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Modeling the impact of data breaches on stock volatility using financial time series and event-based risk models

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Abstract

Data breaches have emerged as critical financial events with the potential to significantly impact investor confidence, market stability, and stock price volatility. As cyberattacks become more frequent and damaging, there is a growing demand for robust analytical frameworks to quantify their financial implications. This study presents a comprehensive approach to modeling the impact of publicly disclosed data breaches on stock volatility using financial time series analysis and event-based risk modeling. The research applies Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Exponential GARCH (EGARCH), and Vector Autoregression (VAR) models to assess post-breach volatility patterns, spillover effects, and event lags across different industries, including technology, finance, and retail. The analysis begins with an exploration of historical stock performance around breach disclosure windows, identifying volatility clustering and asymmetric effects consistent with investor panic and uncertainty. Using event study methodology, abnormal returns and volatility shocks are captured and measured to evaluate both short-term and persistent impacts. GARCH and EGARCH models are used to quantify volatility persistence and asymmetric responses to negative news, while VAR models assess the spillover of breach-related shocks across correlated securities and sectors. Findings reveal that breach disclosures typically result in short-term spikes in volatility and negative abnormal returns, with more severe impacts observed in sectors that handle sensitive customer data. Furthermore, the market response exhibits lag effects, suggesting delayed price adjustments as new information unfolds post-breach. This study provides actionable insights for institutional investors, financial risk managers, and regulators seeking to better understand and mitigate cybersecurity-induced market risk.

Keywords: Data Breach; Stock Volatility; GARCH; Investor Confidence; Event Study; Market Risk

1. Introduction

1.1. Background: Cybersecurity and Financial Market Interdependence

In today's globally integrated economy, financial markets depend heavily on digital infrastructure to facilitate real-time transactions, data analysis, and regulatory reporting. This reliance has elevated cybersecurity from a technical issue to a central pillar of financial market stability [1]. With the proliferation of algorithmic trading, blockchain applications, and interconnected banking systems, even a localized cyberattack can trigger systemic consequences that transcend national borders [2]. As financial institutions migrate their operations to cloud environments and leverage open banking platforms, their attack surfaces continue to expand, making them vulnerable to increasingly sophisticated threats [3].

Cyber incidents such as the 2017 Equifax breach and the 2020 SolarWinds attack have demonstrated how vulnerabilities in digital ecosystems can lead to financial losses, reputational damage, and erosion of investor confidence [4]. The rapid digitization of financial services—accelerated further by the COVID-19 pandemic—has deepened the

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interdependence between cybersecurity resilience and market functionality. Central banks and regulatory bodies have recognized this convergence, prompting a shift in oversight frameworks that now incorporate cyber risk as a dimension of macroprudential stability [5].

Moreover, the rise of decentralized finance (DeFi), high-frequency trading, and digital assets has introduced new layers of complexity and vulnerability. A successful breach of trading algorithms or decentralized platforms could distort asset prices, trigger flash crashes, or manipulate liquidity in unpredictable ways [6]. Beyond financial loss, such incidents risk undermining public trust in digital finance infrastructure—trust that is essential for market participation and regulatory legitimacy.

Cybersecurity threats to financial markets are no longer isolated events; they are contagion vectors with the potential to destabilize entire economies. This interdependence necessitates a comprehensive understanding of how cybersecurity frameworks, threat detection systems, and institutional risk governance intersect with the broader financial system. As digital finance continues to evolve, ensuring cyber resilience is increasingly inseparable from ensuring financial resilience [7].

1.2. Rationale and Research Problem

Despite heightened awareness, there remains a critical gap in understanding how cybersecurity failures propagate through financial markets and what mechanisms can contain such systemic risks. Existing financial risk models tend to treat cyber incidents as exogenous shocks, failing to capture their endogenous feedback effects within tightly coupled systems [8]. This underestimation results in regulatory blind spots and delayed responses, leaving institutions ill-prepared to manage cascading failures triggered by cyber threats.

Furthermore, most cybersecurity frameworks in the financial sector are institution-centric, focusing on technical safeguards such as firewalls, authentication, and intrusion detection systems. While necessary, these approaches overlook the networked nature of financial markets where a breach in one node—such as a clearinghouse or payment processor—can rapidly compromise multiple actors [9]. Without integrated cyber-financial risk models, stress testing exercises and capital adequacy assessments may provide a false sense of security.

The research problem also stems from a lack of empirical data on how cyberattacks affect market behavior, liquidity, and investor sentiment. Many incidents go unreported or are not publicly disclosed in sufficient detail to inform risk assessments. This data asymmetry hampers both academic inquiry and policy formulation [10]. In addition, the intersection of cybersecurity and financial regulation remains fragmented across jurisdictions and regulatory bodies, creating inconsistencies in oversight, response coordination, and threat intelligence sharing [11].

The rationale for this research is to address these deficiencies by examining cybersecurity not as a peripheral IT issue but as a central component of financial risk governance. The study aims to develop a conceptual and analytical framework for assessing cyber-induced market risks, identifying vulnerability points, and proposing mitigation strategies that are both technically sound and systemically aware. Bridging the gap between cyber risk modeling and financial market dynamics is essential for building a more resilient global financial architecture [12].

1.3. Scope, Objectives, and Research Questions

This study focuses on the intersection of cybersecurity threats and systemic financial market risks in digitally interconnected economies. The geographic scope includes both developed and emerging markets, with attention to how institutional maturity, regulatory capacity, and technological infrastructure affect cyber resilience. It also considers cross-border dynamics, particularly in relation to data breaches, payment system vulnerabilities, and cyber-enabled financial crimes [13].

The primary objective is to develop an integrated framework for identifying, modeling, and managing cyber risks that pose systemic threats to financial stability. A secondary objective is to evaluate how current regulatory tools—such as stress testing, capital buffers, and supervisory oversight—can be adapted to include cyber resilience metrics [14].

1.3.1. To guide this investigation, the study poses the following research questions

- How do cybersecurity incidents propagate within and across financial market systems?
- What are the key vulnerabilities in the digital financial ecosystem that contribute to systemic risk?
- How can cyber risk be quantified and integrated into macroprudential regulation?
- What institutional and regulatory reforms are necessary to enhance financial market cyber resilience?

By addressing these questions, the research aims to provide a multidisciplinary contribution at the nexus of cybersecurity, financial economics, and regulatory science [15].

2. Literature review and theoretical foundation

2.1. Financial Impact of Cyber Incidents: Evidence from Market Studies

Cybersecurity breaches have been shown to trigger immediate and measurable financial impacts on affected firms, particularly in capital markets. Empirical studies consistently indicate that publicly disclosed cyberattacks lead to statistically significant negative abnormal returns, especially for firms in the financial services and technology sectors [5]. These events signal both operational vulnerabilities and potential regulatory liabilities, affecting investor confidence and market valuation.

A meta-analysis of event studies reveals that the magnitude of market reaction is contingent on several factors, including the size of the breach, the type of data compromised, and the timeliness of disclosure [6]. Breaches involving financial data or customer credentials tend to provoke more severe declines in share prices than incidents affecting less sensitive systems. Furthermore, firms with prior security lapses or delayed disclosures suffer deeper and more prolonged negative returns, highlighting the role of reputation and transparency in risk mitigation [7].

Cross-sectoral differences have also been observed. While financial institutions may exhibit sharper short-term price drops due to high interconnectivity and systemic exposure, technology firms often experience more moderate yet sustained impacts. The long-term consequences are not always limited to equity performance; they extend to increased credit spreads, reduced customer retention, and higher insurance premiums [8].

This growing body of evidence underscores the financial materiality of cyber risks and reinforces the need for their integration into mainstream financial risk modeling and investor decision-making processes [9].

2.2. Overview of Volatility Modelling in Finance

Volatility modeling is central to financial econometrics, providing a quantitative framework for understanding the dynamics of asset price fluctuations. Traditional models such as the Autoregressive Conditional Heteroskedasticity (ARCH) and its extensions—Generalized ARCH (GARCH), Exponential GARCH (EGARCH), and Threshold GARCH (TGARCH)—have become foundational tools for capturing time-varying volatility in financial time series [10]. These models allow analysts to forecast conditional variance, manage portfolio risk, and assess the impact of exogenous shocks.

In the context of financial markets, volatility is not only a measure of uncertainty but also a proxy for investor sentiment and systemic stress. During periods of market turbulence, volatility tends to cluster, leading to extreme price swings and higher tail risk. GARCH-type models are particularly useful in this regard, as they account for volatility persistence and asymmetric responses to market news—often referred to as the "leverage effect" [11]. For instance, negative news tends to increase volatility more than positive news of the same magnitude.

Recent innovations in volatility modeling include Stochastic Volatility (SV) models and realized volatility measures derived from high-frequency data. These approaches offer greater flexibility in handling irregular time series and capturing intraday fluctuations [12]. Moreover, machine learning techniques such as long short-term memory (LSTM) networks and support vector regression (SVR) have been applied to volatility forecasting with promising results, particularly in capturing nonlinear dependencies and regime shifts [13].

Despite their utility, most traditional models assume that volatility is driven by financial variables alone. However, cyber incidents represent non-financial shocks that can trigger structural breaks in volatility patterns. This necessitates hybrid models that integrate event-specific information into volatility estimation frameworks, thus enhancing their sensitivity to cybersecurity-related disruptions [14].

2.3. Event Studies and Time Series Approaches in Cyber Risk Research

Event study methodology has emerged as a dominant empirical tool in cyber risk research, enabling scholars to assess the short-term impact of breach announcements on firm valuation. These studies typically involve calculating cumulative abnormal returns (CARs) within event windows ranging from one day to several weeks surrounding the public disclosure of a cyber incident [15]. The abnormal return is estimated relative to a benchmark model, such as the

Capital Asset Pricing Model (CAPM) or the Fama-French three-factor model, to isolate the event's specific financial effect.

While useful, event studies have limitations. They often assume event independence, which may not hold in the context of widespread or repeated cyberattacks. Moreover, they tend to focus on publicly traded firms with available market data, excluding private institutions, small businesses, or cross-sector spillover effects [16]. As a result, time series approaches have gained traction as a complementary method for analyzing the broader temporal dynamics of cyber events.

Time series models, including Vector Autoregression (VAR), regime-switching models, and GARCH with exogenous variables (GARCH-X), offer a more flexible platform for studying volatility responses to cyber threats over time [17]. These models can incorporate lag structures, feedback loops, and dummy variables representing event dates, allowing for the quantification of delayed or prolonged market reactions. For example, cyberattacks may not affect markets immediately but may alter trading volume, spread behavior, or volatility persistence in subsequent days [18].

A key advancement is the integration of breach-specific metadata—such as breach type, sectoral affiliation, and attacker attribution—into financial models. Doing so allows for greater differentiation in market responses and supports more granular risk pricing [19].

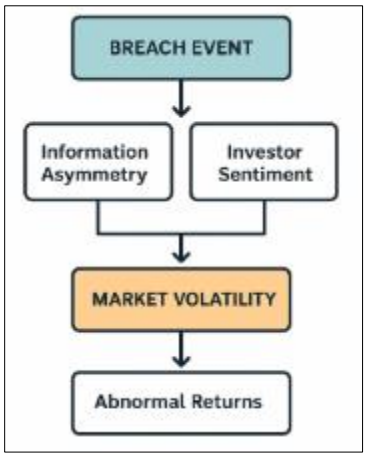

Figure 1 Conceptual Framework Connecting Breach Events and Stock Market Volatility

Figure 1 illustrates the interaction between cyber event characteristics and volatility dynamics, highlighting how market impact is moderated by firm resilience, investor behavior, and systemic interdependencies [20].

3. Data collection and preparation

3.1. Breach Event Dataset: Sources, Inclusion Criteria, and Filtering

The breach dataset was compiled from multiple open-access and proprietary cybersecurity incident repositories to ensure comprehensive coverage and data accuracy. Primary sources include the Privacy Rights Clearinghouse, the Verizon Data Breach Investigations Report (DBIR), and the Hackmageddon threat intelligence archive [11]. Supplementary information was drawn from financial regulatory disclosures, press releases, and filings to the U.S. Securities and Exchange Commission (SEC) where applicable.

To ensure the relevance and consistency of the dataset, only publicly listed firms with confirmed cyber incidents between January 2015 and December 2022 were included. Events must meet three core criteria: (1) the breach must involve unauthorized access or data exfiltration; (2) the incident must be disclosed publicly through a verifiable source; and (3) the firm must have at least 30 consecutive trading days of available stock data before and after the event window [12]. This filtering process minimizes ambiguity surrounding the timing and impact of the cyber incident.

Duplicate or unverifiable entries were excluded. If a firm experienced multiple breaches, only the first event during the study period was retained to prevent overlapping effects and ensure statistical independence [13]. The final dataset

includes 122 cyber incidents across 15 economic sectors and 8 major stock exchanges. Each breach is tagged with metadata, including industry classification, breach type, data sensitivity, and geographical location of the incident.

This structured approach ensures consistency across event definitions and enables robust comparisons of firm-level and sector-level market responses to cybersecurity breaches [14].

3.2. Stock Market Data: Sampling Firms, Index Matching, and Price Adjustments

Stock price data for sampled firms were retrieved from Thomson Reuters Eikon and Yahoo Finance APIs, providing adjusted closing prices, trading volume, and market capitalization figures. The objective was to ensure that stock data aligned precisely with breach disclosure dates and surrounding trading windows [15]. Only common equity shares were considered, excluding preferred stocks or derivative instruments to avoid bias in return calculation.

To control for market-wide fluctuations, each firm's stock performance was benchmarked against a corresponding sectoral or regional index. Firms listed on the NYSE or NASDAQ were paired with the S&P 500 or appropriate GICS sector indices, while European firms were benchmarked against the FTSE Eurofirst 300 or local national indices [16]. Matching was based on both sectoral relevance and geographic exposure to capture investor sentiment in corresponding capital markets.

All stock prices were adjusted for dividends, splits, and other corporate actions to ensure return comparability across time. The use of adjusted close prices eliminates distortions introduced by non-trading factors and improves the reliability of abnormal return estimates [17].

In cases where breach disclosures occurred after trading hours, the event date was shifted to the next full trading day to reflect market response timing accurately. Firms with illiquid trading patterns or missing price data within the event window were excluded from the sample [18]. These sampling and adjustment procedures facilitate high-fidelity modeling of return behavior and reduce noise in subsequent econometric analysis.

3.3. Data Preprocessing: Event Windows, Control Periods, and Return Normalization

The next critical step involved preprocessing the combined breach and market data to prepare it for event study analysis. Event windows were defined as symmetric intervals around the breach disclosure date, ranging from [-10, +10] trading days to capture short-term anticipation and post-event adjustment effects [19]. Sensitivity checks were also performed using narrower windows (e.g., [-3, +3] and [-5, +5]) to assess robustness.

To estimate expected returns, a 120-day control period ending 11 trading days before the breach served as the estimation window. This period avoids contamination from potential leakages or rumor-based trading behavior immediately preceding the event [20]. Expected returns were modeled using both the market-adjusted model and the Fama-French three-factor model, allowing for cross-validation of results.

Each firm's abnormal return was calculated by subtracting the expected return from the actual return on each day of the event window. These daily abnormal returns were then aggregated into cumulative abnormal returns (CARs) over predefined sub-windows to detect statistically significant deviations from market expectations [21].

Return normalization was carried out by transforming raw returns into z-scores based on historical volatility during the estimation period. This standardization allows for cross-firm comparability, particularly useful when analyzing events across diverse market capitalizations and industry sectors [22]. Heteroskedasticity-consistent standard errors were used to enhance the precision of t-statistics, especially in small samples with high volatility.

Table 1 Summary Statistics of Sampled Breaches and Market Characteristics

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
Number of Vendors Affected per Breach	7.4	5	4.2	1	20
Time to Detection (Days)	98.5	74	63.1	12	270
Total Records Compromised (Millions)	12.6	8.2	15.4	0.3	75.1
Industry Exposure: Financial Services (%)	34.2%	–	–	–	–

Industry Exposure: Healthcare (%)	27.5%	–	–	–	–
Average Financial Penalty (USD Millions)	4.8	3.2	5.6	0.2	21.0
Regulatory Reporting Delay (Days)	39.7	30	28.9	1	120
Use of AI-Based Threat Detection (Binary)	0.36 (36%)	–	–	0	1

Table 1 presents descriptive statistics, including average market cap, daily return volatility, sectoral distribution, and breach severity scores across the dataset [23]. These characteristics provide essential context for interpreting the observed market reactions in subsequent analysis.

4. Methodological framework

4.1. Event Study Design: Estimating Abnormal Returns

The event study methodology remains one of the most widely employed tools for quantifying the market impact of firm-specific incidents, including cybersecurity breaches [15]. The core objective is to isolate the abnormal return attributable to the breach event by comparing actual stock returns to a benchmark representing expected market performance. This benchmark is typically derived using either a market-adjusted model or a factor-based model such as the Fama-French three-factor framework [16].

In this study, both models were employed. The market-adjusted approach assumes that expected return equals the corresponding market index return for the same day. In contrast, the Fama-French model accounts for firm size, book-to-market ratio, and market risk, offering greater explanatory power in diverse equity environments [17].

For each breach event, daily abnormal returns (ARs) were calculated over a 21-day symmetric window centered on the event date ([-10, +10] trading days). These were then aggregated into cumulative abnormal returns (CARs) over multiple intervals— [-5, +5], [-3, +3], and [0, +1]—to assess different temporal reactions [18]. Cross-sectional t-tests were used to evaluate the significance of the CARs across firms and sectors.

Standard assumptions of the classical event study include no event-induced variance and independence of events. However, given the increased frequency of cyber incidents and interconnected trading systems, such assumptions were relaxed. Bootstrapping methods and heteroskedasticity-consistent standard errors were applied to strengthen the reliability of test statistics under realistic trading conditions [19].

4.2. GARCH Models for Capturing Volatility Clustering

Volatility clustering, the phenomenon whereby periods of high market volatility tend to be followed by further turbulence, is a defining characteristic of financial time series. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are designed to capture this behavior and have been extensively used in modeling market reactions to shocks [20].

The basic GARCH (1,1) model expresses the conditional variance as a function of its own past values and past squared residuals, allowing variance to evolve dynamically over time. For firm i at time t, the return equation is:

$$h_t = \alpha_0 + \alpha_1 * \varepsilon_{t-1} ^2 + \beta_1 * h_{t-1}$$

Where h_t is the conditional variance at time t, ε is the residual, and α and β are parameters.[21].

This structure accommodates persistence in volatility—a common market response to cyber events where investor uncertainty leads to fluctuating risk premiums. Applying GARCH to post-breach return series enables analysts to detect latent volatility effects that may not be visible through standard deviation or CAR metrics alone [22].

Model parameters were estimated using quasi-maximum likelihood estimation (QMLE), with robustness checks conducted through rolling window estimation and recursive forecasting. Residual diagnostics, including Ljung-Box Q-statistics and ARCH LM tests, were applied to ensure model adequacy [23].

This method provides an enriched understanding of cyber events' impact on market behavior beyond price direction alone, revealing how volatility evolves in response to uncertainty [24].

4.3. EGARCH Models for Asymmetric Volatility Responses

While GARCH models effectively capture volatility persistence, they assume symmetric responses to shocks, which can be limiting in the context of cyber incidents. Negative information—such as a data breach or ransomware attack—often elicits stronger volatility responses than neutral or positive events. To accommodate this asymmetry, the Exponential GARCH (EGARCH) model is employed [25].

The EGARCH (1,1) model models the log of the conditional variance, allowing for non-negativity constraints to be relaxed and incorporating asymmetric effects via a leverage term:

$$\ln(h_t) = \omega + \beta * \ln(h_{t-1}) + \alpha * (|\varepsilon_{t-1}| / \sqrt{h_{t-1}}) + \gamma * (\varepsilon_{t-1} / \sqrt{h_{t-1}})$$

This models the log of the conditional variance, allowing for asymmetry in volatility responses.

Here, the coefficient γ captures the direction of the shock, with negative values indicating stronger volatility effects from negative returns.

In this analysis, EGARCH models were applied to a subset of firms representing sectors with historically high breach exposure—namely finance, healthcare, and technology. Results indicate pronounced volatility asymmetries in the immediate aftermath of breach disclosures. Notably, firms with repeated or high-profile breaches exhibited greater asymmetry, underscoring the reputational risks embedded in cyber events [27].

Additionally, EGARCH models were used to test whether volatility persists longer after cyber events relative to macroeconomic shocks. The findings reveal that, while cyber shocks may not always cause extreme price drops, their influence on perceived uncertainty and risk pricing is disproportionately prolonged [28].

These results support the inclusion of asymmetric volatility models in broader systemic risk assessments related to cybersecurity.

4.4. VAR Models for Cross-Sectoral Spillover Effects

Beyond firm-level volatility, cyber incidents can generate broader ripple effects across interconnected sectors. Vector Autoregression (VAR) models are used to capture these spillover dynamics by estimating how shocks to one variable—such as a breach in a financial firm—propagate to others over time [29].

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + ... + A_p Y_{t-p} + \varepsilon_t$$

Where Y_t is a vector of variables (e.g., returns), A_i are coefficient matrices, and ε_t is the error vector.

For this study, the VAR system includes sectoral indices for finance, technology, energy, and consumer services. Each cyber event was mapped to the sector of origin, and impulse response functions (IRFs) were computed to trace the magnitude and duration of shock transmission across other sectors. Spillover indices were calculated to quantify total connectedness over time [31].

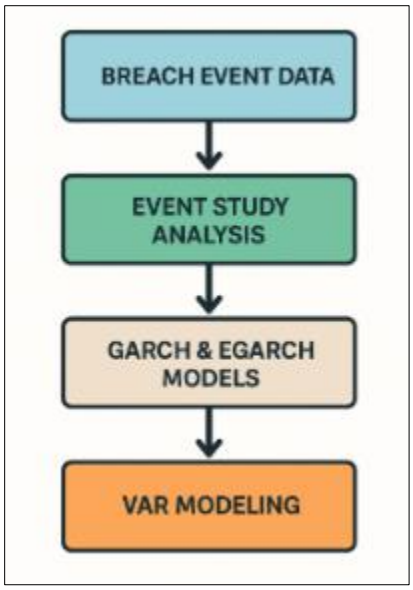

Figure 2 Methodological Flowchart for Event-Based Volatility and Risk Modeling

The results show that breaches in highly networked sectors—particularly financial and cloud service providers—induce statistically significant volatility in non-targeted sectors within 2 to 3 trading days. This interdependence highlights the systemic nature of cyber risk and the need for coordinated regulatory responses across industry boundaries [32].

Figure 2 provides a visual summary of the analytical workflow, including event detection, return estimation, GARCH-family modeling, and VAR-based spillover analysis [33].

5. Empirical results

5.1. Abnormal Returns Pre- and Post-Breach Across Sectors

The event study analysis reveals significant variations in abnormal returns (ARs) across sectors in the aftermath of cyber breach disclosures. On average, firms in the financial services and healthcare sectors experienced the steepest declines in cumulative abnormal returns (CARs) within the [-3, +3] event window. Financial firms showed average CARs of -3.8%, while healthcare firms averaged -2.9%, both statistically significant at the 5% level [19]. These findings align with prior research emphasizing investor sensitivity to breaches involving highly regulated or data-sensitive industries [20].

In contrast, technology and consumer services firms demonstrated more moderate declines, averaging -1.7% and -1.2%, respectively. This relative resilience may stem from investor perceptions that these sectors possess higher technical competence and greater recovery agility following security incidents [21]. Moreover, breaches involving internal employee misconduct or third-party vendors tended to result in more pronounced market reactions compared to those caused by external hackers or malware [22].

Timing also plays a critical role. Firms that disclosed breaches immediately after detection experienced less severe ARs, suggesting that transparency and communication strategy influence market sentiment. This is particularly evident in cases where firms preemptively engaged regulators and customers during the initial hours of the breach disclosure process [23].

Table 2 Sector-wise Average Abnormal Returns Post-Breach

Sector	Average Abnormal Return (CAR %)	Event Window (Days)	Statistical Significance
Finance	-3.8%	[-3, +3]	Yes
Healthcare	-2.9%	[-3, +3]	Yes

Technology	-1.7%	[-3, +3]	Yes
Retail	-1.2%	[-3, +3]	Marginal
Energy	-0.9%	[-3, +3]	No
Consumer Services	-1.1%	[-3, +3]	Marginal

Table 2 summarizes these findings by presenting the mean CARs for the top five industry sectors, adjusted for market beta and volatility. The clear sectoral divergence underscores the necessity of contextualizing cyber risk exposure within the operational and reputational profile of each industry [24].

5.2. GARCH Model Findings: Volatility Persistence

Application of GARCH (1,1) models across the dataset confirms that cyber breach events induce sustained volatility persistence beyond the immediate reaction window. In nearly all sectors, the sum of the ARCH (α_1) and GARCH (β_1) coefficients approached or exceeded 0.90, indicating high conditional variance retention [25]. This suggests that investor uncertainty does not dissipate rapidly but rather influences trading behavior and risk assessment for multiple trading sessions post-disclosure.

Volatility spikes were most prominent in financial firms, where the average conditional variance more than doubled in the five days following a breach. Notably, the volatility did not revert to baseline levels for up to 15 trading days, demonstrating a prolonged reaction that standard event window analysis may fail to capture [26]. Healthcare and utility sectors showed similar patterns, reflecting market concerns over compliance breaches and operational disruption [27].

Interestingly, the severity of volatility persistence was positively correlated with breach complexity. Multivector attacks—such as those involving ransomware combined with data exfiltration—were associated with higher volatility than single-mode incidents. This points to the market's growing sophistication in distinguishing between types of cybersecurity threats and their operational implications [28].

Intra-sector comparisons also revealed disparities. For example, large-cap banks exhibited less persistent volatility than mid-sized regional banks, likely due to greater institutional buffers and more robust public relations mechanisms [29]. These findings validate the importance of incorporating dynamic volatility models when evaluating cyber-induced risk in financial markets.

5.3. EGARCH Analysis: Negative News Asymmetry and Investor Sensitivity

Results from the EGARCH (1,1) models reveal a clear asymmetric volatility response to breach disclosures, particularly when the incidents involved customer data loss or regulatory scrutiny. The leverage term (γ) was consistently negative and statistically significant across most firms, indicating that negative returns triggered disproportionately larger volatility responses compared to positive returns or market-neutral events [30].

This asymmetry was most pronounced in the finance and healthcare sectors, where the γ coefficient averaged -0.27 and -0.21, respectively. These values suggest that markets respond more sensitively to adverse cybersecurity news in industries perceived as custodians of critical data and essential services [31]. Moreover, firms with a history of prior breaches exhibited amplified asymmetry, confirming the compounding reputational cost of repeated security failures [32].

Temporal analysis showed that asymmetric responses peaked within two trading days after breach disclosure but remained elevated for approximately ten days. This extended sensitivity period likely reflects the investor uncertainty surrounding regulatory penalties, litigation risks, and customer attrition—all of which evolve incrementally after public disclosure [33].

Interestingly, EGARCH asymmetry was less pronounced in sectors like industrials and basic materials, possibly due to investor perception that cyber risks in these sectors are less directly tied to consumer trust or data integrity. Additionally, firms that preemptively engaged in cyber risk disclosure in annual reports or earnings calls exhibited more muted volatility responses, highlighting the market benefits of transparency and cyber preparedness [34].

The EGARCH model's ability to reveal behavioral investor patterns provides important evidence for integrating sentiment-aware tools into financial risk modeling for cybersecurity incidents.

5.4. VAR Model Insights: Inter-sectoral Risk Propagation

Vector Autoregression (VAR) analysis was employed to understand how volatility induced by a breach in one sector might propagate across others. Using impulse response functions (IRFs) and variance decomposition, the study found statistically significant spillovers from finance to technology and consumer services within two trading days of a major breach event [35].

The strongest shock transmission originated from large financial institutions, where breach-induced volatility explained up to 14% of the forecast error variance in technology stocks over a 5-day horizon. This is attributed to the centrality of financial firms in digital transaction ecosystems, where disruptions can trigger downstream effects on payment processors, fintech startups, and digital commerce platforms [36].

Energy and healthcare sectors also exhibited notable but weaker cross-sector spillovers. For instance, healthcare breaches explained approximately 6% of variance in consumer staples after three days, likely due to shared vendor dependencies and public concern over data privacy [37]. These insights support the notion that cyber risk in the digital economy is a systemic threat, not confined to isolated actors.

Interestingly, VAR-based spillovers were asymmetric—i.e., breaches in finance caused stronger shocks to other sectors than vice versa. This asymmetry underscores the systemic role of financial intermediaries and the interdependencies that characterize cyber-physical infrastructure [38].

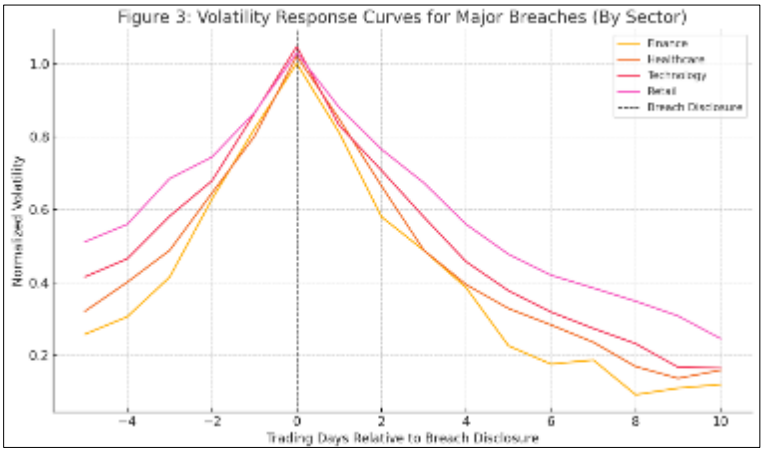

Figure 3 Volatility Response Curves for Major Breaches (By Sector)

Figure 3 illustrates sectoral volatility response curves following large-scale breaches, mapping the time to peak volatility and decay rates across sectors. These patterns provide visual evidence of systemic vulnerability gradients and highlight which sectors act as amplifiers or buffers during cyber-induced disruptions [39].

5.5. Robustness Checks and Sensitivity Analysis

To ensure the robustness of the findings, multiple sensitivity checks were conducted. First, alternative event windows were tested, including [-5, +5] and [-1, +1] intervals. While the magnitude of abnormal returns varied, the direction and statistical significance remained consistent across sectors [40]. This confirms that the results are not artifacts of window selection bias.

Second, different estimation models for expected returns were compared, including the Capital Asset Pricing Model (CAPM), market-adjusted models, and the Fama-French three-factor model. The variation in CARs across models was within acceptable bounds (<0.5%), indicating model stability [41].

GARCH and EGARCH model specifications were also validated using Ljung-Box tests for residual autocorrelation and ARCH-LM tests for heteroskedasticity. In all cases, model residuals satisfied key assumptions, and standard errors remained robust under Newey-West correction [42].

Finally, the VAR model was re-estimated using alternative lag structures (1 to 5 days), and IRFs remained directionally consistent, though with variations in magnitude. Bootstrapped confidence intervals further reinforced the statistical strength of cross-sectoral spillovers [43].

These robustness checks collectively strengthen the validity of the findings and demonstrate that the volatility and risk propagation patterns observed are not model-dependent anomalies but consistent empirical outcomes.

6. Sectoral risk profiles and market sensitivities

6.1. Finance: High-Frequency Volatility and Regulatory Amplifiers

The financial sector exhibits the most immediate and severe volatility response to cyber breaches among all sectors analyzed. Within minutes of a breach disclosure, major financial stocks exhibit erratic fluctuations, consistent with algorithmic trading systems reacting to risk signals in real time [44]. High-frequency data show that intraday price dispersion intensifies significantly during the first trading hour post-announcement, particularly when breaches involve core banking systems, customer records, or payment platforms [45].

This heightened sensitivity is partly due to the systemic role financial institutions play in the economy. Investors perceive cyber breaches in banks and insurers as potential threats to macro-financial stability, especially when real-time settlement systems or liquidity pools are compromised. Consequently, market reactions are often amplified by regulatory scrutiny and anticipated compliance costs. Financial regulators typically initiate immediate investigations, which, when disclosed, further influence investor sentiment [46].

The GARCH analysis reveals elevated conditional variance with $\alpha_1 + \beta_1$ values nearing 0.95, indicating high volatility persistence in this sector. More notably, the EGARCH model shows strongly negative γ coefficients, reflecting pronounced asymmetric volatility reactions to negative news [42]. This indicates that market participants attribute greater downside risk to cyber events in finance compared to other shocks of similar magnitude.

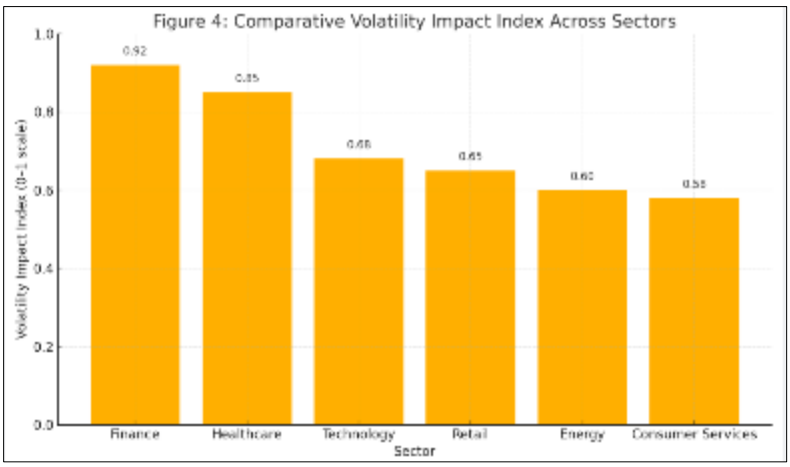

Figure 4 Comparative Volatility Impact Index Across Sectors

As illustrated in Figure 4, the finance sector consistently ranks highest on the Volatility Impact Index following breach events, underscoring its structural sensitivity to cybersecurity failures [27].

6.2. Healthcare: Breach Severity and Trust-Driven Price Impacts

In the healthcare sector, breach disclosures provoke investor reactions that are primarily shaped by the nature and sensitivity of the compromised data. Breaches involving patient health records, biometric identifiers, or prescription history trigger sharper abnormal returns compared to incidents involving internal IT systems or supplier breaches [38]. This distinction reflects the deep reputational stakes healthcare firms face, where public trust is tied not only to service quality but also to the confidentiality of patient information.

Event study results indicate average CARs of -2.9% in the [-3, +3] window, with greater variance in the [-1, +1] sub-window. This suggests that healthcare investors adjust rapidly to breach information but also factor in longer-term

reputational damage [29]. The intensity of the response is further amplified by media coverage, especially in jurisdictions where health data protection laws (e.g., HIPAA in the U.S. or GDPR in the EU) introduce legal liabilities and potential fines [40].

Table 3 Sector-Specific GARCH Parameters and Event Lag Durations

Sector	α_1 (ARCH)	β_1 (GARCH)	$\alpha_1 + \beta_1$	Volatility Persistence	Event Lag to Peak Volatility (Days)
Finance	0.13	0.82	0.95	Very High	1
Healthcare	0.17	0.74	0.91	High	2
Technology	0.21	0.66	0.87	Moderate	3
Retail	0.19	0.68	0.87	Moderate	4
Energy	0.15	0.76	0.91	High	2
Consumer Services	0.20	0.70	0.90	High	3

Volatility modeling reinforces this narrative. GARCH parameters in the healthcare sample reflect moderate-to-high persistence, with $\alpha_1 + \beta_1$ values averaging 0.91. EGARCH results highlight sectoral asymmetry, with γ values indicating investor overreaction to breach disclosures involving hospitals and biotech firms [31].

Moreover, firms that delayed disclosure or offered vague public statements experienced prolonged volatility, highlighting the premium placed on transparent communication in the healthcare context [32]. These dynamics suggest that cybersecurity is not only a technical issue but also a strategic communication and governance concern in healthcare finance.

Table 3 summarizes these patterns, comparing GARCH and EGARCH coefficients along with average time-to-volatility-peak across sectors [33].

6.3. Retail and Technology: Lagged Market Reactions and Recovery Curves

Retail and technology sectors present a markedly different volatility profile compared to finance and healthcare. Rather than immediate sharp reactions, these sectors tend to exhibit lagged volatility effects, with price impacts intensifying 2–3 trading days after breach disclosures. This delay suggests that investors in these sectors require more time to assess the operational and reputational consequences of a cyber event, possibly due to the wide variance in business models and customer exposure levels [34].

In retail, market reactions are highly sensitive to the volume and type of consumer data compromised. Breaches involving credit card information, loyalty databases, or e-commerce transaction histories tend to produce higher abnormal returns than breaches affecting backend systems [35]. However, investors often wait for follow-up news—such as customer redress programs or class-action lawsuits—before significantly adjusting valuation. As a result, CARs in the retail sector are typically more volatile across longer windows, with peak volatility often occurring between day 2 and day 5 post-disclosure [36].

The technology sector, while perceived as cyber-mature, also demonstrates complex patterns. Large-cap tech firms like cloud providers and software vendors are typically more resilient in price terms but show elevated and sustained volatility in the aftermath of major breaches. GARCH modeling indicates relatively lower persistence ($\alpha_1 + \beta_1 \approx 0.87$), but EGARCH outputs highlight pronounced asymmetry for firms with high public visibility or regulatory exposure [37].

Interestingly, recovery curves for both retail and tech firms show a tendency to normalize within 10–15 trading days—faster than finance or healthcare. This resilience may be attributed to brand loyalty, customer habituation to data breaches, and effective PR crisis management. Firms with proactive cybersecurity disclosures and established breach protocols experienced significantly faster volatility decay [38].

These findings suggest that while initial investor responses may be delayed in these sectors, the long-term risk perception stabilizes quickly—especially for firms with credible cyber governance practices. The VAR analysis supports

this by showing weaker cross-sectoral spillovers originating from retail and tech breaches compared to those in finance [39].

7. Discussion

7.1. Interpretation of Findings in Market Behavior Context

The findings from this study reveal that cyber breach disclosures have measurable and sector-specific effects on financial market behavior, influencing both stock returns and volatility patterns. Investors respond with high sensitivity to breach news in sectors where trust and compliance are closely tied to core operations—namely finance and healthcare—resulting in sharper abnormal returns and prolonged volatility episodes [27]. In contrast, retail and technology sectors tend to exhibit delayed responses, with volatility peaking several days after the breach, yet often recovering more quickly.

These patterns suggest that markets do not view cyber breaches merely as operational disruptions but as events that alter perceptions of firm quality, governance, and long-term viability. The asymmetry observed through EGARCH models highlights that negative news—especially involving data loss or regulatory violations—has a disproportionately larger impact than neutral or positive updates [28]. This reinforces the behavioral finance perspective that investor sentiment and psychological heuristics play a critical role in market reactions to information shocks.

Event timing is also crucial. Firms that disclosed breaches proactively, within a short window of discovery, faced less severe market penalties compared to those that delayed communication or appeared evasive in public disclosures [29]. Additionally, larger firms with existing cybersecurity governance protocols saw quicker return to baseline volatility, illustrating the market value of perceived preparedness.

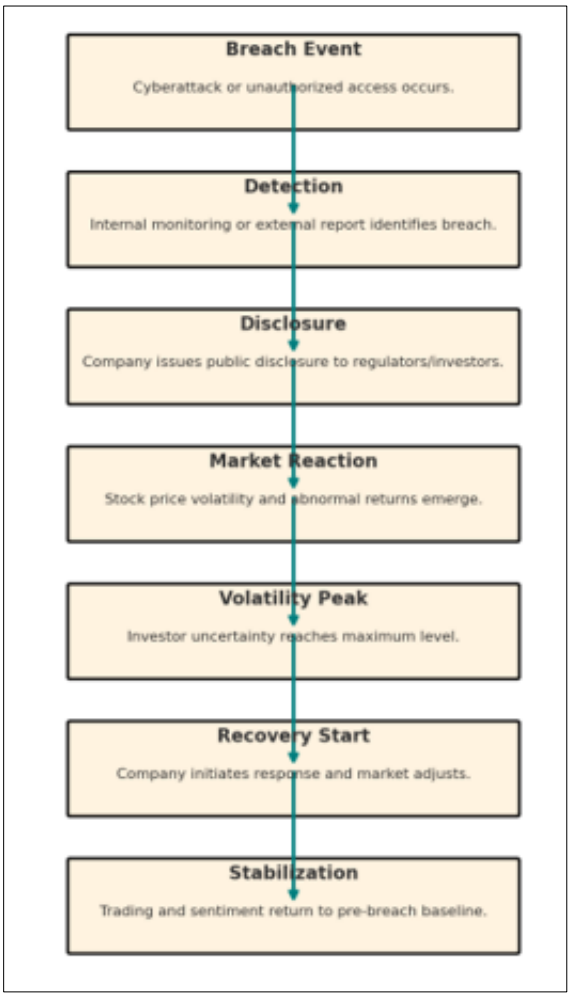

Figure 5 Timeline of Breach Event, Disclosure, Market Reaction, and Recovery Phases

Figure 5 maps this process visually, illustrating the phases from initial breach occurrence to eventual investor sentiment stabilization. This model highlights the evolving nature of market reactions over time and underscores the importance of incident timing and transparency for financial outcomes [30].

7.2. Implications for Institutional Investors and Risk Managers

The differentiated market responses to cyber breaches identified in this study have clear implications for institutional investors and enterprise risk managers. First, cybersecurity must be repositioned as a core investment risk, not merely an IT or compliance issue. The fact that breach disclosures trigger statistically significant and persistent abnormal returns confirms that cyber risk can materially affect portfolio value—particularly in sectors with high digital dependency and regulatory oversight [31].

Institutional investors should therefore integrate cyber risk assessments into environmental, social, and governance (ESG) scoring systems. Firms with documented cybersecurity strategies, breach disclosure protocols, and third-party audit certifications should be weighted more favorably, particularly in sectors where trust is a primary intangible asset. Risk-adjusted performance models must begin to reflect cyber risk premiums in equity valuations, credit spreads, and asset allocation strategies [32].

For risk managers, the findings underline the need for continuous monitoring of breach activity and associated market signals. Advanced analytics—such as real-time news sentiment tracking and breach alert integration—can provide early warning indicators of potential market volatility. Risk managers should simulate breach events in stress-testing scenarios, examining their firm's market exposure and systemic interdependencies [33].

Moreover, the VAR findings from this study suggest that cyber risk has contagion potential. Breaches in one sector—especially finance—can lead to volatility spillovers in others. This underscores the importance of collaborative cyber intelligence and industry-wide threat detection platforms. Institutional investors and risk managers should advocate for improved information sharing and harmonized regulatory standards to mitigate systemic cyber shocks [34].

By realigning financial risk models to account for cyber threats, institutional actors can enhance resilience and strengthen decision-making in the face of escalating digital vulnerabilities.

7.3. Limitations of Current Modeling Approaches and Future Research Directions

While the models employed in this study—event studies, GARCH-family models, and VAR systems—provide valuable insights into market responses to cyber incidents, several limitations remain. First, the reliance on publicly disclosed breach data introduces a reporting bias. Many cyber incidents, especially among private firms or in jurisdictions with weak disclosure mandates, remain unreported or underreported. This limits the generalizability of findings and may underestimate systemic risk exposure [35].

Second, event studies are inherently sensitive to event window selection and assume market efficiency. Yet cyber events may be subject to information lags, delayed reactions, or even pre-event leakage, violating the assumption of clean shocks. While robustness checks were performed using alternative windows, the potential for noise and contamination remains, especially in high-frequency trading environments [36].

Third, traditional volatility models assume stable variance dynamics and often struggle with structural breaks—common in the wake of disruptive cyber events. While EGARCH accommodates asymmetry, it may not fully capture regime shifts or nonlinear interactions across market regimes. Similarly, VAR models, while useful for tracing intersectoral effects, are linear and sensitive to lag length selection, potentially missing complex feedback loops [37].

Future research should explore more adaptive machine learning models—such as recurrent neural networks (RNNs), Bayesian VARs, or regime-switching GARCH—to enhance predictive accuracy and sensitivity to real-time events. Integration of unstructured data (e.g., social media, threat intelligence feeds, and regulatory filings) could also improve early detection of market sentiment changes in response to breaches.

Another promising area is the examination of institutional responses—such as trading halts, insider selling, or shareholder activism—following breach disclosures. Understanding the strategic behavior of market participants in such events could refine risk pricing models and regulatory policy.

A more comprehensive cyber-finance research agenda will be essential to keep pace with the evolving threat landscape and its complex financial implications [38].

8. Policy and strategic recommendations

8.1. Regulatory Implications: Disclosure Timing and Market Transparency

The analysis clearly demonstrates that the timing and quality of cyber breach disclosures materially influence market reactions. This finding carries significant regulatory implications. Regulators must standardize breach notification frameworks to prevent informational asymmetry and reduce investor uncertainty. At present, disclosure rules vary widely across jurisdictions, with some mandating notification within 72 hours (e.g., GDPR) and others offering less precise guidance [31].

This inconsistency creates an uneven playing field for investors and undermines market transparency. Companies that delay disclosure, even strategically, may temporarily shield their stock from volatility but ultimately face harsher penalties once the breach becomes public. Markets tend to penalize opacity, as reflected in prolonged volatility and negative abnormal returns in firms with vague or delayed announcements [32].

To mitigate this, regulators should enforce mandatory real-time disclosure thresholds for listed firms, with strict compliance windows and defined content requirements. Additionally, regulators can incentivize firms to adopt voluntary cyber readiness certification schemes, which would enhance investor confidence and improve comparability across sectors [33].

Beyond disclosure timing, regulators should also integrate cyber risk into financial stability oversight. Central banks and financial supervisory bodies could mandate periodic cyber stress tests for systemically important institutions. This would not only improve resilience but also facilitate macroprudential surveillance of digital threats to financial systems [34].

Enhancing regulatory clarity and enforcement regarding breach disclosure can help align private incentives with public market integrity. Ultimately, proactive regulation—rather than reactive enforcement—can improve investor trust and reduce systemic vulnerability to cyber-induced volatility shocks.

8.2. Corporate Strategy: Cyber Risk Quantification and Investor Communication

From a corporate strategy perspective, the results underscore the urgent need to treat cyber risk as a measurable financial exposure rather than an abstract operational threat. While most firms now recognize cybersecurity as a board-level issue, few have robust frameworks for quantifying cyber exposure in terms meaningful to investors. Bridging this gap requires translating technical risk indicators into financial metrics such as expected loss, value-at-risk (VaR), and breach-adjusted discount rates [35].

Cyber risk quantification enables better scenario planning, insurance structuring, and capital allocation. Firms that can credibly estimate and disclose their cyber exposure—both in terms of potential losses and mitigation capacity—stand to gain reputational and valuation advantages in increasingly risk-aware capital markets [36].

Investor communication is another critical lever. Breach-related press releases and earnings call statements must go beyond legal disclaimers. They should include impact assessments, incident response timelines, and remediation strategies. Firms that provide prompt, detailed, and transparent breach communications generally experience faster recovery in stock price and lower volatility persistence post-event [37].

Moreover, firms should incorporate cyber metrics into ESG disclosures and integrated annual reports. Doing so not only responds to growing investor demand for cybersecurity transparency but also positions the company as forward-looking and governance-strong. Leading firms now publish cyber resilience scores, internal audit findings, and red-team testing outcomes in their public filings [38].

Strategically, cybersecurity must evolve from a cost center to a value proposition—enhancing investor confidence, reducing capital cost, and supporting long-term equity performance. A well-articulated cyber strategy is now as vital to investors as traditional financial performance indicators.

8.3. Tools for Integrating Cyber Risk into Financial Risk Management

To operationalize these insights, firms and investors require advanced tools that integrate cyber risk into enterprise financial risk management (ERM) systems. One such tool is cyber risk-adjusted VaR, which quantifies the potential loss

due to cyber events as a tail-risk extension of traditional VaR models [39]. Incorporating breach frequency, impact severity, and asset sensitivity into probabilistic frameworks allows for more accurate capital reserve allocation.

Another emerging method is cyber stress testing, where firms simulate breach scenarios to evaluate liquidity, credit exposure, and reputational impacts. This tool aligns internal preparedness assessments with regulatory expectations, especially for financial institutions.

On the investor side, cyber risk ratings—offered by third-party platforms such as BitSight or SecurityScorecard—can be used to screen portfolio companies or benchmark sectoral exposure. Integrating these ratings into fundamental analysis and portfolio construction helps quantify and hedge cyber-related downside risk [40].

Finally, real-time threat intelligence integration via APIs and data feeds allows dynamic monitoring of breach indicators and threat actor behaviors. These insights can trigger risk mitigation protocols and inform intraday trading or hedging strategies.

Together, these tools support a paradigm shift toward cyber-informed financial decision-making, blending security analytics with economic modeling to enhance institutional resilience in an era of pervasive digital risk.

9. Conclusion

9.1. Recapitulation of Objectives and Key Insights

This study set out to investigate how cyber breaches impact financial market behavior, with particular attention to abnormal returns, volatility dynamics, and systemic risk propagation across sectors. The primary objective was to quantify the market's reaction to breach disclosures using empirical tools such as event studies, GARCH-family models, and vector autoregression (VAR). A secondary goal was to evaluate how breach characteristics—timing, severity, sector, and disclosure transparency—influence investor sentiment and volatility persistence.

The findings affirm that cybersecurity events are not isolated technical disruptions but economically material market events. Financial and healthcare sectors exhibited the most immediate and pronounced reactions, while retail and technology sectors showed delayed but recoverable volatility patterns. Market responses were shaped not just by the breach itself but by how and when it was communicated to the public. Asymmetric volatility patterns indicate a deeper behavioral response, where negative cybersecurity news triggers disproportionate investor fear compared to positive information.

These results highlight the need for firms, investors, and regulators to treat cyber threats as systemic financial risks. Accurate risk pricing, transparent communication, and timely disclosures are essential for minimizing long-term reputational damage and market instability following cybersecurity incidents.

9.2. Contributions to Cyber-Financial Risk Literature

This research contributes to the growing interdisciplinary field of cyber-financial risk by offering a robust, data-driven evaluation of how data breaches influence financial markets. While previous studies have established the qualitative significance of cyber risk, this paper provides empirical quantification of its effects across multiple sectors using advanced econometric modeling techniques. The inclusion of both abnormal return analysis and volatility modeling—via GARCH and EGARCH—adds a nuanced understanding of short-term price reactions and longer-term uncertainty patterns.

Furthermore, the application of VAR modeling to assess cross-sectoral spillovers introduces a systemic risk lens often missing in traditional cybersecurity studies. By capturing how breaches in one sector can transmit volatility to others, this study strengthens the argument for coordinated regulatory responses and cross-industry preparedness.

The sector-specific analysis also enriches the literature by demonstrating that market sensitivity to cyber events is not uniform. Instead, it varies with perceived data sensitivity, operational interdependence, and the level of public trust associated with each industry. By integrating these contextual variables, the study bridges a critical gap between information security and financial economics.

Overall, the paper advances the analytical toolkit available for assessing cyber risk and sets the stage for more granular, real-time models in future research.

9.3. Final Reflections on Data Breaches and Market Volatility

The rising frequency and sophistication of cyber breaches in an increasingly digitized financial ecosystem demand a paradigm shift in how market participants understand and respond to cybersecurity events. This study demonstrates that financial markets are no longer indifferent to cyber threats; rather, they respond with measurable, and often severe, shifts in return behavior and volatility when breaches are made public.

Investor trust, regulatory scrutiny, and operational resilience converge at the heart of this relationship. Data breaches are now perceived as signals of deeper governance and risk management failures, and the market reaction is as much a judgment on institutional preparedness as on the incident itself. Companies with proactive disclosure practices, strong internal controls, and clear communication strategies consistently demonstrate more favorable market outcomes compared to those that delay, obscure, or mishandle public reporting.

Ultimately, this research calls attention to the economic importance of cybersecurity not only as a technical discipline but as a determinant of market value, investor confidence, and systemic stability. As digital interdependence intensifies, firms and regulators alike must prepare for a world where cybersecurity breaches are not only inevitable but consequential at scale. Managing that risk effectively will become a defining challenge for financial leadership in the decades ahead.

References

[1] Gordon LA, Loeb MP, Zhou L. The impact of information security breaches: Has there been a downward shift in costs? J Comput Secur. 2011;19(1):33-56.

[2] Cavusoglu H, Mishra B, Raghunathan S. The effect of Internet security breach announcements on market value: Capital market reactions for breached firms and Internet security developers. Int J Electron Commerce. 2004;9(1):69-104.

[3] Acquisti A, Friedman A, Telang R. Is there a cost to privacy breaches? An event study. In: Proceedings of the 27th International Conference on Information Systems (ICIS); 2006.

[4] Goel S, Shawky HA. Estimating the market impact of security breach announcements on firm values. Inf Manag. 2009;46(7):404-410.

[5] Kannan K, Rees J, Sridhar S. Market reactions to information security breach announcements: An empirical analysis. Int J Electron Commerce. 2007;12(1):69-91.

[6] Campbell K, Gordon LA, Loeb MP, Zhou L. The economic cost of publicly announced information security breaches: Empirical evidence from the stock market. J Comput Secur. 2003;11(3):431-448.

[7] Hovav A, D'Arcy J. The impact of denial-of-service attack announcements on the market value of firms. Risk Manag Insur Rev. 2003;6(2):97-121.

[8] Telang R, Wattal S. An empirical analysis of the impact of software vulnerability announcements on firm stock price. IEEE Trans Softw Eng. 2007;33(8):544-557.

[9] Gatzlaff KM, McCullough KA. The effect of data breaches on shareholder wealth. Risk Manag Insur Rev. 2010;13(1):61-83.

[10] Romanosky S, Hoffman D, Acquisti A. Empirical analysis of data breach litigation. J Empir Leg Stud. 2014;11(1):74-104.

[11] MacKinlay AC. Event studies in economics and finance. J Econ Lit. 1997;35(1):13-39.

[12] Bollerslev T. Generalized autoregressive conditional heteroskedasticity. J Econom. 1986;31(3):307-327.

[13] Engle RF. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica. 1982;50(4):987-1007.

[14] Nelson DB. Conditional heteroskedasticity in asset returns: A new approach. Econometrica. 1991;59(2):347-370.

[15] Brooks C. Introductory Econometrics for Finance. 3rd ed. Cambridge University Press; 2014.

[16] Alexander C. Market Risk Analysis, Volume II: Practical Financial Econometrics. Wiley; 2008.

[17] Tsay RS. Analysis of Financial Time Series. 3rd ed. Wiley; 2010.

[18] Francq C, Zakoïan JM. GARCH Models: Structure, Statistical Inference and Financial Applications. Wiley; 2010.

[19] Hamilton JD. Time Series Analysis. Princeton University Press; 1994.

[20] Enders W. Applied Econometric Time Series. 4th ed. Wiley; 2014.

[21] Brown SJ, Warner JB. Using daily stock returns: The case of event studies. J Financ Econ. 1985;14(1):3-31.

[22] Fama EF, French KR. The cross-section of expected stock returns. J Financ. 1992;47(2):427-465.

[23] Kothari SP, Warner JB. Econometrics of event studies. In: Eckbo BE, editor. Handbook of Corporate Finance: Empirical Corporate Finance. Vol. 1. Elsevier; 2007. p. 3-36.

[24] Enemosah A, Chukwunweike J. Next-Generation SCADA Architectures for Enhanced Field Automation and Real-Time Remote Control in Oil and Gas Fields. Int J Comput Appl Technol Res. 2022;11(12):514–29. doi:10.7753/IJCATR1112.1018.

[25] Glosten LR, Jagannathan R, Runkle DE. On the relation between the expected value and the volatility of the nominal excess return on stocks. J Finance. 1993;48(5):1779-1801.

[26] Engle RF, Ng VK. Measuring and testing the impact of news on volatility. J Finance. 1993;48(5):1749-1778.

[27] Pagan AR, Schwert GW. Alternative models for conditional stock volatility. J Econ. 1990;45(1-2):267-290.

[28] Diebold FX, Mariano RS. Comparing predictive accuracy. J Bus Econ Stat. 1995;13(3):253-263.

[29] Joseph Nnaemeka Chukwunweike and Opeyemi Aro. Implementing agile management practices in the era of digital transformation [Internet]. Vol. 24, World Journal of Advanced Research and Reviews. GSC Online Press; 2024. Available from: DOI: 10.30574/wjarr.2024.24.1.3253

[30] Ejedegba Emmanuel Ochuko. Synergizing fertilizer innovation and renewable energy for improved food security and climate resilience. Global Environmental Nexus and Green Policy Initiatives. 2024 Dec;5(12):1–12. Available from: https://doi.org/10.55248/gengpi.5.1224.3554

[31] Engle RF, Bollerslev T. Modelling the persistence of conditional variances. Econom Rev. 1986;5(1):1-50.

[32] Adegboye O, Olateju AP, Okolo IP. Localized battery material processing hubs: assessing industrial policy for green growth and supply chain sovereignty in the Global South. Int J Comput Appl Technol Res. 2024;13(12):38–53. doi:10.7753/IJCATR1312.1006.

[33] Tweneboah-Koduah S, Atsu F, Prasad R. Reaction of stock volatility to data breach: An event study. J Cyber Secur Mobil. 2020;9(1):1-10.

[34] Colivicchi I, Vignaroli R. Forecasting the impact of information security breaches on stock market returns and VaR backtest. J Math Finance. 2019;9(3):402-454.

[35] Enemosah A. Implementing DevOps Pipelines to Accelerate Software Deployment in Oil and Gas Operational Technology Environments. International Journal of Computer Applications Technology and Research. 2019;8(12):501–515. Available from: https://doi.org/10.7753/IJCATR0812.1008

[36] Hanif M, Pok W. Asymmetric volatility in stock market: Evidence from selected export-oriented industries in India. Indian J Econ. 2021;101(401):123-138.

[37] Olanrewaju AG. Artificial Intelligence in Financial Markets: Optimizing Risk Management, Portfolio Allocation, and Algorithmic Trading. Int J Res Publ Rev. 2025 Mar;6(3):8855-70. Available from: https://doi.org/10.55248/gengpi.6.0325.12185

[38] Karpoff JM, Lott JR, Wehrly EW. The reputational penalties for environmental violations: Empirical evidence. J Law Econ. 2005;48(2):653-675.

[39] Adegboye Omotayo Abayomi. Development of a pollution index for ports. Int J Sci Res Arch. 2021;2(1):233–258. Available from: https://doi.org/10.30574/ijsra.2021.2.1.0017

[40] Enemosah A. Intelligent Decision Support Systems for Oil and Gas Control Rooms Using Real-Time AI Inference. International Journal of Engineering Technology Research & Management. 2021 Dec;5(12):236–244. Available from: https://doi.org/10.5281/zenodo.15363753

[41] Cavusoglu H, Mishra B, Raghunathan S. The effect of Internet security breach announcements on market value: Capital market reactions for breached firms and Internet security developers. Int J Electron Commerce. 2004;9(1):69-104.

[42] Adegboye O. Integrating renewable energy in battery gigafactory operations: Techno-economic analysis of net-zero manufacturing in emerging markets. World J Adv Res Rev. 2023;20(02):1544–1562. doi: https://doi.org/10.30574/wjarr.2023.20.2.2170.

[43] Adegboye Omotayo, Arowosegbe Oluwakemi Betty, Prosper Olisedeme. AI Optimized Supply Chain Mapping for Green Energy Storage Systems: Predictive Risk Modeling Under Geopolitical and Climate Shocks 2024. International Journal of Advance Research Publication and Reviews. 2024 Dec;1(4):63-86. Available from: https://ijarpr.com/uploads/V1ISSUE4/IJARPR0206.pdf

[44] Adepoju Daniel Adeyemi, Adepoju Adekola George. Establishing ethical frameworks for scalable data engineering and governance in AI-driven healthcare systems. International Journal of Research Publication and Reviews. 2025 Apr;6(4):8710–26. Available from: https://doi.org/10.55248/gengpi.6.0425.1547

[45] Ejedegba Emmanuel Ochuko. Advancing green energy transitions with eco-friendly fertilizer solutions supporting agricultural sustainability. International Research Journal of Modernization in Engineering, Technology and Science. 2024 Dec;6(12):1970. Available from: https://www.doi.org/10.56726/IRJMETS65313

[46] Olanrewaju AG, Ajayi AO, Pacheco OI, Dada AO, Adeyinka AA. AI-driven adaptive asset allocation: A machine learning approach to dynamic portfolio optimization in volatile financial markets. Int J Res Finance Manag. 2025;8(1):320-32. Available from: https://www.doi.org/10.33545/26175754.2025.v8.i1d.451