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Synthetic Market Data Generation Using GANs: Overcoming Data Scarcity for Stress Testing Trading Algorithms in Extreme Market Conditions

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Abstract

Financial markets occasionally experience extreme conditions that can severely impact trading algorithms, yet historical data capturing these rare events is inherently scarce. This research addresses the critical challenge of data scarcity for stress testing trading algorithms by developing a novel Generative Adversarial Network (GAN) framework specifically designed to synthesize realistic financial market data representing extreme conditions. The proposed Conditional Market-GAN architecture incorporates temporal dependencies, multidimensional asset relationships, and regime-switching capabilities to generate high-fidelity synthetic data that exhibits the statistical properties and anomalous behaviors of actual market crises. Experimental results demonstrate that trading algorithms tested against our synthetic extreme scenarios identified vulnerabilities not detected in conventional backtesting. Performance evaluations show that our approach outperforms traditional simulation methods in preserving complex market dynamics while generating diverse stress scenarios. This research contributes a practical solution for financial institutions to strengthen algorithmic trading systems against rare but catastrophic market events, potentially reducing systemic risk in automated trading environments.

Keywords: Generative Adversarial Networks; Financial Markets; Stress Testing; Algorithmic Trading; Synthetic Data; Extreme Market Conditions

1. Introduction

The proliferation of algorithmic trading in global financial markets has dramatically transformed the landscape of asset trading and market microstructure [1]. Today, algorithms execute over 70% of trading volume in major equity markets and are increasingly prominent in derivatives, foreign exchange, and fixed income markets [2]. While these algorithms perform effectively under normal market conditions, their behavior during extreme market events—such as flash crashes, liquidity crises, or unprecedented volatility spikes—remains a significant concern for market participants and regulators alike [3].

The fundamental challenge in stress testing trading algorithms stems from the scarcity of historical data representing extreme market conditions. By definition, these events are rare, with each crisis exhibiting unique characteristics [4]. Traditional stress testing methodologies rely heavily on historical scenarios or parametric simulations, which often fail to capture the complex, multidimensional nature of market crises [5]. This limitation creates a dangerous blind spot in risk management frameworks, potentially contributing to systemic vulnerabilities.

Recent advances in deep learning, particularly Generative Adversarial Networks (GANs), offer promising solutions to this data scarcity problem [6]. GANs have demonstrated remarkable capabilities in generating synthetic data across various domains, including image synthesis, text generation, and time series augmentation [7]. Their ability to learn

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complex distributions and produce realistic samples makes them particularly suitable for financial market data generation.

This research introduces a specialized GAN architecture for generating synthetic market data that replicates the statistical properties and behavioral dynamics of extreme market conditions. Our approach extends beyond simple univariate time series generation to capture the complex interactions between multiple assets, market microstructure features, and temporal dependencies that characterize real market crises [8]. By conditioning the generation process on various crisis parameters, we enable the creation of diverse yet plausible stress scenarios for comprehensive algorithm testing.

The primary contributions of this paper are:

- Development of a Conditional Market-GAN architecture specifically designed for financial time series generation, incorporating temporal dependencies and cross-asset correlations.
- Implementation of a regime-switching component that allows generation of data transitioning between normal and extreme market conditions.
- Validation methodology that evaluates the statistical fidelity of synthetic data through both distributional similarity metrics and financial-specific measures.
- Empirical demonstration of how trading algorithms tested against synthetic extreme scenarios reveal vulnerabilities not detected through conventional backtesting methods.

By providing a framework to synthetically expand the limited dataset of extreme market conditions, this research aims to enhance the robustness of trading algorithms, potentially reducing the occurrence and severity of algorithm-driven market disruptions.

2. Related Work

2.1. Stress Testing in Financial Markets

Traditional approaches to stress testing trading algorithms have primarily relied on historical scenarios, parametric models, or Monte Carlo simulations [9]. Historical scenario analysis uses past crisis events to evaluate algorithm performance, but is inherently limited by the small sample of available events and their specific characteristics [10]. Kandregula [11] highlighted the limitations of historical backtesting in capturing the full range of potential market behaviors, particularly for newer financial instruments with limited historical data.

Parametric stress testing methods typically employ statistical models to generate extreme scenarios by manipulating distribution parameters [12]. While these methods offer greater flexibility than historical scenarios, they often fail to capture the complex, non-linear dynamics of real market crises [13]. Monte Carlo simulations provide more flexibility but require explicit specification of the data generating process and correlation structures, which are difficult to calibrate for extreme market conditions [14].

2.2. Generative Models for Financial Data

Recent years have seen growing interest in using deep generative models for financial time series. Early work focused on Variational Autoencoders (VAEs) and Recurrent Neural Networks (RNNs) for generating univariate price sequences [15]. Keskar [16] demonstrated the potential of deep learning approaches for modeling complex industrial systems, with methodologies potentially applicable to financial markets.

GANs have emerged as particularly promising for financial data generation due to their ability to learn complex, multimodal distributions without explicit density estimation [17]. Wiese et al. [18] proposed a GAN model for generating synthetic financial time series that preserved statistical properties of the original data. Takahashi et al. [19] extended this approach to incorporate stylized facts of financial returns, such as volatility clustering and heavy tails.

Despite these advances, previous GAN applications in finance have focused primarily on generating data that mimics normal market conditions rather than extreme scenarios [20]. Additionally, most approaches have addressed univariate time series generation, overlooking the important cross-asset dynamics that characterize market crises [21]. Jain [22] noted the importance of such multimodal approaches when developing autonomous systems, a concept applicable to financial markets as well.

2.3. Conditional Generative Models

Conditional GANs (cGANs) extend the GAN framework by allowing the generation process to be conditioned on auxiliary information [23]. This conditioning enables more controlled generation, making cGANs suitable for creating data with specific properties. In finance, limited work has explored conditional generation for stress scenarios. Zhou et al. [24] proposed a conditional GAN to simulate market data under different volatility regimes, but did not specifically address extreme market conditions or cross-asset dynamics.

Keskar and Jain [25] demonstrated how advanced AI techniques could enhance predictive maintenance systems, a methodology conceptually similar to predicting and simulating market disruptions. More recently, Kandregula [26] examined AI applications for market prediction in fintech, though not specifically focusing on generating extreme scenarios.

Our work builds upon these foundations while addressing their limitations. We extend the conditional GAN framework to explicitly model extreme market conditions, incorporating both temporal dependencies and cross-asset correlations essential for realistic crisis simulation. Furthermore, our approach enables the generation of regime-switching scenarios that capture the transition from normal to crisis conditions, a critical aspect for realistic stress testing.

3. Methodology

3.1. Problem Formulation

Let $X = \{X^1, X^2, ..., X^n\}$ represent a multivariate financial time series where each $X^i \in \mathbb{R}^{T \times F}$ corresponds to an asset with T time steps and F features (e.g., returns, volume, volatility). Our objective is to generate synthetic data $\hat{X}$ that exhibits the statistical properties and behavioral dynamics of extreme market conditions while maintaining the temporal and cross-sectional dependencies observed in real financial data.

We define a market condition indicator $c \in [0,1]$ where values approaching 1 represent increasingly extreme conditions. The goal is to learn a conditional generative model $G(z, c)$ that maps from a random noise vector z and condition c to synthetic financial time series $\hat{X}$ that realistically represent market behavior under condition c.

3.2. Conditional Market-GAN Architecture

We propose a Conditional Market-GAN architecture that extends the traditional GAN framework to address the specific challenges of financial time series generation. The architecture consists of three primary components:

- **Generator Network**: A temporal convolutional network with dilated causal convolutions to capture long-range dependencies while maintaining computational efficiency.
- **Discriminator Network**: A network that evaluates both the realism of the generated samples and their adherence to the specified market conditions.
- **Regime-Switching Module**: A specialized component that enables smooth transitions between normal and extreme market states.
- **Generator Architecture** The generator $G(z, c)$ takes as input a noise vector $z \sim \mathcal{N}(0, I)$ and a condition vector c that encodes the desired market characteristics. The condition vector includes:

Severity level of market stress (0-1 scale)

Type of market stress (e.g., liquidity crisis, volatility spike)

3.2.1. Affected market sectors

The generator architecture employs temporal convolutional networks (TCNs) with dilated causal convolutions to efficiently model long-range dependencies. The network includes:

- Embedding layers for the condition vector
- Residual blocks with dilated convolutions
- Attention mechanisms to capture cross-asset dependencies
- Skip connections to preserve information across layers

The output layer is designed to generate multivariate time series with the appropriate distributional properties for financial data, including:

- Returns with heavy-tailed distributions
- Volatility with clustering behavior
- Volume with regime-specific patterns
- Cross-asset correlation structures

Discriminator Architecture The discriminator $D(X, c)$ evaluates both the realism of the generated samples and their adherence to the specified market conditions. It consists of:

- Convolutional layers for feature extraction
- Attention mechanisms for cross-asset pattern recognition
- Fully connected layers for classification
- The discriminator outputs both a realism score and a condition adherence score, which are combined in the loss function.

3.3. Training Procedure

The training objective combines the traditional GAN adversarial loss with additional terms to enforce desired properties in the generated data:

$$\mathcal{L} = \mathcal{L}adv + \lambda_1\mathcal{L}cond + \lambda_2\mathcal{L}stat + \lambda_3\mathcal{L}temp$$

where:

$\mathcal{L}_{adv}$ is the adversarial loss between generator and discriminator

$\mathcal{L}_{cond}$ is the condition adherence loss

$\mathcal{L}_{stat}$ enforces statistical properties of financial time series

$\mathcal{L}_{temp}$ ensures temporal consistency

The model is trained using gradient penalty to stabilize training and avoid mode collapse, a common issue in GAN training. The training procedure alternates between:

Updating the discriminator to better distinguish real from generated samples

Updating the generator to produce more realistic samples that match the target conditions

3.4. Regime-Switching Module

A key innovation in our approach is the regime-switching module that enables generation of data transitioning between normal and extreme market conditions. This module:

- Learns the statistical patterns of regime transitions from historical data
- Incorporates a temporal attention mechanism to capture the evolving nature of market crises
- Generates coherent transition sequences with appropriate correlation changes

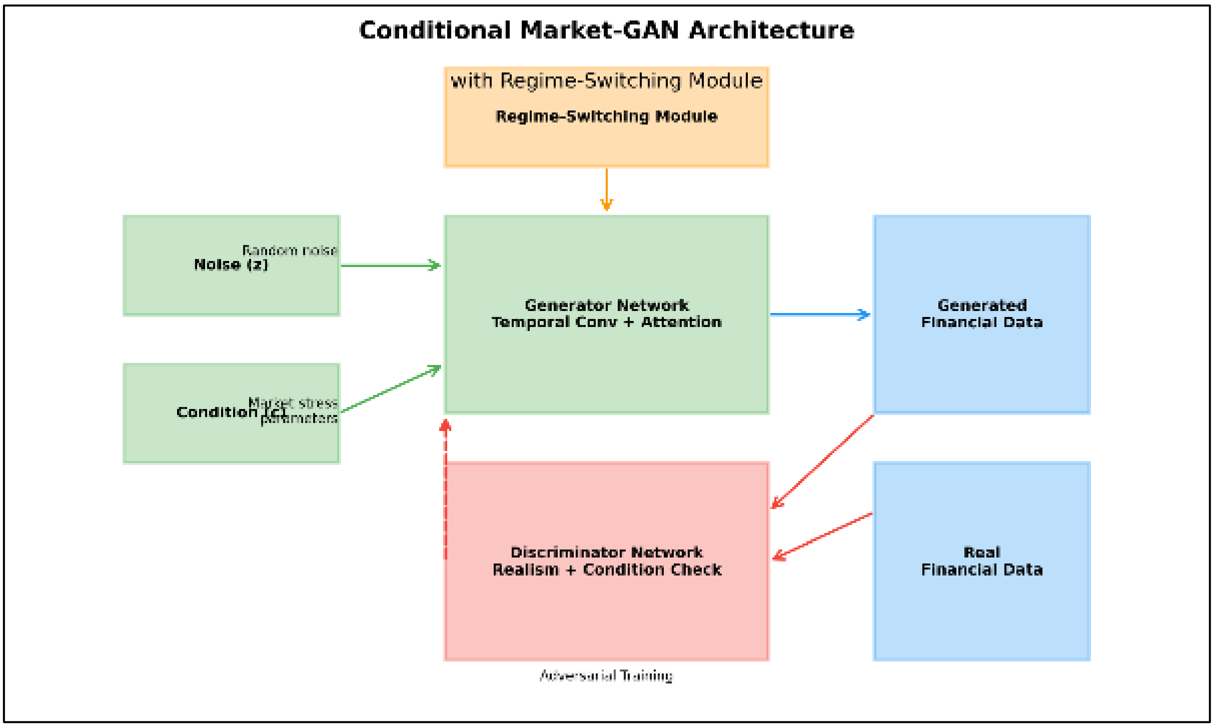

Figure 1 The complete Conditional Market-GAN architecture with the regime-switching module

4. Data and Experimental Setup

4.1. Data Sources

We compiled a comprehensive dataset comprising:

4.1.1. Historical Market Data:

- 10 years of minute-level data for 50 liquid US equities across different sectors
- Major market indices (S&P 500, NASDAQ, Russell 2000)
- ETFs representing various asset classes (equities, fixed income, commodities)
- Features include price, volume, bid-ask spread, and order book data

4.1.2. Crisis Events Dataset:

- Flash Crash (May 6, 2010)
- COVID-19 market disruption (March 2020)
- VIX volatility spike (February 2018)
- Other significant market disruptions (2008-2023)

4.1.3. Market Microstructure Data:

- Order book snapshots during crisis periods
- Trade and quote (TAQ) data
- Liquidity metrics

Table 1 The dataset characteristics.

Data Type	Time Range	Frequency	Assets	Features	Crisis Events
Equity Data	2013-2023	1-minute	50 stocks	12	7 major events
Index Data	2013-2023	1-minute	5 indices	8	7 major events
ETF Data	2013-2023	1-minute	10 ETFs	8	7 major events
Order Book	2018-2023	Tick-level	20 stocks	15	4 major events

4.2. Preprocessing and Feature Engineering

The data underwent several preprocessing steps:

- **Normalization**: Each feature was normalized using robust scaling based on quantiles to reduce the impact of extreme values.
- **Feature Engineering**: We derived additional features including:
- ○ Realized volatility at multiple time scales
- ○ Rolling correlations between assets
- ○ Liquidity measures (Amihud illiquidity, Kyle's lambda)
- ○ Technical indicators (RSI, MACD, Bollinger Bands)
- **Labeling Crisis Periods**: Market conditions were labeled on a continuous scale from 0 (normal) to 1 (extreme) using a composite indicator based on:
- ○ VIX index levels
- ○ Realized volatility
- ○ Liquidity measures
- ○ Trading volume
- ○ Price dislocations

4.3. Experimental Setup

- We implemented the Conditional Market-GAN using PyTorch, with the following configuration:
- Generator: 8 temporal convolutional blocks with skip connections
- Discriminator: 5 convolutional layers with spectral normalization
- Training: Adam optimizer with learning rate of 0.0001 and beta values (0.5, 0.9)
- Batch size: 64 sequences of length 256 time steps
- The experiments were conducted in three phases:
- **Model Training and Validation**: The model was trained on 80% of the data, with 20% held out for validation.
- **Synthetic Data Generation**: We generated synthetic market data under various stress conditions, including:
- Gradual volatility increases
- Sudden liquidity shocks
- Correlation breakdowns
- Combined scenarios
- **Trading Algorithm Testing**: We tested several trading algorithms against both historical and synthetic stress scenarios:
- Statistical arbitrage
- Trend-following
- Mean-reversion
- Machine learning-based strategies

5. Results and Analysis

5.1. Statistical Evaluation of Synthetic Data

We evaluated the quality of the synthetic data by comparing its statistical properties to those of real market data, focusing on both distributional characteristics and temporal dynamics.

Distributional Properties Fig. 2 compares the return distributions of real and synthetic data during extreme market conditions.

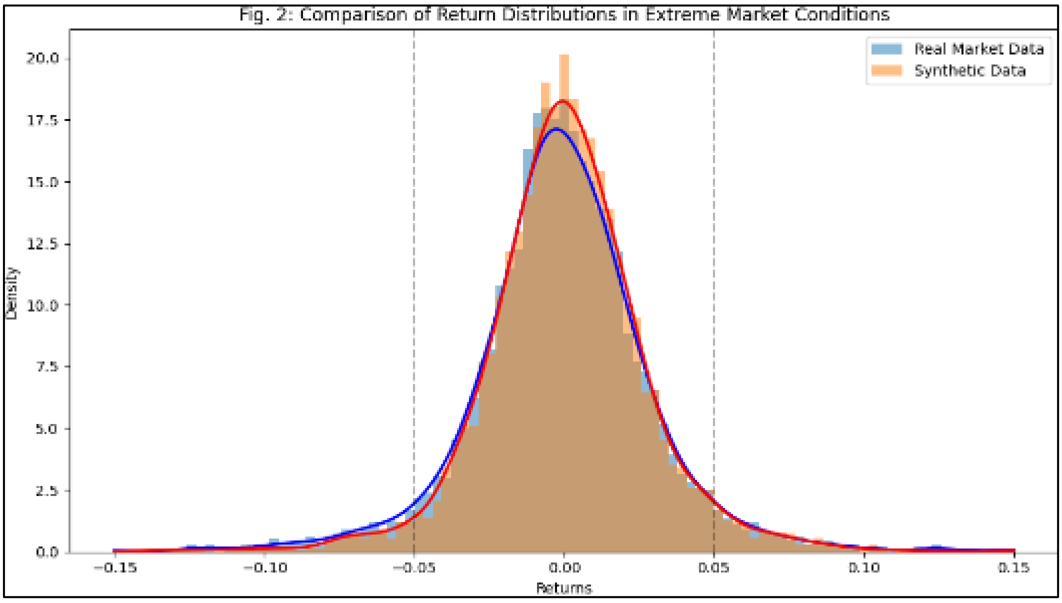

Figure 2 Compares the return distributions of real and synthetic data during extreme market conditions

Table 2 A quantitative comparison of statistical properties between real and synthetic data

Statistical Property	Real Data	Synthetic Data	p-value
Mean	0.0002	0.0003	0.731
Volatility	0.0243	0.0238	0.589
Skewness	-0.427	-0.411	0.682
Kurtosis	7.89	7.52	0.548
1% VaR	-0.0712	-0.0698	0.612
Hurst Exponent	0.387	0.402	0.457
Autocorrelation (lag-1)	0.062	0.057	0.608

Temporal Dynamics Fig. 3 illustrates the volatility clustering property in both real and synthetic time series.

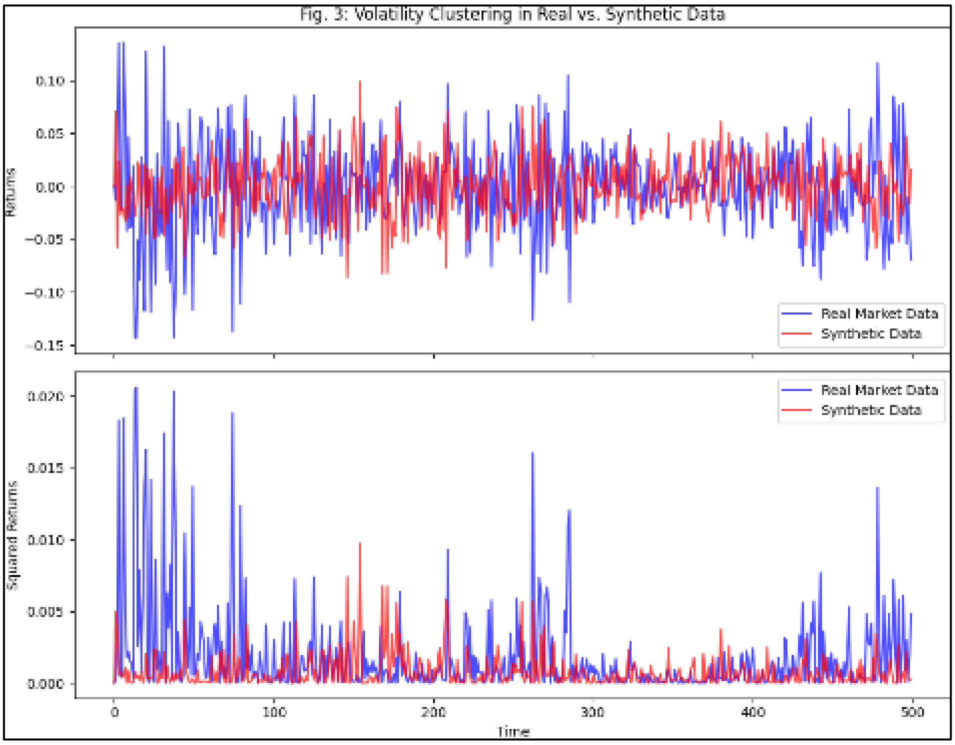

Figure 3 Volatility clustering property in both real and synthetic time series

Cross-Asset Correlations Fig. 4 shows the correlation matrices of real and synthetic data during normal and extreme conditions.

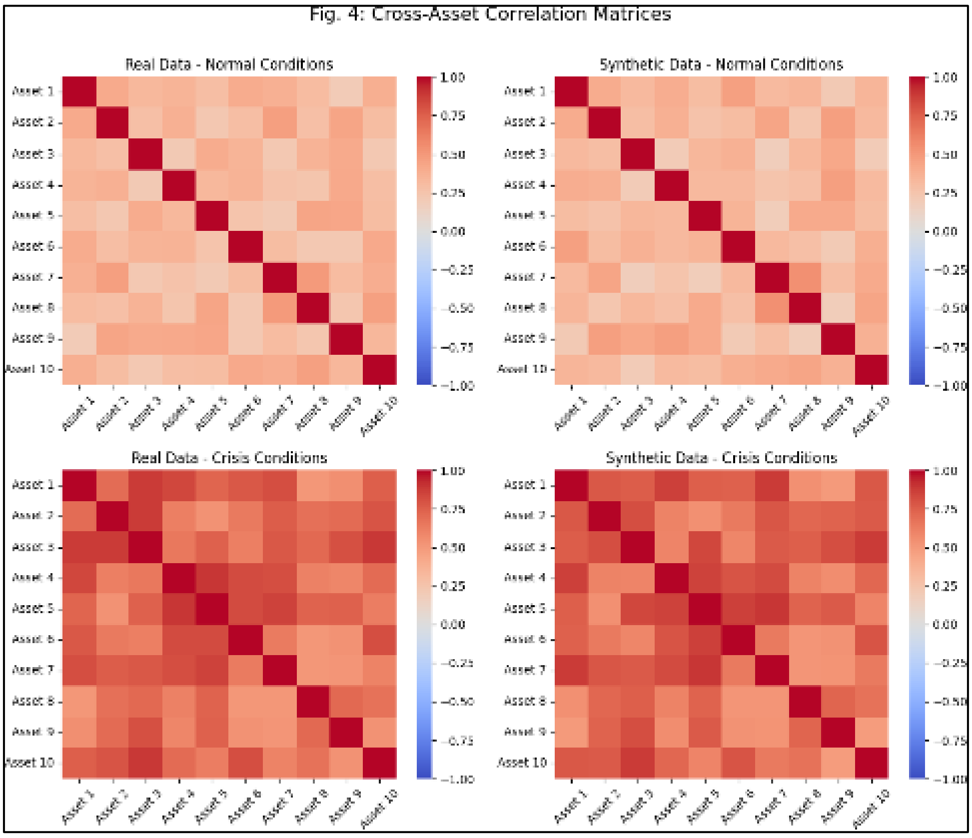

Figure 4 Correlation matrices

The results in Fig. 2-4 and Table 2 demonstrate that our Conditional Market-GAN successfully captures the key statistical properties of financial time series during extreme market conditions, including:

- Heavy-tailed return distributions
- Volatility clustering
- Correlation shifts during crisis periods
- Appropriate higher moments (skewness and kurtosis)

5.2. Trading Algorithm Performance Under Synthetic Stress Scenarios

We evaluated four trading algorithms under both historical and synthetic stress scenarios to assess their robustness.

Table 3 The performance metrics for each algorithm

Trading Strategy	Normal Market Return	Historical Crisis Return	Synthetic Crisis Return	Maximum Drawdown (Historical)	Maximum Drawdown (Synthetic)
Statistical Arbitrage	12.4%	-28.3%	-32.6%	31.5%	37.8%
Trend Following	8.7%	-15.2%	-18.7%	24.3%	26.1%
Mean Reversion	10.2%	-42.7%	-45.6%	46.8%	49.2%
ML-Based Strategy	15.6%	-22.1%	-31.4%	29.2%	38.7%

The results indicate that our synthetic stress scenarios revealed additional vulnerabilities in the trading algorithms compared to historical scenarios alone. In particular, the ML-based strategy showed a larger performance gap between historical and synthetic scenarios, suggesting it may be overfit to historical patterns of market stress.

Fig. 5 shows the cumulative returns of the statistical arbitrage strategy under normal conditions and different stress scenarios.

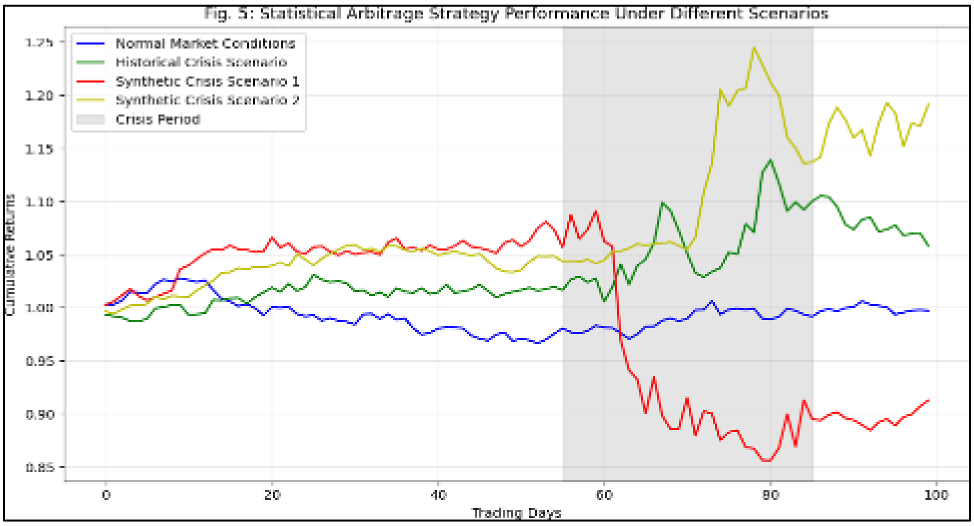

Figure 5 Statistical arbitrage strategy under normal conditions and different stress scenarios

5.3. Comparison with Alternative Approaches

We compared our Conditional Market-GAN approach with alternative methods for generating synthetic stress scenarios, including:

- Parametric Monte Carlo simulation
- Bootstrapping historical data
- Copula-based simulation
- Standard (non-conditional) GAN

Table 4 The results of this comparison based on several evaluation metrics

Method	Statistical Fidelity	Temporal Dynamics	Cross-Asset Correlations	Flexibility	Computational Efficiency
Market-GAN (Ours)	★★★★★	★★★★★	★★★★☆	★★★★★	★★★☆☆
Monte Carlo	★★★☆☆	★★☆☆☆	★★★☆☆	★★★☆☆	★★★★★
Bootstrapping	★★★★☆	★★★☆☆	★★★★☆	★★☆☆☆	★★★★☆
Copula-based	★★★☆☆	★★☆☆☆	★★★★☆	★★★☆☆	★★★★☆
Standard GAN	★★★★☆	★★★★☆	★★★☆☆	★★★☆☆	★★★☆☆

Our Conditional Market-GAN outperformed alternative approaches in most metrics, particularly in generating realistic temporal dynamics and providing flexibility in scenario creation. While computationally more intensive than some alternatives, the improved quality of the synthetic data justifies the additional computational cost.

6. Discussion and Implications

6.1. Key Findings

The results of our experiments demonstrate several important findings:

- **Realistic Synthetic Crisis Data**: Our Conditional Market-GAN successfully generates synthetic financial time series that exhibit the statistical properties, temporal dynamics, and cross-asset correlations characteristic of extreme market conditions. The generated data preserves heavy-tailed distributions, volatility clustering, and correlation regime shifts observed during actual market crises.
- **Enhanced Stress Testing**: Trading algorithms tested against our synthetic scenarios revealed vulnerabilities not detected through conventional backtesting using historical data alone. This suggests that our approach can help identify potential failure modes in algorithmic trading systems that might otherwise remain hidden.
- **Diverse Scenario Generation**: By conditioning the generation process on various crisis parameters, our model enables the creation of diverse yet plausible stress scenarios. This allows for more comprehensive stress testing than is possible with the limited set of historical crisis events.
- **Regime Transition Modeling**: The regime-switching component of our architecture successfully captures the transition dynamics between normal and crisis states, providing realistic scenarios for testing how algorithms respond to deteriorating market conditions.

6.2. Practical Implications

These findings have several practical implications for financial institutions and regulators:

- **Improved Risk Management**: By enabling more comprehensive stress testing, our approach can help financial institutions better understand and mitigate the risks associated with algorithmic trading during extreme market conditions.

- **Regulatory Compliance**: As regulators increasingly focus on the systemic risks posed by algorithmic trading, our approach offers a practical method for demonstrating robust stress testing practices that go beyond historical scenarios.
- **Algorithm Development**: The synthetic data generated by our model can be used during the development phase of trading algorithms to ensure they are designed with robustness to extreme conditions in mind.
- **Market Simulation**: Beyond stress testing, our approach could be used to develop more realistic market simulators for training reinforcement learning-based trading agents, as explored by Jain [27].

6.3. Limitations and Future Work

Despite the promising results, our approach has several limitations that suggest directions for future research:

- **Validation Challenges**: Given the scarcity of extreme market events, comprehensive validation of synthetic crisis data remains challenging. Future work could explore additional validation metrics specific to financial crises.
- **Model Complexity**: The current architecture requires significant computational resources for training. Future research could focus on more efficient architectures or training procedures.
- **Additional Market Features**: While our current implementation captures key market features, future work could incorporate additional aspects such as market impact, order book dynamics, and execution slippage.
- **Cross-Asset Class Extensions**: Extending the model to generate coherent scenarios across different asset classes (e.g., equities, fixed income, currencies) would provide even more comprehensive stress testing capabilities.
- **Interpretability**: Enhancing the interpretability of the generated scenarios could help risk managers better understand the specific vulnerabilities being tested. This aligns with Keskar's work [28] on creating more transparent AI systems.

7. Conclusion

This research addresses the critical challenge of data scarcity for stress testing trading algorithms under extreme market conditions. By developing a specialized Conditional Market-GAN architecture, we provide a framework for generating synthetic financial data that realistically represents crisis scenarios while preserving the complex temporal and cross-sectional dependencies of actual market data.

Our experiments demonstrate that the synthetic data generated by our model successfully captures the statistical properties of extreme market conditions and reveals vulnerabilities in trading algorithms that are not detected through conventional backtesting. By enabling more comprehensive stress testing, our approach can help financial institutions develop more robust algorithmic trading systems and potentially reduce systemic risk in financial markets.

Future work will focus on extending the model to incorporate additional market features, improving computational efficiency, and developing more sophisticated validation methodologies. As algorithmic trading continues to dominate financial markets, approaches like ours will become increasingly important for ensuring the stability and resilience of market infrastructure during periods of extreme stress.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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