenses as follows:

$$\frac{DISEXP_{i,t}}{AT_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{Sale_{i,t}}{AT_{i,t-1}} + \varepsilon_{i,t} \qquad \text{(b)}$$

Discretionary expenditures, *DISEXP*, is the sum of R&D, advertising and selling, general, and administrative expenses. I set missing R&D expenditures, advertising and selling, general, and administrative expenses to be zero. *AT* is the firm's total assets, *SALES* is the firm's sales revenue, and ε is the error term.

I estimate Equation (b) for each two-digit SIC code industry in each year and require each industry-year to have at least 20 observations. I define abnormal discretionary expenses, *ABDISX*, as the residuals from the regressions. Managers have the discretion to cut R&D, advertising and selling, general, and administrative expenses to increase reported earnings. Lower values of *ABDISX* indicate more income-increasing real earnings management. I multiply it by minus one so that higher values indicate more income-increasing real earnings management.

I estimate abnormal production costs as follows:

$$\frac{PROD_{i,t}}{AT_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{Sale_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{\Delta Sale_{i,t}}{AT_{i,t-1}} + \beta_4 \frac{\Delta Sale_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{i,t} \qquad \text{(c)}$$

Production costs, *PROD* is the sum of the cost of the goods sold and the change in inventory from year t-1 to year t. I conduct the same industry-year regressions and define abnormal production costs, *ABPROD*, as the regression residuals from the industry-year regressions.

Overproduction refers to producing more goods than necessary to increase earnings. Higher values of *ABPROD* indicate more income-increasing real earnings management.

Last, I estimate abnormal operating cash flow as follows:

$$\frac{CFO_{i,t}}{AT_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{Sale_{i,t}}{AT_{i,t-1}} + \beta_3 \frac{\Delta Sale_{i,t}}{AT_{i,t-1}} + \varepsilon_{i,t} \quad \text{(d)}$$

CFO is the firm's operating cash flow. All other variables are defined previously. I conduct the same industry-year regressions and define abnormal operating cash flow, *ABCFO,* as the residuals from these regressions. *ABCFO* captures sales manipulation, reflecting managers' attempts to increase sales during the year by offering discounts or more lenient credit terms. Lower values indicate more income-increasing real earnings management. I multiply it by negative one so that higher values indicate more income-increasing real earnings management.

To capture the aggregate effects of real earnings management, I follow the prior literature (e.g., Garel et al., 2021; Roychowdhury, 2006) and combine the three individual measures as follows: *REM = Abnormal Production Costs + Abnormal Discretionary Expenses + Abnormal Operating Cash Flow.*

3.4. Independent Variables

The main variable of this study is focused on terrorist attacks. This variable varies with time and location but remains consistent across different firms. Specifically, I create the following variable: $LOG\_VICTIMS_{s,t} = \log\left(1 + \sum_{t-1}^{t} VICTIMS_{s,t}\right)$, where *VICTIMS* is the total number of victims caused by terrorist attacks for location *s*, in year *t*. I calculate this variable as a rolling sum because back-to-back events are likely to increase the saliency of these events. The availability heuristics occurs when an individual judges the likelihood of an event based on how easily similar events can be recalled. Back-to-back events are more easily recalled, thereby increasing their saliency. Lastly, PTSD symptoms usually begin within three months of the traumatic incident

(American Psychiatric Association, 2013) and it will take some time to observe the impact of traumatic events on managers. Thus, the current year's information by itself may not be enough to capture the psychological effects.[11]

Second, I measure annual bid-ask spread as a proxy for information asymmetry. Bid-ask spread is commonly used in the literature as a proxy for firm information asymmetry (e.g., Flannery et al., 2004; Oz, 2020). When information asymmetry among market participants is high, informed traders can exploit their informational advantage at the expense of uninformed traders. Trading costs increase with the degree of information asymmetry between the uninformed and informed investors. This will result in a wider bid-ask spread (Kyle, 1985). I calculate the daily value of the bid-ask spread in the following manner:

$$SPREAD_{i,d} = \frac{Ask_{i,d} - Bid_{i,t}}{Midpoint_{i,t}} \qquad \text{(e)}$$

I define *Bid* and *Ask* as the bid and ask prices of firm, *i* on day, *d*, respectively. *Midpoint* is the midpoint of the bid and ask prices of firm *i* on day *d*. Once I have the daily values, I calculate the yearly average of the spread measure for each firm.

[11] The results remain consistent even when I use the number of events, instead of the number of victims. However, I note that the total number of victims serves as a more suitable proxy for capturing the saliency of terrorist attacks. These events tend to garner more attention when there are a higher number of victims involved. Attacks with fewer victims might not generate the same psychological impact on managers. In support of this notion, Kaufman et al. (2020) suggest that the public relies on media coverage to gather information on violent incidents, and incidents with multiple victims receive greater media attention.

I include two measures to capture the negative and positive sentiment of annual reports (i.e., 10-Ks). I use the negative and positive word lists created by Loughran and McDonald (2011). Their word lists have been widely used in both the accounting and finance literatures to measure sentiment in financial documents, newspaper articles, analyst reports, and even earnings conference call transcripts (Kearney & Liu, 2014; Loughran & McDonald, 2015). The most-used negative words in annual reports are "loss, losses, claims, impairment, against, adverse, and restated," while the positive words are "achieve, profitable, overturn." I define $NEGATIVE\_SENT_{i,t}$ ($POSITIVE\_SENT_{i,t}$) as the number of Loughran-McDonald financial negative (positive) words in the document divided by the total number of words in the document that occur in the master dictionary for firm *i* in year *t*.[12]

Following Biddle, Hilary, and Verdi (2009), I calculate investment, *INVESTMENT*, as the sum of research and development expenditure, capital expenditure, and acquisition expenditure less cash receipts from sale of property, plant, and equipment, scaled by total assets. Finally, I create two dummy variables to capture firms' incentives to engage in earnings management (Gunny, 2010; Haga et al., 2019). *BENCH_A* (*BENCH_B*) takes the value of one if ROA (the change in net income scaled by total assets) is in the semi open interval [0, 0.01).

3.5. Control Variables

I include a wide array of control variables to control for firm characteristics. Since large firms have been found to have less earnings management in prior research (Ge & Kim, 2014), I control for firm size by including *SIZE,* calculated as the natural logarithm of the total assets. Prior studies reveal that firm performance is associated with earnings management (Brown, 2015; Call et al., 2014). To control for the influence of firm performance, I include return on assets (*ROA*). Some

[12] Please see Loughran and McDonald (2011) for the master dictionary.

previous studies indicate that firms with a net loss are more likely to "take a big bath" and less likely to manage earnings (Boone et al., 2012). I create a loss indicator variable, *LOSS*, taking the value of 1 if a firm has a net loss.

According to prior literature (Boone et al., 2012; Dutillieux et al., 2016; Jha, 2013), debt covenants provide firms with more debt incentives for earnings management. I include firm leverage (*LEV*), calculated as total short-term and long-term debt as a percentage of total assets, to control for firm performance and debt holdings (Francis et al., 2008). Prior research suggests that high-growth firms are more likely to manage earnings upward (Park & Shin, 2004). Thus, I include the book-to-market ratio (*BTM*) and operating cash flows, scaled by total sales (*CFO_SALE*).

To control for firm growth, investment opportunities, volatility in firm operations, and firm risk, I include the standard deviation of operating cash flows over the previous five years (*STD_CFO*), the standard deviation of sales over the previous five years (*STD_SALE*), and the standard deviation of monthly returns over the previous 60 months (*STD_RET*). To control for the implication of a firm's dividend policy (e.g., He et al., 2017), I include an indicator variable, *DIV_DUMMY*, that takes the value of one if the firm paid a dividend. I also include an indicator variable for Big 4 audit companies, *BIG4*, to control for the impact of audit quality on earnings management activities. Finally, to ensure that the results are not driven by macroeconomic conditions in each state, I include the natural logarithm of the unemployment rate and GDP for state *s*, in year *t*, denoted as $LOG\_UNEMP_{s,t}$ and $LOG\_GDP_{s,t}$, respectively.

3.6. Sample Construction and Descriptive Statistics

My sample begins with all firm-years available in the Compustat universe for the period from 2000 through 2020. I eliminate utilities and financial firms (SIC codes 4900-4999, and 6000-6900) because these industries are heavily regulated. I require firms to have all necessary information to calculate discretionary accrual measures and firm characteristics (e.g., sales, total assets, receivables, BIG4) and require a U.S. state to have at least five firms headquartered in the state to be included in the sample.

To merge firm characteristics with terrorist attacks, I collapse these events into yearly frequency by calculating the yearly total for each affected firm. I use the geographical distance between a firm's historical headquarters and the locations of attacks to determine affected firms. Specifically, I classify a firm as affected if it is located within 100 miles of the city where the attack happened. Following the merger, the final sample has 47,434 yearly observations pertaining to 5,645 unique firms and 716 terrorist attacks. There are 47 U.S. states included in the final sample. Table 2 presents the distribution of firms and attacks by state. The total number of firms reported in Table 2 is greater than 5,645 because some firms have changed their headquarters location. In such cases, I count these firms again in their new headquarters state. The states most heavily represented by firms are California, Texas, New York, Massachusetts, Florida, and New Jersey. The states of California, Texas, New York, Florida, and Washington have the greatest numbers of attacks reported.

Table 3 shows the descriptive statistics for the dependent, interest, and control variables used in my analyses. All continuous firm-specific variables are winsorized at the top and bottom 1 percent of distributions. *DA_JONES* has a mean (median) value of 0.0015 (0.01). The mean values of *ABCFO*, *ABPROD* and *ABDISX* are -0.0039, -0.0036 and 0.0027, respectively. The mean (median) log of total assets (*SIZE*) is 6.1 (6.08), while the mean (median) return on assets (*ROA*) is -0.0495 (0.0286). The mean (median) book-to-market ratio (*BTM*) is 0.53, implying that my sample firms trade at a premium above book value. The descriptive statistics reported are consistent with the prior literature (Griffin et al., 2021; Guay et al., 2016).

Table 4 provides the Spearman correlations among this study's variables. Firm size (*SIZE*) is negatively correlated with discretionary accruals and positively correlated with the real earnings management measure, suggesting larger firms engage in less accrual-based earnings management but more real earnings management. Growth and profitable firms engage in higher levels of earnings management, as discretionary accruals are positively correlated with market-to-book ratio (*BTM*) and return on assets (*ROA*). I find that the state unemployment rate (LOG_UNEMP) is negatively correlated with *DA_JONES*, suggesting that as macroeconomic state conditions deteriorate, firms engage in less earnings management. I report that the state GDP (LOG_GDP) is negatively correlated with *DA_JONES.* Finally, I report that *LOG_VICTIMS* is negatively correlated with *DA_JONES* and *REM*. These results are consistent with the availability heuristics hypothesis.

3.7. Empirical Model

I test my hypotheses by estimating the following ordinary least squares (OLS) regression model:

$$DA\_JONES_{i,s,t} \text{ or } REM_{i,s,t}$$

$$= \alpha + \beta_1 \, LOG\_VICTIMS_{s,t} + \gamma Control_{i,s,t} + Fixed\ Effects + \varepsilon_{ijt}$$

Equation (1)

The dependent variable, *DA_JONES*, represents the signed discretionary accrual measure and captures the accrual-based earnings management. *REM* represents the real earnings management based on abnormal production costs, abnormal cash flows, and abnormal discretionary expenses. I discuss the formation of the dependent variables in Sections 3.2 and 3.3. Subscripts *i*, *s* and *t* represent firm, state, and year, respectively.

Earnings management may be affected by unobservable variables that systematically vary across firms and time in my panel. I include an extensive list of control variables to control for such variation. I include the following variables as control variables: the natural logarithm of the total assets (*SIZE*), book-to-market ratio (*BTM*), firm leverage (*LEV*), return on assets (*ROA*), operating cash flows (*CFO_SALE*), the volatility in operating cash flows, sales, and returns (*STD_CFO*, *STD_SALE*, *STD_RET*, respectively), loss, dividend and Big 4 audit company indicators (*LOSS*, *DIV_DUMMY*, *BIG4*, respectively). Finally, I include the natural logarithm of the state unemployment rate (LOG_UNEMP) and the natural logarithm of the state GDP (LOG_GDP). I explain the reasons for including these control variables and their formation in detail in Section 3.5.

In each OLS regression, I include state and industry (two-digit SIC industry classification level) fixed effects to control for temporal patterns and potential omitted variables and year fixed effect to remove unobserved heterogeneity across time. To account for situations where observations within each firm are not independently and identically distributed, I cluster standard errors by firm.

4. EMPIRICAL RESULTS

4.1. Terrorist Attacks and Earnings Management

My first hypothesis, the availability heuristics argument, predicts a negative association between the magnitude of earnings management and primary interest variables, while my second hypothesis, the rent-extraction argument, predicts a positive association among these variables.

Table 5 presents the estimates of Equation (1). Models (1) and (2) report the results relating to *DA_MJONES* and *REM* as dependent variables, respectively. I find significantly negative coefficients on *LOG_VICTIMS* (significant at the 5% level, at least). The results confirm that firms located within 100 miles of terrorist attacks with higher number of victims experience a significant decrease in discretionary accruals and real earnings management. Model (1) reports a coefficient on the primary interest variable, *LOG_VICTIMS*, of (-0.0014), suggesting that a one standard deviation increase in *LOG_VICTIMS* (1.1365) causes a decrease in income-increasing discretionary accruals equal to 0.16 percent of total assets. Model (2) reports a coefficient on the primary interest variable of (-0.0076), suggesting that a one standard deviation increase in *LOG_VICTIMS* causes a decrease in real earnings management equal to 0.86 percent of total assets.

Eilifsen and Messier (2015) indicate that for most firms, the materiality threshold is between 0.5 and 1.5 percent of total assets. Firms are less likely to engage in earnings management when they are concerned about getting flagged by auditors. Therefore, the magnitude of earnings management I observe is plausible because it falls below the materiality thresholds used by audit firms. I note that auditors tend to be more concerned about accrual-based earnings management and perceive real earnings management as strategic decisions rather than auditory concerns. For instance, Commerford, Hermanson, Houston and Peters (2019) suggest that for auditors, real earnings management appears to be primarily a "people" issue and does not pose a significant audit risk. However, Pacheco-Paredes and Wheatley (2021) note that auditors react to real earnings management. Specifically, audit report lags have been shown to be positively associated with real earnings management. Thus, the economic magnitude of my results remains important for both types of earnings management.

The results in Table 5 support the availability heuristics argument that firms manage earnings less in the face of these attacks. I do not find evidence supporting the rent-extraction argument around terrorist attacks. Models 1 and 2 reveal that the impact of these attacks on accrual-based earnings management and real earnings management is qualitatively similar. Table 5 also shows that the control variables are generally significant, with the expected coefficient signs and consistent with previous studies, as discussed in Section 3.5. As the results on control variables are relatively similar across all models reported in this paper, I do not report them in the remainder of the paper, unless I present a new model.

Second, I explore the impact of terrorist attacks on individual components of real earnings management. Models 1 to 3 of Table 6 report the results relating to *ABPROD*, *ABDISX*, and *ABCFO*, respectively.[13] Model 1 with *ABPROD* as the dependent variable shows that abnormal production costs are negatively associated with *LOG_VICTIMS* ($\beta_1 = -0.0028$), significant at the 1% level. This suggests that firms located near attacks with a higher number of victims reduce their real earnings management through lower abnormal production costs. Model 2 with *ABDISX* as the dependent variable reveals the coefficient on *LOG_VICTIMS* ($\beta_1 = -0.0044$) to be significantly negative. This indicates a second channel of real earnings management and shows that affected firms reduce their real earnings management via abnormal discretionary expenses

[13] Higher values of ABPROD, ABDISX and ABCFO indicate more income-increasing real earnings management. Please see Section 3.3. for the construction of these variables.

(e.g., advertising, R&D, and SG&A expenses). Finally, Model 3 with *ABCFO* as the dependent variable reveals insignificant results. I find no evidence that affected firms manipulate abnormal cash flows from operations.

4.2. Information Asymmetry and Annual Report Sentiment

To shed light on how terrorist attacks affect earnings management, I conduct cross-sectional analyses conditional on information asymmetry and annual report sentiment.

Previous research points to the existence of information asymmetry between management and investors. Richardson (2000) finds that there is a systematic, positive relationship between the levels of earnings management and information asymmetry. On the one hand, high levels of information asymmetry may make irregularities difficult to catch. If so, managers in firms with high levels of information asymmetry may not have any incentives to alter their behavior. Thus, the decrease in earnings management may be more pronounced for firms with low levels of information asymmetry. In contrast, firms characterized by higher levels of information asymmetry may incentivize their managers to reduce earnings management activities. This is due to the potentially elevated costs associated with earnings management in such firms. Elayan, Li, and Meyer (2008) have demonstrated that firms with greater information asymmetry tend to engage in more accounting irregularities, including restatements. These restatements, in turn, are associated with higher costs of capital and increased required rates of return for investors (Hribar & Jenkins, 2004). Moreover, higher information asymmetry is linked to elevated audit fees, indicating a rise in audit compensation (Frino et al., 2022). Consequently, the impact of earnings management reduction in response to terrorist attacks will likely be more prominent in firms characterized by greater information asymmetry. This can be attributed to the fact that managers in these firms may possess a heightened awareness of the risks associated with earnings management.

Next, I investigate the role of annual report sentiment in the association between terrorist attacks and earnings management. The literature suggests that 10-K reports contain useful information about future firm performance (You & Zhang, 2009), and the sentiment reported in annual reports can be an indication of financial distress (Gandhi et al., 2019). To the extent that annual report sentiment captures managers' risk assessment, I expect firms with pessimistic annual reports to overestimate earnings management costs. I conjecture that my main results are more prominent when managers exhibit pessimism in 10-K filings.

To conduct these analyses, I split my sample into two based on the information asymmetry or annual report sentiment. First, I use *SPREAD* as my proxy for information asymmetry. Firms that are above (below) the yearly average of *SPREAD* are in the high (low) information asymmetry sub-sample. Second, I split my sample into two sub-samples based on firm sentiment, proxied by $NEGATIVE\_SENT$ and $POSITIVE\_SENT$. These measures capture the number of Loughran-McDonald financial negative and positive words, respectively. Firms that are in the top two-thirds and bottom third of *NEGATIVE_SENT (POSITIVE_SENT)* and *POSITIVE_SENT (NEGATIVE_SENT)*, respectively are in the pessimistic (optimistic) annual report sub-sample.

I report my findings in Table 7. Models 1 and 2 in Panel A of Table 7 show results relating to accrual-based earnings management and information asymmetry. The results show that firms with low levels of information asymmetry do not exhibit a significant change in the magnitude of their accrual-based earnings management when faced with terrorist attacks. On the other hand, I find significant results for the sub-sample of high levels of information asymmetry. The estimate on the primary interest variable is significant at the 1% level and consistent with prior findings. The coefficients on *LOG_VICTIMS* reported in Models 1 and 2 are statistically different from each other (*t*-val = 1.76).

Models 3 and 4 in Panel A of Table 7 show results relating to real earnings management and information asymmetry. I report that the association between *LOG_VICTIMS* and real earnings management remains significantly negative across the two sub-samples, while I do not find significant differences between these sub-samples. The overall results are consistent with my primary findings. However, the findings in Panel A suggest that information asymmetry is a channel that explains the variation in accrual-based earnings management, but not necessarily real earnings management.

Next, I discuss my findings about annual report sentiment. Panel B of Table 7 shows results relating to the annual report sentiment. The results reveal that firms that use pessimistic language in their 10-K filings are the ones that decrease the magnitude of their earnings management when faced with terrorist attacks. For instance, Model (7) shows that the estimate on *LOG_VICTIMS* is negative and significant at the 5% level. On the other hand, I do not report significant results for the sub-sample of firms that use optimistic language in their 10-K filings. The coefficients on *LOG_VICTIMS* reported in Models 5 and 6, and Models 7 and 8 are statistically different from each other (*t*-val = 1.71 and *t*-val = 1.65, respectively).

The results in Table 7 corroborate the evidence that terrorist attacks decrease the magnitude of earnings management. The results suggest that information asymmetry levels and pessimism in annual reports are two channels explaining the decrease in earnings management activities.

4.3. Alternative Explanations

There are alternative explanations, such as increasing firms' profitability, investment opportunities, or opportunistic behavior that may drive firms' incentives for earnings management.

I conduct various tests to assess these alternative explanations.[14] I report my findings in Tables 8 and 9, where the dependent variables are *DA_MJONES* and *REM*, respectively.

First, I re-estimate my baseline regression by additionally controlling for future profitability. Following the design of Gao, Zhang and Zhang (2018), I include the current *ROA*, *ROA*s for the future two years, and the interaction term between the current ROA and my interest variable (i.e., *LOG_VICTIMS*). By doing so, I mitigate the concern that the estimated effect of terrorist attacks on earnings management is explained by expected changes in future profitability. My results are reported in Model (1) of Tables 8 and 9. The coefficient on *LOG_VICTIMS* remains significant at the 5% level and is consistent with my primary findings reported earlier. Model (1) of Table 8 reports that the interaction variable between current *ROA* and *LOG_VICTIMS* is significantly negative, while the coefficient is insignificant in Model (1) of Table 9. These results suggest that the impact of *LOG_VICTIMS* on accrual-based or real earnings management cannot be explained by increasing profitability.

Second, I investigate whether increasing investment opportunities play a role in explaining my primary findings. I measure firm's overinvestment as the following: $OVERINVESTMENT = INVESTMENT_{i,sic2,t} - \overline{INVESTMENT_{sic2,t}}$. Subscripts *i*, *sic2*, and *t* represent firm, 2-digit SIC industry and year, respectively. $\overline{INVESTMENT_{sic2,t}}$ represents the yearly average of INVESTMENT for a 2-digit SIC industry. A positive (negative) number would indicate that a firm is overinvesting (underinvesting) compared to its peers in the 2-digit SIC industry in the same year. On the one hand, overinvestment may be positively associated with earnings management because earnings management can be used opportunistically to influence the perception of investments (Chen et al., 2010; Raman & Shahrur, 2008). On the other hand, firms may be overinvesting

[14] The number of observations in these tests is slightly lower due to data availability.

because they are expecting current and future benefits (e.g., positive cash flows), which would reduce the need to engage in earnings management.

I present my results in Model (2) of Tables 8 and 9. In Table 8, I find a significantly positive coefficient on *OVERINVESTMENT*, significant at the 1% level. On the other hand, in Table 9, the coefficient on *OVERINVESTMENT* becomes significantly negative. These results suggest that firms increase accrual-based earnings management when overinvesting, plausibly to create a positive perception about their investments. However, I find a negative association between real earnings management and *OVERINVESTMENT*. Prior research shows that managers choose between accruals-based and real earnings management depending on their relative benefits and costs. Even if managers engage in accruals manipulation, they may engage in real activities manipulation less, because real earnings management will probably decrease future cash flows (Di Meo et al., 2017). Both models reveal insignificant estimates on the interaction variables. Most importantly, the estimates on *LOG_VICTIMS* remain consistent with the remainder of my paper, suggesting that overinvestment is not an alternative explanation.

Last, I examine the role of opportunistic behavior of managers in explaining my results. Gunny (2010) shows a positive association between opportunistic behavior of managers (i.e., incentives to meet or beat earnings benchmarks) and earnings management activities. Specifically, she shows that real earnings management is positively associated with firms just meeting earnings benchmarks and argues that her evidence is consistent with the firm attaining current-period benefits that allow the firm to perform better in the future. Haga et al. (2019) show that long-term oriented cultures rely less on real earnings management to meet or beat earnings benchmarks. Their results suggest corporate cultures may play a role in explaining incentives for earnings management. Taken together, the primary interest variable in this paper (*LOG_VICTIMS*) may be an imperfect proxy for managerial incentives.

Roychowdhury (2006) suggests that usage of incentives is crucial when capturing the actual effect of earnings management. Analyzing earnings management without using an incentive setting may cause ambiguous results because it may capture both opportunistic and prudent business decisions. I use *BENCH_A* and *BENCH_B* to capture managerial incentives to meet or beat earnings benchmarks and present my results in Models (3) and (4) of Tables 8 and 9. All the models reveal that the estimates on *BENCH_A* and *BENCH_B*[15] are positively (significant at the 1% level) associated with accrual-based and real earnings management. These results are consistent with those reported in Gunny (2010). In both models, *LOG_VICTIMS* remains significantly negative, consistent with my main results. Finally, I report that the interaction variables remain mostly insignificant.

The analyses in Tables 8 and 9 suggest that the effect of terrorist attacks on earnings management activities cannot be explained by future profitability, overinvestment activities, or managerial incentives. I continue to find a negative association between *LOG_VICTIMS* and earnings management metrics even after controlling for alternative explanations.

4.4. Financial Statement Readability

The main argument of this paper is that terrorist attacks lead managers to overweigh the possibility of unrelated negative outcomes. This, in turn, leads to a pessimistic assessment of earnings management risk. My results support this argument. This section explores whether terrorist attacks lead to a more complex narrative disclosure. Because managers overweigh the

[15] Section 3.4 explains the formation of these variables.

possibility of unrelated negative outcomes, they may prefer to obfuscate plausible bad news or their pessimism via the narrative disclosures in 10-K reports.

10-K annual reports are the primary source of company information for capital market participants and policymakers. Hence, stakeholders are highly reliant on narrative disclosures to understand and interpret basic accounting and financial data in 10-K reports. However, it is the extent of the readability of the narrative disclosures that gives these documents the credibility and importance for conveying vital information to market participants in an effective way (Loughran & Mcdonald, 2014). Prior research finds that managers attempt to distort information through complex readability disclosure in order to obfuscate firms' actual performance: they tend to issue less-readable disclosure, which considerably increases information asymmetry (Chakrabarty et al., 2018). Managers may also use complex narrative disclosure in an impression management strategy (Ben-Amar & Belgacem, 2018).

I use the Gunning Fog Index (*FOG*) and the Automated Readability Index (*ARI*) to measure readability. Both variables have been used widely and have seen increasing usage in the accounting literature (Guay et al., 2016; Lo et al., 2017; Miller, 2010; Rennekamp, 2012). A higher *FOG* or *ARI* implies a less-readable document. The Fog Index and Automated Readability Index are computed as follows:

$$FOG = 0.4 \times (number\ of\ words/number\ of\ sentences) + 40 \times (number\ of\ words\ with\ more\ than\ two\ syllables/number\ of\ words) \quad \text{(f)}$$

$$ARI = 4.71 \times (number\ of\ characters/number\ of\ words) + 0.5 \times (number\ of\ words\ /number\ of\ sentences) \quad \text{(g)}$$

I repeat my main analysis by using *FOG* or *ARI* as the dependent variable instead of earnings management measures. I report my results in Table 10. I find that *LOG_VICTIMS* is positively associated with *FOG* and *ARI* (significant at the 5% level, at least), suggesting that firms affected by terrorist attacks produce less-readable annual reports.

Prior research shows that companies with high variability and low readability will be associated with "bad news" and high levels of press coverage (Courtis, 1998), and managers are more forthcoming in the disclosure of information when their respective firms are performing well (Li, 2008). My results support these findings and suggest that firms with managers affected by traumatic events are likely to obfuscate their pessimistic assessments.

4.5. Robustness Tests

In this section, I conduct four robustness tests. First, I calculate the percentile rank of absolute values of *DA_MJONES* and *REM*. Specifically, *MJONES_RANK* (*REM_RANK)* takes a value of 1 (lowest) to 4 (highest), depending on the absolute value of *DA_MJONES* (*REM*) ranking within a year. To control for the potential inverse relationship between two types of earnings management, I include *MJONES_RANK* (*REM_RANK)* as an additional control variable when I use *REM* (*DA_MJONES*) as the dependent variable. Second, I limit my sample period to the post-2010 period. Cohen, Dey and Lys (2008) find that after the passage of SOX, while accrual-based earnings management declined, real earnings management increased, suggesting that firms switched from accrual-based to real earnings management methods after the passage of SOX. Further, in 2007, the subprime mortgage market's collapse led to a severe global financial crisis. The financial crisis of 2007–2009 was followed by several regulatory changes (e.g., SFAS 166/167, Dodd–Frank Act) and changed the face of several industries (Oz, 2020). These two events led to significant regulatory changes, which might create confounding events for my sample. For these two primary reasons, I conduct a robustness test by creating a sub-sample and focusing on the post-2010 period.

Panel A of Table 11 presents my results relating to the percentile ranking of earnings management, while Panel B of Table 11 presents my results for the post-2010 period. The results remain qualitatively similar to those reported in Table 5. I note that the association between *LOG_VICTIMS* and *DA_MJONES* becomes weaker (significant at the 10% level). This is consistent with the prior literature (e.g., Cohen et al, 2008) noting that post-SOX, there was a decline in accrual-based earnings management. Overall, I conclude that regulatory changes during my primary sample period or the reversal nature of accrual-based earnings management are unlikely to explain my findings.

Third, I conduct a matched sample analysis. Firms with *LOG_VICTIMS* greater than zero but lower than one in a year form the control sample, and firms with *LOG_VICTIMS* greater or equal to one create the treatment sample. Then, I match one treatment firm with three control firms by *SIZE, STD_RET*, *BTM*, and industry for each fiscal year. Using the matched samples, I re-estimate Equation (1). The matched sample analysis allows me to hold firm characteristics constant, and finding results would give more confidence in attributing my results to terrorist attacks. I present the results of the matched sample analysis in Table 12. The results remain consistent with those reported in the earlier analyses.

Finally, I create a model-free measure of earnings management to check the robustness of my results. I define *NEGATIVE_SPI* as an indicator variable that takes the value of one if the firm records negative special items in the year and zero otherwise. Table 13 reports the OLS regression results, where the dependent variable is *NEGATIVE_SPI*. The coefficient on *LOG_VICTIMS* is significantly positive. This suggests that the odds of negative special items are increased by the number of total victims.

5. CONCLUSION

This study examines whether salient events lead managers to overestimate the costs of earnings management and consequently lead to a change in income-increasing earnings management. I use terrorist attacks and mass shootings (terrorist attacks) across the U.S. as salient events and provide plausibly causal evidence that firms headquartered in affected regions experience a decrease in the magnitude of accrual-based and real earnings management. These effects are mainly driven by firms with high information asymmetry and pessimistic annual reports. The results suggest that salient events lead managers to overestimate the costs of earnings management, which eventually reduces the magnitude of earnings management. Overall, my evidence points to a cognitive bias, the use of availability heuristics, influencing financial reporting decisions.

I conduct additional analyses to rule out future profitability, investment opportunities, and managers' opportunistic behavior as alternative explanations. Further, I explore the annual reports' readability of firms affected by terrorist attacks. My results show that affected firms produce less-readable annual reports. A decrease in readability suggests that affected firms are likely to obfuscate their pessimistic assessments. Finally, I show that my results hold even when I control for the inverse relationship between earnings management types, focus on the post-2010 period, conduct a matched sample analysis and use the reporting of negative special items as a binary dependent variable.

To the best of my knowledge, this is the first paper examining the role of availability heuristics in earnings management. My study contributes to the literature by identifying the role of terrorist attacks in earnings management activities. Given the large and increasing diversity of risks that must be assessed daily by firms' decision-makers, my results suggest that the role of this bias in corporate earnings manipulation could be considerable. My findings can help market participants to better interpret managers' incentives to engage in earnings management. To obtain a deeper understanding of reporting strategies, future research could consider the impact of these or similar events on financial restatements and how these events affect firms with significant financial reporting problems. Last, the rent-extraction argument in this paper implies that there may be a (temporary) reduction in media coverage of firms affected by terrorist attacks. I should note that this study does not empirically address this assumption. Future research may focus on expanding our understanding of firms' media coverage around significant events.

6. REFERENCES

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APPENDIX A. VARIABLE DEFINITIONS

(1)	**DA_MJONES**	Signed value of discretionary accruals determined using modified Jones model (Jones, 1991 and Dechow et al, 1995). Please see Section 3.2. for details.
(2)	**REM**	Real earnings management, calculated as the sum of Abnormal Production Costs + Abnormal Discretionary Expenses + Abnormal Operating Cash Flow.
(3)	**ABCFO**	Abnormal operating cash flow. Please see Section 3.3. for details.
(4)	**ABPROD**	Abnormal production costs. Please see Section 3.3. for details.
(5)	**ABDISX**	Abnormal discretionary expenses. Please see Section 3.3. for details.
(6)	**SIZE**	Firm size, calculated as the natural logarithm of the total assets.
(7)	**BTM**	Book-to-market ratio.
(8)	**LEV**	Firm leverage, calculated as total short-term and long-term debt as a percentage of total assets.
(9)	**ROA**	Return on assets.
(10)	**CFO_SALE**	Operating cash flow, scaled by total revenue.
(11)	**STD_CFO**	Standard deviation of operating cash flows over the previous five years.
(12)	**STD_SALE**	Standard deviation of sales over the previous five years.
(13)	**STD_RET**	Standard deviation of monthly returns over the previous 60 months.
(14)	**LOSS**	Loss indicator variable.
(15)	**DIV_DUMMY**	Dividend indicator variable.
(16)	**BIG4**	Indicator variable for Big 4 audit companies.
(17)	**NEGATIVE_SENT**	The number of Loughran-McDonald financial negative words in the document divided by the total number of words in the document that occur in the master dictionary.
(18)	**POSITIVE_SENT**	The number of Loughran-McDonald financial positive words in the document divided by the total number of words in the document that occur in the master dictionary.
(19)	**SPREAD**	Yearly average of spread, calculated as the difference between ask and bid prices, scaled by the midpoint.

(20)	**INVESTMENT**	The sum of research and development expenditure, capital expenditure, and acquisition expenditure less cash receipts from sale of property, plant, and equipment, scaled by total assets
(21)	**OVERINVESTMENT**	$OVERINVESTMENT = INVESTMENT_{i,sic2,t} - \overline{INVESTMENT_{sic2,t}}$. Subscripts *i*, *sic2*, and *t* represent firm, 2-digit SIC industry and year, respectively. $\overline{INVESTMENT_{sic2,t}}$ represents the yearly average of INVESTMENT for a 2-digit SIC industry.
(22)	**BENCH_A**	Indicator variables that take the value of one if ROA is in the semi open interval [0, 0.01), and zero otherwise.
(23)	**BENCH_B**	Indicator variables that take the value of one if the growth in net income scaled by total assets is in the semi open interval [0, 0.01), and zero otherwise.
(24)	**FOG Index**	The Gunning Fog Index, calculated as follows: $FOG = 0.4 \times (number\ of\ words/number\ of\ sentences) + 40 \times (number\ of\ words\ with\ more\ than\ two\ syllables/number\ of\ words)$
(25)	**ARI Index**	The Automated Readability Index, calculated as follows: $ARI = 4.71 \times (number\ of\ characters/number\ of\ words) + 0.5 \times (number\ of\ words\ /number\ of\ sentences)$
(26)	**EM_RANK**	MJONES_RANK (REM_RANK) takes a value of 1 (lowest) to 4 (highest), depending on the absolute value of DA_MJONES (REM) ranking within a year.
(27)	**NEGATIVE_SPI**	An indicator variable that takes the value of one if the firm records negative special items in the year.
(28)	**LOG_STATEGDP**	The natural logarithm of the state GDP.
(29)	**LOG_UNEMP**	The natural logarithm of the unemployment rate.
(30)	**LOG_VICTIMS**	The natural logarithm of the total number of victims caused by terrorist attacks and mass shootings (terrorist attacks).

TABLE 1. TERRORIST ATTACKS AND MASS SHOOTINGS

This table reports descriptive statistics regarding terrorist attacks and mass shootings (terrorist attacks).

Mass Shooting Events (2000 - 2020)								
Variable	**N**	**Min**	**25th Pctl**	**Mean**	**Median**	**75th Pctl**	**Max**	**Std Dev**
Fatalities		0	0	2	0	1	60	5
Injured		0	0	4	0	1	850	39
Total Victims		0	0	6	0	2	910	42
Number of Events	716							
Number of Unique States	46							
Number of Unique Cities	442							

TABLE 2. SAMPLE DISTRIBUTION

This table reports the number of unique firms, and terrorist attacks for each U.S. state included in this study.

Headquarter State	N of Unique Firms	N of Terrorist attacks
California	1,242	122
Texas	628	55
New York	481	55
Florida	293	55
Washington	131	54
Oregon	58	33
Pennsylvania	246	27
Illinois	243	23
Georgia	164	21
Colorado	199	20
Michigan	109	20
Massachusetts	389	19
Tennessee	77	19
District of Columbia	17	19
Virginia	155	18
Ohio	146	18
Arizona	93	18
Missouri	79	18
Wisconsin	75	18
Nevada	56	17
Maryland	112	16
Indiana	63	16
North Carolina	119	14
New Mexico	5	14
Minnesota	166	13
New Jersey	274	12
Utah	62	11
Nebraska	19	11
Iowa	23	10
South Carolina	23	10
Connecticut	125	7
Alabama	29	7
New Hampshire	23	7
Mississippi	9	7
Kansas	27	6
Arkansas	20	6
Kentucky	31	5
Delaware	22	5
Oklahoma	65	4
Idaho	17	4
Hawaii	8	2
Montana	5	2
Wyoming	5	2
South Dakota	4	2
Rhode Island	16	1
West Virginia	7	1
Maine	9	0

TABLE 3. DESCRIPTIVE STATISTICS

This table reports descriptive statistics of this study's main variables. All the variables are defined in Appendix A.

	N	25th Pctl	Mean	Median	75th Pctl	Std Dev
Dependent Variables						
DA_MJONES	47,434	-0.0341	0.0015	0.0100	0.0531	0.1564
REM	43,322	-0.1835	-0.0048	0.0263	0.2154	0.4206
ABCFO	43,322	-0.0702	-0.0039	-0.0112	0.0444	0.1443
ABPROD	43,322	-0.0894	-0.0036	0.0031	0.0908	0.1906
ABDISX	43,322	-0.0800	0.0027	0.0275	0.1421	0.2812
Firm-specific Independent Variables						
SIZE	47,434	4.5425	6.0995	6.0759	7.5756	2.1051
BTM	47,434	0.2274	0.5309	0.4295	0.7396	1.0327
LEV	47,434	0.0152	0.2316	0.1800	0.3518	0.2797
ROA	47,434	-0.0609	-0.0495	0.0286	0.0746	0.2988
CFO_SALE	47,434	0.0091	-1.0057	0.0776	0.1520	8.4027
STD_CFO	47,434	0.0272	0.0936	0.0485	0.0891	0.2846
STD_SALE	47,434	0.0664	0.1834	0.1225	0.2235	0.2170
STD_RET	47,434	0.0821	0.1487	0.1203	0.1803	0.1123
LOSS	47,434	0.0000	0.3711	0.0000	1.0000	0.4831
DIV_DUMMY	47,434	0.0000	0.3621	0.0000	1.0000	0.4806
BIG4	47,434	0.0000	0.7248	1.0000	1.0000	0.4466
NEGATIVE_SENT	42,903	0.0140	0.0171	0.0171	0.0201	0.0046
POSITIVE_SENT	42,903	0.0072	0.0084	0.0083	0.0095	0.0019
SPREAD	47,418	0.0009	0.0116	0.0028	0.0128	0.0221
INVESTMENT	47,349	0.0417	0.1408	0.0909	0.1820	0.1557
BENCH_A	47,434	0.0000	0.0378	0.0000	0.0000	0.1908
BENCH_B	47,434	0.0000	0.0956	0.0000	0.0000	0.2940
Location-specific Independent Variables						
LOG_STATEGDP	47,434	12.6482	13.2801	13.2411	14.1208	0.9202
LOG_UNEMP	47,434	1.5041	1.7378	1.7047	1.9601	0.3321
LOG_VICTIMS	47,434	0.0000	0.5590	0.0000	0.0000	1.1365

TABLE 4. CORRELATION TABLE

This table presents Spearman's correlation matrix. All the variables are defined in Appendix A.

	Variable Name	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	**DA_MJONES**	1.000															
(2)	**REM**	0.181	1.000														
(3)	**SIZE**	-0.051	0.056	1.000													
(4)	**BTM**	0.068	0.259	-0.071	1.000												
(5)	**LEV**	-0.076	0.154	0.384	-0.106	1.000											
(6)	**ROA**	0.252	-0.163	0.346	-0.123	-0.076	1.000										
(7)	**CFO_SALE**	-0.139	-0.243	0.447	-0.072	0.085	0.585	1.000									
(8)	**STD_CFO**	0.003	-0.082	-0.560	-0.083	-0.261	-0.292	-0.384	1.000								
(9)	**STD_REV**	-0.007	0.031	-0.287	0.040	-0.093	-0.055	-0.256	0.416	1.000							
(10)	**STD_RET**	-0.046	-0.003	-0.434	0.047	-0.041	-0.447	-0.352	0.408	0.205	1.000						
(11)	**LOSS**	-0.232	0.063	-0.360	0.025	0.001	-0.837	-0.511	0.326	0.081	0.454	1.000					
(12)	**DIV_DUMMY**	0.044	0.059	0.396	-0.018	0.134	0.320	0.249	-0.328	-0.134	-0.399	-0.321	1.000				
(13)	**BIG4**	-0.068	-0.054	0.493	-0.096	0.124	0.143	0.187	-0.243	-0.153	-0.183	-0.152	0.143	1.000			
(14)	**LOG_GDP**	-0.031	-0.057	0.014	-0.059	-0.065	-0.086	-0.029	0.064	-0.037	0.031	0.093	-0.093	-0.034	1.000		
(15)	**LOG_UNEMP**	-0.031	-0.025	0.030	0.021	-0.077	-0.008	0.021	0.015	0.022	0.036	0.008	-0.029	0.041	0.221	1.000	
(16)	**LOG_VICTIMS**	-0.017	-0.042	0.037	-0.064	0.012	-0.045	0.000	-0.013	-0.048	-0.013	0.043	-0.025	-0.034	0.335	-0.007	1.000

TABLE 5. TERRORIST ATTACKS AND EARNINGS MANAGEMENT

This table reports coefficient estimates of the following OLS specification: $DA\_MJONES_{i,s,t}$ or $REM_{i,s,t} = \alpha + \beta_1 LOG\_VICTIMS_{s,t} + \gamma Control_{i,s,t} + Fixed\ Effects + \varepsilon_{ijt}$. The subscripts i,s,t represent firm, state and year, respectively. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Each model includes industry, year, and state fixed effects. Standard errors are clustered by firm. The sample period covers between 2000 and 2020. Please see Appendix A for variable definitions.

	(1)	*(2)*
Variable	**Dep: DA_MJONES**	**Dep: REM**
Constant	-0.1509	-0.0148
	-0.8039	-0.1325
LOG_VICTIMS	-0.0014 **	-0.0076 ***
	-2.2534	-3.1381
SIZE	-0.0147 ***	0.0293 ***
	-13.2191	7.0611
BTM	0.0024 *	0.0615 ***
	1.8704	9.6475
LEV	0.0018	0.1788 ***
	0.1120	5.8253
ROA	0.3541 ***	-0.0883
	13.0202	-1.5306
CFO_SALE	-0.0029 ***	-0.0040 ***
	-11.1077	-3.9203
STD_CFO	0.0461 ***	-0.0828 ***
	2.7311	-2.7375
STD_SALE	-0.0183 ***	0.0758 **
	-3.6314	2.2959
STD_RET	0.0261	-0.0095
	1.5022	-0.2556
LOSS	0.0102	0.0362 **
	1.5040	2.4918
DIV_DUMMY	0.0033 *	0.0401 ***
	1.8929	3.4614
BIG4	-0.0028	-0.1030 ***
	-1.1822	-7.2781
LOG_STATEGDP	0.0213	-0.0145 **
	1.2741	-2.1149
LOG_UNEMP	0.0017	-0.0109
	0.2465	-0.3500
Fixed Effects	Industry, Year, State	Industry, Year, State
Clustered St Errors	Firm	Firm
Observations	47,433	43,321
Adj R^2	31.72%	5.51%

TABLE 6. COMPONENTS OF REAL EARNINGS MANAGEMENT

This table reports coefficient estimates of the main OLS specification using the following dependent variables: $ABPROD_{i,s,t}$, $ABDISX_{i,s,t}$ and $ABCFO_{i,s,t}$. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Each model includes industry, year, and state fixed effects. Standard errors are clustered by firm. The sample period covers between 2000 and 2020. Please see Appendix A for variable definitions.

	(1)	*(2)*	*(3)*
Variable	**Dep: ABPROD**	**Dep: ABDISX**	**Dep: ABCFO**
Constant	-0.0691	0.1864 **	-0.1321 ***
	-1.3975	2.5710	-5.2197
LOG_VICTIMS	-0.0028 ***	-0.0044 ***	-0.0004
	0.0794	-1.1489	1.4683
Control Variables	Included	Included	Included
Fixed Effects	Industry, Year, State	Industry, Year, State	Industry, Year, State
Clustered St Errors	Firm	Firm	Firm
Observations	43,321	43,321	43,321
Adj R^2	6.48%	14.30%	31.31%

TABLE 7. INFORMATION ASYMMETRY AND ANNUAL REPORT SENTIMENT

Using a split-sample analysis, this table reports coefficient estimates of the following OLS specification: $DA\_MJONES_{i,s,t}$ or $REM_{i,s,t} = \alpha + \beta_1 LOG\_VICTIMS_{s,t} + \gamma Control_{i,s,t} + Fixed\ Effects + \varepsilon_{ijt}$. Firms that are above (below) the yearly average of *SPREAD* and are in high (low) market attention sub-sample. Firms that are in top two-thirds and bottom third of *NEGATIVE_SENT (POSITIVE_SENT)* and *POSITIVE_SENT (NEGATIVE_SENT)*, respectively are in the pessimistic (optimistic) annual report sub-sample. The subscripts *i,s,t* represent firm, state and year, respectively. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Each model includes industry, year, and state fixed effects. Standard errors are clustered by firm. The sample period covers between 2000 and 2020. Please see Appendix A for variable definitions.

	Dep: DA_MJONES		**Dep: REM**	
	(1) *Low Information Asymmetry*	*(2)* *High Information Asymmetry*	*(3)* *Low Information Asymmetry*	*(4)* *High Information Asymmetry*
Constant	-0.1743	0.0924	-0.1498	-0.0685
	-0.9709	0.2931	-1.0883	-0.4737
LOG_VICTIMS	0.0001	-0.0034 ***	-0.0065 **	-0.0077 **
	0.2278	-3.0207	-2.3854	-1.9772
Control Variables	Included	Included	Included	Included
Fixed Effects	Industry, Year, State	Industry, Year, State	Industry, Year, State	Industry, Year, State
Clustered St Errors	Firm	Firm	Firm	Firm
Observations	23,704	23,713	22,083	21,227
Adj R^2	34.66%	33.85%	12.54%	4.92%

	Dep: DA_MJONES		**Dep: REM**	
	(5) *Pessimistic 10-K*	*(6)* *Optimistic 10-K*	*(7)* *Pessimistic 10-K*	*(8)* *Optimistic 10-K*
Constant	-0.3618	-0.6855 *	0.0995	-0.0503
	-1.0564	-1.8050	0.6179	-0.2522
LOG_VICTIMS	-0.0025 **	0.0004	-0.0091 **	-0.0015
	-2.1483	0.3863	-2.0577	-0.2917
Control Variables	Included	Included	Included	Included
Fixed Effects	Industry, Year, State	Industry, Year, State	Industry, Year, State	Industry, Year, State
Clustered St Errors	Firm	Firm	Firm	Firm
Observations	8,694	8,694	8,191	8,122
Adj R^2	40.32%	20.45%	6.10%	5.71%

TABLE 8. ACCRUAL-BASED EARNINGS MANAGEMENT AND ALTERNATIVE EXPLANATIONS

This table reports coefficient estimates of the main OLS specification described in Table 5 with the addition of future profitability, overinvestment, and benchmark variables. The subscripts *i,s,t* represent firm, state and year, respectively. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Each model includes industry, year, and state fixed effects. Standard errors are clustered by firm. The sample period covers between 2000 and 2020. Please see Appendix A for variable definitions.

Dep: DA_MJONES	*(1) Future Profitability*	*(2) Overinvestment*	*(3) Bench_A*	*(4) Bench_B*
Constant	-0.2000	-0.1361	-0.1490	-0.1485
	-0.9694	-0.7244	-0.7939	-0.7915
LOG_VICTIMS	-0.0016 **	-0.0014 **	-0.0014 **	-0.0012 *
	-2.3738	-2.2752	-2.0772	-1.7752
ROA_t	0.4955 ***			
	11.8026			
ROA_t × LOG_VICTIMS	-0.0321 ***			
	-3.3355			
ROA_{t+1}	-0.1542 ***			
	-6.8422			
ROA_{t+2}	-0.0799 ***			
	-6.8230			
OVERINVESTMENT		0.0536 ***		
		3.8338		
OVERINVESTMENT × LOG_VICTIMS		0.0013		
		0.1559		
Bench_A			0.0124 ***	
			3.8428	
Bench_A × LOG_VICTIMS			-0.0021	
			-1.2609	
Bench_B				0.0101 ***
				6.5783
Bench_B × LOG_VICTIMS				-0.0024 **
				-2.2596
Control Variables	Included	Included	Included	Included
Fixed Effects	Industry, Year, State	Industry, Year, State	Industry, Year, State	Industry, Year, State
Clustered St Errors	Firm	Firm	Firm	Firm
Observations	36,199	47,349	47,433	47,433
Adj R^2	37.74%	31.56%	31.74%	31.75%

TABLE 9. REAL EARNINGS MANAGEMENT AND ALTERNATIVE EXPLANATIONS

This table reports coefficient estimates of the main OLS specification described in Table 5 with the addition of future profitability, overinvestment, and benchmark variables. The subscripts *i,s,t* represent firm, state and year, respectively. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Each model includes industry, year, and state fixed effects. Standard errors are clustered by firm. The sample period covers between 2000 and 2020. Please see Appendix A for variable definitions.

Dep: REM	*(1) Future Profitability*		*(2) Overinvestment*		*(3) Bench_A*		*(4) Bench_B*	
Constant	-0.0423		-0.0696		-0.0188		-0.0208	
	-0.3694		-0.6358		-0.1677		-0.1862	
LOG_VICTIMS	-0.0070	**	-0.0074	***	-0.0082	***	-0.0084	***
	-2.4310		-3.1608		-3.3393		-3.2919	
ROA_t	0.0005							
	0.0225							
ROA_t × LOG_VICTIMS	0.0012							
	0.0108							
ROA_{t+1}	-0.1416	***						
	-3.5696							
ROA_{t+2}	-0.0815	***						
	-3.3195							
OVERINVESTMENT			-0.8813	***				
			-18.5956					
OVERINVESTMENT × LOG_VICTIMS			-0.0358					
			-1.4036					
Bench_A					0.0597	***		
					4.9862			
Bench_A × LOG_VICTIMS					0.0145	*		
					1.9484			
Bench_B							0.0480	***
							6.6206	
Bench_B × LOG_VICTIMS							0.0068	
							1.3653	
Control Variables	Included		Included		Included		Included	
Fixed Effects	Industry, Year, State		Industry, Year, State		Industry, Year, State		Industry, Year, State	
Clustered St Errors	Firm		Firm		Firm		Firm	
Observations	33,324		43,322		43,321		43,321	
Adj R^2	6.85%		12.42%		5.60%		5.63%	

TABLE 10. FINANCIAL STATEMENT READABILITY

This table reports coefficient estimates of the following OLS specification: $FOG_{i,s,t}$ or $ARI_{i,s,t} = \alpha + \beta_1 LOG\_VICTIMS_{s,t} + \gamma Control_{i,s,t} + Fixed\ Effects + \varepsilon_{ijt}$. The subscripts i,s,t represent firm, state and year, respectively. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Each model includes industry, year, and state fixed effects. Standard errors are clustered by firm. The sample period covers between 2000 and 2020. Please see Appendix A for variable definitions.

Variable	*(1)* Dep: FOG Index		*(2)* Dep: ARI Index	
Constant	11.4409	***	12.1406	***
	5.2986		4.4635	
LOG_VICTIMS	0.0149	**	0.0278	***
	2.1760		3.1140	
SIZE	0.0935	***	0.1346	***
	11.0532		13.8070	
MTB	-0.0249	***	-0.0399	***
	-3.3719		-3.9193	
LEV	0.0786	*	0.0951	*
	1.8950		1.8326	
ROA	-0.1437	***	-0.1776	***
	-4.0460		-4.0046	
CFO_SALE	-0.0035	***	-0.0028	***
	-4.8715		-3.0966	
STD_CFO	0.0534	**	0.0632	**
	2.1422		2.0028	
STD_SALE	0.0280		0.0404	
	0.5981		0.7146	
STD_RET	0.1656	**	-0.0892	
	2.5547		-1.0736	
LOSS	0.1235	***	0.1240	***
	6.5734		5.3040	
DIV_DUMMY	-0.1686	***	-0.1176	***
	-6.7794		-3.8234	
BIG4	0.1243	***	0.1340	***
	4.6563		4.1742	
LOG_STATEGDP	0.6866	***	0.9010	***
	3.5688		3.7284	
LOG_UNEMP	0.1370	*	0.0961	
	1.7935		0.9689	
Fixed Effects	Industry, Year, State		Industry, Year, State	
Clustered St Errors	Firm		Firm	
Observations	42,903		42,903	
Adj R^2	13.16%		9.91%	

TABLE 11. REVERSAL OF EARNINGS MANAGEMENT

This table reports coefficient estimates of the following OLS specification: $DA\_MJONES_{i,s,t}$ or $REM_{i,s,t} = \alpha + \beta_1 LOG\_VICTIMS_{s,t} + \gamma Control_{i,s,t} + Fixed\ Effects + \varepsilon_{ijt}$. The subscripts *i,s,t* represent firm, state and year, respectively. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Each model includes industry, year, and state fixed effects. Standard errors are clustered by firm. Panel A includes an additional control variable, *MJONES_RANK* or *REM_RANK*. Panel B focuses on the sample period between 2010 and 2020. Please see Appendix A for variable definitions.

Panel A	**Dep: DA_MJONES**		**Dep: REM**	
	Sample Period = 2000 - 2020		*Sample Period = 2000 - 2020*	
Constant	-0.2042		0.0067	
	-1.0798		0.0598	
LOG_VICTIMS	-0.0010	*	-0.0075	***
	-1.6729		-3.0937	
REM_RANK	0.0003			
	0.3715			
MJONES_RANK			-0.0087	***
			-3.2183	
Control Variables	Included		Included	
Fixed Effects	Industry, Year, State		Industry, Year, State	
Clustered St Errors	Firm		Firm	
Observations	43,321		43,321	
Adj R^2	35.24%		5.55%	

Panel B	**Dep: DA_MJONES**		**Dep: REM**	
	Sample Period = 2010 - 2020		*Sample Period = 2010 - 2020*	
Constant	0.0976		0.0090	
	0.2746		0.0649	
LOG_VICTIMS	-0.0012	*	-0.0071	***
	-1.6852		-2.7004	
Control Variables	Included		Included	
Fixed Effects	Industry, Year, State		Industry, Year, State	
Clustered St Errors	Firm		Firm	
Observations	22,084		20,207	
Adj R^2	23.10%		6.46%	

TABLE 12. MATCHED SAMPLE ANALYSIS

Using a matched sample analysis, this table reports coefficient estimates of the following OLS specification: $DA\_MJONES_{i,s,t}$ or $REM_{i,s,t} = \alpha + \beta_1 LOG\_VICTIMS_{s,t} + \gamma Control_{i,s,t} + Fixed\ Effects + \varepsilon_{ijt}$. The matching procedure is explained in Section 4.5. The subscripts i,s,t represent firm, state and year, respectively. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Each model includes industry, year, and state fixed effects. Standard errors are clustered by firm. The sample period covers between 2000 and 2020. Please see Appendix A for variable definitions.

	(1) **DA_JONES**	*(2)* **REM**
Constant	0.1549 ***	0.1366
	4.9536	0.9940
LOG_VICTIMS	-0.0022 *	-0.0114 ***
	-1.8036	-2.9890
Control Variables	Included	Included
Fixed Effects	Industry, Year, State	Industry, Year, State
Clustered St Errors	Firm	Firm
Observations	15,361	13,593
Adj R^2	28.89%	6.74%

TABLE 13. NEGATIVE SPECIAL ITEMS

This table reports coefficient estimates of the following OLS specification: $NEGATIVE\_SPI_{i,s,t} = \alpha + \beta_1 LOG\_VICTIMS_{s,t} + \gamma Control_{i,s,t} + Fixed\ Effects + \varepsilon_{ijt}$. The subscripts i,s,t represent firm, state and year, respectively. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Each model includes industry, year, and state fixed effects. Standard errors are clustered by firm. The sample period covers between 2000 and 2020. Please see Appendix A for variable definitions.

Variable	**Dep: SPI**	
Constant	-0.0988	*
	-1.8479	
LOG_VICTIMS	0.0099	***
	4.4126	
SIZE	0.0806	***
	35.8901	
BTM	0.0046	*
	1.9220	
LEV	0.0417	***
	3.3751	
ROA	-0.1563	***
	-10.8203	
CFO_SALE	0.0039	***
	11.5975	
STD_CFO	-0.0564	**
	-2.3388	
STD_SALE	0.0274	*
	1.7495	
STD_RET	-0.0247	
	-1.0416	
LOSS	0.1925	***
	28.0473	
DIV_DUMMY	-0.0161	**
	-2.0656	
BIG4	0.0170	**
	2.1054	
LOG_STATEGDP	0.0001	
	0.0304	
LOG_UNEMP	0.0458	***
	5.7901	
Fixed Effects	Industry, Year, State	
Clustered St Errors	Firm	
Observations	47,433	
Adj R^2	12.41%	