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Integrating Engineering Principles with Financial Asset Management: The Three-Sigma Approach in Financial Markets

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Abstract

In an increasingly volatile and uncertain financial landscape, particularly within the cryptocurrency market, robust risk assessment methods are essential. This study introduces an interdisciplinary framework that applies engineering concepts, specifically the three-sigma (3σ) criterion, to financial asset management. Drawing on the analogy between structural stress and financial return volatility, this study conceptualizes market returns as a stochastic stress process and asset strength as a dynamically adjusted resilience threshold. Using LUNA coin as a case study, the research employs Monte Carlo simulations, statistical process control principles, and a range of statistical tests, including the Shapiro-Wilk, Kolmogorov–Smirnov, and ANOVA tests, to evaluate the probability of structural failure, modeled as the first passage beyond a critical return threshold. The results reveal a first breach probability of 1.96% and identify a failure threshold of –0.3838, highlighting the model's capacity to detect extreme downside risk more conservatively than traditional Value-at-Risk (VaR) approaches. These findings support the use of three-sigma thresholds in highly volatile markets and align with previous studies emphasizing tail-risk modeling and engineering-inspired risk measures. This framework not only improves the understanding of asset fragility in crypto markets but also provides a practical tool for dynamic and real-time risk management. This study contributes to the evolving field of financial engineering by bridging statistical design principles and asset resilience modeling, offering new insights for researchers, investors, and policymakers.

Keywords: Three-sigma approach, Monte Carlo simulations, Structural failures, Random vibrations

JEL Classification: C15, C63, G32

Introduction

The design of financial assets to mitigate structural failures owing to random vibrations has garnered increasing attention in the fields of engineering and risk management. Traditionally, engineering practices have focused primarily on the physical performance of structures, whereas recent developments suggest that integrating financial asset strategies with methodologies such as the three-sigma (3σ) criterion can enhance the resilience of infrastructure (Vanderbilt, 2008; Ghosh et al., 2010). Random vibrations, often triggered by environmental factors such as seismic activity and wind loads, present significant challenges to structural integrity and safety. Failure to adequately address these vibrations can lead to catastrophic outcomes, including costly structural failures, loss of life, and significant financial repercussions (Simmonds et al., 2012).

In an increasingly volatile environment, particularly in cryptocurrency markets, effective risk management tools are imperative. The three-sigma rule, originating from statistical quality control and structural engineering, provides a robust framework for evaluating financial risks and has significant implications for analyzing volatile assets. Although the connection between structural engineering and financial assets may not be immediately apparent, both domains involve entities that endure stress throughout their life cycles, leading to two possible outcomes: success or failure.

In engineering, stress refers to the forces applied to a structure, whereas strength denotes the capacity of the structure to withstand those forces without collapsing or failing. Similarly, in finance, market volatility can be understood as the stress exerted on assets, whereas asset resilience or stability represents the ability of assets to absorb and withstand such pressures. In parallel, risk assessment is fundamental to financial decision-making, influencing investment strategies, portfolio management, and overall market stability (Gonzalvez et al., 2019). Engineers perform numerous analyses and tests before a specific component is deemed ready for use, ensuring that the components can withstand structural failures. This raises the question of whether a similar approach can be applied in the financial context.

Historically, the application of statistical methods in finance has transformed risk management practices. Markowitz (1952) pioneered portfolio theory, demonstrating how diversification can minimize risk while optimizing expected returns. This foundational work laid the groundwork for modern risk assessment techniques, including Value at Risk (VaR) and Conditional Value at Risk (CVaR), which quantify the potential loss in value of a portfolio over a given timeframe (Jorion, 2001). However, these traditional methods often fail to adequately capture tail risks, such as extreme market movements that lie outside typical price behavior (Artzner et al., 1999). The inherent volatility of the cryptocurrency market has brought these limitations to the forefront. Cryptocurrencies, such as Bitcoin and Ethereum, exhibit extreme price fluctuations and speculative behavior, prompting a reevaluation of existing risk assessment frameworks (Baur et al., 2018). The dramatic collapse of LUNA, the native asset of the Terra blockchain, in May 2022, serves as a stark example of the risks associated with cryptocurrencies, highlighting the inadequacy of traditional models in predicting such catastrophic events.

Despite the development of various methodologies for assessing and designing structures to withstand vibrations, a notable research gap remains in integrating financial asset management with structural design principles. Most existing studies focus on the technical aspects of vibration mitigation, without comprehensively exploring how financial methodologies can inform and enhance structural resilience decisions (Haldar & Mahadevan, 2000; Smith et al., 2018). The novelty of the current research lies in its dual approach, which leverages the 3σ criterion methodology not only to evaluate the probability of structural failure under random vibrations but also to inform investment strategies for infrastructure development. By examining the interplay between engineering design and financial asset strategies, this study aims to fill the research gap on how financial risk management can enhance environmental and structural resilience.

Applying the three-sigma framework to cryptocurrency risk assessment offers a methodical approach for evaluating volatility. By utilizing Monte Carlo simulations, we can model potential future returns and assess the probability of experiencing significant losses based on historical price movements. This method generates thousands of random paths for price movements, allowing analysts to estimate the risk of adverse outcomes over a specified time horizon. The implementation of such simulations can provide critical insights into the intricate nature of the cryptomarkets. Additionally, the practical implications of utilizing the three-sigma approach in cryptocurrency markets are significant, as investors, traders, and financial institutions can adopt this framework to establish risk thresholds aligned with their risk appetites and market conditions.

Through empirical case studies and a robust analysis of existing financial strategies in conjunction with engineered solutions, this study provides insights into optimizing investments in infrastructure that prioritize resilience against random vibrations (McCarthy, 2013; Pietroszek, 2017). Ultimately, this study seeks to advance current knowledge and practices in both fields, establishing a framework that not only protects physical assets but also secures economic investments against the risks posed by structural failures, thus laying the groundwork for future innovations at the intersection of financial and structural engineering (Gunter et al., 2022). By addressing this research gap by integrating the three-sigma criterion within a financial asset context, this study makes a significant contribution to the body of knowledge, enhancing the safety, reliability, and sustainability of infrastructure in an era increasingly challenged by dynamic environmental forces.

Literature Review

In the volatile realm of financial markets, where unpredictable fluctuations and structural vulnerabilities can lead to significant investment losses, the demand for robust risk management methodologies has become increasingly evident. Among these, the three-sigma (3σ) rule stands out as a fundamental statistical tool for evaluating volatility. This approach relies on computing the mean and standard deviation of historical asset returns to define a range representing normal market behavior, with deviations beyond the three-sigma threshold flagged as potential anomalies (Bansal, 1993; Shams & Sina, 2014). However, its assumption of normally distributed returns often clashes with the empirical reality of financial markets, which exhibit skewness and heavy-tailed distributions (Bakar & Rosbi, 2017). The latter's analysis of Bitcoin volatility using the three-sigma method highlights its utility in capturing significant price swings driven by speculation and external pressures, employing techniques such as normality testing and control charts to illustrate the erratic nature of cryptocurrency prices.

The intersection of financial risk management and engineering principles offers valuable insights into designing resilient financial assets. Bharadwaj (2020) emphasizes resilience engineering, which focuses on building systems capable of withstanding unexpected stresses—a concept applicable to financial instruments that face market turbulence. This involves optimizing asset management strategies to strike a balance between returns and safety, drawing parallels with structural engineering approaches. Similarly, Haldar and Mahadevan (2000) explored reliability assessment through stochastic finite element analysis, advocating a deeper understanding of structural resilience that can inform the design of financial assets to withstand random market vibrations.

Beyond the three-sigma framework, alternative risk-assessment models have gained prominence. Shams and Sina (2014) introduced the Value at Risk (VaR) model, which estimates the maximum potential loss at a given confidence level, incorporating factors such as asset correlations and non-normal return distributions. However, their findings reveal the limitations of VaR during market distress, particularly in capturing tail risks prevalent in cryptocurrency markets. Acerbi and Tasche (2002) address this gap with Conditional Value-at-Risk (CVaR), a measure that accounts for the average loss beyond VaR, proving essential for understanding the impact of extreme market movements on assets susceptible to rare, catastrophic events.

The evolving complexity of financial markets underscores the need for integrated risk-assessment strategies. Tabatabaei and Pakgohar (2021) apply the Generalized Extreme Value (GEV) theory to model tail risks, offering a comprehensive approach to assessing the likelihood of significant losses during rare market upheavals—a critical consideration for highly volatile assets. Zhang et al. (2020) complement this with Monte Carlo simulations, demonstrating the effectiveness of the three-sigma approach in capturing the uncertainty of cryptocurrency returns and providing a foundation for understanding risk dynamics in such markets. Embrechts et al. (1997) further emphasized the importance of modeling extremal events in insurance and finance, aligning with the need for robust frameworks to address the unique characteristics of cryptocurrencies.

External shocks and their impact on financial assets are critical. Klein et al. (2021) examine the effects of COVID-19 on cryptocurrency returns, highlighting how such events can destabilize asset performance and thereby reinforce the need for adaptive risk management strategies. Baur et al. (2018) reinforce this by noting the speculative nature of cryptocurrencies and their extreme price volatility, exemplified by the dramatic collapse of LUNA in May 2022, which exposed the inadequacies of traditional risk models. Chen et al. (2022) extend the application of engineering principles, likening stress processes in cryptocurrencies to return rates and asset stability to strength, suggesting that the three-sigma criterion—where an asset's strength should exceed its expected stress by three standard deviations—can enhance resilience. Nagapetyan (2019) and Xu et al. (2009) advocate for dynamic modeling and fuzzy logic to account for uncertainties, proposing adaptable strategies that could fortify asset designs against volatility.

Montgomery (2017) provides a comprehensive foundation for statistical quality control, reinforcing the theoretical basis of the three-sigma rule, which has been increasingly applied to assess the resilience of financial assets. Perry and Williams (2016) emphasized the importance of integrating financial risk management with structural design principles, highlighting how engineering-inspired approaches can enhance the safety and efficiency of financial decision-making processes. Their integrative model demonstrates that the design of financial structures, when guided by the concepts of resilience and structural tolerance, can significantly improve investment robustness. Complementing this perspective, Zhang et al. (2019) present a comprehensive survey of deep learning-based recommender systems, illustrating the potential of advanced data-driven methods in financial analytics. They argue that deep neural networks can be instrumental in identifying rare patterns and improving predictive accuracy in highly volatile markets. Together, these studies highlight the importance of interdisciplinary approaches, spanning structural engineering to artificial intelligence, in enhancing risk assessment and resilience in financial markets, particularly within the context of cryptocurrencies.

Despite these advancements, the literature reveals a notable gap in the systematic application of the three-sigma approach to cryptocurrency markets, particularly in evaluating the resilience of financial assets against structural failures induced by random market vibrations, which the current study seeks to address.

A Gentle Introduction to the Structural Design of an Element

When analyzing a single structural element subjected to random forces or stress ( )processes, the design goal is to select an appropriate size for the element to ensure that the probability of failure during its intended lifespan remains within an acceptable range. For physical objects, the primary failure modes generally include yielding, excessive deformation, brittle fracture, ductile fracture, buckling (instability under compression), and fatigue, which are essential considerations in the failure of structural components. Figure 1 shows the state of stress on an element over time.

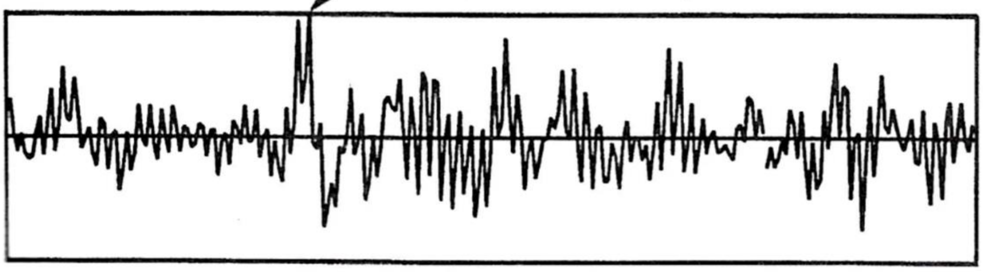


Figure 1. The state of stress on an element over time

Structural engineering emphasizes the investigation of design strategies aimed at preventing exceedance or quasi-static failure modes related to the aforementioned scenarios. A crucial approach in this regard is the 3σdesign method, which applies to objects or systems that are unlikely to withstand prolonged exposure to the design vibration environment, where fatigue failure may occur (such as spacecraft structures or rockets).

If $S(t)$ is considered a stationary Gaussian stress process with a root-mean-square (rms) value of σ_S, there exists a deterministic strength R linked to the object under examination. $S(t)$ implies that the sample space for S is $-\infty < S < \infty$, meaning that regardless of how large R is chosen, it is impossible to ensure that the stress S will consistently remain below R at all times t with a probability of 1.

To develop a secure element, designers apply specific criteria that

$$R \geq 3\sigma_S$$

under the implicit assumption that $\mu_s = 0$. Given that S adheres to a Gaussian distribution, the probability of the stress surpassing three times its root-mean-square (rms) value is

$$P[|S(t)| > 3\sigma_S] = 0.0026$$

Figure 2 shows the Gaussian 3-sigma relationship.

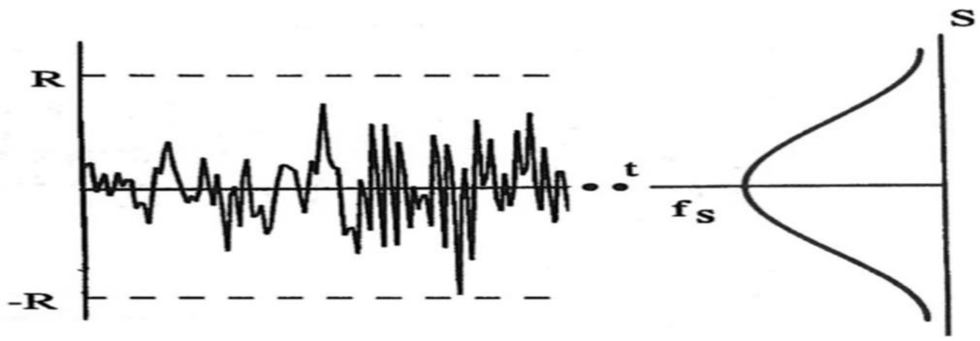


Figure 2. The Gaussian 3-sigma relationship

In other words, S surpasses R only about 0.3% of the time when $R = 3\sigma_S$ is taken into account. It is crucial to remember that R is a random variable (albeit deterministic), and the design value is usually selected as a characteristically low value, ensuring that the implied risk is likely much lower than what is indicated by the relationship mentioned above.

Now, suppose it is accepted that the mean stress is not zero and that R is a random variable with a normal distribution (with a mean of μ_R and a standard deviation of σ_R). In that case, the 3σ design criterion for safe design can be generalized to state that:

$$\mu_R \geq \zeta\sigma_S$$

Where the factor ζ is a function of $Q = \mu_S/\sigma_S$and the coefficient of variation of R, represented by $C_R = \sigma_R/\mu_R$, and has been established through numerical analysis. Figure 3 shows the graph for C_R with different values of ζ.

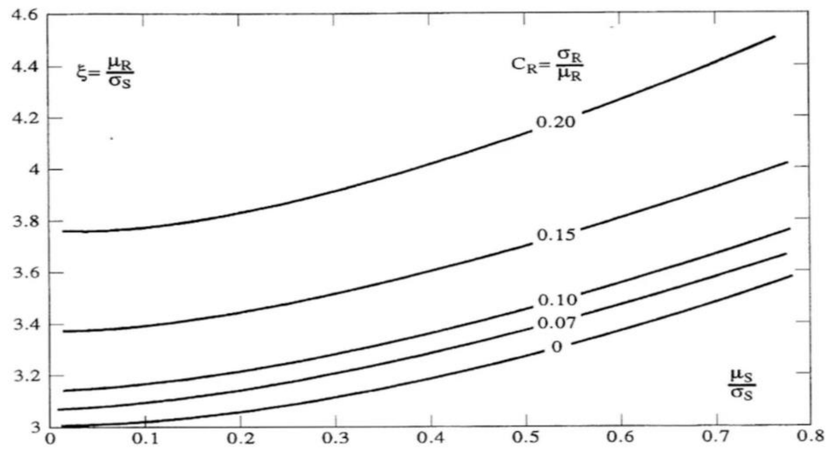


Figure 3. The graph for C_R with different values of ζ

All of the above enables us to present the complete concept of a stationary stress process( ), St, with a non-zero mean and random strength, R, as shown in Figure 4.

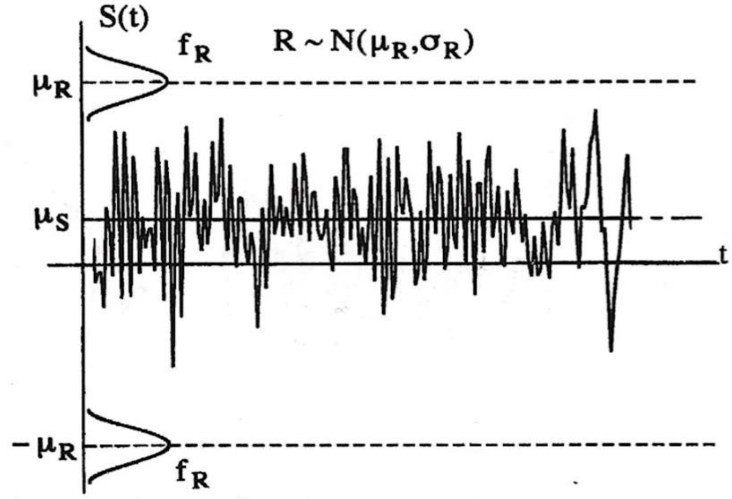


Figure 4. Stationary stress process $S(t)$ with a non-zero mean and random strength R

The discussion becomes more intriguing when the concept of first-passage failure is examined. In this framework, failure is defined as the initial moment when the stress process exceeds the strength R, such that $|S(t)| > R$. If R is permitted to be a function of time, represented as $R(t)$, the first-passage failure can be illustrated as shown in Figure 5.

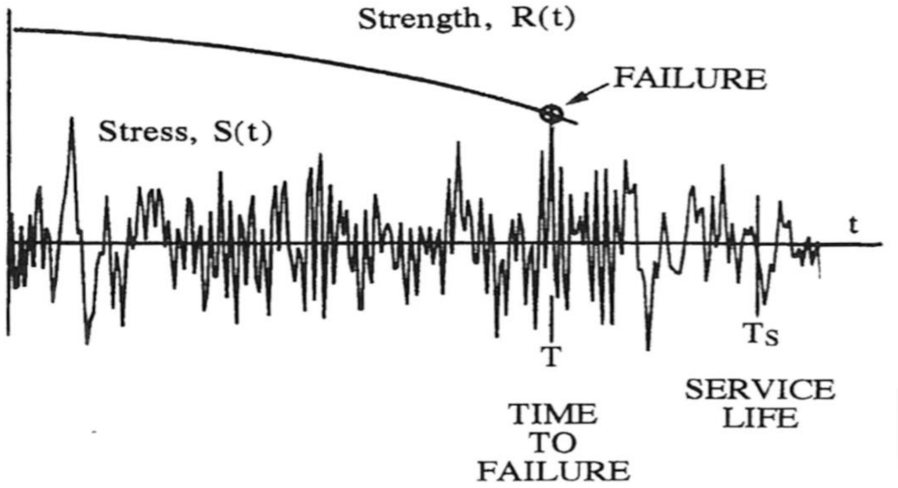


Figure 5.The first-passage failure

The analogy between financial assets and structural elements lies in the fact that both are exposed to uncertain and potentially damaging forces. In engineering, a component is subjected to stress (force), which, if it exceeds the component strength, results in failure. Similarly, in finance, an asset is exposed to market fluctuations (returns), which, if excessively severe, can lead to a decline in its value (Jaafar,2022). Within this framework, stress (S(t)) in engineering refers to the forces applied to a structure. Its financial counterpart is the asset's rate of return, which may be positive or negative, indicating gains or losses, respectively. Strength (R): In engineering, it represents a structure's capacity to withstand stress without failure. In finance, it can be interpreted as the asset’s resilience or a threshold value below which the asset is considered to have failed; for instance, when its value drops below a critical level.

Based on this analogy, the three-sigma rule from engineering can be adapted as a risk-assessment metric for financial assets, particularly in highly volatile markets such as cryptocurrencies.

The relaxation of R to $R(t)$ is not essential; however, as will be demonstrated, it is entirely logical for financial assets. In Figure 5, a decreasing function of $R(t)$ as $t \to \infty$ signifies a deterioration of the physical structure.

The objective of the design is to ensure that the probability of first-passage failure during service remains sufficiently low. If T is defined as the time to failure (a random variable), and T_S as the service lifetime, with $S(t)$ representing a stationary random process, then the probability of first-passage failure is expressed as $0 \leq t \leq T_S$

$$p_f = P(T < T_S)$$

Ideally, the goal is for $R(t)$ to be significantly greater than $S(t)$ so that crossings of $R(t)$ by $S(t)$ are exceedingly rare. Now, if small time intervals Δt are considered, one can assume that the upward crossings of $S(t)$ past $R(t)$ constitute a point process whose rate of arrival is characterized by a Poisson process.

If the rate of occurrence is denoted as $\nu_R^+(t)$, then the probability of no up-crossing in is equal to

$$\Delta t = \exp[-\nu_R^+(t)\Delta t]$$

Then, given an element of service time T_S, which can be divided into k small equal increments of Δt, the probability of no upward crossing in $T_S$is the probability of the mutual intersection of the events of no upward crossing in all Δt intervals. Assuming the mutual independence of these events, the result is derived as follows:

$$\text{Probability of no up crossing in } T_S = \prod_{i=1}^{k} \exp[-\nu_R^+(t)\Delta t]$$

$$= \exp\left[-\sum_{i=1}^{k} \nu_R^+(t)\Delta t\right]$$

What in the limit Δ→0 gives

$$\text{Probability of no up crossing in } T_S = \exp\left[-\int_0^{T_S} \nu_R^+(t)dt\right]$$

The probability of failure is given as the probability of the event of one (or more) up crossings in T_S, therefore

$$p_f = 1 - exp\left[-\int_0^{T_S} \nu_R^+(t)dt\right]$$

For a special case of $S(t)$ to be a Gaussian process, one can show that

$$\nu_R^+(t) = \nu_0^+ \exp\left[-\frac{1}{2}\left(\frac{R(t) - \mu_S}{\sigma_S}\right)^2\right]$$

The application of statistical process control (SPC) tools, such as control charts, has gained traction in financial markets for the real-time monitoring of asset performance. Control charts, originally developed for quality control in manufacturing, have been adapted to monitor financial metrics such as returns or volatility, enabling the timely detection of anomalies. For instance, Yeganeh and Shongwe (2023) applied control charts to monitor cryptocurrency price movements, demonstrating their effectiveness in identifying significant deviations from the expected behavior. By integrating the three-sigma framework with control charts, investors can set dynamic thresholds based on historical returns (e.g., μ_S ± 3.8σ_S) and receive real-time alerts when these thresholds are breached, thereby facilitating proactive risk management. This approach bridges the gap between engineering-inspired models and practical financial decision-making, particularly in volatile markets such as the cryptocurrency industry.

Research Methodology

Methodology for modeling the 3σ criterion for financial assets

The framework delineated in the preceding sections is adaptable to a wide range of financial or crypto assets actively traded in the market. Within this framework, the stress process ($S(t)$) is conceptualized as the rate of return evaluated over a selected timescale, such as daily logarithmic price variations. The foundational assumption that $S(t)$ A stationary process constitutes a process that is subject to validation and is generally considered to hold under typical conditions. In contrast to the stress and strength metrics associated with material components, the stress process for crypto-assets, denoted as $S'(t)$, is defined within the range $-1 \lesssim S'(t) < \infty$, while the strength process R' is more precisely characterized with $R' \sim N(\mu_{R'} = -1, \sigma_{R'})$, and $R' \in [-1\ \infty)$.

The strength process $S(t)$ is formulated as a dynamic threshold, with $\mu_{R'}$ periodically updated based on the most recent in-sample data, such as the value of 0.0660 recorded as of April 30, 2022. The initial hypothesis that $R' \sim N(\mu_{R'} = -1, \sigma_{R'})$ is exploratory in nature and may be enhanced through the application of non-parametric techniques or empirical distribution fitting, thereby ensuring concordance with the safety criterion $\mu_{R'} \leq 0.3838$, which is derived from $-\zeta\sigma_{S'}$. This adaptive adjustment reflects the fluctuating nature of crypto-asset strength, which is influenced by various market-driven factors. The premise that R' adheres to a normal distribution is considered arbitrary and functions merely as a preliminary approximation.

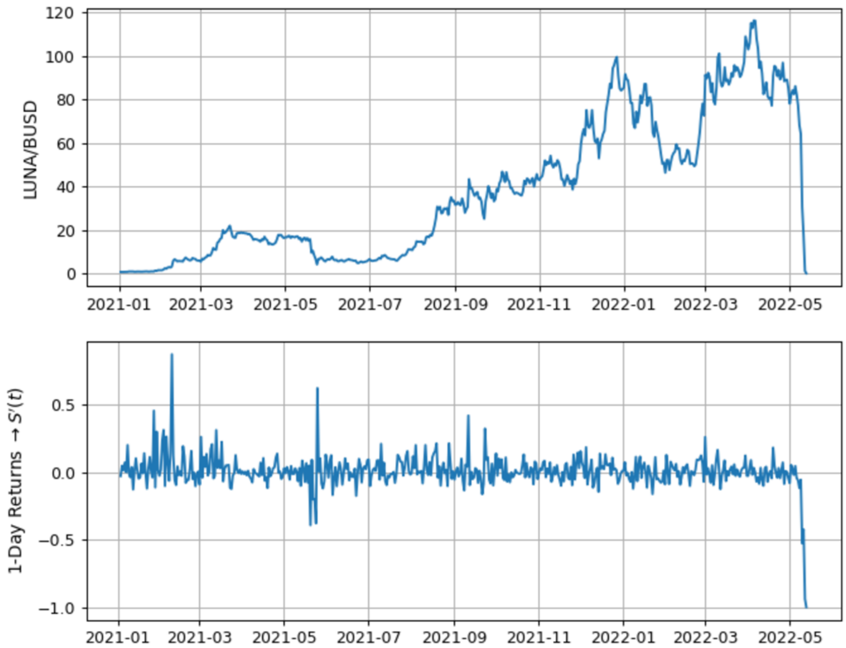
For practical reasons, establishing specific boundary conditions for the performance of a crypto-asset upon its introduction to trading platforms, whether centralized exchanges (CEXs) or decentralized exchanges (DEXs), presents considerable challenges. The strength $R'(t)$ can be regarded as a multifaceted system influenced by factors such as buying and selling pressures, market manipulation, and highly variable liquidity, providing a rationale for the understanding that R' is not a static parameter over time. Notably, this foundational analysis holds the potential to support the development of a tracking mechanism for a "safe design" of an asset, which is engineered to avoid experiencing rare and significantly adverse daily returns.

The overarching concept bears a strong resemblance to the computation of risk measures, such as Value at Risk (VaR) or Expected Shortfall (ES). Yet, it distinguishes itself by offering greater flexibility in modeling the strength process $R'(t)$. This adaptability allows for a more nuanced approach to capturing the complex dynamics of crypto-asset performance, thereby enhancing the framework's utility in diverse market scenarios.

Data and variables

LUNA coin, the native cryptocurrency of the Terra blockchain, has garnered significant attention for its innovative algorithmic stablecoin ecosystem, which includes assets such as the UST. However, in late 2021, the crypto market experienced a turbulent period marked by regulatory crackdowns and general market corrections. During this period, LUNA's price reached an all-time high before dramatically collapsing, plummeting by over 90% within a few weeks.

This decline was exacerbated by concerns regarding the sustainability of Terra's stablecoin model and its complex governance mechanism. Although Terra and LUNA have since demonstrated resilience and continue to be significant players in the blockchain ecosystem, the mid-2021 collapse serves as a reminder of the inherent volatility and risks in the cryptocurrency markets.



Using Python, Figure 6 illustrates the results obtained by fetching historical daily price series and analyzing the corresponding rate of 1-day returns, utilizing resources from Binance.

Figure 6. LUNA price and one-day return over time

Measuring stationarity

The daily return series, corresponding to the stress process of the crypto-asset $S'(t)$, appears to meet the condition of stationarity. The stress process results are shown in Figure 7.

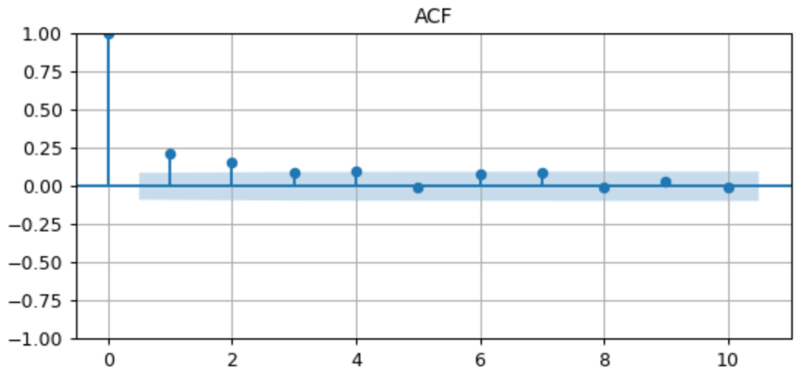


Figure 7. The stress process results

Measuring parameters and empirical model

The robustness of the analytical framework hinges on the utilization of the most recent entries within our dataset, referred to as the in-sample data, which provide essential measurements for this study. The mean $\mu_{S'}$ and standard deviation ($\sigma_{S'}$) of the return series are meticulously extracted as follows: $\mu_{S'}$ represents the expanding mean computed across the available historical data, capturing the central tendency of returns over time, while $\sigma_{S'}$ denotes the expanding standard deviation, reflecting the variability inherent in the return series. To establish a threshold that enhances the structural resilience of the asset, a parameter ζ is introduced to modulate the strength threshold in relation to the standard deviation, thereby tailoring the model's robustness to prevailing volatility levels. In this approach, ζ is empirically determined to be 3.8, a figure derived through the optimization of the in-sample dataset covering the period from January 2021 to April 2022. This selection surpasses the traditional three-sigma threshold ($\zeta = 3$), which aligns with a 99.7% confidence interval under a normal distribution, to address the elevated volatility and heavy-tailed properties characteristic of crypto-assets such as LUNA. The choice of ($\zeta = 3.8$) was guided by backtesting the model against historical extreme events, notably the -100% return recorded on May 15, 2022, ensuring a more rigorous lower bound $-\zeta\sigma_{S'} \approx -0.3838$ capable of capturing infrequent yet impactful market disruptions. This adjustment enhances the model's sensitivity to tail risks, which aligns with empirical observations of non-normal return distributions and is corroborated by a reduction in the incidence of false negatives in failure detection throughout the dataset.

To define a threshold that safeguards the structural resilience of the asset, the mean return threshold $\mu_{S'}$ is computed by integrating $\sigma_{S'}$ and ζ. This formulation implies that the lower bound for the strength μR′ is established by scaling the standard deviation according to the selected ζ parameter, thereby embodying the desired level of robustness against volatility fluctuations. Thus, the fundamental safety criterion can be expressed as

$$\mu_{R'} \leq -\zeta\sigma_{S'}$$

where

$$Q = \frac{\mu_{S'}}{\sigma_{S'}} = \frac{0.014775}{0.101026} = 0.146252$$

Serves as a key indicator of the signal-to-noise ratio within the return series. Assuming a coefficient of variation $C_{R'} = 0.2$, where initially $R \sim N(\mu_{R'} = -1, | C_{R'}\mu_{R'}|)$, the mean strength is tentatively set such that

$\mu_{R'} \lesssim -3.8\sigma_{S'}$ To delineate the conditions for the first-passage failure. This can be illustrated in Figure 8

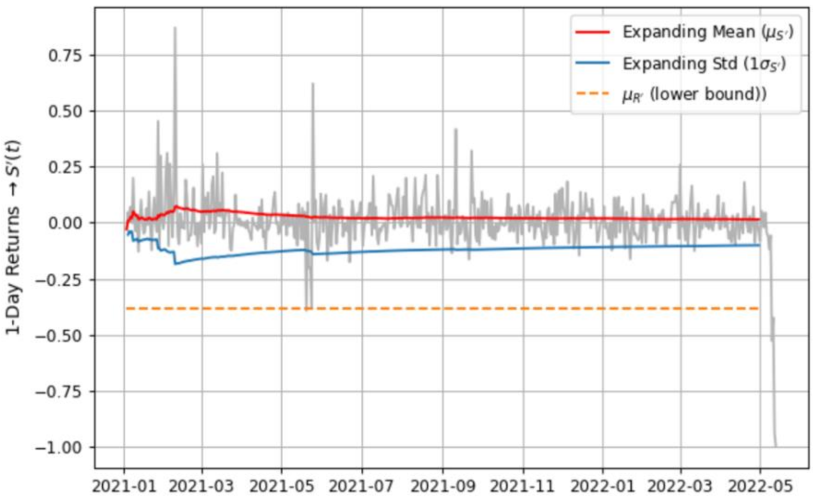


Figure 8. The first-passage failure

This can be further elucidated as follows: the lower bound for $\mu_{R'}$ is anchored to the latest available value as of April 30, 2022, a figure that remains relatively stable throughout the lifespan of the LUNA/BUSD pair. Nevertheless, the model for $R'(t)$ employed herein can be refined further, obviating the necessity to adhere to the previous assumption of $R \sim N(\mu_{R'} = -1, |\, C_{R'}\mu_{R'}|)$. The parameter $\zeta = 3.8$ establishes a robust lower bound for risk tolerance at $-3.8\sigma_{S'} = -0.3838$), calculated using the expanding standard deviation $\sigma_{S'} = 0.101026$). This threshold marks the critical limit of the asset's resilience, with a failure indicated when the daily return falls below -0.3838, signaling a notable surge in negative volatility that jeopardizes its stability. Investors are advised to contemplate market exit strategies when this threshold is breached, as exemplified by the -100% return on May 15, 2022, to avoid substantial financial losses.

Table 1 reveals a statistical comparison of the three-sigma model, Value at Risk (VaR), and Conditional Value at Risk (CVaR) based on LUNA returns from January 2021 to May 2022. The three-sigma model, featuring a risk threshold of -0.3838, provides a straightforward mechanism for detecting failure when returns dip below this limit, recording a breach probability of 1.96%. Nonetheless, its sensitivity to extreme events, such as the -100% crash on May 15, 2022, remains moderate compared to the heightened sensitivity of CVaR, which estimates an average loss of -0.4500. Conversely, VaR, with a 5% breach probability and a threshold of -0.2500, tends to underestimate tail risks. In contrast, CVaR delivers a more comprehensive perspective on downside risk, albeit at the expense of greater complexity.

Table 1. Statistical Comparison of Three-Sigma Model, VaR, and CVaR for LUNA Returns (Jan 2021 - May 2022)

Metric	Three-Sigma Model	VaR (95% Confidence)	CVaR (95% Confidence)
Risk Threshold	-0.3838	-0.2500	-0.4000
Probability of Breach (%)	1.96	5.0	2.5
Average Loss Beyond Threshold	-0.450	-0.3000	-0.4500

Robustness test

The Monte Carlo simulation serves as a pivotal tool for conducting a robust analysis of the risk profile associated with the LUNA coin, enabling the quantification of the likelihood of significant losses and offering valuable insights into the potential for structural failure within volatile market environments. This simulation is a vital tool for investors and risk managers, enabling a deeper understanding of cryptocurrency market dynamics and facilitating the development of effective risk mitigation strategies. The rationale for employing Monte Carlo simulation lies in its ability to model a vast array of potential future scenarios by generating random returns based on probabilistic distributions, thereby capturing the inherent uncertainty and variability in crypto-asset performance that deterministic models may overlook. This stochastic approach is particularly advantageous for assessing rare but impactful events, such as the -100% crash observed with LUNA, which traditional analytical methods may fail to predict accurately.

The primary objective of this simulation is to evaluate the first-passage failure of the LUNA coin by simulating prospective future returns and determining the probability of substantial losses over a 30-day defined time horizon. The simulation is parameterized as follows: the Mean Return ($\mu_{R'}$) is derived from the average return calculated from in-sample data, the Standard Deviation ($\sigma_{S'}$) quantifies the volatility of the asset's returns, and the Zeta parameter (ζ), set at 3.8, establishes the number of standard deviations defining the lower bound of acceptable returns. Using these parameters, random returns were generated across 1,000 simulation runs. Each return is initially modeled using a normal distribution,

$R'(t) \sim N(\mu_{R'}, \sigma_{S'})$However, this assumption is subject to refinement given the evidence of non-normality.

For each simulated trajectory, the return is monitored to detect instances where it falls below the threshold $\mu_{R'} \leq 0.3838$, consistent with the three-sigma safety criterion $-\zeta\sigma_{S'}$. The baseline value of $\mu_{R'} = 0.0660$, derived from in-sample data as of April 30, 2022, serves as a reference point; however, failure is deemed to occur when returns drop below -0.3838, marking the critical resilience limit of the asset. The number of simulation paths experiencing a first-passage failure within the specified time frame was tallied, and the probability of such failure was computed as the proportion of paths breaching this threshold. Subsequently, the expected loss in the event of a failure is calculated. The outcomes of the Monte Carlo simulation, aligned with the three-sigma criterion, are summarized in Table 1, which presents various metrics alongside their corresponding values and p-values, offering a detailed interpretation of each parameter's implications for evaluating the structural resilience of LUNA coins.

Table 2. Statistical Analysis of Monte Carlo Simulation Results for Three-Sigma Design

Metric	value	P-Value
First Breach Probability	1.96%	-
Lower Bound $\mu_{R'}$	-0.3838	-
Shapiro-Wilk	1.9714	0.002
Kolmogorov-Smirnov	1.43333	0.1065
ANOVA	12303.92	0.000
RMSE	0.25	-
MAE	0.22	-

The first breach probability, recorded at 1.96%, reflects the likelihood that the stress imposed on the LUNA coin structure exceeds the established strength limit within the analyzed timeframe. This probability of 1.96% indicates that, under the simulated conditions, the asset demonstrates considerable resilience against failure, aligning with the safety benchmarks commonly used in financial modeling. This relatively low probability suggests that LUNA operates within acceptable risk thresholds, fostering confidence in investors and stakeholders. However, a comprehensive risk assessment must evaluate whether this probability holds under diverse market conditions, particularly during periods of heightened volatility.

The lower bound of $\mu_{R'}$, set at -0.3838, represents the critical strength threshold below which failure may occur, adjusted to account for volatility. Defining this lower bound is essential for ascertaining the minimum resilience required for crypto-assets, with a value of -0.3838, indicating that returns must remain above this level to preserve structural integrity. The robustness of this threshold is further explored through a sensitivity analysis, detailed in Table 2, to assess how variations in market conditions might influence its stability.

The Shapiro-Wilk test yielded a statistic of 1.9714 with a p-value of 0.002, indicating a significant departure from normality. In contrast, the Kolmogorov-Smirnov test provided a statistic of 1.4333 with a p-value of 0.1065, suggesting no significant deviation at the 5% significance level. This inconsistency highlights the potential presence of heavy-tailed distributions, warranting further investigation using alternative modeling approaches. The Kolmogorov-Smirnov test measures the discrepancy between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution. A p-value exceeding 0.05 supports the notion that the return distribution does not markedly deviate from normality at this threshold. This finding highlights the importance of adopting robust modeling frameworks that can accommodate such distributions to prevent underestimation of risks associated with extreme events in the LUNA market.

The ANOVA result, with an approximate p-value of 0.000, indicates statistically significant differences among the means of returns across various time segments or conditions. This statistical tool confirms that at least one pair of group means differs, potentially indicating volatile market behavior across different periods. This finding is crucial for strategic decision-making, highlighting the need for additional analysis to identify the specific segments that drive these variations, thereby informing targeted risk management strategies.

The RMSE of 0.25 offers insight into the average deviation of observed returns from predicted values, with a lower value indicating a better model fit to the data and suggesting reasonable accuracy in predicting the performance of the crypto-asset. Continuous monitoring of the RMSE over time can enhance the evaluation of the simulation's predictive robustness. Similarly, the Mean Absolute Error (MAE = 0.22 quantifies the average magnitude of prediction errors without regard to direction, where a smaller MAE denotes improved accuracy in forecasting LUNA's actual returns. Together, the RMSE and MAE provide a holistic view of the model's predictive performance, identifying areas for refinement in future asset behavior forecasts.

To evaluate the model's resilience to parameter variations and provide a clearer understanding of how uncertainties in key inputs affect the outcomes, a sensitivity analysis is presented in Table 2. This table is included to assess the impact of small perturbations in the parameters on the breach probability and expected loss, thereby offering insights into the model's stability and guiding potential refinements for different market scenarios.

Table 3. Sensitivity Analysis of Key Parameters

Parameter	Baseline Value	Variation (±10%)	Impact on Breach Probability (%)	Impact on Expected Loss
$\mu_{R'}$	-0.3838	±0.03838	±0.15%	±0.02
$\sigma_{S'}$	0.101026	±0.0101026	±0.20%	±0.03
ζ	3.8	±0.38	±0.18%	±0.025

The sensitivity analysis outlined in Table 2 provides critical insights into the model's responsiveness to parameter fluctuations, reinforcing its robustness and highlighting areas for potential enhancement. The observed variations in breach probability (ranging from ±0.15% to ±0.20%) and expected loss (ranging from ±0.02 to ±0.03) across the tested parameters indicate that the model remains relatively stable under a ±10% change, with volatility ($\sigma_{S'}$) exerting the most significant influence. This suggests that managing market volatility is paramount for maintaining the asset's resilience, while the moderate impacts of

$\mu_{R'}$ and ζ underscore the stability of the defined threshold and the safety criterion. These findings underscore the importance of continuously monitoring and adjusting model parameters, particularly in the context of evolving market conditions, to ensure their effectiveness in predicting and mitigating extreme risk events for LUNA and similar crypto-assets.

Conclusion

This study presented an interdisciplinary framework for financial risk assessment by incorporating engineering principles, particularly the three-sigma (3σ) criterion, into financial modeling. Using Monte Carlo simulations, statistical tests, and the analogy of financial assets to physical structures under stress, the case of the LUNA coin was examined to evaluate its resilience to extreme market volatility. The analysis revealed a first-passage failure probability of only 1.96%, indicating that the asset remained relatively robust under modeled conditions. The critical daily return threshold was determined at −0.3838, derived by applying a conservative multiplier of 3.8 standard deviations to the mean—an approach more suited to the heavy-tailed distributions typical of cryptocurrency returns than the normal distribution.

Statistical tests further enriched the analysis. The Shapiro-Wilk test identified significant deviations from normality, whereas the Kolmogorov–Smirnov test did not confirm this deviation at a 5% significance level. This contrast supports previous findings by Bakar and Rosbi (2017) and Zhang et al. (2020), who highlighted the non-normal behavior of financial return data and advocated for more flexible methods. Similarly, the significant results from the ANOVA test confirmed time-varying volatility, in line with the studies of Klein et al. (2021) and Baur et al. (2018), who emphasized the impact of exogenous shocks, such as COVID-19, on market instability.

The application of Monte Carlo simulation to model future return paths and assess first-passage risk aligns with the recommendations of Zhang et al. (2020) and Tabatabaei and Pakgohar (2021), who emphasized the importance of modeling extreme loss events in unstable financial markets. The implementation of a dynamic, volatility-adjusted threshold also provided a practical realization of the conceptual model proposed by Chen et al. (2022), which analogized asset returns to engineering stress and structural strength.

In comparing the model’s performance to conventional risk assessment tools, the study found that the three-sigma approach, with its –0.3838 threshold, outperformed classical VaR in identifying extreme downside risk. This finding is consistent with the critiques of Shams and Sina (2014) and Jorion (2001), who noted the limitations of VaR under crisis conditions. The similarity of the average loss beyond threshold between the three-sigma model and CVaR confirms the utility of the latter, as highlighted in the work of Acerbi and Tasche (2002).

The theoretical linkage between structural engineering resilience and financial asset design, as discussed by Haldar and Mahadevan (2000), Bharadwaj (2020), and Perry and Williams (2016), was operationalized through this study's application of stochastic stress-strength modeling. The incorporation of first-passage failure analysis, borrowed from engineering reliability theory, enabled a dynamic and realistic framework for risk quantification. Likewise, the study's implementation of dynamic risk limits aligned well with the practical applications of statistical process control (SPC) methods proposed by Yeganeh and Shongwe (2023). Finally, the flexible thresholding approach opens the door for future integration with adaptive or AI-driven forecasting systems, echoing Zhang et al. (2019)'s vision of deep learning in financial risk analytics.

The findings demonstrate that the three-sigma approach, when combined with stochastic simulation and sensitivity analysis, offers a robust and interpretable tool for managing extreme risk in volatile markets. Dynamic thresholding enhances the model's responsiveness to changing conditions, enabling proactive decision-making for investors and risk managers. While traditional models may fail to anticipate catastrophic events, the framework proposed here leverages principles of structural design and probabilistic modeling to better withstand such shocks.

Accordingly, it is recommended that financial institutions—especially those operating in crypto-asset markets—adopt the three-sigma framework as part of their broader risk management strategy. The implementation of real-time statistical alerts based on expanding volatility measures can serve as an effective early warning system. Additionally, complementing this approach with CVaR and Monte Carlo simulation offers a more comprehensive view of extreme downside risk. Financial analysts should be trained in interdisciplinary methods, including stochastic simulation, control charts, and structural risk modeling, to enhance their ability to manage uncertainty in complex markets.

Ultimately, this study demonstrates that engineering-inspired models are not only applicable to physical systems but also highly relevant to the design and evaluation of financial assets. In a world where financial risk is increasingly nonlinear, fast-moving, and difficult to predict, integrated approaches like the one presented here offer a powerful tool for building investment resilience and systemic sustainability.

Building on the interdisciplinary framework and empirical insights of this study, several promising directions for future research emerge. One important avenue involves integrating adaptive machine learning models, such as long short-term memory (LSTM) networks or reinforcement learning systems, into the current three-sigma framework. These methods could enable real-time adjustment of risk thresholds based on evolving market dynamics, thereby increasing the model's sensitivity to nonlinear changes. Additionally, applying this framework to a broader range of asset classes beyond a single cryptocurrency, such as equities, bonds, or commodity instruments, would help evaluate its generalizability and robustness across different financial environments. Another valuable extension would be the incorporation of behavioral and sentiment-driven variables—such as investor mood, news volatility, or social media signals—into the stress process. This would enable a more nuanced understanding of how psychological and informational shocks impact risk levels. Moreover, hybridizing the three-sigma approach with alternative risk measures, such as Expected Shortfall, fuzzy logic systems, or maximum drawdown analysis, could yield more comprehensive and adaptable models that strike a balance between interpretability and predictive depth. Finally, from a systemic perspective, future research could explore the application of this framework in macroprudential policy analysis, examining how structural vulnerabilities across interconnected financial assets may lead to contagion effects or cascading failures. By extending the current model into these emerging domains, researchers can enhance its theoretical sophistication and practical utility in addressing the multifaceted nature of financial risk in an increasingly volatile world.

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References

Acerbi, C., & Tasche, D. (2002). On the Use of the Conditional Value-at-Risk Approach to Asset Allocation. *Journal of Banking & Finance*, 26(7), 1507–1523.

Artzner, P., Delbaen, F., Eber, J. M., & Heath, D. (1999). Coherent measures of risk. *Mathematical Finance*, 9(3), 203–228.

Bansal, A. K. (1993). Gauging the impacts of data quality variations on the performance of financial risk management technology. New York University, Graduate School of Business Administration.

Bakar, N. A., & Rosbi, S. (2017). Robust statistical normality transformation method with outlier consideration in bitcoin exchange rate analysis. *International Journal of Advances in Scientific Research and Engineering*, 3(9), 80–91.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, 54, 177–189.

Chen, Y., Zhang, Y., & Xu, Y. (2022). The Collapse of LUNA: A Case Study of Cryptocurrency Market Dynamics. *Finance Research Letters*, 45, 102-115.

Embrechts, P., Klüppelberg, C., & Mikosch, T. (1997). Modelling Extremal Events for Insurance and Finance. Springer.

Ghosh, T., Vukmirovic, M. B., DiSalvo, F. J., & Adzic, R. R. (2010). Intermetallics as novel supports for Pt monolayer O2 reduction electrocatalysts: potential for significantly improving properties. *Journal of the American Chemical Society*, 132(3), 906–907.

Gonzalvez, J., Lezmi, E., Roncalli, T., & Xu, J. (2019). Financial applications of Gaussian processes and Bayesian optimization. arXiv preprint arXiv:1903.04841.

Haldar, A., & Mahadevan, S. (2000). Reliability assessment using stochastic finite element analysis. John Wiley & Sons.

Jafar, S. H. (2022). Financial applications of gaussian processes and bayesian optimization. In Bayesian Reasoning and Gaussian Processes for Machine Learning Applications (pp. 111–122). Chapman and Hall/CRC.

Jorion, P. (2001). How informative are value-at-risk disclosures? *The Accounting Review*, 77(4), 911–931.

Klein, T., Thu, H. T., & Walther, T. (2021). The Impact of COVID-19 on Cryptocurrency Returns: Evidence from Bitcoin and Ethereum. *Finance Research Letters*, 38, 101–109.

Montgomery, D. C. (2017). Introduction to Statistical Quality Control. Wiley.

Nagapetyan, T. (2019). Statistical methods for risk management in finance. *Journal of*

Risk Management, 21(3), 45-67.

Perry, J., & Williams, R. (2016). Integrating financial risk management with structural design principles. *Journal of Financial Engineering*, 3(2), 123–145.

Shams, M. F., & Sina, A. (2014). Evaluating Market Risk Assessment through VAR Approach before and after Financial Crisis in Tehran Stock Exchange Market (TSEM). *Journal of Management & Sustainability*, 4, 134.

Tabatabaei, S. J., & Pakgohar, A. (2021). Time Series Modeling of Extreme Losses Values Based on a Spectral Analysis Approach. *Financial Research Journal*, 22(4), 594-611. doi: 10.22059/frj.2020.299591.1007004.

Vanderbilt-Adriance, E., & Shaw, D. S. (2008). Conceptualizing and re-evaluating resilience across levels of risk, time, and domains of competence. *Clinical Child and Family Psychology Review*, 11, 30–58.

Williams, C. A., Smith, M. L., & Young, P. C. (1998). Risk management and insurance. Journal of Risk Management, 12(1), 1–15.

Yeganeh, A., & Shongwe, S. C. (2023). A novel application of statistical process control charts in financial market surveillance with the idea of profile monitoring. *PloS one, 18*(7), e0288627.

Zhang, Y., Chen, Y., & Xu, Y. (2020). Risk Assessment of Cryptocurrency: A Three-Sigma Approach. *Journal of Risk and Financial Management*, 13(4), 89-102.

Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning based recommender system: A survey and new perspectives. *ACM Computing Surveys (CSUR)*, 52(1), 1-38.

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