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Firm-Level Investor Sentiment and Risk: Insight from Behavioral Finance

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ABSTRACT

The aim of this study to analyses the investor sentiment, attentions and types of risk which are incurred after specific event like scam etc. This study used monthly dataset of prices from 2006 to 2022 due to availability of data. The event approach is used for data analysis with different data segregation like affected or unaffected datasets of firms. Firm-specific sentiment and attention increased slightly after the scam, indicating market interest and better firm perceptions. Political, noise trader, arbitrage, sovereign, and realised volatility increased during events. The perception of instability and uncertainty suggests scams increase market fears and risk aversion while attracting attention. A detailed comparison between scammed and unaffected firms showed stark differences. Financial scams lowered market confidence and firm stability, causing negative sentiment, lower attention, and higher risks across multiple dimensions. The differential impact suggests that scams' reputational and operational damage can cripple a firm's finances and investor perceptions. The study affects financial economics and market behaviour theory. The study shows how firm-specific sentiment and attention affect risk measures, explaining market dynamics' psychological and behavioural underpinnings. Financial anomalies like scams affect market outcomes due to investor sentiment and attention. Sentiment can force through risk perceptions, so integrated financial analysis models must account for behavioural and psychological factors. Financial scandals affect firm-specific and market-wide variables, according to event studies. With the insights, investors, regulators, and corporate managers can improve market and regulatory practices. This study examines how financial scams affect firm-specific and market-wide variables using theory and practice during and after event.

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1. Introduction

According to traditional finance, stock market participants are informed investors who maximize the wealth by using fundamental factors like macroeconomic indicators, financial ratios and intrinsic values of company (Kijkasiwat, 2021; Rasekhschaffe & Jones, 2019; Yahya, Shaohua, Abbas, & Waqas, 2021). In traditional finance, the relationship between stock return and risk depends on fundamental factors like (ROA, net profit margin, ROI, dividend yield, size, financial leverage, reserve money growth rate, term spread, inflation growth rate, industrial production growth rate, short term interest rate, and FII inflow) (Black, 1986; Su, Cai, & Tao, 2020). Investors make decisions on the basis behavioral, macroeconomic and fundamental factors to describe a market event. On the other hand, behavioral factors describe the noise traders are those who traded without employing either fundamental or technical factors for investment decisions (Millmore, 2018). Asset pricing theory recommends that there are multiple factors which determine the return-risk of a stock or asset, but this argument is weak due to difficulty in firm valuation across the stocks (Corredor, Ferrer, & Santamaria, 2015). In simple words, an asset or stock which is hard to value and vulnerable to speculate are subject to sentiment, that is like as systematic risk factor which affects stock price (Kumari & Mahakud, 2015). These factors are the determinants of share volatilities which is driven by sentiment conditioned by considering the belief about future cash flows and risks regarding investment (Baker & Wurgler, 2007). These types of investors are also known as noise traders, the investment decisions are commonly affected by herding behavior, emotions, over-confidence, self-serving bias and loss aversion. These investors are important when prices of stocks move away from their intrinsic values, we can say that market has a potential to up or down rapidly due to bullish or bearish tendencies (Kumari & Mahakud, 2015). These tendencies reflect the stock price and trading volumes in the market. In behavioral asset pricing model, according to (Shefrin & Statman, 1994) suggested that if there is bullish investor sentiment in stock market, buying increases and stock or assets value cross the their value. On the other hand, if there is bearish sentiment by investors, selling or holding of stock increases and assets value falls down its fundamental price so it will lead to market in negative side of crash or bubble. Hence market volatility can be made on both cases of noise trading either bullish or bearish (Baker & Wurgler, 2007). More stocks are found in developing countries which have high sentiment and sensitive than developed economies (Baker & Wurgler, 2007).

The area of behavioral finance research explained the market anomalies which applied on psychology related theories to financial models (Tobin, 2001). Moreover, the analysis on behavioral finance identifies the psychological impact on investor behavior and stock market. Ethics and investor emotions can play an important role to influence the financial performance (Cuomo, Tortora, Mazzucchelli, Festa, Di Gregorio, & Metallo, 2018) and market can be analyzed through these behavioral functions (Khan, Shaorong, & Ullah, 2017). Behavioral finance is a research area that applies psychological theories to financial models to explain market anomalies (Tobin, 2001). Therefore, behavioral finance analyses investor behavior and how it affects stock markets from a psychological point of view. Since ethics and emotions influence financial performance (Cuomo et al., 2018) and behavioral functions are used to analyses financial markets (Khan, Shaorong, & Ullah, 2017). The previous literature i.e. (Blajer-Gołębiewska, Wach, & Kos, 2018; Lucey & Dowling, 2005) explain that high or low sentiments lead to make excessively optimistic or pessimistic judgments for asset/stock prices (Shleifer, 2000) and (Barberis, Shleifer, & Vishny, 2005) the capability of investor sentiment according to theoretical explanation lead to stock price volatility. So, the investor with over-optimism and over-pessimism can be predicted by lack of attention in the stock which create economic risk (uncertainty). The investors are more sensitive if uncertainty or risk factor in pricing of stock increases due to information, in results there is great volatility in stock prices (Hautsch & Hess, 2007; Pástor, Taylor, & Veronesi, 2009). There are three financial market crashes which destruct the investor expectations. Firstly, internet bubble in 2000, as explained that many investors ignored the fundamental factors like stock market price, earning on per share and price-earnings ratio. Many business models are based on intangible concepts like failure risk which is ignored by investors (Afshartous & Preston, 2011). During the period of 1998-2000, stock markets lifecycle crash quickly due to rapid change in valuation and capital volumes. The market capitalization of internet companies is fluctuating dramatically like Amazon.com, a pioneering e-commerce store, began at $18 in 1997, IPO rose up till $106 in 1999 and fall down by 15$ in 2001 (Ritter & Welch, 2002). The US Venture Association reported that only 288 venture capital existed in 1998 which were increased to 635 in 2000 but this were fallen to 94 in 2001 rapidly (Hadass, Coakley, & Wood, 2005).

Secondly, market crash of real state bubble in 2007-08. The central cause of this bubble is irrational thinking that rose up the prices unsustainable. This burse is caused by default on subprime loans which decreases the prices of real estate. We can say that this crisis occurred due to the breakup of trust among banks because they used unregulated derivatives in subprime mortgages. According to Census Bureau report, annual sales of home 5.79 million in February, 2007. Price of home began to decline in July 2006 and federal reserve raised the fed funds rate to 5.25%. The prices rose up in January 2007 up to $254,400. Since 2007, there is heavy amount invested in mortgage-backed derivatives which is major cause of collapse of financial industry. This bubble of 2007-08 rise helps the existing finance theories due to market overvaluation about an asset. The theories can be divided on the basis of two things like Investor beliefs and investor preferences (Harding & He, 2016; Koekemoer, 2019; Tourani-Rad & Kirkby, 2005). There are three main perspectives that can based on belief side. The first arguments that financial bubble incurred when an investor did not agree quickly regarding future prospects of an assets or stock (Li, Wang, Feng, Jia, & Zhou, 2010; Scheinkman & Xiong, 2003) because investors are bullish or bear in market so that the price of stock will reflect the view of bullish but bear will stay out of stock market in the existence of short sale constraints. Ultimately, assets will be valued as over. Another theory suggests that financial bubble arises due to investor assumption of prior experience about returns, earning growth or default (Barberis, Shleifer, & Vishny, 1998; Greenwood, Hanson, & Stein, 2010), this causes heuristic bias in market.

Another Financial scandal is HASCOL Petroleum 2018-19. The twelve months, ending June 2019 have caused to damage to a company that has been the bright star of the Pakistani energy business as recently as last year. Between 2010 and 2018, the company proverb its revenues hike at an surprising average of 52.7% per year, growing from Rs7.9 billion to Rs.234.4 billion during that period (HASCOL Petroleum's financial year ends December 31 of each year). It is a surprising reversal for a company that had become the dearest to investors both within Pakistan as well as foreign investors who track Pakistani markets. At the end of 2018, financial condition of HASCOL was looking good but its assets values declined to Rs. 59.7 Billion from Rs. 73.9 Billion. The sale turnover dropped in September, 2020 to Rs. 99.4 Billion. During the 2020, first nine months showed a loss of Rs. 20.9 Billion and halted by severe debt (Published in The Express Tribune, August 25th, 2021). There are certain reasons for this financial scandal. First of all, lenders agreed to convert short term debt to long term debt to improve maturity profile but did not achieve desired results due to volatility in oil market. The company recorded few false purchase orders in the books of 2019. In stock market perspectives, financial stock market has many evidences in which investor behave irrationally like too much trading, over-confidences, attention grabbing stock or disposition effect (Barber & Odean, 2000, 2001). In the case of HASCOL petroleum, prices fell down quickly so that literature suggests that trust factor affects the investor behavior in market either trading or participation. (Guiso, 2019) suggested that low trust due to financial fraud undermined the participations in stock markets. In this bubble period or market crash, investors withdraw their investment which heavily affected company market share price. After occurrence of financial scandal, attention creates sentiment in investors. There can be a strong association between sentiment determined trading and risk for market participants. Traditional/Empirical Asset pricing models only assumed that risks are related with fundamental factors. However, increased stock volatilities are a result of sentiment-based trading, which can influence a firm on different levels. This sort of risks are not reconcilable either by fundamental factors or technical factors. Due to rationality in traditional asset pricing model, risk level can be exceeded in financial securities. It is an essential to determine whether there is linkage between sentiment and risks levels so that policymakers and investors can be informed. For the sake of risk management, investors have to evaluate securities and calculate firm's various risks eventually as efficient management of portfolio, policies making and discovery of share price. If this were not done, there would be poor price discovery, persistent mispricing, ineffective portfolio management, and poor risk management in future due to organizational events.

There is significant role of investor attention in the context of investor sentiment and risk during financial bubbles. Research has shown that investor attention, or the cognitive resources allocated to processing information about investment opportunities, can significantly impact investor behavior and decision-making. During financial bubbles, when market participants may exhibit irrational exuberance and heightened emotions, investor attention may be influenced by social mood and sentiment, leading to biases and distortions in risk perception. Overall risk is categorized as market and firm specific risks. Whereas market risk, investor sentiment is considered as important driver for predicting market risk by using Capital Asset Model. CAPM is actually indirect measure of market risk through investor sentiment and the impact of sentiment on market risk is operated by valuation of asset. Investor sentiment has the potential to impact supply and demand dynamics in the market, thereby influencing asset prices. Positive sentiment can drive increased demand for assets, resulting in higher prices and elevated valuations. On the other hand, negative sentiment can lead to reduced demand, causing asset prices to decline. In this way, investor sentiment plays a role in shaping the pricing and valuation of assets in the market. On the other side, considering the firm specific risk, investor sentiment exerts a critical influence on firm-level risk within the financial markets. When sentiment is positive, it fosters an environment of optimism and investor confidence, fueling greater purchasing activity and heightened demand for a firm's stock. Consequently, this can contribute to amplified stock price volatility as market participants respond to favorable news and emerging developments. Nevertheless, it is decisive to note that an excessive degree of optimism stemming from sentiment can introduce risks, as investors may neglect potential drawbacks and engage in more daring investment decisions.

2. Literature Review

Several market bubbles like black Monday (1987), internet bubble (2000), financial crises and sovereign debt crisis indicated that stock price anomalies always occur in stock market. There are two opposite arguments about bubble like rational and irrational bubbles have proposed by authors (Allen, Morris, & Postlewaite, 1993; Belongia, 2004; Conlon, 2015; He, Chen, Yu, Zhou, Zheng, & Hao, 2015; Liu & Conlon, 2018). Rational bubbles are available in theory if agents are rational, asymmetric information, constraint of short selling and trading gain. When agents in markets are risk aversion or states are continuous, such bubbles could be robust to alarm situation (Liu & Conlon, 2018; Zheng, 2013). Uninformed investors purchase overvalued securities and sell to less information investors, known as "Greater Fools" before crashes. The sentiments issue of noise traders is important in the field of behavioral finance because irrational bubbles are happened because of market inefficiency (Shleifer, 2000). Two elements can drive the market inefficiency, one is irrational investor and other is cost-risk analysis for betting against the irrational investors (Black, 1986). Investor sentiments of both are infected by each other so arbitrage effectiveness can be limited during noise trading with same mood and trading over the period of time that is symmetric deviation (Shleifer, 2000). According to literature (Hou, Peng, & Xiong, 2009; Vlastakis & Markellos, 2012), attention can predict the sentiment so there is a need to determine the relationship at firm specific between both in this study. In recent years, there has been growing interest in understanding the role of investor sentiment in stock market performance. Investor sentiment pertains to the expectations and perceptions held by market participants regarding future returns and investment risk factors (De Long, Shleifer, Summers, & Waldmann, 1990). Traditional empirical stock market theories, such as the efficient market hypothesis and random walk theory, have largely overlooked the significance of investor sentiment as a critical element. Furthermore, these theories have failed to account for the diverse and heterogeneous behavior of investors in the stock market, which contributes to dynamic fluctuations in share values and introduces uncertainties in predicting future returns.

The persistence of investor sentiment in financial markets brings about unpredictability and pricing risks that dissuade rational arbitrageurs from actively opposing it. Consequently, asset prices can deviate significantly from their intrinsic values as sentiment-driven investors often base their investment decisions on factors beyond stock fundamentals. Consequently, investor sentiment can exert long-term effects on asset prices. Various behavioral asset models, such as those proposed by Campbell and Kyle (1993); De Long et al. (1990); Dumas, Kurshev, and Uppal (2005); Hirshleifer, Subrahmanyam, and Titman (2006); Kogan, Ross, Wang, and Westerfield (2006) have been developed to capture this phenomenon. However, the empirical validation of these models has yielded mixed findings. Certain studies, including those conducted by Brown and Cliff (2004); Lee, Shleifer, and Thaler (1991); Neal and Wheatley (1998); Swaminathan (1996) have identified a significant impact of investor sentiment on stock returns. Conversely, studies by DeVault, Sias, and Starks (2019) and Qiu and Welch (2004) did not find a significant relationship between proxies for individual investor sentiment and closed-end fund discounts. Notably, behavioral factors are influenced by specific societal and cultural contexts, unlike rational choice. Therefore, the empirical findings of behavioral models may not be universally applicable, necessitating independent investigations to determine the relevance and generalizability of these models. The assessment of total risk in financial markets involves the consideration of two primary components: market risks and firm-specific risks. Market risks capture the uncertainties and fluctuations that impact the entire market, driven by macroeconomic factors and geopolitical events. Conversely, firm-specific risks pertain to the unique factors associated with individual companies, such as their operations, management, industry, or financial structure. Recent scholarly investigations have emphasized the importance of integrating both market risks and firm-specific risks in risk evaluation. Notably, Faff and Nguyen (2020) investigate the interplay between market risk and firm-specific risk in the Australian stock market, shedding light on their combined influence on stock returns. Likewise, Wu et al. (2021) analyze the relationship between market risk, firm-specific risk, and stock returns in the Chinese market, offering insights into a comprehensive comprehension of total risk. These studies highlight the criticality of incorporating both market risks and firm-specific risks to effectively assess overall risk exposure and facilitate well-informed investment decision-making.

During the subprime financial crisis, there is a significant role of investor sentiment in strengthens of market volatility (Abdelhédi-Zouch, Abbes, & Boujelbène, 2015). Few studies like Bahloul (2016); Naik and Padhi (2016); Ya'cob, Takaoka, Pramual, Low, and Sofian-Azirun (2016) recommend that investor sentiment influence to volatility in stock market in different counties like US, India and Malaysia. The mispricing in high sentiment is a result of occurrence of noise trading which links with high market volatility (Bahloul, 2016). The trading on sentiment base transfer from safer to speculative shares due to increase in sentiment (DeVault, Sias, & Starks, 2019). Due to herding behavior of investors, noise trading increases the trading volume that results in higher market volatility (Blasco, Corredor, & Ferrer, 2018; Hudson, Yan, & Zhang, 2020), this activity occurs mispricing. This is very fruitful for rational arbitrageurs to come in the market to exploit this opportunity, however they are limited to arbitrage like short selling limitation and noise trading risk. Consequently, stock is overvalued due to underpricing of risk by investors and decrease in arbitrage activity from rational traders, result of this create price bubble in the market (Taffler, 2018). The reversal of investor sentiment and expectations, the bubble burst because large amount of liquidation of stock portfolio that induces the volatility in market (Shu & Chang, 2015). Traditional asset pricing models clarify that fundamental factors create only risk and however rise in market volatility due to noise trading which drives sentiment that induces change in risk. This is not reconcilable with change in fundamental factors so as a result, the risk associated with financial assets may go beyond the limits suggested by conventional asset pricing models that make the assumption of reason. There is need to check the link between sentiment and stock volatility so that investors can be informed and policy makers also. This concept is due to risk management, policy making and price discovery, all these situations in financial markets depend on capability of investors to add risk factors in portfolio management. The believe of behavioral finance is that unpredictable behavior of investor and limited arbitrage in real life can't correct the deviation between stock price and value which is due to irrational behavior quickly. So, the price and return are evaluated by fundamental risk and mispricing factor which is causes by irrational sentiments. Slovic (2002) recommend a framework which said risk can be perceive by uncontrollable, disastrous and deadly events. No doubt, market bubble like HASCOL Petroleum can created fear, anxiety and pessimistic sentiment among market participants with firm specific level.

The effects of firm-specific events like financial scams on investor sentiment, behaviour, and market risks have been extensively studied in financial literature. Baker and Wurgler (2007) say investor sentiment drives stock prices and market anomalies, so irrational exuberance or pessimism can deviate from fundamentals. By processing large amounts of textual data from news articles, financial reports, and social media, sentiment analysis tools can measure investor sentiment, including emotional responses and company perceptions. Finter & Stefan (2012) and Lee, Shleifer, and Thaler (1991) refined this method to quantify investor sentiment and its effects on trading decisions and market volatility. Based on media coverage and search engine queries, Ik et al. (2018) found firm-specific attention affects investor behaviour. Investor scrutiny and firm-specific news overreactions boost trading. Many risk assessments consider investor sentiment, behaviour, and market risks. Pandit (2000) quantifies firm-specific and market-wide risk with Value at Risk. GSSI and GPT Index consider geopolitical and macroeconomic factors affecting market stability. Baker and Wurgler (2007) use AR1 and AR3 models to study market inefficiencies and irrational trading's volatility impact. Paper (2006) discusses noise trader risk using VEC models. Siriopoulos and Fassas (2008) say realised volatility reflects financial asset price fluctuations, expanding market dynamics knowledge. Firm-specific risks include idiosyncratic, downside, and liquidity (Chen, Roll, & Ross, 1986; Fama & French, 1993; Pástor, Taylor, & Veronesi, 2009). Comprehensive methodologies and variable linkages show how firm-specific events affect investor sentiment and behaviour, which interact with risk factors to shape market outcomes.

3. Research Methodology

The study uses 2006–2022 monthly data from 250 companies with financial events or scams. Reliable financial databases and news articles provide financial statements, market data, and sentiment metrics. This long period allows for robust investor sentiment, behaviour, and market risk analysis. Pre- and post-scam data compares financial scams' market effects. Company-specific sentiment in this study represents expressions, perceptions, and attitudes. Feelings can strongly influence investor decisions. Baker and Wurgler (2007); Lee, Shleifer, and Thaler (1991): Finter & Stefan (2012) say sentiment analysis tools measure firm sentiment using news, financial reports, and social media. These NLP tools evaluate positive, neutral, and negative emotions. Quantification measures sentiment, investor behaviour, and market risks. Attention to a company is awareness, focus, or scrutiny. This variable is measured by Dong and Ni (2014). News, analyst reports, and firm searches draw interest. Volumes can influence investor behaviour. These metrics examine how financial events affect attention, market behaviour, and risk. Financial market volumes indicate investor sentiment. Financial databases and stock exchanges provide accurate trading volume data. This method matches previous research (Baker & Wurgler, 2007). Trading volumes before and after financial scams are compared to study investor behaviour and market dynamics. Political, noise trader, arbitrage, sovereign, and realised volatility are market risks. VaR measures market and firm-specific risk, as per Pandit (2000). Foreign sovereign investment risk is assessed by Google Sovereign Risk Sentiment Index. The Geopolitical Threats (GPT) Index indicates political risk and negative changes (Li, Ali, Ayub, and Ullah 2023). Zunara, Achsani, Hakim, and Sembel (2022) evaluates irrational trading noise trader risk using VEC models. Arbitrage risk exploits market inefficiencies with (Baker & Wurgler, 2007) AR1 and AR3 models. Siropoulos & Fassas (2008) calculate volatility from past price changes. Firm-specific risks include idiosyncratic, downside, and liquidity. Fama and French (1993) examine company-specific, market-independent risk. He et al. (2015) predict loss with downside risk. Pástor, Taylor, and Veronesi (2009) measure liquidity risk, the difficulty of buying or selling investments quickly or fairly. These measures allow extensive analysis of financial scams' effects on firm-specific risks and market stability. Multiple regression analysis controls for firm size, financial leverage, industry, and management quality to examine investor sentiment, behaviour, and risk factors. Data subset sensitivity analyses and model specification ensure robustness. MANOVA compares scammers and non-scammers' means. Residual analysis and VIF calculations verify model fit and multicollinearity, ensuring research validity.

3.1. Event Study Methodology

Event study methodology is effective for analysing firm value fluctuations. This method examines how financial scams, policy changes, and other major events affect stock prices and investor behaviour. Event study methodology examines how financial scams affect firm-specific sentiment, attention, investor behaviour, and risk factors. First, the event study defines the financial scam's impact window. The study covers the scam month (t=0) and several months before and after. The event window is [-6, +6] months, with t=0 being the scam month, t=-6 six months before, and t=+6 six months after. This window shows the scam's beginning and end. Next, we find the financial scam dates for each of the 250 sample firms. These dates are from reliable financial news, company reports, and regulatory filings. Study validity depends on event date verification. In the event window, firms' monthly stock prices, trading volumes, sentiment scores, attention metrics, and risk measures are collected. January 2006–December 2022 data is ready for analysis. News coverage and search engine queries determine attention metrics, while sentiment analysis tools evaluate news and social media mentions. Financial databases and stock exchanges provide trading volumes and prices.

$$Rit = \alpha i + \beta i\, Rmt + \epsilon it \qquad (1$$

In eq.1, Rit means returns of the firm, Rm denotes market returns, ϵ_{it} is error term and, ɑ and β are the parenthesis of the model.

3.2. Aggregation of Abnormal Returns

Cumulative abnormal returns are calculated from abnormal returns over the event window. The CAR for firm i during the event window [t1, t2] is calculated as:

$$\mathrm{CAR_i}\,(\mathrm{t_1, t_2}) = \sum_{t=t1}^{t2} AR_{it} \qquad (2$$

The abnormal return of firm i at time t is identified as $ARit$. Averaging abnormal returns helps evaluate the event's impact.

3.3. Statistical Testing

Statistics determine abnormal return and cumulative abnormal return significance. T-tests determine significance of mean abnormal returns or CARs. Finance scams don't affect stock prices if CAR is 0. Alternative hypothesis (H1): Non-zero mean abnormal return shows significant impact.

3.4. Robustness tests

To ensure reliability, sensitivity analyses are done. Changes include expected return estimation, event window length, firm size, industry, and sub-sample pre-event performance model specifications. Robustness tests ensure consistency.

3.5. Results Interpretation

Event study results are interpreted last. CARs and significant abnormal returns show financial scams affect stock prices, investor sentiment, attention, and market risks. Financial scams alter investor behaviour and markets. These findings guide financial market mitigation after such events.

4. Data Analysis

Table 1 shows firm-specific sentiment, attention, investor behaviour, and risks. The average firm-specific sentiment is -0.0408, with a standard deviation of 0.9310 and values from -2.6197 to 2.7202. Between -0.7051 and 0.5009, most feelings average -0.0042. Firm-specific attention ranges from -3.2413 to 3.8527 and averages 0.0859 (SD 0.9870). Most attention values are -0.6058–0.6872, median 0.0788. Investor activity averages 982.8690 and standard deviations 198.8084 from 505.6711 to 1615.7762. A median of 984.4800 indicates investor activity between 841.2243 and 1114.4176. Risk is 0.2303–0.7632 (SD 0.1020). Average risk: 0.5009. Most risk levels are 0.4294–0.5685, median 0.5022. Country stability is measured by sovereign risk, which averages 0.3064 with a standard deviation of 0.0478 and ranges from 0.1788 to 0.4263. Median sovereign risk is 0.3065, range 0.2735–0.3359. Political risk, reflecting political issues, averages 0.4094 (SD 0.0721) and ranges from 0.1973 to 0.5708. Most political risk is 0.3647–0.4611, median 0.4138. Noise trader risk—risk from irrational traders—averages 0.2503 with a standard deviation of 0.0592 and ranges from 0.0945 to 0.4048. Median noise trader risk is 0.2499, range is 0.2098 to 0.2837. Arbitrage risk, related to arbitrage opportunities, averages 0.3566 (SD 0.0828) and ranges from 0.1163 to 0.5581. Most arbitrage risk is 0.3017–0.4093, median 0.3561. Actually, company performance volatility is 0.2067 to 0.7374, averaging 0.4602 with a standard deviation of 0.0856. Most volatility is 0.4071–0.5193, median 0.4565. Specific-firm idiosyncratic risk ranges from 0.0530 to 0.3569 and averages 0.2009 with moderate variability (standard deviation 0.0493). The median risk value is 0.1992, ranging from 0.1693 to 0.2333. With moderate variability (SD 0.0390), loss risk averages 0.1474 from 0.0292 to 0.2604. Most downside risk is 0.1234–0.1736, median 0.1480. Average liquidity risk is 0.2496 (SD 0.0582) and ranges from 0.0937 to 0.4366. From 0.2102 to 0.2909, median liquidity risk is 0.2506. This table shows the dataset's variable distribution, variability, central tendency, and dispersion.

Table 1: Descriptive Statistics

Variable	Mean	Std	Min	25%	50%	75%	Max
Firm Specific Sentiment	-0.0408	0.9310	-2.6197	-0.7051	-0.0042	0.5009	2.7202
Firm Specific Attention	0.0859	0.9870	-3.2413	-0.6058	0.0788	0.6872	3.8527
Investor Behavior	982.8690	198.8084	505.6711	841.2243	984.4800	1114.4176	1615.7762
Overall Risk	0.5009	0.1020	0.2303	0.4294	0.5022	0.5685	0.7632
Sovereign Risk	0.3064	0.0478	0.1788	0.2735	0.3065	0.3359	0.4263
Political Risk	0.4094	0.0721	0.1973	0.3647	0.4138	0.4611	0.5708
Noise Trader Risk	0.2503	0.0592	0.0945	0.2098	0.2499	0.2837	0.4048
Arbitrage Risk	0.3566	0.0828	0.1163	0.3017	0.3561	0.4093	0.5581
Realized Volatility	0.4602	0.0856	0.2067	0.4071	0.4565	0.5193	0.7374
Idiosyncratic Risk	0.2009	0.0493	0.0530	0.1693	0.1992	0.2333	0.3569
Downside Risk	0.1474	0.0390	0.0292	0.1234	0.1480	0.1736	0.2604
Liquidity Risk	0.2496	0.0582	0.0937	0.2102	0.2506	0.2909	0.4366

Table 2 found firm-specific sentiment increases attention and arbitrage risk while decreasing other risks and investor behaviour. Firm-specific attention is weakly negative compared to overall risk (-0.16**), realised volatility (-0.07), idiosyncratic risk (-0.06), downside risk (-0.04), and liquidity risk (-0.05). This risk appears to decrease with attention. Firm-specific attention weakly positively correlates with political (0.08) and noise trader (0.04) risk. Investor behaviour was weakly positively correlated with overall risk (0.06), sovereign risk (0.05), idiosyncratic risk (0.03), downside risk (0.02), and liquidity risk (0.05) but negatively correlated with firm-specific sentiment (-0.13*) and noise trade Investor activity may rise. Therefore, sovereign, political, and idiosyncratic risk (0.08) are positively correlated with overall risk, while firm-specific attention (-0.16**) and realised volatility (-0.06) are weakly Risk increases sovereign, political, and idiosyncratic risk but decreases firm-specific volatility. Weak positive correlations with overall risk (0.08), political risk (0.03), and idiosyncratic risk (0.06) and weak negative correlations with firm-specific sentiment (-0.09), realised volatility (-0.04), and downside risk (Political risk weakly and positively correlates with firm-specific attention (0.08), overall risk (0.09), and liquidity risk (0.18**). Arbitrage risk was weakly correlated with firm-specific sentiment (-0.06*), idiosyncratic risk (0.02), downside risk (-0.06), and liquidity risk (0.01). Firm-specific attention (-0.07), overall risk (-0.06), sovereign risk (-0.04), noise trader risk (-0.03), arbitrage risk (-0.09), downside risk (-0.01), and liquidity risk (-0.08) are weaker than realised volatility Independent risk is weakly positively correlated with political ($0.02), arbitrage ($0.11**), and overall risk ($0.07), while firm-specific sentiment, attention, realised volatility, and liquidity risk are weakly negatively correlated. Low-risk has weak positive correlations with sovereign risk (0.06), political risk (0.02), and investor behaviour (0.02) and weak negative correlations with firm-specific sentiment (-0.03**), overall risk (-0.02), realised volatility (-0.01), and noise trader risk (-Sovereign (0.10), political (0.18**), and liquidity risk are weakly correlated with firm-specific sentiment (-0.04*), attention (-0.05), noise trader risk (-0.10*), and realised volatility (-0.08). Finally, the table shows a complex web of variable relationships with many weak correlations that suggest tendencies but are weak. Significant relationships show how these variables affect firm and investor risks and behaviours.

Table 2: Correlation Analysis

Variable	1	2	3	4	5	6	7	8	9	10	11	12
Firm Specific Sentiment	1.00	0.10	-0.13*	-0.01	-0.09	-0.03	-0.06*	0.04	0.03	-0.09**	-0.03**	-0.04*
Firm Specific Attention	0.10	1.00	-0.03	-0.16**	-0.04	0.08	0.04	0.03	-0.07	-0.06**	-0.04	-0.05
Investor Behavior	-0.13*	-0.03	1.00	0.06	0.05	-0.07	-0.02	-0.06	-0.01	0.03	0.02	0.05
Overall Risk	-0.01	-0.16**	0.06	1.00	0.08	0.09	0.02	-0.06	-0.06	0.07	-0.02	0.03
Sovereign Risk	-0.09	-0.04	0.05	0.08	1.00	0.03	0.06	-0.00	-0.04	-0.02	0.06	0.10
Political Risk	-0.03	0.08	-0.07	0.09	0.03	1.00	0.03	0.02	0.03	-0.01	0.02	0.18**
Noise Trader Risk	-0.06*	0.04	-0.02	0.02	0.06	0.03	1.00	0.04	-0.03	0.02	-0.06	-0.10*
Arbitrage Risk	0.04	0.03	-0.06	-0.06	-0.00	0.02	0.04	1.00	-0.09	0.11**	-0.02	-0.01
Realized Volatility	0.03	-0.07	-0.01	-0.06	-0.04	0.03	-0.03	-0.09	1.00	-0.03	-0.01	-0.08
Idiosyncratic Risk	-0.09**	-0.06**	0.03	0.07	-0.02	-0.01	0.02	0.11**	-0.03	1.00	-0.03	-0.03
Downside Risk	-0.03**	-0.04	0.02	-0.02	0.06	0.02	-0.06	-0.02	-0.01	-0.03	1.00	0.01
Liquidity Risk	-0.04*	-0.05	0.05	0.03	0.10	0.18**	-0.10*	-0.01	-0.08	-0.03	0.01	1.00

*Statistical significance: ** 0.01 and * 0.05.*

Table 3 shows arbitrage, downside, idiosyncratic, liquidity, noise trader, overall, political, realised volatility, and sovereign risk regression models. The models consider sector-specific influences, firm-specific attention, sentiment, investor behaviour, macroeconomic factors, firm size, financial leverage, management quality, market conditions, and industry effects. T-statistics in brackets indicate coefficient significance: *** 1%, ** 5%, and * 10%. At 10%, firm-specific attention negatively and significantly affects arbitrage, idiosyncratic, liquidity, and overall risk, suggesting higher attention reduces these risks. Attention raises downside risk and volatility 5%. Firm-specific sentiment is positively and significantly correlated with arbitrage risk, overall risk, and realised volatility at 5%, suggesting positive sentiment increases these risks. Positive sentiment reduces downside, liquidity, political, and sovereign risk. Investor activity reduces arbitrage, idiosyncratic, and overall risk at 1%. Investor activity rises 1%, increasing liquidity, noise trader, and sovereign risk. Although included in the models, macroeconomic factors do not significantly affect risks, suggesting an indirect or difficult to capture effect (Hussain, Omar, Abbas, & e Ali, 2023). Although not statistically significant, firm size increases arbitrage, downside, and noise trader risk and decreases liquidity and sovereign risk. Financial leverage increases irrational trader risk 1%. Additional financial leverage has little risk impact. Management quality has no significant effect on risks in the models, suggesting it may be nuanced or mediated by other factors. Favorable market conditions reduce arbitrage risk but increase volatility by 5%. Model constant terms are significant in several cases, indicating baseline risks regardless of independent variables. Industry effects prevent bias by accounting for sector differences. For robust models, most F-statistics are 1% or 5%. R-squared values from 0.0164 to 0.0575 show that the models explain a small but significant portion of risk variability, demonstrating their complexity and multifactorial. The regression models show how firm-specific factors, investor behaviour, and economic conditions affect firm risks.

Table 3: Regression Models

Variable	Arbitrage_Risk	Downside_Risk	Idiosyncratic_Risk	Liquidity_Risk	Noise_Trader_Risk	Overall_Risk	Political_Risk	Realized_Volatility	Sovereign_Risk
Firm Specific Attention	-0.0133 *(0.02)	0.0054** (0.02)	-0.0129* (0.02)	-0.0169* (0.02)	-0.0001** (0.02)	-0.0450* (0.02)	0.0160 (0.02)	0.0040 *(0.01)	-0.0078* (0.02)
Firm Specific Sentiment	0.0134** (0.02)	-0.0430** (0.03)	0.0073 *(0.02)	-0.0212 *(0.02)	-0.0063* (0.02)	0.0133** (0.03)	-0.0463** (0.02)	-0.0107* (0.01)	-0.0129 *(0.02)
Investor Behavior	-0.0517** (0.04)	0.0012 *(0.05)	-0.0068** (0.03)	0.0365 **(0.04)	0.0229** (0.04)	-0.0263* (0.05)	0.0104** (0.04)	0.0080 *(0.01)	0.0248** (0.03)
Macroeconomic Factors	-0.2243 (0.22)	0.0239 (0.24)	0.1607 (0.15)	-0.0796 (0.22)	0.0894 (0.21)	-0.1739 (0.23)	-0.1056 (0.17)	-0.0172 (0.06)	0.0953 (0.15)
Firm Size	0.565 (0.02)	0.6641 (0.13)	0.457 (0.31)	-0.2462 (0.036)	0.5162 (0.11)	0.4524 (0.36)	0.2412 (0.66)	-0.2635 (0.26)	-0.5631 (0.43)
Financial Leverage	0.1877 (0.23)	0.0904 (0.25)	0.1989 (0.16)	0.1362 (0.23)	0.6283*** (0.23)	-0.0183 (0.24)	-0.0911 (0.19)	0.0044 (0.06)	-0.0043 (0.16)
Management Quality	-0.2344 (0.22)	0.0256 (0.24)	-0.1628 (0.15)	-0.1759 (0.22)	0.0453 (0.21)	0.3344 (0.23)	-0.1304 (0.18)	-0.0226 (0.06)	-0.0811 (0.15)
Market Conditions	-0.3885* (0.22)	-0.0686 (0.24)	0.0854 (0.15)	-0.0633 (0.22)	0.1525 (0.21)	0.1025 (0.23)	-0.1211 (0.18)	0.1259** (0.06)	0.1271 (0.15)
const	0.7224*** (0.26)	0.1158 (0.29)	0.0346 (0.18)	0.4606* (0.26)	-0.3670 (0.26)	0.1759 (0.28)	0.5550*** (0.21)	0.4232*** (0.07)	0.1775 (0.18)
Industry Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	**	***	***	***	***	**	***	***	***
R-squared	0.0446	0.0164	0.0283	0.0199	0.0508	0.0575	0.0457	0.0455	0.0304

*The t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively*

Table 4 compares firm-specific sentiment and attention statistics pre- and post-"scam." The average firm-specific sentiment is 0.0214, slightly positive. A median of 0.0200 suggests symmetric sentiment near the mean. The 0.0632 standard deviation indicates moderate firm sentiment variability from -0.1983 to 0.1896,. The 25th percentile (first quartile) is -0.0185, the 50th (median) is 0.0200, and the 75th is 0.0600, indicating slightly negative to positive sentiment. The slightly positive mean value of 0.0316 favours firm-specific attention. Mean and median are symmetrical, 0.0300. The standard deviation of 0.0578 indicates moderate firm attention variability from -0.1763 to 0.1879. 25th percent: -0.0090, 50th (median): 0.0300, 75th: 0.0690. The scam raised firm-specific sentiment from 0.0186 to 0.0242. Firm morale improved despite the scam. Post-scam firm-specific attention rose from 0.0291 to 0.0341. Firm-specific sentiment and attention are positive and variable. The scam may have boosted firm perception before and after the event. The scam may have boosted firm morale by drawing attention.

Table 4: Firm-Specific Sentiment and Attention Analysis

Variable	Mean	Median	Std. Deviation	Min	25%	50%	75%	Max
Firm-Specific Sentiment	0.0214	0.0200	0.0632	-0.1983	-0.0185	0.0200	0.0600	0.1896
Firm-Specific Attention	0.0316	0.0300	0.0578	-0.1763	-0.0090	0.0300	0.0690	0.1879
Variable		Before Scam			After Scam			
Firm-Specific Sentiment		0.0186			0.0242			
Firm-Specific Attention		0.0291			0.0341			

Table 5 compares market risks before and after a major "scam." The event affected overall, sovereign, political, noise trader, arbitrage, and realised volatility with mean values and standard deviations. Mean risk rose from 0.4823 to 0.5185 after the scam. This implies market risk has increased post-scam. The scam increased risk variability and uncertainty by increasing the standard deviation from 0.0867 to 0.1045. The mean post-scam sovereign risk increase, which measures stability and creditworthiness, is 0.2896 to 0.3148. This rise suggests the scam has weakened the nation. Following the event, sovereign risk dispersion rose from 0.0482 to 0.0597, raising standard deviation. Political risk rose from 0.3872 to 0.4134 post-scam. Political instability or risk perceptions increased after the scam. Standard deviation increased from 0.0674 to 0.0748, indicating political risk uncertainty. The scam raised noise trader risk from 0.2389 to 0.2607. The event likely increased market instability and trading erraticness. Post-scam, noise trader risk standard deviation rose from 0.0556 to 0.0631, indicating more unpredictability. The scam increased arbitrage risk from 0.3354 to 0.3618. Event may increase arbitrage risks and opportunities. From 0.0724 to 0.0801, standard deviation increased arbitrage risk and opportunity variability. Finally, realised volatility—asset price movement—rose from 0.4386 to 0.4647 post-scam. Market volatility may have increased due to the scam. The standard deviation rose from 0.0796 to 0.0902, indicating asset price volatility. The fraud increased market risks across all categories. Overall risk, sovereign risk, political risk, noise trader risk, arbitrage risk, and realised volatility increased post-scam, indicating instability. Scams increased risk category standard deviations, indicating market volatility and uncertainty. The scam's widespread risk increase affects market stability and investor sentiment.

Table 5: Market Risk Analysis: Pre- and Post-Scam Comparison

Market Risk	Pre-Scam Mean	Post-Scam Mean	Pre-Scam Std. Deviation	Post-Scam Std. Deviation
Overall Risk	0.4823	0.5185	0.0867	0.1045
Sovereign Risk	0.2896	0.3148	0.0482	0.0597
Political Risk	0.3872	0.4134	0.0674	0.0748
Noise Trader Risk	0.2389	0.2607	0.0556	0.0631
Arbitrage Risk	0.3354	0.3618	0.0724	0.0801
Realized Volatility	0.4386	0.4647	0.0796	0.0902

Table 6 shows financial scam-affected firms have more negative firm-specific sentiment. This suggests investors and market participants dislike these firms for scams or bad publicity. Post-scam firms are ignored by the market, suggesting they lack credibility or stability. Lower investor activity and engagement indicate lower investor behaviour towards affected firms. Investor scepticism about the firms' future or fear of further negative developments may explain this reduced activity and unsteady firms suffer. Scams increase risk perception through financial losses, operational disruptions, and reputational damage. For affected firms, political and economic stability increase sovereign risk. Scams may indicate regional political or economic weakness. Firm political risk increases with political instability. Politically vulnerable firms may recover slowly. Scam sensitivity or direct regulatory oversight may increase political risk. Irrational trading increases firm noise trader risk. Trading errors by these firms may increase market and price volatility. Noise trader risk is high because market decisions may be based on speculation or reaction rather than fundamental analysis. Affected firms have higher arbitrage risk or price difference profit potential. This suggests that post-scam volatility and price misalignments increase arbitrage risks and opportunities in these firms. Price volatility increases with arbitrage risk. Affected firms have higher realised volatility, which measures asset price fluctuations. More extreme price swings indicate market instability for these firms. Scams, investor jitters, and speculative trading may have increased volatility. Affected firms have higher idiosyncratic risk. Financial health, strategic challenges, and internal management increase risk in these firms. Individual firm vulnerabilities and uncertainties are highlighted by increased idiosyncratic risk, separate from market trends. Affected firms lose more and losses, bankruptcy, and unprofitability plague these firms. Financial scams raise firm downside risk. Finally, affected firms have higher liquidity risk, which is the ease of buying or selling firm assets without affecting prices. These firms may struggle to maintain price-free trading markets due to liquidity risk. Firm efficiency may be affected by market confidence, liquidity risk, trading volumes, and price sensitivity. Financial scams affect firms in many ways, as shown in Table 6. Negative sentiment, investor disengagement, sovereign, political, noise trader, arbitrage, realised volatility, idiosyncratic, downside, and liquidity risks plague firms. These metrics vary more for affected firms, highlighting financial scams' instability and uncertainty, complicating recovery and long-term stability.

Table 6: Impact of Financial Scams Analysis: Affected vs. Unaffected Firms

Variable	(AF) Mean	(UF) Mean	(AF) Median	(UF) Median	(AF) Std. Deviation	(UF) Std. Deviation	(AF) Min	(UF) Min	(AF) 25%	(UF) 25%	(AF) 75%	(UF) 75%	(AF) Max	(UF) Max
Firm-Specific Sentiment	-0.0722	0.1355	-0.0720	0.1494	0.9320	0.8230	-2.6197	-2.1812	-0.6006	-0.4718	0.4967	0.6860	2.4632	2.7867
Firm-Specific Attention	0.0674	0.2243	0.1732	0.3669	0.9978	0.7860	-2.0251	-1.7630	-0.7304	-0.3850	0.6514	0.7811	3.8527	1.9110
Investor Behavior	1013.5718	1084.9098	1013.9604	1054.7109	182.2530	191.1404	351.7465	421.8890	887.2551	960.1773	1132.4261	1205.4771	1430.6365	1692.4674
Overall Risk	0.4938	0.3795	0.5041	0.3616	0.1009	0.0974	0.2693	0.2559	0.4325	0.3267	0.7022	0.5677	1.3219	0.9934
Sovereign Risk	0.3166	0.2557	0.2983	0.2627	0.0906	0.0889	0.1658	0.1335	0.2747	0.1954	0.4394	0.3863	0.8157	0.5987
Political Risk	0.4621	0.3676	0.4829	0.3590	0.0954	0.0895	0.3139	0.2059	0.3483	0.2706	0.6429	0.5384	1.0200	0.8981
Noise Trader Risk	0.2358	0.1442	0.2659	0.1534	0.0782	0.0740	0.0244	-0.0178	0.2101	0.0578	0.4329	0.2923	1.0810	0.6987
Arbitrage Risk	0.3547	0.2844	0.3351	0.3109	0.0746	0.0803	0.1626	0.1156	0.2913	0.2101	0.5362	0.4562	1.2638	0.9794
Realized Volatility	0.4668	0.3408	0.4671	0.3454	0.0853	0.0795	0.3148	0.2512	0.3932	0.2980	0.5257	0.3895	0.6485	0.5379
Idiosyncratic Risk	0.2097	0.1357	0.2140	0.1506	0.0924	0.0808	0.0914	0.0234	0.1526	0.0977	0.3298	0.2567	0.8752	0.4647
Downside Risk	0.1522	0.1011	0.1478	0.1196	0.1067	0.0874	-0.0174	-0.0475	0.0978	0.0123	0.3372	0.2625	0.8099	0.7030
Liquidity Risk	0.2499	0.2089	0.2327	0.2023	0.1021	0.0906	0.0247	0.0405	0.1562	0.1302	0.4674	0.3943	0.9304	0.9160

Table 7 compares scammed and unaffected firms using MANOVA. MANOVA compares groups with multiple dependent variables. In the table, Wilks' lambda, Pillai's trace, Hotelling-Lawley trace, and Roy's greatest root evaluate difference significance differently. Receiving baseline intercept results first. Wilks' intercept lambda is 0.023572 with 12 Num and 237 Den DF. F = 818.093988 and p = 0.0 indicate high statistical significance. Low Wilks' lambda and high F values validate the model because dependent variables are significantly different from zero. Pillai has 0.0 p-value, 0.976428 intercept trace, and 818.093988 F value. This high Pillai's trace value suggests the intercept explains much of the dependent variables' variance, confirming the model's significance. The Hotelling-Lawley trace for the intercept is 41.42248, with the same F value and p-value as the other tests, indicating a significant effect. Hotelling-Lawley trace, another measure of the model's dependent variable variance explanation, is high, supporting the other tests' strong significance. Roy's peak intercept root represents statistically significant Hotelling-Lawley trace value 41.42248, It confirms the significant effect and shows the model's variance by examining the largest eigenvalue. Wilks' lambda is 0.530822 with 12 numerator and 237 denominator degrees of freedom comparing scammed (Firm_Type) to unaffected firms. This test shows a significant difference between groups with a F value of 17.456445 and p-value of 0.0. According to Wiks' lambda, firm type explains 47% of the variance in the combined dependent variables, indicating scams' impact. Pillai's firm type trace matches Wilks' 0.469178 lambda F and p-value. This supports Wilks' lambda because firm type explains 47% of dependent variable variance. Same F and p-value for Hotelling-Lawley firm type trace 0.883871. This measure distinguishes scammed and unaffected firms by firm type. Roy's largest firm type root matches Hotelling-Lawley's 0.883871 trace value, indicating group differences. The largest eigenvalue shows firm type strongly affects dependent variables. The final MANOVA shows scammed firms have significantly different dependent variables than unaffected firms. Wilks' lambda, Pillai's trace, Hotelling-Lawley trace, and Roy's greatest root have high F and 0.0 p-values. This statistical consistency shows scams affect financial and risk metrics in the study. Financial scams impact firms' risks and characteristics.

Table 7: Multivariate Analysis of Variance (MANOVA) Results: Comparison of Firms Involved in Scams vs. Unaffected Firms

Effect	Statistic	Value	Num DF	Den DF	F Value	Pr > F
Intercept	Wilks' lambda	0.023572	12	237	818.093988	0.0
	Pillai's trace	0.976428	12	237	818.093988	0.0
	Hotelling-Lawley trace	41.42248	12	237	818.093988	0.0
	Roy's greatest root	41.42248	12	237	818.093988	0.0
Firm_Type	Wilks' lambda	0.530822	12	237	17.456445	0.0
	Pillai's trace	0.469178	12	237	17.456445	0.0
	Hotelling-Lawley trace	0.883871	12	237	17.456445	0.0
	Roy's greatest root	0.883871	12	237	17.456445	0.0

Firm-specific sentiment, attention, investor behaviour, overall risk, sovereign risk, political risk, noise trader risk, arbitrage risk, realised volatility, idiosyncratic risk, downside risk, and liquidity are fitted and diagnosed in Table 8. Each dependent variable is assessed using AIC, BIC, mean residual, standard residual, residual skewness, residual kurtosis, and Variance Inflation Factor. A well-calibrated model has good firm-specific sentiment AIC and BIC. Mean residual proves average model predictions are impartial. For residuals near zero, standard residual predicts accurately. Skewness indicates slight asymmetry, while kurtosis indicates normal residual distribution. VIF values show no predictor multicollinearity. A model with slightly lower AIC and BIC than sentiment may be better for firm-specific attention. The standard residual is close to expected and the mean residual is unbiased, indicating stable accuracy. Kurtosis and skewness indicate mild asymmetry and low peak distributions. In VIF values, multicollinearity was absent again. Investor behaviour has higher AIC and BIC values than other variables, indicating a more complex model or poorer fit. Mean residual is unbiased, standard residual scales data. Skewness and kurtosis indicate near-normal distribution and mild asymmetry. No VIF multicollinearity. Risk fits AIC/BIC well. Mean residuals predict unbiasedly, while standard residuals' variability is low. Kurtosis and skewness prove symmetry and normality. No VIF multicollinearity. Effective sovereign risk models have low AIC and BIC. Mean residual is unbiased and standard residual variability low. Curve and kurtosis are flat with minor asymmetry. AIC/BIC promotes political risk. Mean residual predicts without bias, while standard residual is moderately variable. Skewness and kurtosis suggest a near-normal, slightly negative asymmetric distribution. Noise trader risk matches AIC/BIC. Mean residual is unbiased and standard residual variability low. Kurtosis and skewness prove symmetry and normality. Similar arbitrage risk to AIC/BIC. Mean residual indicates no prediction bias, while standard residual shows moderate variability. Skewness and kurtosis indicate near-symmetry and normal distribution. Realised volatility matches low AIC/BIC. Standard and mean residuals are steady and impartial. Skewness and kurtosis indicate near-normality. Low AIC and BIC indicate unique risk. No prediction bias and low variability characterise normal and standard residuals. Peaks and asymmetry are higher with skewness and kurtosis. AIC and BIC support the model, and bottom risk fits. Mean residual is unbiased and standard residual variability low. Skewness and kurtosis suggest a near-normal, slightly negative asymmetric distribution. BIC and AIC support liquidity risk. Mean residual is unbiased and standard residual variability low. Skewness and kurtosis indicate near-symmetry and flatter distribution than normal. Diagnostics and dependent variable model fit show robust and calibrated models. BIC and AIC values consistently support model validity. Mean residuals around zero indicate unbiased predictions, and low standard residuals indicate close matches. Skewness and kurtosis show residuals are mostly normal with minor deviations. VIF values without multicollinearity show model robustness.

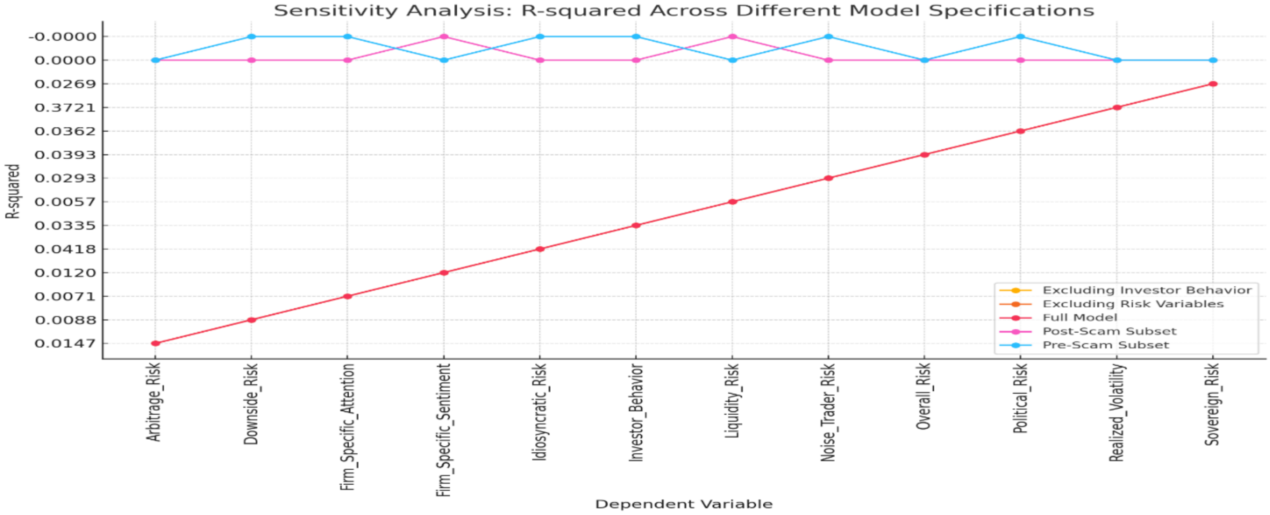
Table 8: Model Fit and Diagnostics

Dependent Variable	AIC	BIC	Mean Residual	Std Residual	Skew Residual	Kurt Residual	VIF
Firm Specific Sentiment	683.13	690.18	0.0000	0.9430	0.0780	0.1704	2.00, 1.00
Firm Specific Attention	676.26	683.31	0.0000	0.9302	0.2597	0.5505	2.00, 1.00
Investor Behavior	3341.47	3348.52	-0.0000	192.0995	0.2015	0.3843	2.00, 1.00
Overall Risk	81.49	88.53	-0.0000	0.2831	0.0208	0.0739	2.00, 1.00
Sovereign Risk	-135.34	-128.30	-0.0000	0.1835	0.1484	-0.5102	2.00, 1.00
Political Risk	8.21	15.25	-0.0000	0.2445	-0.2359	0.2316	2.00, 1.00
Noise Trader Risk	47.35	54.39	0.0000	0.2644	-0.0864	0.0340	2.00, 1.00
Arbitrage Risk	91.48	98.52	-0.0000	0.2888	0.0110	0.3084	2.00, 1.00
Realized Volatility	-538.04	-531.00	-0.0000	0.0820	-0.1665	0.1212	2.00, 1.00
Idiosyncratic Risk	-152.29	-145.25	-0.0000	0.1774	-0.0932	0.8525	2.00, 1.00
Downside Risk	60.47	67.51	-0.0000	0.2714	-0.1591	0.1192	2.00, 1.00
Liquidity Risk	61.21	68.26	-0.0000	0.2719	0.0504	-0.5200	2.00, 1.00

R-squared sensitivity analysis for dependent variables across model specifications is shown in figure. Arbitrage, downside, firm-specific attention, sentiment, idiosyncratic, investor behaviour, liquidity, noise trader, overall, political, realised volatility, and sovereign risk depend. Colour lines separate Excluding Investor Behaviour (orange), Risk Variables (red), Full Model (green), Post-Scam Subset (pink), and Pre-Scam Subset (blue). R-squared measures the proportion of dependent variable variance explained by independent variables to indicate model fit. A high R-squared indicates model explanatory power. The orange line models without investor behaviour have low R-squared values for most dependent variables. Investor behaviour explains much of these variables' variance, so excluding it reduces model fit. Red lines, risk-free models, have low R-squared values. This suggests that risk variables explain dependent variable variance and reduce model explanatory power if excluded. The full model (green line) has higher R-squared values for all dependent variables. For maximum explanatory power, the model must include all relevant variables. The full model's higher R-squared values show investor behaviour and risk variables explain dependent variable variance better. The pink line shows post-scam data with variable R-squared values higher than models without key variables. All model variables describe post-scam traits better. Models without key variables have lower R-squared than the pre-scam blue line. Different variable relationships between pre- and post-scam subsets suggest market or firm-specific changes. The sensitivity analysis shows that the full model, with all relevant variables, best explains all dependent variables. Model fit decreases when investor behaviour or risk variables are excluded, emphasising their importance. Pre- and post-scam R-squared patterns indicate variable relationship changes. This analysis emphasises the need for comprehensive modelling that includes all relevant factors to accurately explain financial and risk-related dependent variable variance.

The descriptive statistics in Table 1 show that firm-specific sentiment, attention, and risk measures vary widely among firms and investors. Firm-specific sentiment and attention affect perceptions and interest. Investor engagement and activity vary widely across the dataset. The prevalence of sovereign, political, and noise trader risk presents many challenges and uncertainties for firms and markets. Table 2's correlation analysis shows complex firm-specific sentiment, attention, investor behaviour, and risk relationships. Firm-specific attention raises political risk. Negative correlations between firm-specific sentiment and downside and liquidity risks suggest positive sentiment reduces risks. Correlations show investor sentiment and risk attention affect multiple market perceptions. Table 3 shows significant regression risk predictors. Sentiment and firm-specific attention affect multiple risk measures. Firm-specific attention reduces arbitrage, idiosyncratic, and overall risk, while sentiment reduces downside and political risks but increases overall and realised volatility.

Figure 1: Sensitivity Analysis: R-squared Across Different Model



These models show how investor behaviour, macroeconomic factors, firm size, financial leverage, management quality, and market conditions affect risk. As shown in Tables 4, 5, and 6, financial scams affect firms differently. Firm-specific sentiment and attention increased after the scam, indicating market interest and slightly better firm perception (Table 4). Table 5 shows that post-scam sovereign, political, noise trader, arbitrage, and realised volatility risks increased, indicating instability and uncertainty. Scams lower market confidence and firm stability due to negative sentiment, lower attention, and higher risks (Table 6). These findings are reliable and valid per Table 7 MANOVA and Table 8 model fit diagnostics. MANOVA shows scammed firms differ from unaffected firms in financial and risk metrics. AIC, BIC, mean residuals, standard residuals, skewness, kurtosis, and VIF indicate good to excellent model fits with low residual variability and no multicollinearity. The sensitivity analysis shows that the full model consistently has the highest explanatory power, emphasising the need to include all relevant variables to capture the full impact. These extensive analyses show that financial scams affect firm sentiment, attention, investor behaviour, and risk.

5. Conclusion and Implications

This comprehensive study examined how major negative events like financial scams affected firm financial metrics using monthly data from 2006 to 2022. The study examined 250 firms' sentiment, attention, investor behaviour, and risks before and after scams. To understand how scams affect market perceptions and behaviour, scam-affected firms were compared to others. Analysis of scam event temporal effects was possible with event study methodology. This method separated scams from market trends to show how they affect firms' finances. From defined windows before and after scams, firm-specific and market-wide variables were examined for immediate and long-term changes. Descriptive statistics show that firm-specific sentiment, attention, and risk measures vary widely, reflecting firm and investor market reactions. These variables have complex correlations, so sentiment strongly affects risk perceptions. Because of interconnectedness, market dynamics analysis must be holistic. Regression models predicted risks using firm-specific sentiment and attention. Higher firm-specific attention reduced arbitrage, idiosyncratic, and overall risk, suggesting scrutiny and interest lower risks. Firm-specific sentiment increased average risk and volatility but decreased downside and political risks. These findings demonstrate that market perceptions complexly shape risk profiles. Comparisons helped understand financial scams. Firm-specific sentiment and attention increased slightly after the scam, indicating market interest and better firm perceptions. Political, noise trader, arbitrage, sovereign, and realised volatility increased. The perception of instability and uncertainty suggests scams increase market fears and risk aversion while attracting attention. A detailed comparison between scammed and unaffected firms showed stark differences. Financial scams lowered market confidence and firm stability, causing negative sentiment, lower attention, and higher risks across multiple dimensions. The differential impact suggests that scams' reputational and operational damage can cripple a firm's finances and investor perceptions. MANOVA showed significant financial and risk metrics differences between affected and unaffected firms. MANOVA and model fit diagnostics like AIC, BIC, and residual analyses verified robustness, model calibration, and accuracy. The full model had the most explanatory power, so the sensitivity analysis must include all relevant variables. This study extensively discusses financial scams' effects on firms. These complexly affect firm-specific sentiment, attention, investor behaviour, and risks. +Research emphasises market oversight, risk management, and financial scam prevention. These insights will help investors, regulators, and policymakers maintain market stability, investor protection, and financial market integrity during financial irregularities. Understand their effects helps stakeholders prepare and respond to future events, making the market more resilient and transparent.

Study affects financial economics and market behaviour theory. The study shows how firm-specific sentiment and attention affect risk measures, explaining market dynamics' psychological and behavioural underpinnings. Financial anomalies like scams affect market outcomes due to investor sentiment and attention. Sentiment can cascade through risk perceptions, so integrated financial analysis models must account for behavioural and psychological factors. Financial scandals affect firm-specific and market-wide variables, according to event studies. A 15-year dataset and robust event study methodology enhance market responses to financial irregularities. This study's nuanced findings on scams' effects on affected versus unaffected firms support market efficiency theory and the long-term effects of reputational damage and operational disruptions. Research helps business managers, regulators, and investors. Investors can invest wisely by understanding how financial scams affect firm-specific sentiment and risk. Knowing major event sentiment and attention helps investors predict market reactions and adjust portfolios. Post-scam firms get strategic investments and reduce losses with awareness. Findings emphasise regulators' need for strict oversight and vigilant financial scam prevention. Regulators can improve policies and interventions by understanding the complex effects of such events on market stability and investor confidence. By preventing fraud, transparent, accountable, and fast regulations protect market integrity and investor interests. This study emphasises monitoring and quick response in financial sector regulation. This research covers corporate managers. To reduce risks and stabilise firms, the study emphasises positivity and attention. Manager communication, transparency, and investor engagement boost market perception. After a financial scandal, managers can create operational and reputational recovery plans by understanding sentiment and risk's long-term effects. An active manager can boost investor confidence and firm finances. Contributions: This study improves financial scam theory and practice. This study shows how sentiment and attention affect financial markets and how they react to negative events. The study's large dataset and rigorous methodology benchmark event and market behaviour analysis. With the insights, investors, regulators, and corporate managers can improve market and regulatory practices. This study examines how financial scams affect firm-specific and market-wide variables using theory and practice. It shows how negative events affect financial market dynamics. The study emphasises integrated psychological, behavioural, and operational financial analysis and decision-making in academia and practice.

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