The Impact of Industrial Incidents on Stock Market Volatility

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Abstract

We examine stock market volatility attributed to industrial incidents involving publicly traded US companies, with contributing factors identified as company violations and safety errors, equipment failure, human error and vandalism. Incidents identified as safety violations elicited the highest costs in terms of equity price reductions, but the volatility effects of these incidents tend to mitigate within two weeks. Incidents caused by vandalism experience the sharpest volatility increases, but reduce within two days. Volatility associated with incidents caused by equipment failure tends to persist for almost four weeks. Injuries cost publicly traded companies $14 million each while fatalities lead to equity market capitalisation reductions of between $465 and $720 million. These results shed light on the equity market's role as a driver for enhanced compliance with health and safety regulation and with industry good practice.

Keywords: Chemical incidents; Stock markets; Crisis Management; GARCH; Risk management.

1. Introduction

There are many ways to create incentives for companies to minimise the risk as well as impact of potential incidents that might harm their employees, stakeholders and the environment. The most explicit method is to implement health and safety legislation which in turn imposes penalties and/or lawsuits if breached. In addition, the insurance market is also likely to place a further cost in the form of higher premium on firms with weaker safety standards. But these are not the only disciplinary methods since the loss of shareholder value for the company that experiences a chemical incident can in itself be a strong motivator to limit the probability as well as costs of such incidents.

In an efficient exchange, equity market prices reflect the present value of cash flows expected by the equity investors of the company. Using event study methodology such as that pioneered by Fama et al. [1969], it has been documented, that stock prices adjust quickly to new information as investors reassess the market value of equity by evaluating the impact of new information on the expected future cash flows and the risk-adjusted discount rate. An event such as a chemical incident that results in property damage, injuries and/or the loss of life will cause investors to reassess the company, its financial prospects, and its risk profile. Thus, this revaluation will be reflected in changes in the market value of equity.

The risk-adjusted discount rate, which represents compensation for market risk, is unlikely to be affected since a chemical incident should be expected to increase only firm-specific risk. There is no reason, a priori, to expect an increase in systemic risk. On the other hand, an event like a chemical incident is likely to impact future cash flows in a variety of ways. Changes in cash flows could be brought about by actual cost of damages, potential legal penalties and possible lawsuits by employees and other stakeholders directly affected by the incident. In addition, if there is a temporary break or change in operations due to the physical damage caused by the incident, future cash flows may very well be affected as the company may need to adapt its operations until the damage is rectified. Finally, the company may be affected by reputational damage, loss of goodwill or negative sentiment towards it or more widely to the sector in which it operates. The incident may also result in increased regulation or monitoring which may lead to an increase in compliance costs for the company and its competitors.

Of course, it is possible that investors have already captured some expected losses due to incidents (taking the expected cost and probability of an incident into account) in their value assessments, and the actual incident will not have a significant impact on the valuation unless the incident is unusual from the type of incidents experienced within the sector. Moreover, insurance against some losses can help mitigate the effects of the incident, though companies cannot insure against increased future premiums, loss of future demand, increased wage bills or loss of reputation.

The net effect of these different factors on the market value of equity, of the incident firm, is an empirical question and one that this paper addresses. This is completed by focusing on the chemical industry and its potential to impact on the environment should an incident occur; thus, this research draws knowledge gained due to workplace incidents as well as the environmental management field in order to better understand variables that might explain the cross-sectional differences in stock price reaction.

The paper is organised as follows: Section 2 presents a review of the relevant literature and the motivation for the study. Section 3 presents the data used in the analysis and details of its compilation. Section 4 explains the methodology used to analyse equity market response to chemical incidents. Section 5 presents the results of the analysis while section 6 concludes.

2. Background and Literature

In the area of environmental management, research has focused how the stock market reacts to a company's record on environmental management which is measured by self-assessments completed by firms (Jacobs et al. [2010]), by awards by third parties (Klassen and McLaughlin [1996]; Jacobs et al. [2010]), by ratings performed by third parties (Gupta and Goldar [2005]) and by environmental crises (Klassen and McLaughlin [1996]). For example, Klassen and McLaughlin [1996] find that strong environmental management (proxied by awards) results in positive stock price reaction while weak environmental management (proxied by environmental incidents) elicits a negative stock price reaction reflecting a loss, on average, of $390 million or $0.70 per share. Moreover, the reaction is stronger for companies that are first time award winners suggesting that the market sees the initial external validation as a more informative signal of information regarding a company's environmental programme. Jacobs et al. [2010] document that equity markets respond positively to philanthropic gifts for environmental causes, but react negatively to pledges or realisations of voluntary emission reductions which are perceived as expensive as well as potentially growth reducing (Smith and Sims [1985]). Gupta and Goldar [2005] evaluate the market reaction to environmental ratings in India (provided by India's leading environmental NGO) and document that capital markets in developing countries also react as expected - there is a negative stock price reaction for companies that have lower than expected ratings.

Research in the area of stock market reaction to workplace incidents has also focused on particular events (for example, the Deepwater Horizon explosion in 2010 or the Buncefield oil depot fire in 2006) or can be broader in considering incidents over a set time period. Capelle-Blancard and Laguna [2010] and Sabet et al. [2012] include the first, single incident, type. For the most part, the results indicate that the market is able to distinguish between companies which play a greater role in the incident, or are more directly involved in the chain of events, as the share price in these companies show a stronger negative reaction to the incident. Related event studies have been carried out documenting similar results for the Exxon-Valdex oil spill of 1989 and the Bhopal explosion of

1984 (Salinger [1992]; Herbst et al. [1996]). For one single incident, Lee and Garza-gomez [2012] investigate the Deepwater Horizon Oil spill of 2010 to find that stock market valuations indicated a $104.8 billion loss, but this recovered to a loss of $68.2 billion six months later when the well was permanently sealed. This was found to significantly outweigh the cost that BP allocated in its annual report of $53.5 billion. In such, one can see clearly the substantial costs that are incurred from incidents of such a severe nature.

Studies taking a broader view and investigating a portfolio of industrial incidents, rather than a single event, tend to show that, on average, the market responds negatively, to such. We specifically develop on similar work that investigate issues stock market performance in the aftermath of shocks to the chemical sector (Brown et al. [2015]), terrorist attacks (Corbet et al. [2018]) and broad financial crisis issues (Corbet [2016]; Meegan et al. [2018]; Corbet et al. [2017]). Broder and Morrall [1991] models the expected losses from faulty products or workplace incidents caused by faulty products and predicts losses resulting from decreased product demand, as well as an increased wage bill in addition to increased costs due to property damage and down-time. She documents that losses are greater for more serious incidents (as measured by a greater number of deaths per incident) as well as for products or workplaces that had lower perceived risk prior to the incident. This confirms earlier research by Viscusi et al. [1988] highlighting Bayesian decision-making in face of greater information about risk. Luo and Zhang [2019] specifically investigated economic policy uncertainty and stock price crash risk while Poshakwale et al. [2019] examined the relationship and the cross-sectional asset pricing implications of risk arising from the innovations in the short and the long-term implied market volatility on excess returns of the FTSE100 and the FTSE250 indices and the 25 value-weighted Fama-French style portfolios in the UK. Sprecher and Pertl [1983] document losses of 4% on the date a large loss is incurred by a firm. Capelle-Blancard and Laguna [2010] find event companies suffer abnormal returns between -0.76% and -1.26% on average over the two days following a chemical incident. The cumulative abnormal returns remain negative for about six months and the losses are greater for firms with incidents that result in human harm or environmental damage. Their study documents losses of $164 million for each casualty and $1 billion for a toxic/chemical discharge.

There is also some research that documents no or weak reaction to industrial incidents on stock prices. Scholtens and Boersen [2011] find no significant reaction to 209 energy incidents that occurred between 1973 and 2007 indicating that the market prices in the expectation of incidents and the stock price is discounted to reflect these expectations. Interestingly, they find no significant reaction even for incidents that result in above median costs. Similarly, Jones and Rubin [2001] do not find significant results using 14 incidents in the oil and power sector between 1970 and 1992. Another set of post-incident costs that companies may face are regulatory penalties and lawsuits (Dasgupta et al. [2006]; Gupta and Goldar [2005]). Several studies show a drop in stock value for companies that fail to comply with regulations in the areas of product safety , workplace safety (Fry and Lee 1989), and environmental regulations (Muoghalu et al. [1990]). Laplante and Lanoie's theoretical model, developed using a sample of 47 events involving Canadian firms, between 1982 to 1991, document no significant reaction at the announcement of lawsuits (Laplante and Lanoie [1994]). This is at odds with evidence from the US that shows a strong negative reaction for US firms on the day of lawsuit filing. This may be due to softer enforcement of regulations in Canada along with a longer resolution time and lower fines relative to the US. While Muoghalu et al. [1990] find no significant reaction on the date of settlement for US data, Laplante and Lanoie [1994] do find a negative reaction at settlement of the lawsuit, though they posit whether a loss of 1.65-2% is large enough to act as a deterrent in the future.

Rao and Hamilton [1996] finds a drop in shareholder value when reports on environmental pollution are published in the Wall Street Journal and attributes this to the penalties imposed by the market on a company behaving in an unethical manner. Jones and Rubin [2001] study the previously documented large unexplained losses suffered by firms involved in negative incidents which show that losses in equity value are greater than direct and estimated indirect costs of the incident. These losses are attributed to the loss of reputation or in other words 'goodwill' (Dowdell et al. [1992]). On the other hand, Karpoff et al. [2005] document that the loss in market value for companies accused of environmental violations is due to legal penalties and not reputational loss. Using a sample of 478 environmental violations, they find significant losses in the firms' share values with the average abnormal return of -1.69%. They then use a sub-sample of 148 firms, for whom information on legal penalties, fines or damages awarded is available, to show that the losses in shareholder value suffered by these companies is not significantly larger than the actual penalties, fines or damages incurred, leading to their conclusion that discipline for environmental violations is not due to reputational damage.

Finally, another body of research focuses on the contagion or the impact of an industrial incident in one company on other companies in the same industry. Basse Mama and Bassen [2013] investigate the contagion effects of the Fukishima nuclear incident to uncover an abrupt increase in the systemic risk of conventional electric utilities immediately following the event. Similarly, Ho et al. [2013] investigate the effects of airline crashes on equity market contagion. They propose that the direction of the impact of aviation disasters on the stock price of the crash airline's rivals (competitors) depends on the interaction of the 'contagion' effect and the 'switch' effect; incident at one firm may provide, on the one hand, opportunities for its competitors but it may also results in losses for competitors if the incident is likely to lead to increased regulatory and future health and safety costs.

3. Data

This paper builds on the studies reviewed above, as well as the larger literature exploring industrial incidents and equity market performance. A Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model is used to investigate specific equity market shocks across a cohort of industrial incidents in the United States between 2000 and 2013. Daily equity market return data were used representing the time period both one year before and one year after an industrial incident. The GARCH volatility estimate provided information about the 'shock' offering substantial evidence of investor perceptions about the incident.

We focus on the financial performance and investor perceptions of the events though a thorough analysis of share price volatility of the identified companies, along with a thorough analysis of the contagion effects of such volatility as sourced from the selected corporate account data is taken from Bloomberg. Stock price data is taken from Thomson Reuters Eikon. We utilise standard news selection rules based on the source of the data. We develop on a combined search of Bloomberg and Thomson Reuters Eikon, search for the keywords relating to industrial incidents for the period 1997 through 2014. For additional robustness of our developed dataset, we leverage upon that of the analysis of all industrial incidents from the United States CSB (Chemical Safety Board) database with an accompanying broader search of the LexusNexus database using a variety of keywords. To obtain a viable observation, a single observation must be present across each of the selected search engines and the source was denoted as an international news agency, a mainstream domestic news agency or the company making the announcement itself. This method identified 179 individual incidents involving substantial property damage, injury and/or death involving publicly traded companies. The number of incidents would have been considerably greater if not limited to those occurring in publicly traded companies. Data limitations, such as incomplete data and substantial market illiquidity, reduced this sample to seventy-seven incidents from which the results were obtained. Forums, social media and bespoke news websites were omitted from the search. Finally, the selected observation is based solely on the confirmed news announcements being made on the same day across all of the selected sources. If a confirmed article or news release had a varying date of release, it was omitted due to this associated ambiguity. All observations found to be made on either a Saturday or Sunday are denoted as active on the following Monday morning. All times are adjusted to GMT, with the official end-of-day closing price treated as the listed observation for each comparable company when analysing associated contagion effects.

The two year period around each of the industrial incidents was chosen as the best investigation period, one year before and one year after. This was selected to minimise the effects of non-incident coordinated events on the results of the GARCH methodology. Proxies then had to be selected to quantify the effects of the numerous international crises that occurred during the investigated horizon. These crises include the dot com collapse, the terrorist attacks of 9/11, the subprime collapse of 2007 and the European sovereign debt crisis that ensued from 2008 onward. Numerous variables were included such as United States dollar weighted exchange rate proxy, oil and gold prices. The S&P500 Index and the VIX were found to be the variables that increased confidence in the GARCH methodology, while mitigating non-industrial incident effects on the results. The CBOE Volatility Index, also known by its ticker symbol VIX, is a popular measure of the stock market's expectation of volatility implied by S&P 500 index options, calculated and published by the Chicago Board Options Exchange (CBOE). It is colloquially referred to as the fear index or the fear gauge. The S&P 500 is a stock market index based on the market capitalisation's of 500 large companies listed on the NYSE and NASDAQ. It represents current, perceived financial conditions within the United States. The VIX is a popular measure of option implied volatility of the S&P500 options and is often referred to as the 'fear gauge'. It represents a forward looking estimation of stock market volatility over the next thirty days and offers a valuable variable towards the GARCH methodology to identify current market conditions at the time of our investigated industrial incidents.

4. Equity Market Valuation of Industrial Incidents

The basic empirical strategy is to use the GARCH (1,1) to obtain volatility changes in the immediate aftermath of an industrial incident involving a publicly traded company in the United States. These results are then used to estimate the perceived depth of each incident as observed through equity market reaction. Based on the identified cause of the incident from that of the CSB final incident reports, the selected incidents are sub-divided into groups, denoted as company violations/safety errors, equipment failure, human error and vandalism. Equity market reaction can then be regressed upon the number of injuries and fatalities based on each incident to obtain the estimated cost to the company as observed through a reduction in market capitalisation after the incident.

The GARCH specification was developed by Bollerslev [1986] and was designed to include lagged conditional variance terms as autoregressive terms. The general GARCH (p,q) model has the following form:

$$R_t = a + b\prime X_t + \varepsilon_t, \tag{1}$$

$$\varepsilon_t|\Omega_t \sim iidN(0, h_t) \tag{2}$$

$$h_t = \omega + \Sigma_{i=1}^{p}\alpha_i h_{t-i} + +\Sigma_{j=1}^{q}\beta_j \varepsilon_{t-j}^2 \tag{3}$$

which says that the value of the variance scaling parameter h_t now depends both on the past value of the shocks, which are captured by the lagged square residual terms, and on past values of itself, which are captured by the lagged h_t terms. Specification tests found that the GARCH (1,1) model served as the best fitting to estimate volatility effects after industrial incidents for publicly traded companies.

It is also necessary to mitigate the effects of the widespread international financial crises that took place after 2007. To do so, we include signalling variables in the mean equation (1), to incorporate the effects on financial markets of external volatility, that is, volatility not relating specifically to the particular industrial incident that we are observing. The VIX and the S&P500 were found to have the most informational benefit when added to the model and are incorporated throughout all the regressions undertaken. To specifically investigate volatility changes on the days around the incident, dummy variables are incorporated into the volatility equation (3) of the model. The dummy variables obtain a value of zero on the days before the incident and one thereafter. Dummy variables used in this manner have a tendency to provide non-sensical results when outweighed by days not needing a dummy value. The lagged equity returns for one, two and three days before the incident were also found to provide explanatory significance and are therefore included in the mean equation. The GARCH (1,1) methodology used in this study has the following form:

$$R_t = a_0 + b_1 R_{t-1} + b_2 R_{t-2} + b_3 R_{t-3} + b_4 VIX_t + b_5 S\&P_t + \varepsilon_t \tag{4}$$

$$\varepsilon_t | \Omega_t \sim iidN(0, h_t) \tag{5}$$

$$h_t = \omega + \alpha_1 h_{t-1} + \beta_1 u_{t-1}^2 + d_t \tag{6}$$

R_{t-n} represents the lagged value of returns, n days before R_t is observed. $b_4 VIX_t$ represents the value of the VIX on the day the estimate R_t was observed and $b_5 S\&P_t$ the S&P500. These values are included to mitigate international crises and non-equity specific market effects. d_t is included in the variance equation (4) to provide a coefficient relating to the included dummy variables. Bollerslev [1986] showed that restrictions on the parameters for positivity, $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$, and the wide-sense stationarity condition, $\alpha + \beta < 1$. Nelson [1990] proved that the GARCH (1,1) process is uniquely stationary if $E[log(\beta + \alpha\epsilon_t^2)] < 0$, where Bougerol and Picard [1992a] and Bougerol and Picard [1992b] generalise this for any GARCH (p,q) order model. Bollerslev [1986] also proved that if the fourth order moment exists, then the model can handle leptokurtosis.

The dummy variables d_t, adapt to the daily changes in volatility, thus providing a daily estimate of volatility. It would be expected that the volatility shock would be positive and the scale would represent the perceived risk to the company's long term survival as witnessed by investors. The GARCH models were re-estimated daily for five trading days (one week) before the incident until twenty trading days after (four weeks). This presents evidence as to when the shock died or when the market returned to a level of volatility similar to those experienced in the period directly before the shock. The shocks can be segregated by incident to identify key driving forces, particularly, which types of incidents lead to the largest shocks to equity market volatility.

5. Results

Each individual incident involves approximately five hundred and twenty four observations, and the GARCH (1,1) model is regressed with the value of the dummy variables changing for each individual day around the incident. Tables 1, 2 & 3 list the individual incidents included in this study, sub-divided based on the designated causation factor attributed to each incident by the United States CSB. Table 1 represents the cases attributed to company violations and safety errors, including the source of the incident data, the company name and equity market ticker, the date of the incident, the location, the type of incident and the number of injuries and fatalities. In 24 included incidents, there were 337 injuries and 68 fatalities, stemming from disasters including fires, explosions, chemical leaks and spills, asphyxiation and toxic releases. To be included in this sub-set, there was substantial evidence, through regulatory and legal investigation, specifically blaming the parent company for operational failings that related directly to the cause of the incident.

Insert Tables 1 and 2 about here

Table 2 represents 25 industrial incidents that were attributed directly to equipment failure. 14,132 people were injured and 7 people died as a result of these incidents. Again, regulatory reports directly linking the causation factor of the incident to faulty equipment were included, ranging from faulty regulators and thermostats to broken seals and valves. Table 3 combines incidents that were attributed directly to human error and vandalism. There were 28 specific incidents, in which there were 86 injuries and 19 fatalities. The 3 cases identified as vandalism were investigated both from a regulatory and criminal law stance. Overall, there were 77 separate incidents, from which the GARCH(1,1) analysis could obtain results.

Insert Table 3 about here

The GARCH(1,1) analysis was sub-divided for each company based on the nature and causation factor of the incident. Each model was regressed to obtain a rolling ten day estimate of equity price volatility at the time of the incident, ranging from volatility the day before, volatility the day after and then daily volatility for the next four weeks. Table 4 includes the GARCH(1,1) results for the companies included in the sample with causation attributed to company failings. The volatility estimate for the twenty trading days after the incident is also included. Table 5 presents the specific day-to-day volatility change for two weeks after the incident. The $Z(t)$ and $\rho(t)$ estimates relate directly to the Augmented Dickey Fuller (ADF) and Phillips-Perron tests, which included an intercept and a deterministic trend to capture the change in average volatility that took place in the period after the industrial incident. The ADF model tests whether the equity series contained a unit root in order to correct for serial correlation. The Phillip-Perron model employs a non-parametric estimator of the variance-covariance matrix with d truncation lags. The models test down by sequentially removing the last lag until a significant lag is reached giving the order of augmentation for the ADF test that minimised the Akaike information criterion. The results indicated rejection of the null-unit root hypotheses at the minimum of the one per cent level of significance.

Insert Tables 4 and 5 about here

The high significance levels attached to the coefficients of the GARCH(1,1) models found in table 4 offers substantial support towards the use of the models in this study. The VIX and S&P500 are used to mitigate the effects of the international financial crisis that occurred during the sample time horizon as the investigated sample. The α_1 and β_1 estimates of the GARCH models do not accumulate to more than one, with this non-explosive behaviour adding further support to the choice of the methodology. When investigating the data presented in table 5, it is important to note that day 0 refers to the day on which the industrial incident occurred. However, some of the incidents occurred after market close on day 0, therefore the true effect of the market reaction is not visible until day 1 (one day after). The average GARCH volatility estimate for the day before any incident is 0.0048, where only five incidents showed a reduced volatility level on day 0, but all estimates showed a dramatic increase on either day 0 or day 1. This presents evidence that equity markets responded as expected to the industrial incident, where volatility increased substantially. The two most serious incidents in this sub-sample include the BP explosion in 2005, which caused 180 injuries and 15 fatalities and the Imperial Sugar explosion in 2008 which caused 42 injuries and 14 fatalities (incident 6 (BP) and 11 (IPSU) respectively above). Both incidents created significant increases in trading volatility between day -1, day 0 and day 1, with BP's equity volatility increasing from 0.0041 to 0.0257 on day 0 and 0.1801 on day 1. This dramatic increase in volatility represents the increased perceived risk associated with the equity by investors at this time. Volatility fell significantly in the following days after the incident as investor panic and negative perceptions relinquished. Imperial Sugar presented GARCH volatility of 0.002 on day 0, but this increased substantially to 0.016 on day 1 and 0.014 on day 2. Again, estimates of the change in volatility are negative on day 4 (4 days after the incident) presenting evidence that the effects of these incidents on equity market volatility are a short term phenomenon.

Insert Tables 6 and 7 about here

Tables 6 and 7 present the results for the GARCH (1,1) specification models for companies which experienced industrial incidents attributed to equipment failures. Tables 8 and 9 present results for companies which incurred industrial incidents attributed to human error and vandalism. It is clear that some of the GARCH-calculated volatility occurred on d_0 as news of the incident disseminated. The average GARCH volatility for the day before the incident, d_{t-1} is 0.0048. We can see the strong market reactions in most cases when comparing volatility increases from day to day. There is a high degree of confidence in the S&P500 variable included in the mean equation throughout, indicating a successful inclusion as a mitigating proxy for international effects. Incidents relating to all causation factors present significant volatility changes in the two days after an industrial incident. This presents evidence that equity markets take a dim view of these incidents as represented in the volatility and deterioration of the associated equity prices. Of most interest is the type of reaction. Incidents related to equipment failure and human errors tend to persist, whereas incidents linked with vandalism tend to return to normal volatility levels quite quickly. Vandalism cannot generally be directly attributed to failings of company policy, perhaps at most, it can be blamed on lax security.

But at the time of each incident, one overpowering fact remained, media attention could not segregate a single causation factor, with equipment failure being the commonly reported cause. Therefore, volatility linked to human error and equipment failure tend to persist for weeks after the incident as an investigation into the main causation factor is carried out. Reports by agencies such as the CSB can take up to three years to complete, but the announcement of an expected causation factor is sometimes enough to mitigate market fears of further litigation. The results vary significantly, but one key finding is that equipment failure leads to sharper immediate increases in equity market volatility with less persistence (sometimes less than one week) whereas human error attributed volatility can persist for up to three weeks. The volatility of equity prices appears to be correlated with market perceptions of the future compensation, legal and clean-up costs associated with rectifying the damage of the incident.

Insert Table 8 about here

5.1. The economic cost of industrial incidents

The GARCH(1,1) estimates provide valuable evidence surrounding the market reaction and investor perceptions of the incidents included in this study. Figure 1 presents a visual representation of these estimates, sub-divided by the attributed causation factor - company violations and safety errors, human error, equipment failure and vandalism. These estimates are further divided based on the size of the company being investigated. Companies falling under each category are segregated, with companies possessing net market capitalisation of less than $10 billion denoted as small.

Insert Table 9 about here

Figure 1 helps to portray the equity market impact in the periods thirty days before and after a chemical incident in a large company. Figure 2 presents the 20 day GARCH(1,1) volatility estimates representing the average stock market volatility impact. Segregating the results between large and small companies offer some interesting results. Primarily, we can see how there is very little equity market punishment apportioned to small companies that suffer chemical incidents attributed to human error and vandalism. In this situation, both events may be attributed to external factors that the company may not be able to directly influence, therefore there is little punishment. Alternatively, company violations and equipment failure experience substantial reductions in market capitalisation, and given the relative lower level of smaller companies, this can become a significant issue in terms of long term aspirations of company survival. Larger companies portray slightly different dynamics in terms of equity market punishment. Vandalism tends to cause some short terms market capitalisation decreases, but the effects tend to die out after 15-18 days. Equipment failure causes short term volatility in market capitalisation, but this volatility tends to mitigate quickly in the periods 5-10 days after the event.

Insert Figures 1 and 2 about here

Chemical incidents attributed to human error experience a substantial shock on day T, but also experience an immediate rebound the day after the event. The most interesting finding relates to company violations for large companies. In this situation, there is a dramatic decrease in market capitalisation on day T which sustains throughout the 30 day period after the chemical incident. This portrays valid evidence that equity markets effectively punish companies that do not adhere or indeed enable a lapse in health and safety standards.

Company violation and safety errors would be perceived to be the most reputational and financially damaging causation factor associated with these incidents, with a large increase in GARCH estimated volatility (increasing to 0.02 one day after the incident on average) and persisting for nine trading days after the incident. This carries additional reputation cost, including public perceptions and of course employee distrust, but the results indicate that equity markets calm significantly shortly after the incident. Incidents caused by vandalism carry the sharpest equity market response, but tend to die out almost immediately. There appears to be a sharp investor reaction, potentially attributed to the behaviour of 'noise traders', in equity markets. The GARCH estimated volatility tends to decrease by 0.01 one day after the incident and returns to normal levels between eight and nine days after the incident.

Incidents relating to human error are associated with a volatility increase of 0.015, but this tends to reduce to negative levels between two and five days after the incident. But the volatility tends to stay negative (reduced) for almost eighteen to twenty trading days (four weeks) after the incident. Equipment failure leading to an industrial incident is found to cause significant volatility increases and persist for almost three weeks after the event. These particular findings can be attributed to investor uncertainty about the specific cause of the incident, as the identifying cause may not be made public for a significant period, with investor knowledge being based on media coverage (which may be speculative) and personal perceptions based on the incident. These GARCH results present evidence of the turmoil and stress that can affect a traded company, even after an industrial incident which would have caused significant suffering already. The increased volatility, though financially unquantifiable in the accounting sense, provides an additional cost to the company through a reduction in market capitalisation resulting from falling equity prices. This, combined with equity market dysfunction in the short term, may have direct negative impacts on the future finance-raising ability of the company, in a period where they may need it most. Longer term, this may impact on the survival prospects of the company itself.

The final part of this study involves quantifying an estimate of the cost per incident. As explained in section 3 above, we can regress the market capitalisation loss (based on the estimated market capitalisation and the immediate share price loss for five days after the incident) against the type of incident, the number of injuries and the number of fatalities. Table 10 provides the regression results.

Insert Table 10 about here

In all the investigated cases, each injury stemming from an industrial incident is found to cost the company $14 million in stock market decreases (as measured by the fall in market capitalisation). There are minor differences between incident types, but this is a significant amount of money. For example, the Chevron fire in Richmond in 2012 led to 14,003 official injuries as the immediate population were poisoned with toxic fumes directly caused by the incident. The fire was attributed directly to equipment failure. In the initial aftermath its share price fell nearly 9%, wiping approximately $21.31 billion off its market capitalisation value. The model presented in table 10 estimates a loss of $21.38 billion, but of this cost $196 million is directly attributed to these injuries.

For a case involving company violations, the average equity market fall leads to a $720 million reduction in market capitalisation for each fatality. This significantly dwarfs the $14 million estimate associated with an injury and presents evidence that equity markets take these events very seriously. For a publicly traded company, deaths relating to equipment failure are found to cost the company $606 million each, with human error slightly lower at $545 million and death relating to vandalism $465 million. It appears as though equity markets place a significant cost on fatalities directly associated with company violations, with significant, but reduced, cost allocated to events that may not be directly the fault of the company. This point alone reinforces the role of equity markets as enforcers of environmental regulation. It must also be noted, that companies with lower market capitalisation and cash reserves are at significant risk of default in the event of a serious industrial incident.

6. Conclusions

In an efficient market, discipline is imposed on companies by the shareholders adjusting the price they are willing to pay for shares as new information is revealed. Information about industrial incidents will be expected to lower share value due to possible costs, both certain (clean-up, lost business due to interruption in production, regulatory fines and penalties) as well as potential (lost future business, lawsuits, and additional future regulatory burdens). Part of these costs are going to be 'expected' and factored into the price even before the incident so the adjustment should reflect the unexpected costs - as a result, incidents with higher cost implications should have larger adverse stock price reactions.

This study of 77 industrial incidents involving publicly traded companies in the US show a loss in shareholder value as well as increase volatility after industrial incidents. Results also indicate that the identified cause of the incident is associated with important differences in stock market reactions. Using a GARCH methodology, this paper shows a sharp increase in volatility immediately after the incident. The volatility decreases most immediately for incidents where the cause is identified as vandalism while the higher volatility tends to persist for companies that experienced incidents where the cause is identified as equipment failure or human error. This is consistent with a market factoring in the liability that may be attributed to the incident company itself. Results also vary by firm size - small firms tend not to have adverse stock market reaction to incidents caused by human error and vandalism while incidents brought about by company violations and equipment failure generate a more adverse reaction. Large firms, on the other hand, recover more quickly from incidents caused by equipment failure and this may be related to greater financial slack in larger companies.

These results have implications for risk management strategies of companies in the chemical sector. While external threats (for example, vandalism) also matter, risk management strategies need to pay special attention to internal threats that may be mitigated by investment in health and safety training programmes, comprehensive maintenance routines, regular testing of equipment and ensuring that the company is compliant with regulatory requirements. Not doing so will expose organisations to an increased risk of exposure to high costs in the event of an incident. This study provides estimates of these costs and can serve as counter-argument to costs of the risk management strategies mentioned above.

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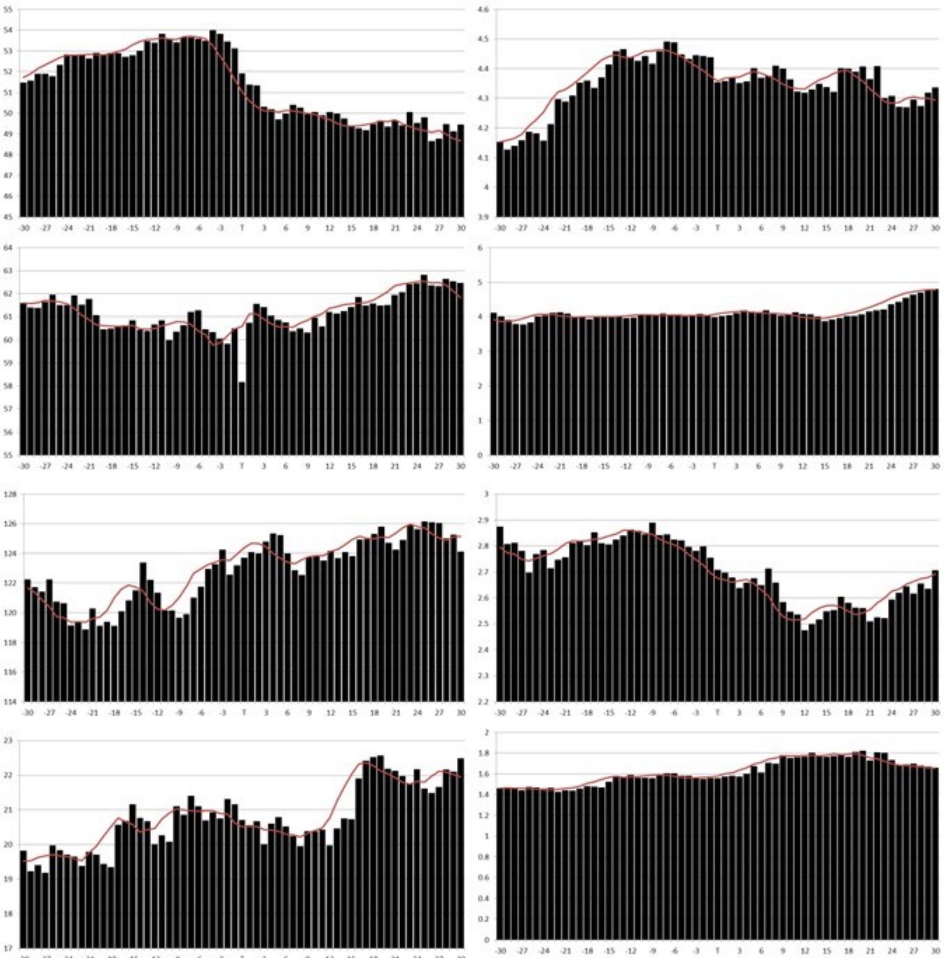
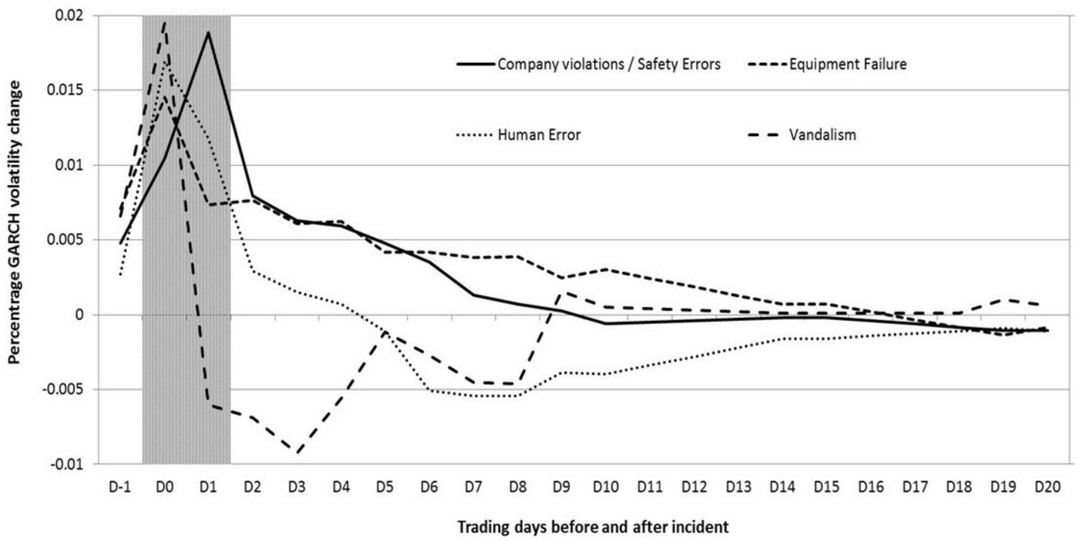
Figure 1: The impact of chemical incidents on estimated market capitalisation (US$)



Note: The above figures represent the estimated reaction of average market capitalisation rates in the period after a chemical incident. The figures are segregated to identify key differences between large and small companies, simply denoted as above and below $10 billion market capitalisation. The grey line represents the five day moving average of market capitalisation (US$ billions). The sample represents the thirty days before the chemical incident, denoted as day T, and thirty days after the incident. The samples are segregated to represent incidents attributed to company violations, human error, equipment failure and vandalism. From top to bottom, the above figure represents company violations, human error, equipment failure and vandalism respectively. The left hand graphs represents the results for the average large company, whereas the right hand graphs represents the results for the average small company.

Figure 2: 20 day GARCH(1,1) volatility estimates representing the average equity market 'shock'



Note: The shaded area above represents the trading days in which the included industrial incidents occurred. The GARCH(1,1) methodology was repeated to obtain daily volatility changes in the equity prices of the total sample.

Table 1: Stock market tickers for companies (ranked by market capitalisation) in the same sector as those who experienced an industrial accident.

Regression	Data Source	Company	Ticker	Disaster Type	Date	Location	Injuries	Fatalities
1	LN	Diaz Chemical Corp	SQM	Chemical Explosion	05/01/2002	Holley	0	0
2	CSB	First Chemical Corp	2121	Fire & Explosion	13/10/2002	Pascgoula	3	0
3	CSB	West Pharmaceuticals	WST	Fire & Explosion	29/01/2003	Kinston	36	6
4	LN	Able Energy	ABLE	Explosion	14/03/2003	New Jersey	16	0
5	CSB	Sigma Aldrich	SIAL	Fire & Explosion	21/09/2003	Miami	1	0
6	CSB	BP	BP	Fire & Explosion	23/03/2005	Texas City	180	15
7	RTN	Tyson Foods	TSN	Chemical Leak	31/10/2006	South Hutchinson	1	2
8	CSB	Valero Refinery	VLO	Fire & Explosion	16/02/2007	Sunray	4	0
9	CSB	Xcel Energy	XEL	Asphyxiation	02/10/2007	Georgetown	3	5
10	LN	BP	BP	Chemical Explosion	14/01/2008	Houston	0	1
11	CSB	Imperial Sugar Co.	IPSU	Fire & Explosion	07/02/2008	Port Wentworth	42	14
12	CSB	Packaging Corp of America	PKG	Fire & Explosion	29/07/2008	Tomahawk	1	3
13	RTN	Delek Refining	DEDR.L	Fire & Explosion	20/11/2008	Tyler	3	2
14	CSB	Veolia Environnement	VE	Chemical Leak	04/05/2009	West Carrollton	2	0
15	CSB	ConAgra Natural Gas	CAG	Chemical Explosion	09/06/2009	Garner	25	4
16	RTN	CF Industries	CF	Chemical Exposure	16/11/2009	Rosemount	0	2
17	LN	Conmed Linvatech	CNMD	Chemical Explosion	03/12/2009	Anaheim	0	0
18	CSB	E. I. DuPont De Nemours Co	DD	Chemical Leak	23/01/2010	Belle	0	1
19	RTN	Tesoro	TSO	Fire & Explosion	02/04/2010	Anacortes	0	7
20	LN	BP	BP	Chemical Spill/Release	20/04/2010	Texas	2	0
21	LN	Du Pont	DD	Chemical Leak	09/11/2010	Tonawanda	0	0
22	CSB	Donaldson Enterprises	DCI	Fire & Explosion	08/04/2011	Waikele	1	5
23	LN	SM energy	SM	Chemical Leak	07/03/2012	Bismark	0	0
24	LN	Arens Controls	CW	Chemical Explosion	22/05/2012	Arlington	17	1

Note: The above table presents a list of industrial accidents attributed to company violations and safety errors. Company violations and safety errors in this case were identified in thorough investigations after the incident, where clear evidence of wrongdoing was identified and produced. The data in this table was compiled after a thorough search of all available material on LexisNexis (LN) and The United States Chemical Safety Board (CSB) database. The ticker for each company is linked directly to the traded equity of the domicile country of the company in question. The ticker represents the equity data used in the GARCH analysis.

Table 2: Industrial incidents attributed to equipment failure.

Regression	Data Source	Company	Ticker	Disaster Type	Date	Location	Injuries	Fatalities
25	LN	Chevron	CVX	Fire	04/10/2001	Bakersfield	1	0
26	CSB	Honeywell	HON	Chemical Leak	20/07/2003	Baton Rouge	8	0
27	LN	Frontier Oil	FOSI	Fire	19/01/2004	Houston	0	0
28	CSB	Praxair	PX	Fire & Explosion	25/06/2005	St. Louis	0	0
29	CSB	BP	BP	Fire & Explosion	28/07/2005	Texas City	1	0
30	LN	Mapa Spontex	JAH	Chemical Explosion	14/09/2006	Columbia	1	0
31	LN	CAI Inc	CAP	Chemical Explosion	24/11/2006	Danvers	0	0
32	LN	Frontier Scientific	TMO	Chemical Explosion	30/03/2007	Logan	1	0
33	LN	Pacific States Cast Iron	BRK.A	Explosion	17/02/2008	Springville	11	0
34	CSB	Goodyear	GT	Fire & Explosion	11/06/2008	Houston	0	1
35	RTN	Oxydental Chemical Group	OXY	Chemical leak	18/11/2008	Deer Park	15	0
36	CSB	Silver Eagle	EAGLU	Fire & Explosion	12/01/2009	Woods Cross	2	0
37	RTN	Praxair	PX	Fire & Explosion	08/12/2009	Port Arthur	0	0
38	RTN	Dow Chemical Company	DOW	Chemical Explosion	10/03/2010	Freeport	1	0
39	RTN	Seneca Food Corp	SENEB	Chemical Leak	24/05/2010	Montgomery	0	0
40	CSB	Horsehead	ZINC	Fire & Explosion	22/07/2010	Monaca	0	2
41	RTN	Dow Chemical Company	DOW	Chemical Explosion	26/01/2011	Freeport	2	0
42	RTN	Dow Chemical Company	DOW	Chemical Explosion	29/06/2011	Freeport	3	0
43	LN	Oasis Petroleum	OAS	Fire & Explosion	14/09/2011	North Dakota	2	2
44	RTN	Dover Chemical Corp	DHR	Fire	14/11/2011	Dover	5	0
45	LN	SM energy	SM	Fire	11/05/2012	Cheyenne	0	0
46	RTN	Chevron	CVX	Fire	06/08/2012	Richmond	14003	0
47	LN	Samson Resources Company	SSN	Fire & Explosion	29/08/2012	Casper	0	0
48	RTN	Valero Refinery	VLO	Fire & Explosion	03/12/2012	Memphis	3	1
49	LN	Westlake Vinyls	WLK	Chemical Explosion	13/06/2013	Geismar	73	1

Note: The above table presents a list of industrial accidents attributed to equipment failure. This definition applies strictly to the scenario where a chemical disaster was directly attributed to a fault connected with equipment on the companyâĂŹs premises as identified after the incident. The data in this table was compiled after a thorough search of all available material on LexisNexis (LN) and The United States Chemical Safety Board (CSB) database. The ticker for each company is linked directly to the traded equity of the domicile country of the company in question. The ticker represents the equity data used in the GARCH analysis.

Table 3: Industrial incidents attributed to human error and vandalism.

Regression	Data Source	Company	Ticker	Disaster Type	Date	Location	Injuries	Fatalities
Human Error								
50	CSB	BP	BP	Fire	13/03/2001	Augusta	0	3
51	RTN	Kraft Foods	KRFT	Chemical Leak	23/12/2001	Maddison	1	1
52	CSB	Honeywell	HON	Chemical Leak	29/07/2003	Baton Rouge	0	1
53	CSB	Honeywell	HON	Chemical Leak	13/08/2003	Baton Rouge	1	0
54	CSB	Formosa Plastics	1301	Fire & Explosion	23/04/2004	Illiopolis	2	5
55	LN	Plains Exploration	PXP	Fire	31/08/2004	Baldwin Hills	1	0
56	CSB	Marcus Oil	MCS	Fire & Explosion	03/12/2004	Houston	6	0
57	CSB	Acetylene Service Co.	4093	Fire & Explosion	25/01/2005	Perth Amboy	1	3
58	LN	Union Pacific	UNP	Chemical Spill	06/03/2005	Salt Lake City	12	2
59	RTN	Ralcorp	RAH	Explosion	19/07/2005	Louisville	0	0
60	CSB	Formosa Plastics	1301	Fire & Explosion	06/10/2005	Point Comfort	16	0
61	RTN	Delek Refining	DEDR.L	Fire	26/10/2005	Tyler	1	0
62	CSB	Valero Refinery	VLO	Asphyxiation	05/11/2005	Delaware	0	2
63	RTN	Nalco Holding	NLC	Chemical Leak	08/01/2007	Sugar Land	14	0
64	RTN	Dover Chemical Corp	DHR	Fire	14/09/2007	Dover	1	0
65	RTN	Dow Chemical Company	DOW	Chemical Spill	13/11/2007	Freeport	1	0
66	LN	News Corp	NWSA	Chemical Leak	17/12/2007	New York	5	0
67	RTN	Dow Chemical Company	DOW	Chemical Spill	11/04/2008	Freeport	1	0
68	LN	Wasatch Laboratories	WSHP	Chemical Explosion	27/07/2009	Ogden	3	0
69	RTN	Valero Refinery	VLO	Fire & Explosion	29/04/2010	Memphis	1	0
70	RTN	Dow Chemical Company	DOW	Chemical Explosion	17/05/2010	Freeport	4	0
71	RTN	Bonduelle	BON	Chemical Explosion	12/06/2010	Oakfield	1	0
72	RTN	Dow Chemical Company	DOW	Chemical Explosion	13/09/2010	Freeport	3	0
73	RTN	Valero Refinery	VLO	Fire & Explosion	06/03/2011	Norco	1	1
74	RTN	Goodyear	GT	Fire & Explosion	11/06/2011	Houston	7	1
Vandalism								
75	LN	Sumco	3436	Fire	20/01/2002	Indianapolis	0	0
76	LN	Federal Mogul	FDML	Fire & Explosion	30/12/2010	Blacksburg	3	0
77	LN	Cabot Oil & Gas Corporation	COG	Chemical Spill	20/08/2012	Susquehanna	0	0

Note: The above table presents a list of industrial accidents attributed to either human error or vandalism. These definitions apply strictly to the scenario where a chemical disaster was directly attributed to an act of human error or indeed a case of vandalism with clear evidence provided as identified after the incident. The data in this table was compiled after a thorough search of all available material on LexisNexis (LN) and The United States Chemical Safety Board (CSB) database. The ticker for each company is linked directly to the traded equity of the domicile country of the company in question. The ticker represents the equity data used in the GARCH analysis.

Table 4: GARCH(1,1) model estimates for industrial incidents attributed to company failings and safety errors.

Ticker	α_0	R_{t-1}	R_{t-2}	R_{t-3}	VIX_1	$S\&P_1$	α_1	β_1	d_{20}	$Z(t)^*$	$\rho(t)^{**}$
1. SQM	0.0003	0.0906**	-0.1046**	0.0844**	-0.0332*	0.2454**	0.0660***	0.8864***	0.0005*	21.502***	491.496***
2. 2121	0.0003	0.0810*	-0.0335	-0.0034	-0.0086	0.1607	0.0696***	0.8689***	-0.0026**	21.17***	498.749***
3. WST	0.0005	0.0600	0.1120**	0.1272**	-0.0266	0.2540***	0.2824***	0.5253***	0.0016	19.482***	451.692***
4. ABLE	0.0026	-0.1701***	-0.0524	-0.1475***	-0.1622***	-0.5526***	0.0618***	0.7346***	-0.0065**	26.956***	545.667***
5. SIAL	0.0001***	-0.0264	-0.1315***	0.0066	-0.0043	0.9692***	0.1347***	0.7368***	-0.0012*	23.119***	477.3***
6. BP	0.0007*	0.0715**	-0.0619*	0.0218	-0.0901***	-	0.0427***	0.6728***	-0.0013**	21.772***	467.882***
7. TSN	0.0013**	0.1458***	-0.0270	0.0064	-0.0155	0.5932***	0.0407***	0.7860***	0.0023***	20.395***	439.589***
8. VLO	0.0007*	0.1135**	-0.0683	0.0163	-0.0216	0.9897***	0.0677***	0.8814***	0.0058**	19.063***	384.58***
9. XEL	0.0005	-0.0942**	-0.0771**	-0.0324	-0.0243***	0.6148***	0.1122***	0.8135***	0.0029***	23.875***	477.248***
10. BP	0.0002	0.0904***	-0.0221	0.0172	0.0013	0.8954***	0.0764***	0.9222***	-0.0012***	22.185***	464.852***
11. IPSU	0.0028***	-0.2219***	0.0232**	0.1850***	0.0912***	0.8995***	0.2322***	0.5334***	0.0002	20.199***	459.075***
12. PKG	0.0010	0.0205	-0.0798**	-0.0003	0.8616***	0.4393***	0.2584***	0.2582***	-0.0003***	22.869***	471.384***
13. DEDR	0.0003	-0.0397	0.0123	0.0366	0.0201***	0.7429***	0.3185***	0.6746***	0.0001*	25.796***	558.875***
14. VE	0.0003	0.1187***	0.0607*	0.0314	-0.0459**	1.0015***	0.3002***	0.6947***	0.0026	20.6***	446.302***
15. CAG	0.0002	0.0581	0.0179	0.0316	-0.0417***	0.2748***	0.3987***	0.5689***	-0.0023	22.305***	501.48***
16. CF	0.0011	-0.0635**	-0.0305	-0.0256	0.8858*	0.8858***	0.0438***	0.9287***	0.0035***	23.985***	495.059***
17. CNMD	0.0008	0.0677*	-0.0038	0.0111	-0.1393***	-	0.0109***	0.9795***	0.0003	21.29***	466.784***
18. DD	0.0006	-0.0027	-0.0012	0.0186	0.0357***	1.4534***	0.2701***	0.7154***	0.0002	23.323***	564.42***
19. TSO	0.0006*	0.0472	-0.0215	0.0352	-0.0084	1.3024***	0.0530***	0.4602***	0.0010**	19.781***	418.132***
20. BP	0.0002	0.0341	0.0888***	0.0169	0.0171*	1.0842***	0.1577***	0.7938***	-0.0205***	24.079***	579.97***
21. DD	0.0005	0.0314	0.0140	-0.0106	-0.0051	1.1541***	0.0263***	0.0915***	-0.0006***	23.351***	555.247***
22. DCI	0.0004	-0.0353**	-0.0353*	-0.0762***	-0.0065	1.1719***	0.2491***	0.7154***	-0.0012*	25.076***	582.332***
23. SM	0.0008	0.0286	0.0389	-0.0146	0.0082	1.6643***	0.0135***	0.6738***	-0.0061***	19.888***	403.269***
24. CW	0.0009*	-0.0185	0.0438*	-0.0381	-0.1433***	-	0.1095***	0.8390***	-0.0022*	24.819***	539.7***

Note: The above table presents the results of the GARCH(1,1) model (see equations (3) and (4)) estimating the volatility impacts on equity returns of chemical incidents attributed to company failings and safety errors as initially described in table I. ***, ** and * denote the significance of the GARCH(1,1) estimates at the 1%, 5% and 10% levels respectively.

Table 5: 10 trading day GARCH(1,1) model estimates for industrial incidents attributed to company failings and safety errors.

Ticker	d_0	d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8	d_9	d_{10}
1. SQM	0.010***	0.019***	0.012***	0.015***	0.011***	0.008***	0.006***	0.006***	0.008***	0.006***	0.006***
2. 2121	-0.001***	0.043***	0.025***	0.018***	0.023***	0.016***	0.011***	0.008***	0.002***	0.001***	0.007***
3. WST	0.017	0.057***	0.027**	0.027***	0.027***	0.015***	0.012**	0.012***	0.011***	0.012***	0.011***
4. ABLE	0.034***	0.006***	-0.009***	-0.013***	0.011***	0.004***	-0.006***	-0.015***	-0.014	-0.015***	-0.015***
5. SIAL	0.005***	0.007	0.001	-0.003***	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
6. BP	0.026***	0.180***	0.012***	0.009***	-0.006***	-0.004***	-0.003***	-0.002***	-0.002***	-0.002***	-0.002***
7. TSN	0.009***	0.005***	0.006***	0.005***	0.004	0.003	0.004*	0.003	0.002*	-0.001***	-0.002***
8. VLO	0.008***	0.003***	0.001***	0.010***	0.010**	0.009	0.009***	0.010	0.009***	0.008***	0.008***
9. XEL	0.001***	0.000*	-0.001	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.002***	-0.002***	-0.002***
10. BP	0.019***	0.016***	0.009***	0.003***	0.002***	0.007***	0.010***	-0.006***	-0.005***	-0.005***	-0.005***
11. IPSU	0.000	0.016***	0.014***	0.000***	-0.001***	-0.002***	0.000*	-0.001***	-0.001	-0.004***	-0.005***
12. PKG	0.022***	0.001**	-0.001***	0.003***	0.000***	0.000***	-0.003***	-0.003	-0.005***	-0.003***	-0.002***
13. DEDR	0.002	0.002***	0.000***	-0.001***	0.001***	0.001***	-0.000***	-0.001***	0.000***	0.000***	-0.001***
14. VE	0.016***	-0.002*	-0.003***	-0.001***	-0.004***	-0.004***	0.001***	-0.001***	0.000***	0.000***	0.000***
15. CAG	0.012***	0.011***	0.003***	0.002***	0.006***	0.005***	0.005***	0.003	0.003	0.003***	0.002***
16. CF	0.003	0.039***	0.010***	0.007***	-0.004	-0.002***	-0.005***	-0.004	-0.005***	-0.006***	-0.004***
17. CNMD	0.016***	0.014***	0.014***	0.008***	0.009***	0.005***	0.003	0.001***	-0.002***	-0.001***	-0.001***
18. DD	0.005	0.006***	0.002***	0.002***	0.005***	0.006***	0.003***	0.002***	0.003***	0.003***	0.002***
19. TSO	0.010***	0.002*	0.011	0.006***	0.005***	0.006***	0.006***	0.009***	0.008	0.006***	0.004***
20. BP	0.008***	0.031***	0.028***	0.026***	0.020	0.01	0.021***	0.002**	0.002***	0.002***	-0.019***
21. DD	0.007***	0.010***	0.005***	0.004***	0.003	0.002***	0.002***	0.001***	0.000***	0.001***	0.001***
22. DCI	0.006***	0.006***	0.011***	0.009***	0.008***	0.008***	0.008***	0.008	0.006	0.006***	0.006***
23. SM	0.006***	-0.001**	-0.001	-0.001***	0.002***	0.003***	0.002***	0.003*	0.002	0.002***	0.004***
24. CW	0.011*	0.008***	0.008***	0.008***	0.006***	0.005***	-0.004***	-0.005***	-0.006***	-0.007***	-0.006***

Note: The above table presents evidence of the rolling dummy variable estimates of volatility used in the GARCH(1,1) analysis. In this situation, the dummy variable represents the ten days after a chemical incident attributed to company failings and safety errors. Through the use of this methodology, it is possible to present evidence of whether volatility increases or decreases occurred in the period directly after the incident. ***, ** and * denote the significance of the GARCH(1,1) estimates at the 1%, 5% and 10% levels respectively.

Table 6: GARCH(1,1) model estimates for industrial incidents attributed to equipment failure.

Ticker	α_0	R_{t-1}	R_{t-2}	R_{t-3}	VIX_1	$S\&P_1$	α_1	β_1	d_{20}	$Z(t)^*$	$\rho(t)^{**}$
25. CVX	0.0004	-0.0210	-0.0773**	-0.0015	-0.0273**	0.3463***	0.1061***	0.8177***	-0.0036***	22.611***	482.713***
26. HON	0.0002	-0.0187	0.0539**	0.0389	-0.0065	1.2412***	0.0548***	0.9433***	0.0009	25.708***	621.39***
27. FOSI	0.0115**	-0.2532	-	-	0.1943*	-	0.0246***	0.9607***	-0.0071	28.217***	612.826***
28. PX	0.0003	-0.0087	0.0107	-0.0007	-0.0317**	1.1075***	0.0877***	0.5216***	0.0013***	20.15***	395.239***
29. BP	0.0006	0.0461*	-0.0083	0.0487***	-0.0904***	-	0.0376***	0.7923***	0.0020***	22.12***	496.801***
30. JAH	0.0007	0.0477	-	-	0.0208	1.4803***	0.1805***	0.8069***	0.0039	18.263***	379.719***
31. CAP	0.0020***	0.0546*	0.0447	-0.0066**	0.1066***	1.1617***	0.0862***	0.8972***	-0.0139***	22.429***	492.298***
32. TMO	0.0009**	-0.0243	-0.0518	-0.0073	-0.0119	0.7587***	0.1033***	0.8014***	0.0093***	24.892***	582.949***
33. BRK.A	0.0004	0.1062**	0.0273	-0.0269	-0.0235***	-	0.1579***	0.8412***	-0.0026	18.11***	393.877***
34. GT	0.0010	0.0470*	0.0001	0.0279	0.0269	1.8619***	0.0967***	0.8764***	-0.0015*	23.192***	564.907***
35. OXY	0.0019*	0.0179	-0.0222	0.0200	-0.0217	1.2604***	0.0613***	0.9211***	0.0055**	23.411***	462.975***
36. EAGLU	0.0001***	-0.0264	-0.1315***	0.0066	-0.0043	0.9692***	0.1347***	0.7368***	-0.0012*	23.119***	477.3***
37. PX	0.0002	-0.0402*	-0.0319	0.0025	0.0100	0.9880***	0.0505***	0.9344***	-0.0023*	22.064***	471.691***
38. DOW	0.0005	0.0056	0.0051	0.0049	-0.0018	1.6892***	0.0316***	0.9638***	-0.0026	22.847***	531.027***
39. SENEB	0.0000	-0.0700	-	-	-0.0492*	-0.0881***	0.0877***	0.9014***	0.0004	20.972***	472.269***
40. ZINC	0.0009	-0.0150	0.0102	-0.0625**	-0.0017	2.1852***	0.0980***	0.7741***	0.0025	23.799***	545.094***
41. DOW	0.0005	0.0496**	0.0059	-0.0259	0.0043	1.6070***	0.1655***	0.7815***	0.0022*	22.891***	535.741***
42. DOW	0.0001	0.0443**	-0.0234	-0.0272	0.0039	1.6612***	0.0991***	0.9009***	-0.0006*	22.58***	522.318***
43. OAS	0.0002	0.0433	-0.0120	-0.0917**	0.0232	1.9308***	0.2479***	0.6973***	0.0005***	18.837***	386.131***
44. DHR	0.0002	-0.0339*	-0.0370*	0.0232	0.0019	1.1541***	0.1234***	0.5266***	-0.0017***	24.071***	561.14***
45. SM	0.0009	0.0044*	0.0541***	0.0281	-0.0002	1.6259***	0.0130***	0.9706***	-0.0094**	20.631***	422.077***
46. CVX	0.0006**	0.0447*	0.0542**	0.0234	0.0027	1.0349***	0.0554***	0.8989***	0.0008*	21.59***	557.795***
47. SSN	0.0041*	0.0976*	-0.0560	-0.1033***	-0.1524***	0.4800***	0.2156***	0.5938***	-0.0020	17.937***	364.482***
48. VLO	0.0006	-0.0284	-	-	-	1.1419***	0.1656***	0.8002***	0.0006	20.055***	440.076***
49. WLK	0.0014*	0.0097	-0.0324	-0.0520	-0.0198	1.5086***	0.0412***	0.7607***	-0.0033***	19.467***	371.823***

Note: The above table presents the results of the GARCH(1,1) model (see equations (3) and (4)) estimating the volatility impacts on equity returns of chemical incidents attributed to equipment failure as initially described in table I. ***, ** and * denote the significance of the GARCH(1,1) estimates at the 1%, 5% and 10% levels respectively.

Table 7: 10 trading day GARH(1,1) model estimates for industrial incidents attributed to equipment failure.

Ticker	d_0	d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8	d_9	d_{10}
25. CVX	0.022***	0.019***	0.016***	0.018***	0.018***	0.014	0.009***	0.003***	0.003***	0.003***	-0.001***
26. HON	0.024***	0.022***	0.010***	0.008***	0.006***	0.004***	0.003***	0.003***	0.002***	0.002**	0.002***
27. FOSI	0.052***	0.034***	0.027***	0.025**	0.023*	-0.009***	0.008***	0.014***	0.014***	0.029***	0.031***
28. PX	0.001	0.002	0.003***	0.000***	-0.002***	-0.001	-0.004***	-0.002***	-0.001***	-0.001*	0.000***
29. BP	0.004	0.001	0.006***	0.006***	0.008***	0.006***	0.005***	0.007***	0.007***	0.007***	0.006***
30. JAH	0.009	0.002	0.000	-0.001*	-0.006***	-0.009***	-0.007***	-0.004***	-0.005***	-0.005***	0.000**
31. CAP	0.001***	0.005***	0.012***	0.036***	0.040***	0.033***	0.027***	0.023***	0.019*	-0.019***	-0.001*
32. TMO	0.017***	0.003***	0.002***	0.004***	0.007**	0.006	0.005**	0.004***	0.004***	0.004***	0.004***
33. BRK.A	0.000***	-0.001***	-0.001***	-0.004***	-0.006***	-0.005***	-0.005***	-0.003***	-0.003	-0.003***	-0.005**
34. GT	0.011	0.013***	0.003***	-0.004	0.002***	0.004***	0.007*	0.004***	0.005***	0.006***	0.006***
35. OXY	0.012***	0.014***	0.018***	0.005***	0.019***	0.014***	0.013***	0.015***	0.013***	0.009*	0.005***
36. EAGLU	0.005***	0.007***	0.001***	-0.003***	-0.002***	-0.001*	-0.001***	-0.001***	-0.001***	-0.001*	-0.001***
37. PX	0.005	-0.003	0.000***	0.002***	0.002***	0.001***	0.001	0.001***	0.002	0.003**	0.003
38. DOW	0.013***	0.004***	-0.001***	-0.002**	-0.002***	0.000***	0.002***	0.005***	0.003**	0.002***	0.000***
39. SENEB	0.073***	0.042***	0.033***	0.010***	0.007***	0.005***	0.004***	-0.005***	-0.003**	-0.003***	-0.003***
40. ZINC	0.006***	-0.025***	-0.013**	-0.009***	-0.012***	-0.001***	-0.009***	-0.002***	0.000***	-0.001***	-0.001**
41. DOW	0.000	0.000	0.000	-0.001***	-0.001***	-0.001***	-0.003***	-0.003***	-0.003	-0.003	-0.003***
42. DOW	0.005***	0.007***	0.010***	0.007***	0.005***	0.004***	0.003*	0.004***	0.004***	0.006***	0.000**
43. OAS	0.004***	0.007***	0.013***	0.005	0.004***	0.008***	0.005***	0.001***	0.000***	0.000	0.001***
44. DHR	0.009***	0.003*	0.010***	0.014***	0.010***	0.012***	0.011***	0.013***	0.012***	0.005***	0.000***
45. SM	0.002	-0.004**	0.001***	0.009***	0.009***	0.010	0.009**	0.001***	0.004***	0.007***	0.009***
46. CVX	0.004***	-0.001***	0.000***	0.000	0.001***	0.000***	-0.001***	-0.001***	-0.001	-0.001***	-0.001***
47. SSN	0.025***	0.011***	0.012***	0.004***	0.004***	0.006***	0.004***	0.002***	0.002***	0.002	0.011***
48. VLO	0.005***	-0.001***	0.007***	0.004***	0.004***	-0.001	0.000***	0.000***	0.000***	-0.002***	-0.002***
49. WLK	0.044***	0.018***	0.014***	0.012***	0.013***	0.010***	0.012***	0.010***	0.012*	0.013***	0.010***

Note: The above table presents evidence of the rolling dummy variable estimates of volatility used in the GARCH(1,1) analysis. In this situation, the dummy variable represents the ten days after a chemical incident attributed to company failure. Through the use of this methodology, it is possible to present evidence of whether volatility increases or decreases occurred in the period directly after the incident. ***, ** and * denote the significance of the GARCH(1,1) estimates at the 1%, 5% and 10% levels respectively.

Table 8: GARCH(1,1) model estimates for industrial incidents attributed to human error and vandalism.

Ticker	α_0	R_{t-1}	R_{t-2}	R_{t-3}	VIX_1	$S\&P_1$	α_1	β_1	d_{20}	$Z(t)^*$	$\rho(t)^{**}$
Human Error											
50. BP	0.0003	-0.0293	-0.1103***	-0.0226	0.0012	0.3366***	0.0735***	0.8381***	0.0002*	22.935***	465.17***
51. KRFT	0.0002	-0.0672*	-0.0020	-0.0274	0.0064	0.7972***	0.2215***	0.6544***	-0.0016	22.239***	469.831***
52. HON	0.0005***	-0.0146	0.0581**	0.0417	0.0026	1.2645***	0.0542***	0.9375***	-0.0017***	25.511***	625.563***
53. HON	0.0003	0.0031	0.0512*	0.0497*	-0.0022	1.2563***	0.0800***	0.9137***	-0.0024**	25.883***	654.893***
54. 1031	0.0007	0.0705	-0.0722	-0.1101**	0.0067	0.1500***	0.3007***	0.5098***	-0.0103*	20.969***	454.178***
55. PXP	0.0022**	0.0015	0.0237	0.0230	-0.0262	1.1790***	0.0763***	0.9052***	0.0066***	22.239***	469.831***
56. MCS	0.0034***	-0.1580**	-0.0693	0.0168	-0.1247***	-	0.3091***	0.4203***	-0.0033	23.12***	461.229***
57. 4093	0.0016***	-0.0498	-0.0110	0.0161	0.0496	0.2590***	0.0209***	0.7071***	0.0068	23.329***	570.251***
58. UNP	0.0002	0.0038	0.0220	-0.0424	0.0306**	1.0465***	0.0471***	0.1528***	0.0059***	18.99***	382.998***
59. RAH	0.0020***	-	-	-	-	0.8794***	0.0120***	0.7737***	0.0071***	23.588***	462.722***
60. 1031	0.0009	-0.0839*	-0.0516	-0.0187	-0.0107	0.2895***	0.2958***	0.4089***	-0.0034***	22.621***	539.827***
61. DEDR.L	0.0002	-0.1006**	0.0254	0.0136	0.0147**	0.6115***	0.1662***	0.8045***	0.0012***	26.76***	597.568***
62. VLO	0.0030**	0.0961*	-0.0050	-0.0368	-0.0527*	1.1986***	0.0220***	0.9062***	-0.0050**	18.202***	366.595***
63. NLC	0.0001	-0.0801*	0.0047	0.0061	0.0142	0.8444***	0.1258***	0.8566***	0.0054***	22.296***	477.39***
64. DHR	0.0005	-0.0327	-0.0386	0.0002	-0.0199*	0.7849***	0.0657***	0.6115***	0.0011	24.623***	567.444***
65. DOW	0.0002	0.0990***	-0.0595**	0.0378	-0.0058	1.0066***	0.0763***	0.8791***	0.0017*	25.076***	600.31***
66. NWSA	0.0009	-0.0150	0.0102	-0.0625**	-0.0017	2.1852***	0.0980***	0.7741***	0.0025*	23.799***	545.094***
67. DOW	0.0002	0.0748***	-0.0083	0.0089	-0.0015	1.0864***	0.0499***	0.9275***	0.0011***	25.539***	634.619***
68. WSHP	0.0164**	-0.1565***	-0.0753*	-0.0497	-0.1497	-0.2040***	0.4883***	0.2293***	-0.0411***	22.485***	439.831***
69. VLO	0.0012*	0.1448***	-	-	-0.1855***	-	0.0250***	0.9072***	-0.0025*	20.037***	406.749***
70. DOW	0.0004	-0.0059	0.0158	0.0045	0.0005	1.7344***	0.1679***	0.6259***	0.0011***	23.442***	572.29***
71. BON	0.0006	0.0177		0.0651*	-0.0147**	0.0425***	0.0294***	0.7751***	-0.0032***	24.21***	548.24***
72. DOW	0.0001	-0.0019	-0.0158	-0.0071	-0.0226	1.4885***	0.1443***	0.8052***	0.0039**	24.472***	574.387***
73. VLO	0.0003	0.0595*	-0.0019	-0.0347	-0.0115	1.5412***	0.1842***	0.8055***	0.0007	21.045***	433.9***
74. GT	0.0003	0.0425	-0.0380	-	-0.0227	1.6751***	0.1727***	0.8018***	0.0018	21.236***	495.836***
Vandalism											
75. 3436	0.0015	-0.0360	-0.0655*	-0.1028**	0.0202*	0.3122***	0.0846***	0.8873***	0.0037*	21.139***	409.966***
76. FDML	0.0019**	0.0618**	0.0037	0.0209	0.0115*	1.5870***	0.1975***	0.5770***	0.0010*	22.715***	547.951***
77. COG	0.0026**	-0.0013	-0.0644*	-0.0367	-0.1354***	-	0.0081***	0.9904***	0.0003*	22.732***	473.029***

Note: The above table presents the results of the GARCH(1,1) model (see equations (3) and (4)) estimating the volatility impacts on equity returns of chemical incidents attributed to human error and vandalism as initially described in table II. ***, ** and * denote the significance of the GARCH(1,1) estimates at the 1%, 5% and 10% levels respectively.

Table 9: 10 trading day GARCH(1,1) model estimates for industrial incidents attributed to human error and vandalism.

Ticker	d_0	d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8	d_9	d_{10}
Human Error											
50. BP	0.030***	0.018***	0.014***	0.015***	-0.010***	-0.009***	-0.008***	-0.009***	-0.011**	-0.008***	-0.005***
51. KRFT	0.000***	-0.010***	-0.009***	-0.008***	-0.008***	-0.008***	-0.006***	-0.006***	-0.005***	-0.004***	-0.004***
52. HON	0.003***	0.000*	0.002***	0.000***	0.000***	-0.001***	0.000***	0.001***	0.001***	0.002***	0.002***
53. HON	0.012***	0.011***	0.008***	0.009***	0.008***	0.003***	0.003***	0.003***	0.002	0.000***	0.001***
54. 1031	0.035**	0.047***	-0.009***	-0.001***	-0.007***	-0.020***	-0.013***	-0.013***	-0.012***	-0.011***	-0.013***
55. PXP	0.004***	0.000***	-0.013***	-0.009***	-0.006***	-0.004***	-0.002***	-0.003***	-0.005***	-0.004***	-0.005***
56. MCS	0.022***	0.010**	0.010***	0.015***	0.008***	0.007***	0.006***	0.001***	0.001***	0.001***	-0.002***
57. 4093	0.024***	0.114***	0.012***	-0.012***	0.007***	-0.005***	-0.004***	-0.003***	-0.002	0.008***	0.004***
58. UNP	0.000***	0.014***	0.012**	0.006***	0.008***	0.006***	0.005*	0.005***	0.005***	0.005***	0.015***
59. RAH	0.001**	0.005***	0.005***	0.005***	0.006***	0.003***	0.003***	-0.011***	-0.011***	-0.010***	-0.010***
60. 1031	0.023***	0.017***	0.011***	0.009***	0.008***	0.003***	0.006***	0.005***	0.004***	0.004***	0.004***
61. DEDR.L	0.004***	0.000***	0.002***	0.000***	0.000	0.001***	0.002	0.002***	0.002***	0.002***	-0.001***
62. VLO	0.020***	0.006***	0.020***	0.029***	0.022***	0.011***	0.013***	0.010***	0.011***	0.012***	0.011***
63. NLC	-0.004	0.009***	0.008***	0.007***	0.010***	0.009***	0.007***	0.009***	0.008***	0.008***	0.008***
64. DHR	0.010***	0.006***	-0.007***	-0.007***	-0.007***	-0.005***	-0.004***	-0.006***	-0.003***	-0.002***	-0.002***
65. DOW	0.029***	0.004***	0.006***	0.006***	0.005**	0.001***	0.002***	0.002***	0.001***	0.001***	0.001***
66. NWSA	0.063***	-0.025	-0.013***	-0.009***	-0.012***	-0.009***	-0.009*	-0.002***	0.000***	-0.001***	-0.001***
67. DOW	0.007***	-0.006	-0.003***	-0.001***	-0.002***	-0.001***	-0.001***	-0.001***	0.000***	0.000***	-0.001***
68. WSHP	0.120	0.014***	-0.012***	-0.010***	-0.007***	-0.005***	-0.128***	-0.125***	-0.120***	-0.105***	-0.106***
69. VLO	0.007***	0.009***	0.011***	0.004***	0.005	0.005***	0.006***	0.007***	0.004**	0.006***	0.005***
70. DOW	0.018***	0.000*	-0.001***	-0.011***	-0.010***	-0.009***	-0.014**	-0.012***	-0.011***	-0.007***	-0.006***
71. BON	0.011***	0.009***	-0.003***	-0.002***	-0.002***	0.001***	0.001***	0.001***	-0.001***	-0.001***	-0.001***
72. DOW	0.005***	-0.003	-0.003***	-0.001***	0.001***	-0.001***	0.001***	0.002***	0.002***	0.002***	0.003***
73. VLO	0.015*	0.019***	0.008***	0.004***	-0.001*	-0.002***	-0.001	-0.002***	-0.002*	-0.001***	-0.001***
74. GT	0.017***	0.019***	0.015***	0.004***	0.001***	0.001***	0.006***	0.007***	0.005***	0.005***	0.002***
Vandalism											
75. 3436	0.036***	-0.016***	-0.017***	-0.018***	-0.012***	-0.011***	-0.011***	-0.019***	-0.017***	-0.003***	-0.004***
76. FDML	0.004***	0.006***	0.001***	0.001***	0.000***	0.008***	0.006***	0.009***	0.008***	0.011***	0.009***
77. COG	0.016**	-0.008***	-0.004*	-0.010***	-0.004**	-0.001***	-0.003***	-0.003**	-0.004***	-0.002***	-0.008***

Note: The above table presents evidence of the rolling dummy variable estimates of volatility used in the GARCH(1,1) analysis. In this situation, the dummy variable represents the ten days after a chemical incident attributed to human error and vandalism. Through the use of this methodology, it is possible to present evidence of whether volatility increases or decreases occurred in the period directly after the incident. ***, ** and * denote the significance of the GARCH(1,1) estimates at the 1%, 5% and 10% levels respectively.

Table 10: Estimated cost per event, injury and fatality (billions, US$)

Event type	Constant	Est cost per inj	Est cost per fat.	Cost per event	R^2	$Prob > F$
Co. Viol./Safety Err	-6.710**	-0.014***	-0.720*	2.970	0.5790	0.000
Equipment Failure	-5.200*	-0.014***	-0.606**	-2.260	0.5784	0.000
Human Error	-5.490*	-0.014***	-0.545***	-1.540***	0.5779	0.000
Vandalism	-6.360**	-0.014***	-0.465	6.870	0.5792	0.000

Note: The above table presents the results of a regression based on the market capitalisation of each of the firms that experienced a chemical disaster included in this investigation. The market capitalisation level is regressed upon the number of injuries, the number of fatalities and the specific type of event. This provides and estimated equity market cost (or perceived equity market cost) based on the event type. ***, ** and * denote the significance of the GARCH(1,1) estimates at the 1%, 5% and 10% levels respectively.