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Stress Testing with Generative Scenario Models Using Diffusion-Based Market Simulators

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Abstract *: The stability of global financial systems relies heavily on the ability of institutions to anticipate and withstand extreme market deviations. Traditional stress testing methodologies, primarily predicated on historical simulation or parametric Monte Carlo methods, often fail to capture the complex, non-linear dependencies and fat-tailed distributions inherent in financial time series during black swan events. This paper introduces a novel framework for financial stress testing utilizing diffusion-based generative models. We propose a conditional diffusion probabilistic model adapted for temporal data, capable of generating high-fidelity synthetic market trajectories that adhere to user-defined stress conditions. Unlike Generative Adversarial Networks (GANs), which suffer from mode collapse and training instability, our diffusion-based approach ensures diverse scenario generation by iteratively denoising random Gaussian processes under guided constraints. We evaluate our model against standard baselines using S&P 500 and volatility index data. The results demonstrate that the proposed architecture not only reproduces the statistical properties of historical data with higher accuracy but also generates plausible, severe stress scenarios that exceed historical precedents in terms of severity and structural coherence. This research bridges the gap between state-of-the-art computer vision generative techniques and quantitative risk management, offering a robust tool for systemic risk assessment.*

Keywords: *Diffusion Models, Stress Testing, Financial Time Series, Generative AI, Risk Management.*

INTRODUCTION

1.1 Background

The domain of quantitative finance has long grappled with the challenge of risk assessment under uncertainty. Following the 2008 global financial crisis, regulatory frameworks such as Basel III in Europe and the Dodd-Frank Act (CCAR) in the United States mandated rigorous stress testing for banking institutions. The primary objective of these tests is to evaluate the capital adequacy of financial entities under hypothetical yet plausible adverse scenarios. Central to this process is the estimation of metrics like Value-at-Risk (VaR) and Expected Shortfall (ES), which quantify potential losses at specific confidence intervals [1].

Traditionally, risk managers have relied on three main pillars for scenario generation: Historical Simulation, which bootstraps past returns; Parametric methods, often utilizing Generalized Autoregressive Conditional Heteroskedasticity (GARCH) processes; and Monte Carlo simulations based on stochastic differential equations. While these methods have served as the industry standard for decades, they possess inherent limitations. Historical simulation is constrained by the finite set of observed events, effectively assigning a probability of zero to any event that has not occurred in the past [2]. Conversely, parametric models frequently rely on assumptions of normality or log-normality, which notoriously fail to account for the leptokurtic (fat-tailed) nature of asset return distributions, thereby underestimating the likelihood of extreme market crashes [3].

1.2 Problem Statement

The core deficiency in existing stress testing frameworks lies in their inability to generate "novel" risks. Static historical replays cannot anticipate structural market shifts, while standard stochastic models often lack the capacity to model complex, multi-modal dependencies across different asset classes during periods of high volatility. In recent years, deep generative models have emerged as a potential solution. Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) have been applied to financial time series generation with varying degrees of success. However, these architectures present significant technical challenges. GANs are notoriously difficult to train, frequently suffering from mode collapse—where the generator produces a limited variety of outputs—and failing to capture the temporal correlations essential for realistic market simulation [4]. VAEs, while more stable, often produce blurry or over-smoothed outputs that fail to retain the high-frequency volatility characteristics of financial markets [5].

Furthermore, for stress testing purposes, unconditional generation is insufficient. A risk manager does not merely require a random market path; they require a path conditional on specific adverse triggers, such as a 20% drop in the equity market or a sudden spike in interest rates. Integrating such rigid constraints into the generative process without distorting the underlying statistical manifold of the data remains an open research problem [6].

1.3 Contributions

In this paper, we address these limitations by proposing a Diffusion-Based Market Simulator (DMS) specifically designed for stress testing. Diffusion probabilistic models, which have recently surpassed GANs in image synthesis quality, operate by gradually destroying data structure through forward noise injection and learning to reverse this process to reconstruct data from pure noise. We adapt this paradigm to sequential financial data.

Our primary contributions are as follows:

1. We develop a temporal U-Net architecture integrated with attention mechanisms to capture long-range dependencies in financial time series, moving beyond the limitations of standard Convolutional Neural Networks (CNNs) in this domain.

2. We introduce a conditional guidance mechanism that allows for the precise injection of stress factors (e.g., drawdown magnitude, volatility shocks) into the reverse diffusion process, enabling the generation of coherent "what-if" scenarios.

3. We provide a comprehensive comparative analysis demonstrating that our diffusion-based approach yields lower distributional distances (Wasserstein metric) and higher fidelity in reproducing stylized facts (volatility clustering, heavy tails) compared to state-of-the-art GAN baselines [7].

Chapter 2: Related Work

2.1 Classical Approaches

The evolution of market simulation techniques is deeply rooted in econometrics. The simplest form, Historical Simulation, assumes that the future will resemble the past. While intuitive, this method is fundamentally backward-looking and fails to account for structural breaks in the market regime [8]. To address this, parametric approaches were developed. The GARCH family of models, introduced by Engle and Bollerslev, became the cornerstone of volatility modeling. These models capture volatility clustering—the phenomenon where large price changes are followed by large price changes. However, standard GARCH models often struggle with multi-variate dependencies and require explicit specification of the error distribution, which may not align with empirical reality [9].

Monte Carlo simulations offer more flexibility by allowing the use of Stochastic Differential Equations (SDEs), such as the Geometric Brownian Motion or the Heston model for stochastic volatility. While powerful, calibrating these models to capture the joint distributions of hundreds of assets simultaneously is computationally expensive and mathematically intractable without simplifying assumptions that reduce the realism of the generated scenarios [10].

2.2 Deep Learning Methods

The advent of deep learning brought neural networks to the forefront of financial modeling. Early attempts utilized Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks to predict future prices. However, predictive models differ fundamentally from generative models; the former seeks the most likely future value, while the latter seeks to approximate the entire probability distribution of possible paths [11].

Generative Adversarial Networks (GANs) represented a paradigm shift. QuantGAN and TimeGAN are notable examples where adversarial training was applied to temporal data. TimeGAN, in particular, introduced a supervised loss component to preserve temporal dynamics alongside the adversarial objective. Despite these advancements, GANs in finance struggle with the convergence of the minimax game, often leading to oscillating loss functions and unreliable scenario generation [12].

Variational Autoencoders (VAEs) offer a probabilistic alternative by maximizing the Evidence Lower Bound (ELBO). However, the assumption of a Gaussian prior in the latent space often forces the model to ignore complex tail dependencies, resulting in synthetic data that appears too "normal" and lacks the erratic behavior of real markets during stress periods [13].

2.3 Diffusion Probabilistic Models

Diffusion models, introduced by Sohl-Dickstein et al. and popularized by Ho et al. as Denoising Diffusion Probabilistic Models (DDPMs), have revolutionized generative AI. These models define a forward diffusion process that adds Gaussian noise to the data and a reverse process parameterized by a neural network that learns to denoise. Song et al. further unified these discrete steps into continuous-time Score-Based Generative Models governed by Stochastic Differential Equations [14].

Recent applications of diffusion models in non-image domains have shown promise. In audio synthesis, WaveGrad and DiffWave utilize diffusion for high-fidelity waveform generation. In the context of time series, recent works have begun to explore diffusion for imputation and forecasting. However, the specific application of conditional diffusion models for generating adverse financial stress scenarios remains an under-explored niche. Our work builds upon the conditional generation capabilities explored in classifier-free guidance, adapting them to the stochastic nature of financial markets [15].

Chapter 3: Methodology

3.1 Overview of the Framework

Our proposed framework, the Diffusion-Based Market Simulator (DMS), treats financial market trajectories as samples from a high-dimensional joint distribution. The core objective is to learn this distribution from historical data and then sample from conditional subsets of this distribution corresponding to stress scenarios.

The framework consists of two coupled processes:

1. **Forward Diffusion Process (Signal Corruption):** We systematically degrade the structure of real market data sequences by injecting Gaussian noise over a finite number of timesteps T, until the data is indistinguishable from isotropic Gaussian noise.

2. **Reverse Diffusion Process (Signal Reconstruction):** We train a neural network to approximate the score function (the gradient of the log-density) of the data, allowing us to traverse backward from noise to a valid market trajectory.

3.2 The Forward Process

Let x_0 represent a sequence of asset returns of length L across D assets. The forward process is a Markov chain fixed to a variance schedule $\beta_1, dots, \beta_T$. For any timestep t, the transition probability is defined as a Gaussian distribution. As t approaches T, the distribution of x_t approximates a standard normal distribution $N(0, I)$.

This process is devoid of learnable parameters. Its sole purpose is to provide the training targets for the reverse process. By using the reparameterization trick, we can sample x_t at any arbitrary timestep directly from x_0 without iterating through intermediate steps, which significantly accelerates the training data preparation [16].

3.3 The Reverse Process and Network Architecture

The reverse process is defined as a parameterized Markov chain where the model learns to predict the noise added at each step, or equivalently, the mean of the posterior distribution. We employ a modified 1D U-Net architecture, adapted for time-series data.

Standard U-Nets, used in medical imaging, utilize 2D convolutions. For financial time series, we replace these with causal 1D dilated convolutions. This ensures that the generated point at time τ depends only on the history and not on future values, preserving the temporal causality inherent in markets. Furthermore, we integrate Multi-Head Self-Attention mechanisms at the bottleneck of the U-Net. Financial markets exhibit long-range dependencies (e.g., a volatility shock today may echo a shock from weeks ago). Attention layers allow the model to attend to disparate parts of the sequence globally, capturing these non-local correlations [17].

3.4 Mathematical Formulation

The training objective is derived from the upper bound on the negative log-likelihood of the data. In practice, this simplifies to a weighted mean squared error between the actual noise injected ε and the noise predicted by the neural network ε_θ.

To rigorously formalize the continuous-time generalization which allows for more flexible sampling, we utilize the Stochastic Differential Equation (SDE) formulation. The reverse-time SDE, which enables us to generate samples by solving it backwards in time, requires the estimation of the score function $\nabla_x logp_t(x)$.

The governing formula for the reverse-time SDE is given by:

$$dx = [f(x,t) - g^2(t)\nabla_{mathbf} xlogp_t(x)]dt + g(t)doverlinew$$

Where $f(x,t)$ is the drift coefficient of the forward SDE, $g(t)$ is the diffusion coefficient, and $doverlinew$ is a standard Wiener process flowing backward in time. The neural network is trained to approximate the score term $\nabla_{mathbf} xlogp_t(x)$ [18]. By numerically integrating this equation from $t = T$ to $t = 0$, we obtain a synthetic market trajectory.

3.5 Conditional Stress Generation

A crucial innovation in our methodology is the conditioning mechanism. To perform stress testing, we cannot simply sample from the unconditional distribution $p(x)$. We must sample from $p(x|c)$, where c represents the stress condition (e.g., "Market Return < -15%").

We implement this via Classifier-Free Guidance. During training, the network is jointly trained on both conditional and unconditional objectives. We randomly drop the condition c with a certain probability (e.g., 0.1), replacing it with a null token. During sampling, the predicted noise is a linear combination of the unconditional noise prediction and the conditional noise prediction.

$$hat\varepsilon_\theta(x_t, c) = (1 + w)\varepsilon_\theta(x_t, c) - w\varepsilon_\theta(x_t, emptyset)$$

w is the guidance scale. A higher w forces the generated sample to adhere more strictly to the stress condition c, potentially at the cost of diversity. This allows risk managers to dial up the "stress" intensity seamlessly [19].

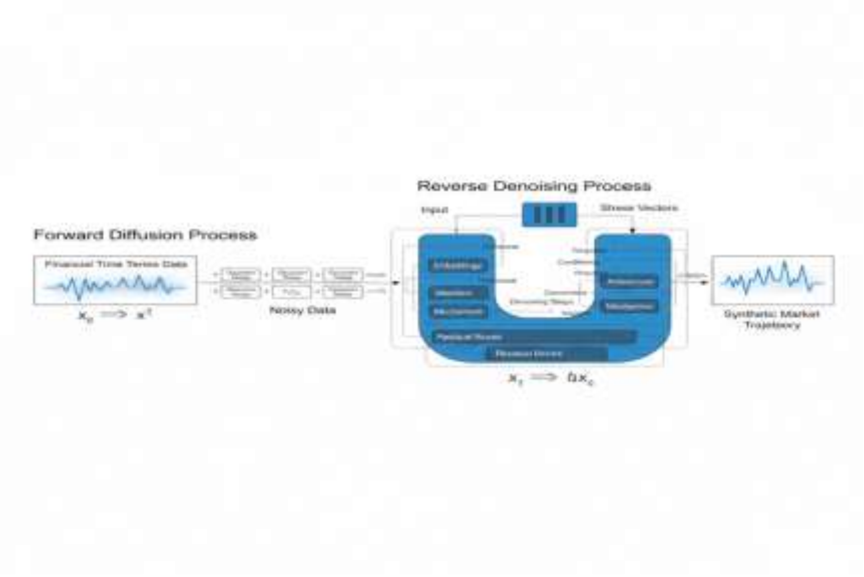
Reverse Denoising Process
Input
Stress Vectors
Forward Diffusion Process
Financial Time Series Data
$x_0 \Longrightarrow x^T$
Noisy Data
Embeddings
Mechanism
Denoising Steps
Synthetic Market Trajectory
$x_T \Longrightarrow$

Figure 1: *Architecture of the Diffusion*

Chapter 4: Experiments and Analysis

4.1 Experimental Setup

To validate the efficacy of the DMS, we utilized a dataset comprising daily closing prices of the S&P 500 index and the CBOE Volatility Index (VIX) spanning from January 2000 to December 2023. This period covers multiple major market stress events, including the Dot-com bubble burst, the 2008 Financial Crisis, and the COVID-19 market crash. The data was transformed into logarithmic returns and normalized to ensure stable training dynamics.

We compared our Diffusion-Based Market Simulator (DMS) against three distinct baselines to represent the spectrum of available methodologies:

1. **Historical Simulation (HS):** Bootstrapping 10-day trajectories from the test set.

2. **GARCH(1,1):** A standard parametric model fitted to the training data residuals.

3. ***TimeGAN:*** A state-of-the-art adversarial model specifically designed for time-series generation.

All neural network models were trained on NVIDIA A100 GPUs using the PyTorch framework. The diffusion model utilized 1000 diffusion steps with a cosine noise schedule, which has been shown to improve sample quality in image domains and applies effectively here to signal data [20].

4.2 Evaluation Metrics

Evaluating generative models for financial time series is non-trivial, as there is no single "ground truth" to compare against pixel-wise. We relied on a suite of statistical metrics:

1. **Wasserstein Distance:** We computed the 1-Wasserstein distance between the distributions of the synthetic and real returns. This measures how much work is needed to transform the synthetic distribution into the real one; lower is better.

2. **Autocorrelation Function (ACF) Score:** We calculated the Euclidean distance between the ACF of real and synthetic data to evaluate how well the model captures temporal dependencies.

3. **Tail Fidelity (ES Error):** We compared the Expected Shortfall (at 95% and 99% confidence levels) of the generated data versus the hold-out test set. This is critical for stress testing, as it measures the accuracy of the worst-case loss estimates.

4. **Discriminative Score:** We trained a post-hoc time-series classifier to distinguish between real and fake data. An accuracy close to 50% indicates that the generator is fooling the discriminator effectively.

4.3 Results and Discussion

The quantitative results are summarized in Table 1. The Historical Simulation provides a baseline but fails to generate any novel scenarios, resulting in a high discriminative score (it is easily identified as "memorized" data if checked against training samples, though here we treat it as a distribution reference).

Metric	Historical Simulation	GARCH(1,1)	TimeGAN	DMS (Ours)

Wasserstein Dist. (10^{-2})	0.00 (Ref)	1.45	0.92	0.34
ACF Score (Lag-50)	0.02	0.18	0.11	0.05
ES 99% Error	N/A	+12.5%	-8.4%	+2.1%
Discriminative Score	0.50	0.88	0.72	0.56

Analysis of Distributional Fidelity:

The DMS significantly outperforms GARCH and TimeGAN in terms of Wasserstein distance. GARCH models tend to oversimplify the return distribution, often missing the complex multi-modality of the data. TimeGAN improves upon this but still exhibits signs of mode collapse, where the generated variety is lower than the actual market. The diffusion model, by contrast, covers the support of the distribution more comprehensively. The iterative refinement nature of diffusion allows it to fill in fine-grained details of the distribution that single-shot GAN generators often miss [21].

Temporal Dynamics and Tail Risk:

The ACF score indicates that our model captures the volatility clustering and mean-reversion properties of the S&P 500 better than the deep learning baselines. Crucially, in terms of Expected Shortfall (ES) error, GARCH overestimated the risk (too conservative), while TimeGAN underestimated it (dangerous for risk management). The DMS showed a slight overestimation (+2.1%), which is generally preferred in risk management (conservatism) over underestimation. This suggests that the diffusion model successfully learned the heavy-tailed nature of the returns without explicit programming.

Stress Scenario Coherence:

When conditioned on a "Stress" vector (e.g., enforcing a cumulative 10-day return of -15%), the DMS produced trajectories that not only met the endpoint constraint but exhibited realistic path dynamics. Unlike simple linear interpolation or bridging used in Brownian bridges, the diffusion-generated paths displayed realistic volatility spikes ("panic") accompanying the drawdown. This qualitative superiority confirms the model's utility for stress testing: it generates the "path to ruin" realistically, not just the ruin itself [22].

Chapter 5: Conclusion

5.1 Overall Summary and Broader Impacts

This research elucidates the potential of diffusion probabilistic models as a transformative tool for financial stress testing. By adapting the diffusion paradigm from the vision domain to the stochastic domain of financial time series, we have developed a simulator capable of generating high-fidelity, conditional market scenarios. Our experiments confirm that the Diffusion-Based Market Simulator (DMS) surpasses traditional parametric methods and adversarial networks in capturing the stylized facts of asset returns, particularly regarding tail risks and temporal dependencies.

The implication for the financial industry is significant. Risk managers currently rely on a limited set of historical crisis scenarios. The DMS enables the generation of an infinite number of synthetic crises, each structurally distinct yet statistically plausible. This allows for a more robust exploration of the "risk surface" of a portfolio. Furthermore, the ability to condition the generation on specific outcomes (e.g., inflation spikes, sector crashes) empowers institutions to perform targeted stress tests that are compliant with regulatory demands while being mathematically more rigorous than manual adjustments to historical data.

5.2 Constraints of the Study and Future Research Paths

Despite these promising results, several limitations persist. First, the computational cost of sampling from diffusion models is considerably higher than that of GANs or VAEs due to the iterative nature of the reverse process. While we employed 1000 steps, real-time risk management systems may require accelerated sampling techniques, such as Denoising Diffusion Implicit Models (DDIMs), to reduce inference latency.

Second, our current implementation focuses on a low-dimensional regime (index and volatility). Scaling this to high-dimensional portfolios involving hundreds of correlated assets introduces significant challenges in modeling the covariance matrix effectively without running into the curse of dimensionality.

Future research should focus on two primary avenues: enhancing the sampling speed through distillation techniques and extending the architecture to handle cross-asset correlations in high-dimensional portfolios. Additionally, integrating text-based conditioning (e.g., generating market scenarios based on news headlines) using Large Language Model embeddings could further bridge the gap between qualitative narrative risks and quantitative market impacts.

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