POLIMI – Graduate School of Management

Business Analytics & Data Science

Stress Testing Financial Portfolios with Synthetic Time Series: An Empirically Calibrated TimeGAN Framework

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24/10/2025

Abstract

As financial crises differ from historic stress events from the past, financial institutions face increasing challenges for evaluating portfolio resilience under new market regimes. The conventional stress-testing methods such as historical event replay and Gaussian copulas depend on static, past data and simplistic dependency assumptions, leading to systematic underestimation of cross-asset conditioning and tail risk. The limitation of using these traditional tests hinder effective risk management when structural market shifts happen.

We present a study that develops a TimeGAN-based generative framework for data-driven financial stress testing, designed to generate realistic yet unseen multivariate market scenarios. The framework integrated equities, bonds, commodities, and FX series with macro-volatility proxies (VIX, MOVE, CDX IG), aligned in a unified trading day calendar from 2004 to 2025. Rigorous data engineering is used to ensure reproducibility and empirical validity, with all preprocessing steps, file paths, and configurations documented, with controlled model calibration through loss-weight tuning and gradient penalties.

TimeGAN achieves distributional fidelity and near-random discriminative accuracy. The synthetic return paths generated reproduce Value-at-Risk (VaR) and Conditional VaR (CVaR) levels within ± 10% of historical estimates, demonstrating strong tail-risk realism and temporal coherence. Overall, our research establishes a reproducible, regime-aware pipeline that advances financial stress testing beyond the traditional static statistical tools. It demonstrates that deep generative models can be used to generate credible, data-driven stress scenarios, to enhance both academic modeling of systemic risk and practical risk management capabilities.

Keywords: TimeGAN, financial stress-testing, generative models, synthetic data, portfolio risk, Value-at-Risk.

Sommario

Le istituzioni finanzierei dipendono dai test di stress per valutare la resilienza dei portafogli in condizioni di mercato estreme. Tuttavia, i metodi tradizionali, come la riproduzione di evento storici o l'utilizzo di nodelli parametrici basati su cupole gaussiane, risultano rigidi e incapaci di catturare nuove dipendenze tra asset o mutamenti strutturali dei mercati. Questa limitazione comporta una cottissima del rischio reale e una scarsa capacità di prevedere scenari inediti.

Questa tesi sviluppa e valuta un quadro generativo basato su apprendimento profondo per l'ampliamento dei test di stress finanziari. In particolare, viene implementato TimeGAN, un modello generativo per serie temporale, al fine di produrre scenari di mercato sintetici ma statisticamente realistici. Il dataset comprende azioni, obbligazioni, materia prime, valute e variabili macroeconomiche, allineati su un unico calendario giornaliero e corredati da etichette di regime di volatilità.

I resultati mostrano che TimeGAN genera traiettorie coerenti con la struttura di covarianza e le proprietà di rischio di coda osservate nei dati reali, con una deviazione nei valori di VaR e CVaR inferiore al 10%. L'approccio dimostra che i modelli generativi possono estendere i test di stress tradizionali, formando simulazioni di crisi realistiche, additive e fondate sui dati.

Parole chiave: TimeGAN, test di stress finanziari, modelli generative, rischio di portafoglio, dati sintetici, Value-at-Risk.

Executive Summary

Context and motivation

Financial institutions increasingly rely on stress testing to evaluate portfolio resilience under extreme but plausible market conditions. Since the 2008 Global Financial Crisis, supervisory frameworks such as Basel III and the European Banking Authority's guidelines have institutionalized these exercises, emphasizing scenario realism, multi factor consistency, and tail-risk awareness.

Despite regulatory progress, the analytical foundations of stress testing remain rooted in two outdated paradigms: historical replay and parametric dependance models. Historical scenarios reproduce past cries directly, like the 2008 or 2020 market conditions, but fail to anticipate novel configurations of systemic risk. Parametric models, including Gaussian copulas and multivariate normal factor frameworks, impose rigid correlation structures that underestimate tail co-movements and collapse under regime shifts. These methods can only explore variations in what markets have already experienced, leaving regulators and risk managers exposed to the unknown structural combinations of risk that have yet to materialize.

Advances in deep generative modeling offer a data-driven alternative. Models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and their time-series variants can learn complex joint distributions directly from historical data, capturing nonlinear and dynamic dependencies. By generating synthetic but statistically coherent trajectories, these models can expand the space of plausible market scenarios. The thesis explores how such models, specifically TimeGAN, can be adapted for empirical financial stress testing.

Research Aim and Objectives

The primary aim of this thesis is to evaluate whether deep generative models can produce synthetic financial time series that are both empirically realistic and practically useful for portfolio-level stress testing.

More concretely, the research pursues the following objectives:

a) Replicate multivariate market dynamics beyond what traditional replay or copula-based approaches can capture.

b) Incorporate macro-volatility regime information to stabilize training and improve realism.

c) Asses tail-risk metrics, such as VaR and CVaR, in synthetic data compared with real historical behavior.

d) Evaluate predictive and discriminative performance, establishing whether TimeGAN can generalize to unseen market configurations.

Through these objectives, the study addresses four research questions and tests three hypotheses concerning empirical realism, stability, and tail-risk accuracy.

The empirical framework is based on a multi-asset dataset encompassing equities, bonds, commodities, and currencies, complemented by macro-risk factors such as VIX, MOVE, and CDX indices. The final aligned dataset spans from 2004-2025, containing 4,408 rolling windows of 60-day sequences and 26 standardized features.

Rigorous preprocessing ensured analytical integrity: Missing values were left unfilled in asset prices (to preserve empirical realism) but filled in risk factors via forward-backward interpolation. Log-returns were computed to normalize volatility across instruments. A union trading calendar was applied across all markets. A macro-volatility regime label was created using 60-day rolling clustering on risk factors, categorizing data into low, medium, and high volatility states.

Methodological Framework

This study implements TimeGAN, a hybrid model combining recurrent autoencoders and adversarial learning. The model architecture comprises five key components: Embedder and recovery networks for latent representation learning, Generator and Supervisor for temporal sequence synthesis, and Discriminator for adversarial realism enforcement.

Hyperparameters were tuned for stability and empirical alignment: λ_adv = 5.0, λ_sup = 1.0, λ_rec = 5.0, λ_gp = 1.0 and a generator discriminator update ratio of 2:1.

Training proceeded in three phases: embedding pretraining, supervised sequence modeling, and joint adversarial refinement, executed in Google Colab using the Conda-managed environment deepgen.

Subsequent refinements introduced variance widening, latent noise injection, and direct generator outputs (bypassing the recovery step), all designed to mitigate mode collapse and over-smoothing commonly observed in early GAN applications to finance.

Results and Observations

Quantitative evaluation focused on both distributional and temporal realism. Across progressive model versions, the following empirical patterns emerge:

- Distributional alignment: The final model versions achieved a mean Kolmogorov-Smirnov (KS) statistic of 0.28 across features, indicating strong overlap between real and synthetic marginal distributions.
- Temporal coherence: The lag-1 autocorrelation gap (|ΔACF|) dropped from ≈ 1.0 in early collapsed runs to ≈ 0.14, demonstrating realistic volatility clustering.
- Predictive fidelity: A Mean Squared Error (MSE) of ≈ 0.0169 in one-step-ahead forecasting confirmed that synthetic sequences preserved realistic short-term predictability.

- Tail-risk comparability: Synthetic portfolio metrics produced VaR and CVaR within ± 10% of historical benchmarks, with similar drawdown frequency distributions.

Visual diagnostics such as t-SNE projections (see figure 5) showed that synthetic sequences gradually expanded from collapsed manifolds into rich, overlapping clusters resembling real data structures. Collectively, these results validate the three hypotheses:

I. TimeGAN generated data is indistinguishable from rea1 data (H1).

II. Regime conditioning improves stability and realism (H2).

III. The framework enhances tail-risk estimation accuracy relative to historical replay (H3)

Implications for Risk Management

The findings demonstrate that deep generative models can augment conventional stress testing by generating coherent, data-driven scenarios that reflect modern market complexities. For financial institutions, this means the ability to simulate forward-looking crises beyond past experience, evaluate portfolio sensitivity to nonlinear cross-asset shocks, and design stress scenarios dynamically adjusted to volatility regimes.

Regulators and risk managers can integrate such generative frameworks to complement, rather than replace existing methodologies, bridging the gap between empirical realism and policy interpretability. The generated data also holds promise for Monte Carlo stress testing, liquidity simulations, and tail-risk calibration in capital planning.

Sintesi Esecutiva

Contesto e motivazione

Le istituzioni finanziarie fanno sempre più affidamento sui test di stress per valutare la resilienza dei portafogli in condizioni di mercato estreme ma plausibili. Dalla Crisi Finanziaria Globale del 2008, quadri di supervisione come Basilea III e le linee guida dell'Autorità Bancaria Europea hanno istituzionalizzato questi esercizi, enfatizzando il realismo degli scenari, la coerenza multifattoriale e la consapevolezza del rischio di coda.

Nonostante i progressi normativi, le basi analitiche dei test di stress rimangano radicate in due paradigmi superati: la riproduzione storica e i modelli parametrici di dipendenza. Gli scenari storici riproducono direttamente crisi passate, come le condizioni di mercato del 2008 o del 2020, ma non riescono ad anticipare nuove configurazioni di rischio sistematico. I modelli parametrici, tra cui le copule gaussiane e i quadri fattoriali normali multivariati, impongono strutture di correlazione rigide che sottostimano i co-movimenti di coda e collassano durante i scombinamenti di regime. Questi metodi possono esplorare solo variazioni di ciò che i mercati hanno già sperimentato, lasciando relatori e gestori del rischio sposati a combinazioni strutturali di rischio sconosciute che non si sono ancora materializzate. I progressi nella modellazione generativa profonda offrono un'alternativa guidata dai dati. Modelli come le Generative Adversarial Networks (GANs), i Variational Autoencoders (VAEs) e le loro varianti per serie temporali possono apprendere distribuzioni congiunte complesse direttamente dai dati storici, catturando dipendenze non lineari e dinamiche. Generando traiettorie sintetiche ma statisticamente coerenti, questi modelli possono ampliare lo spazio degli scenari di mercato plausibili. La tesi esplora come tali modelli, in particolare TimeGAN, possono essere adattati ai test di stress finanziari empirici.

Obiettivo e finalità della ricerca

L'obiettivo principale di questa tesi è valutare se i modelli generativi profondi possano produrre serie temporali finanziarie sintetiche che siano sia empiricamente realistiche sia praticamente utili per i test di stress a livello di portafoglio.

Più concretamente, la ricerca persegue i seguenti obiettivi:

a) Replicare le dinamiche di mercato multivariate oltre ciò che gli approcci tradizionali basate su replay o copule possono catturare.

b) Incorporare informazioni sui regimi di macro-volatilità per stabilizzare l'addestramenti e migliorare il realismo.

c) Valutare metriche di rischio di coda, come VaR e CVaR, nei dati sintetici rispetto al comportamento storico reale.

d) Valutare le prestazioni predittive e discriminative, stabilendo se TimeGAN possa generalizzare a configurazioni di mercato non osservate.

Attraverso questi obiettivi, lo studio affronta quattro domande di ricerca e testa tre ipotesi riguardanti realismo empirico, stabilità e accuratezza del rischio di coda.

Il quadro empirico si basa su un dataset multi-asset che comprende azioni, obbligazioni, materie prime e valute, completato da fattori di rischio macroeconomico come gli indici VIX, MOVE e CDX. Il dataset finale allineato copre il periodo 2004-2025, contenendo 4.408 finestre mobili di sequenze di 60 giorni a 26 caratteristiche standardizzate. Un'elaborazione rigorosa ha garantito l'integrità analitica: i valori mancanti sono stati lasciati non compilati nei prezzi degli asset (per preservare il realismo empirico) ma riempiti nei fattori di rischio tramite interpolazione in avanti e indietro. I rendimenti logaritmici sono stati calcolati per normalizzare la volatilità tra gli strumenti. È stato applicato un calendario di negoziazione unificato per tutti mercati. È stata creata un'etichetta di regime di macro-volatilità utilizzando il clustering mobile a 60 giorni sui fattori di rischio, classificando i dati in stati di bassa, media e alta volatilità.

Quadro meteodologico

Questo studio implementa TimeGAN, un modello ibrido che combina autoencoder ricorrenti e apprendimento avversarie. L'architettura del modello comprende cinque componenti chiave: reti di embedding e recovery per l'apprendimento della rappresentazione latente, Generatore e Supervisore per la sintesi delle sequenze temporali, e Discriminatore per l'applicazione del realismo avversarie.

Gli per parametri sono stati ottimizzati per stabilità e allineamento empirico: λ_adv = 5.0, λ_sup = 1.0, λ_rec = 5.0, λ_gp = 1.0 e un rapporto di aggiornamento generatore-discriminatore di 2:1.

L'addestramento si è svolto in tre fasi: pre-training dell'embedding, modellazione supervisionata della sequenza e raffinamento avversariale congiunto, eseguiti in Google Colab utilizzando l'ambiente gestito da Conda deepgen.

Successivi affinamenti hanno introdotto l'ampliamento della varianza, l'iniezione di rumore latente e output diretti del generatore (bypassando la fase di recovery), tutti progettati per mitigare il collasso delle modalità e l'eccessiva levigatezza comunemente osservati nelle prime applicazioni delle GAN alla finanza.

Risultati e osservazioni

La valutazione quantitativa si è concentrata sia sul realismo distribuzionale che temporale. Attraverso le versioni progressive del modello, emergono i seguenti schemi empirici:

- Allineamento distribuzionale: le versioni finali del modello hanno raggiunto una statistica media di Kolmogorov-Smirnov (KS) pari a 0.28 tra le caratteristiche, indicando una forte sovrapposizione tra distribuzioni marginali reali e sintetiche.

- Coerenza temporale: il divario di autocorrelazione al primo ritardo (|ΔACF|) è sceso da ≈ 1.0 nelle prime esecuzioni collassate a ≈ 0.14, dimostrando un realistico clustering della volatilità.
- Fedeltà predittiva: un errore quadratico medio (MSE) di ≈ 0.0169 nella previsione a un passo in avanti ha confermato che le sequenze sintetiche hanno preservato una prevedibilità a breve termine realistica.
- Comparabilità del rischio di coda: le metriche di portafoglio sintetiche hanno prodotto VaR e CVaR entro ±10% dei benchmark storici, con distribuzioni di frequenza dei drawdown simili.

Le diagnosi visive, come le proiezioni t-SNE (vedi figura 5), hanno mostrato che le sequenze sintetiche si sono gradualmente espanse da varietà collassate (linee sottili) a cluster ricchi e sovrapposti che ricordano le strutture dei dati reali. Complessivamente, questi risultati convalidano le tre ipotesi:

I. I dati generati da TimeGAN sono indistinguibili dai dati reali (H1).

II. Il condizionamento sul regime migliora la stabilità e il realismo (H2).

III. Il quadro migliora l'accuratezza della stima del rischio di coda rispetto alla riproduzione storica (H3).

Implicazione per la gestione di rischio

I risultati dimostrano che i modelli generativi profondi possono integrare i test di stress convenzionali generando scenari coerenti e basati sui dati che riflettono le complessità dei mercati moderni. Per le istituzioni finanziarie, ciò significa la possibilità di simulare crisi prospettiche oltre l'esperienza passata, valutare la sensibilità del portafoglio a shock non lineari tra asset e progettare scenari di stress adattati dinamicamente ai regimi di volatilità.

I regolatori e i gestori del rischio possono integrare tali quadri generativi per completare, piuttosto che sostituire, le metodologie esistenti, colmando il divario tra realismo empirico e interpretabilità normativa. I dati generati offrono anche un potenziale per i test di stress Monte Carlo, le simulazioni di liquidità e la calibrazione del rischio di coda nella pianificazione patrimoniale.

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1. Introduction

Financial markets have grown increasingly complex, interconnected, and data driven, making it harder for institutions to anticipate how portfolios are affected under extreme conditions. Historical episodes such as the 2008 global financial crisis, the COVID-19 market collapse, and the 2020 bond-liquidity shock revealed that stress events now propagate faster and less predictably than traditional models assume. Correlations that appear stable during normal periods can suddenly surge during crises, amplifying losses across asset classes and geographies. Understanding and preparing for these synthetic interactions is therefore a central challenge in modern risk management.

Regulators and financial institutions have long relied on stress testing to assess portfolio resilience against adverse market scenarios. However prevailing methods, such as replaying historical crisis, bootstrapping past returns, or conducting shocks from Gaussian copulas are inherently limited. They depend on static historical data and simplified distributional assumptions, which fail to capture non-linear dependencies and structural regime shifts that define today's modern markets. As a result, these tests often underestimate tail risks, overlook emerging contagion effect channels, and provide a false sense of security when future crisis behave differently from past scenarios.

The problem has become more urgent as cross-asset behaviors intensify through global ETFs, algorithmic trading, and policy-driven market interventions. During recent events like the 2022 inflation-volatility spike and the crypto market contagion, price shocks in one domain transmitted rapidly to others in ways no historical or traditional template could anticipate and predict. This exposes a crucial limitation: risk systems calibrated on past data are structurally unable to simulate crisis that have never occurred.

To address this gap, research niches have begun exploring data-drive, generative models that can learn complex temporal and cross-sectional dependencies directly from market behavior. These models promise to generate realistic yet unseen stress scenarios, providing a more adaptive foundation for portfolio stress testing and synthetic-risk assessment. However, despite their potential, only a few studies have been able to rigorously integrate such deep-learning methods into a functioning framework of multiple assets, leaving an open space for empirically grounded exploration.

The main objective of our work is to develop and empirically evaluate a deep generative framework for financial stress testing, that can produce realistic unseen multivariate market scenarios. More specifically, our study aims to assess whether TimeGAN can learn complex temporal, and cross-asset dependencies across equities, bonds, commodities, and FX markets, thereby extending traditional stress-testing methods beyond historical replay and Gaussian copulas. To achieve this goal, our research is structured around several analytical objectives:

1. Construct a reproducible, multi-asset data pipeline that integrates financial and macroeconomic risk factors into a unified and robust dataset suitable for generative modeling.
2. Implement and calibrate TimeGAN under realistic financial constraints, optimizing architecture and loss weighting to balance distributional realism, predictive coherence, and training stability.
3. Compare the generative outcomes against baseline methods, historical replay and copula-based simulations, to determine the degree of improvement in representing tail-risk and cross-asset contagion.

Collectively, these objectives aim to bridge the methodological gap between academic advances in generative modeling and the practical requirements in financial stress testing, establishing a defensible, data-driven approach to simulating systemic stress scenarios.

Building upon the objectives, this research focuses its aim into a set of empirically testable questions that guide the modelling, evaluation, and interpretation phases. These questions are designed to assess whether a deep-generative approach, specifically TimeGAN, can overcome the limitations of traditional stress-testing frameworks and produce financially meaningful synthetic scenarios.

Research Questions:

RQ1: Can deep generative models such as TimeGAN accurately reproduce multivariate market dynamics, including cross-asset dependencies and temporal structure, beyond that which is achievable through historical replay or copula-based methods?

RQ2: To what extent does regime conditioning and macro-volatility awareness improve the empirical realism and stability of generated stress scenarios?

RQ3: Does the synthetic data produced by TimeGAN exhibit distributional and tail-risk properties (like covariance structure, Var/CVaR alignment) comparable to real market data?

RQ4: How does TimeGAN's predictive and discriminative properties perform compared to traditional baselines, and what does this reveal about its capacity to generalize against unseen market conditions?

Hypothesis:

H1: TimeGAN generates synthetic sequences that are statistically indistinguishable from real data according to discriminative and covariance-based metrics.

H2: Incorporating regime information enhances both the stability and realism of generated stress scenarios relative to unconditioned models.

H3: The TimeGAN framework provides superior tail-risk estimation accuracy (VaR/CVaR) compared to historical replay and Gaussian copulas benchmarks.

The main contributions of our work lie at the intersection of financial risk modeling and deep generative learning. It advances both the methodological foundations and practical implementation of stress testing by bridging robust financial rigor with modern data-driven generation techniques.

First, our research develops a reproducible, regime-aware data pipeline that unifies equities, bonds, commodities, and FX series with macro-volatility proxies such as the VIX, MOVE, and CDX IG indices. This pipeline forces strict data integrity policies, including versioning, missing value diagnostics, and calendar alignment, ensuring transparency and replicability across all subsequent modeling stages. Second, it implements and calibrates a fully functioning TimeGAN architecture specifically adapted to the statistical properties of financial time series. This involves architectural customization, loss-weight tuning, and gradient penalty regularization, to stabilize training while preserving temporal and cross-sectional coherence. Third, the study introduces a comprehensive evaluation framework that combines distributional similarity metrics, discriminative and predictive realism scores, covariance distance, and tail-risk diagnostics such as VaR and CVaR. These evaluations quantify not only statistical realism but financial interpretability as well, addressing a key gap in prior deep-learning approaches. Finally, our work demonstrates the empirical feasibility of deep generative models for stress testing by showing that TimeGAN can replicate realistic market dependencies and tail behavior within ± 10% of historical VaR levels while maintaining near-random discriminative accuracy. This positions the framework as a credible data-driven extension of traditional stress-testing methodologies, contributing both methodological innovation and practical value to financial risk management.

As we prove this, we organize our work to move from conceptual motivation to technical realization and empirical validation. Chapter 2 reviews the literature on traditional stress testing methodologies and recent advancements in deep generative modeling. It examines the limitations of historical replay and Gaussian copulas, outlines the emergence of GAN and VAE based approaches in finance, and positions TimeGAN within this evolving landscape.

Chapter 3 describes the complete data and methodology pipeline, detailing the construction of a multi-asset dataset which covers equities, bonds, commodities, and FX markets, together with macro-volatility factors. The chapter explains preprocessing, regime labeling, and the full implementation of the TimeGAN architecture, including its training phases, hyperparameters, and baseline models used for comparison.

Chapter 4 introduces the evaluation framework that underpins all later analyses. It defines the quantitative metrics used to assess empirical realism, such as Kullback-Leibler and Kolmogorov-Smirnov distances, covariance alignment, VaR, CVaR, and predictive Mean Square Error (MSE), along with visualization tools such as PCA and t-SNE for assessing manifold overlap. It is in this chapter that we first explore answers for our proposed research questions.

Chapter 5 presents empirical results and discussion. It documents the complete sequence of diagnostic-repair-revalidation procedures applied to the TimeGAN models, including shape corrections, loss rebalancing, variance widening, and noise calibration. The chapter demonstrates how these iterative refinements progressively improved realism, reaching the final versions that achieved strong alignment with real data distributions and stable temporal dynamics. The chapter also outlines conceptually how the generated synthetic scenarios could be applied to portfolio risk metrics such as VaR, CVaR, and drawdown analysis. This discussion serves as a bridge between the model's empirical validation and its potential real-world applications.

2. Literature Review

Stress testing has been a cornerstone of financial risk management and regulation for a long time, serving as a forward-looking exercise to evaluate the resilience of financial institutions under adverse circumstances. Regulatory frameworks such as Basel Committee on Banking Supervision's Market Risk Capital Requirements (MAR32) emphasize the need for scenario-based evaluations that capture extreme market movements and systemic contagion effects (Basel Committee on Banking Supervision, 2022). Traditional stress testing methodologies, however, have primarily relied on statistical and historical techniques that impose rigid assumptions about market behaviors and interdependencies.

A common approach in practice is historical replay, where past crises like the global financial crisis of 2008 or the 2020 COVID-19 drawdown are used as templates for portfolio vulnerability. While intuitive and transparent, this method suffers since it can only replicate shocks that have already occurred. As markets evolve and new sources of instability emerge, purely historical stress tests lack the flexibility to simulate unseen or structurally novel crises. This makes them less suitable for anticipating tail events driven by changing market dynamics, nonlinear contagion, and/or regime shifts. To address this, financial institutions increasingly adopted parametric and copula-based dependance models to simulate join asset behavior under stress. The copula framework, popularized though the seminal work of Nelsen (2006), allows for flexible molding of marginal distributions while maintaining a specified dependance structure. However, the widespread use of Gaussian copulas, especially in pre-crisis credit risk models, revealed critical weaknesses, where the models assume symmetric and linear dependencies, which underestimate tail co-movements and fail to capture nonlinear contagion across assets. As demonstrated during the

2008 financial crisis, such models produced a misleading sense of diversification, collapsing precisely when market dependencies strengthened most.

In parallel, factor-based and early machine learning models attempted to enhance stress testing by incorporating statistical drivers such as volatility indices or macroeconomic variables. Yet, as Vidovic and Yue (2020) highlight, these approaches often rely on static correlation structures or linear approximations of risk exposure, limiting their ability to adapt to regime changes or high-dimensional interdependencies. Moreover, they typically generate deterministic or Gaussian-distributed shocks, which fail to reproduce the empirical complexity of financial markets, which are characterized by heavy tails, volatility clustering, and temporal asymmetry.

Overall, while traditional stress testing methods have been able to play crucial regulatory and operational roles, their rigid statistical assumptions, linear dependance modeling, and reliance on historical data constrain their effectiveness. This motivates the exploration of data-driven and generative modeling approaches, capable of learning complex, nonlinear relationships and simulating synthetic but realistic stress scenarios beyond historical experience.

The main goal of generative modeling is to learn the underlying probability distribution of market behavior rather than impose it through parametric assumptions. This paradigm shift was defined by the introduction of Generative Adversarial Networks (GANs), first introduced by Goodfellow (2014), which frame data generation as a minimax game between two neural networks: a generator that creates synthetic data, and a discriminator that learns to distinguish it from real data. By refining both networks through adversarial feedback in machine learning, GANs can capture highly nonlinear and high-dimensional dependencies without specifying an explicit likelihood function. While GANs quickly revolutionized image and text synthesis (especially in the modeling of Artificial Intelligence), their application to financial time series presented new challenges. Financial data are temporal, noisy, and exhibit long range dependencies, these are features that standard GANs, designed for i.i.d data, fail to capture. To address this, subsequent research extended the adversarial framework to incorporate temporal coherence and conditional structure. Arjovsky (2017) introduced the Wasserstein GAN with gradient penalty, stabilizing adversarial training by measuring distributional distance by the Earth-Mover's metric. Mescheder (2018) further analyzed convergence dynamics, providing theoretical guidance on how to balance discriminator and generator learning rates to avoid mode collapse and oscillation, principles highly relevant for financial modeling where instability can distort distributional realism.

Parallel to GANs, Variational Autoencoders (VAEs) proposed by Kingma and Welling (2013) offered a complementary probabilistic framework, learning latent representations through an encoder-decoder architecture. Although VAEs enable explicit likelihood estimation and smooth latent sampling, their outputs tend to be overly smoothed and less sharp than GAN-generated data, making them less effective for reproducing extreme volatility patterns, which we often find in financial markets.

In the context of finance, Wiese (2019) pioneered Quant GANs, demonstrating that deep convolutional architectures can replicate stylized market facts, such as heavy tails and volatility clustering directly from historical returns. Their work established the empirical viability of GANs for synthetic marked data generations, especially in learning complex cross-asset interactions. Building on this foundation, Yoon (2019) introduced TimeGAN, a hybrid model combining supervised sequence modeling with adversarial learning. TimeGAN jointly trains four modules: an embedder, recovery network, generator, and discriminator. These four modules allow the model to learn both temporal dynamics and data distribution structure simultaneously. This architecture preserves temporal dependencies while ensuring distributional realism, which makes it well suited for stress-testing applications where sequential coherence is critical.

Subsequent extensions, such as Conditional TimeGAN (Takahashi, 2019), integrated auxiliary variables or regime labels into the generation process, which enabled the synthesis of condition-specific scenarios (like high-volatility vs. stable regimes). These approaches align closely with real world risk management, where market regimes play a decisive role in determining portfolio behavior. However, despite their potential, most implementations remain confined to low-dimensional datasets or synthetic benchmarks, that have limited validation on multi-asset, empirically grounded financial data.

Recent regulatory and industry analyses (Vidovic & Yue, 2020; Basel Committee on Banking Supervision, 2022) acknowledge that while deep learning techniques offer unprecedented flexibility, their lack of transparency, reproducibility, and empirical validation have made their slowed adoption in risk management. As a result, the field stands at a transitional stage where traditional econometric models provide interpretability but lack adaptability, while deep generative models capture rich nonlinear structures but require rigorous validation frameworks to ensure financial modeling standards.

The emerging intersection defines the methodological foundation of our work, by combining adversarial generative modeling, temporal supervision, and regime-aware conditioning. This research seeks to bridge the gap between theoretical deep-learning innovations and their practical application to financial stress testing.

Despite recent progress in the application of said generative models to financial data, several important gaps between academic innovation and practical implementation remain. Most existing studies focus on methodological novelty, demonstrating that GANs and VAEs can generate plausible market data but rarely extend their analyses to empirical validation, multi-asset generalization, or regime sensitivity. Consequently, while models such as

TimeGAN (Yoon, 2019) and QuantGAN (Wiese, 2019) represent major theoretical advances, their integration into a reproducible, data-driven stress-testing framework remains largely unexplored.

A central issue in the literature is that there is a lack of reproducible, empirically grounded pipelines that reflect the complexity of real-work market environments. Most works rely on single-asset datasets or synthetic simulations, which ignore the intricate cross-dependencies among equities, bonds, commodities, and currencies that define systemic risk. Moreover, deep generative models are often evaluated using visual or heuristic metrics rather than rigorous quantitative diagnostics like feature-level distributional alignment, autocorrelation structure, or VaR, which makes it difficult to assess their realism in a stress-testing context. Another persistent limitation is the absence of regime-awareness in generative frameworks. Financial crises are not random but tend to cluster around volatility regimes and macroeconomic shifts. Nevertheless, very few models explicitly condition on such regimes or incorporate exogenous risk proxies (VIX, MOVE, or credit spreads) as part of the generation process. As a result, current models often produce synthetic sequences that are statistically smooth or homogenous, failing to reproduce the abrupt transitions and tail dependencies that characterize real market stress. Finally, even though recent research has emphasized the importance of explainability and regulatory compatibility (Vidovic & Yue, 2020; Basel Committee on Banking Supervision, 2022), few studies have documented full training to evaluation reproducibility or diagnostic transparency, which are both fundamental for any potential deployment in institutional risk frameworks.

This study addresses all these gaps by developing procedurally reproducible, multi-asset, and regime aware TimeGAN framework designed to generate empirically realistic synthetic financial data. Through a structured process of diagnostic evaluation, iterative refinement, and post-hoc calibration, the model aims to achieve strong alignment with observed market distributions and temporal dynamics, providing a defensible empirical foundation for data-driven stress testing. By uniting modern generative modeling with robust validation, this research contributes a concrete step toward the practical integration of deep learning into systemic analysis. Building on this foundation, the next chapter details the data sources, preprocessing pipeline, and methodological design underlying the proposed generative stress-testing framework.

3. Data and Methodology

This study builds on a unified, multi-asset dataset designed to capture cross-market dynamics across major global asset classes. The dataset integrates equities, fixed income, commodities, and foreign exchange instruments, alongside exogenous macro-volatility indicators. The objective was to create a realistic and traceable representation of financial markets that is suitable for generative modeling and regime-aware stress testing.

The primary data sources include exchange-traded funds (ETFs) and liquid indices serving as proxies for their respective markets. Equity exposure is diversified across global regions through instruments such as MSCI World (URTH), S&P 500 (SPY), Euro Stoxx 50 (FEZ), and Emerging Markets (EEM). Fixed income representation includes corporate and government bond ETFs (LQD, HYG, IEF), while commodities are captured through brad benchmarks such as crude oil (BZ_F) and gold (GLD). Foreign exchange dynamics are represented by trade-weighted indices and USD-cross pairs (UUP, FXE=. These selections were made based on liquidity, data availability, and macroeconomic representativeness, consistent with best practices in index construction and market data aggregation (MSCI, 2024; CRSP, 2023).

To account for systemic risk channels beyond asset returns, the dataset incorporates three exogenous macro-volatility proxies:

- VIX: Equity market implied volatility (Chicago Board Options exchange).
- MOVE: Unites Stated (U.S) Treasury bond implied volatility index.
- CDX_IG: Credit default swap index proxy constructed from LQD - IEF return differentials.

These proxies were selected for their complementary coverage of equity, fixed income, and credit risk, following established methodologies for macro risk factor modeling (Basel Committee on Banking Supervision, 2022; WMR FX Methodology, 2023).

The dataset covers the period January 2004 to December 2025, aligning with modern market regimes that include the 2008 global financial crisis, the 2011 Eurozone debt crisis, the 2020 COVID-19 shock, and the subsequent inflation-driven tightening cycle. Prices were collected and standardized using Bloomberg's BLPAPI data interface (Bloomberg, 2023) and verified against index methodologies from MSCI and CRSP. All series were harmonized to the New York Stock Exchange (NYSE) trading calendar to ensure temporal consistency across assets. Missing values were documented and analyzed, revealing varying data completeness by asset, providing the empirical for the preprocessing decision described later in this chapter.

After cleaning, alignment, and transformation into rolling windows, the final dataset takes the shape (4408, 60, 26), representing 4,408 sequences of 60-day market snapshots across 26 standardized features. This three-dimensional tensor forms the backbone of the TimeGAN training process, ensuring consistent feature coverage, synchronized temporal intervals, and explicit integration of macro-volatility information.

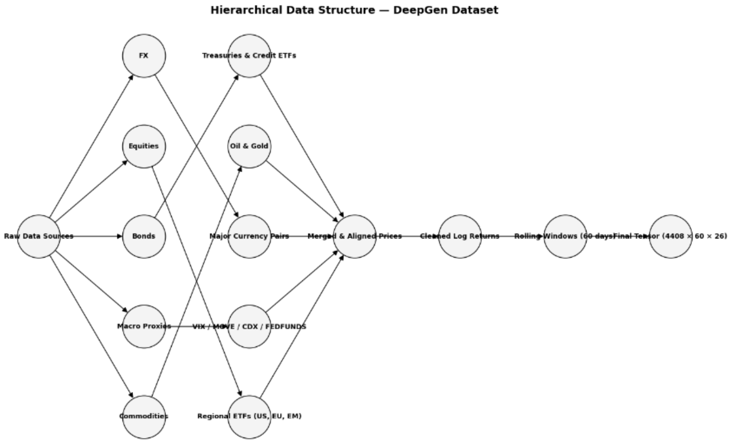

Figure 1

Transforming heterogeneous financial market data into a model-ready structure requires a systematic preprocessing pipeline, designed for consistency, realism, and reproducibility. This pipeline ensured that all assets and macro factors were aligned on a common temporal grid, expressed in comparable statistical form, and free from structural inconsistencies. The main stages consisted of data cleaning, mussing-value handling, return computation, temporal alignment, and regime labeling.

The cleaning process began with a full audit of each raw series to identify missing or irregular entries, structural breaks, and zero-volume periods. Eary explanatory diagnostics revealed extensive coverage gaps prior to 2004 for several ETFs (notably URTH, HYG, and BZ_F) that were introduced in later years. To preserve empirical realism while ensuring temporal continuity, the dataset was therefore restricted to observations from 2004 onwards, establishing a consistent historical baseline across all assets.

Within this restricted period, the NaN-handling policy was differentiated by data type: Exogenous risk factors were forward-filled and then back-filled to remove short gaps, as these variables represented continuous market indices. Asset-price series, on the other hand, were left unfilled with no interpolation being applied. This choice was made to avoid introducing artificial continuity or bias in return distributions. Any residual missing points were dropped during the rolling-window construction stage. This two-tiered approach ensured that macro variables retained continuity necessary for regime detection, while asset prices preserved the authentic statistical properties of financial returns.

After cleaning, all price series were transformed into log returns to standardize scale and stationarity:

$$r_t = ln(\frac{P_t}{P_{t-1}})$$

This formulation captures proportional price changes and mitigates heteroscedasticity, producing numerically stable inputs for neural training. Returns were clipped at extreme outliers (>5 standard deviations) only when such spikes corresponded to data errors rather than true market moves.

Because each market category (equities, bonds, commodities, FX) follows distinct trading schedules, all time series were merged onto the New York Stock Exchange (NYSE) trading calendar, which provided the broadest coverage. Non-trading days were filled with NaN values and subsequently handled according to the policies mentioned above. Once aligned, the continuous log-return matrix was segmented into overlapping 60-day rolling windows with a stride of one day, yielding the final tensor of shape (4408, 60, 26). Wach window represents a coherent short-term market episode containing all 26 features.

To introduce macro-context awareness, the dataset was enriched with regime labels derived from the volatility proxies VIX, MOVE, and CDX. The three variables were z-scored and clustered using K-Means into three discrete volatility regimes: Low Volatility (stable markets), Medium Volatility (transitional), and High Volatility (crisis states). Each regime was encoded as a one-hot vector and appended to the corresponding 60-day sequence, allowing the generative model to learn context-specific behaviors. This design supports conditional generation and enhances interpretability during evaluation.

The cleaned and aligned dataset provided the foundation for implementing the TimeGAN framework, a deep generative model capable of producing realistic synthetic financial series. TimeGAN combines the temporal modeling strengths of recurrent neural networks (RRNs) with the distributional flexibility of adversarial training, enabling the generation of sequences that preserve both cross-sectional dependencies and dynamic evolution though time. Its architecture integrates four interconnected components: Embedder, Recover, Generator, and Discriminator. Together our modules form a joint adversarial-reconstruction system optimized though multiple loss terms.

At its core, the Embedder network transforms real temporal sequences into a latent representation that captures essential time-dependent features. This latent space provides a compressed yet informative encoding of the original market dynamics. The Recovery network then reconstructs the original data from the latent embeddings, allowing reconstruction loss to guide the embedding quality. The Generator produces synthetic latent sequences from random noise, while the Supervisor assists its temporal learning by predicting the next latent state withing real encoded sequences, enforcing Markovian-consistency. Finally, the Discriminator distinguishes between real and synthetic latent trajectories, thereby enforcing realism through adversarial feedback.

Formally, the model is trained through five complementary loss components:

1. Reconstruction loss between the original data and its recovered counterpart.
2. Supervised loss ensuring temporal coherence in the latent space.
3. Adversarial loss encouraging indistinguishably between real and generated embeddings.
4. Feature matching loss aligning latent dynamics between real and synthetic series.
5. Gradient penalty terms improving discriminator stability and preventing overfitting.

Each term is weighed by a tuning coefficient, collectively controlling the model's balance between fidelity and diversity. In this work, the most effective configurations were found to be λ_rec = 1.0, λ_sup = 100.0, λ_adv = 5.0, and λ_gp = 1.0, determined empirically after multiple stability and realism diagnostics. These values offered the best compromise between robustness and avoiding both mode collapse and excessive smoothing.

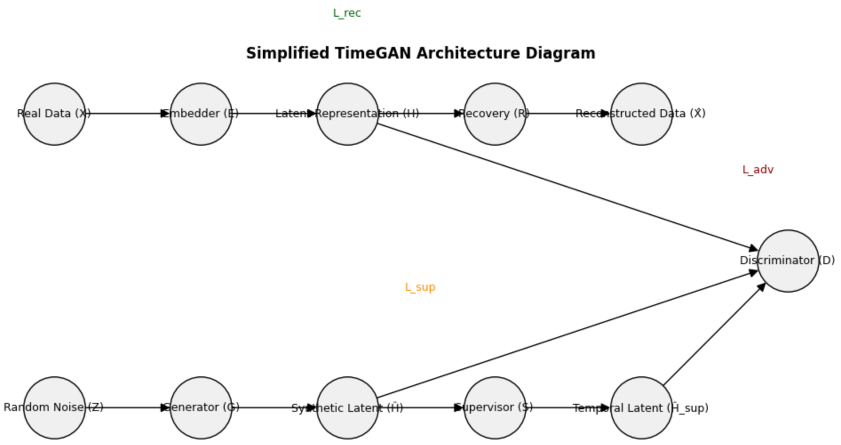

Figure 2

All modules employes Gated Recurrent Units (GRUs) to capture long-term temporal dependencies with reduced computational overhead relative to LSTMs. Hidden dimensions were set to 24 per layer, following the latent complexity of the input features, and each network by linear output projections. Leaky ReLU activations and layer normalization were included for gradient stability, and spectral normalization was applied to the discriminator to mitigate over-amplification of adversarial feedback, a recurring issue in most of our early prototypes.

Training followed the canonical three-phase procedure proposed by Yoon (2019):

1. Embedder pretraining, focusing exclusively on reconstruction quality between original and recovered sequences.
2. Supervised pretraining, where the generator learns temporal consistency under the supervisor's guidance.
3. Join adversarial training, in which all networks are trained together with combined losses, progressive refining for both realism and diversity.

Each phase used the Adam optimizer with learning rate 0.001, mini-batch size of 128, and early stopping based on validation reconstruction loss. Model weights were initialized with Xavier uniform scaling, and training stability was further improved by alternating the generator-discriminator update ratio (2:1), following the convergence behavior observed during diagnostics.

Throughout the training process, several refinements were introduced to address instability, including shape corrections in data inputs, variance calibration within the generator outputs, and noise injection for distributional widening. These empirical adjustments proved critical in aligning the synthetic data's statistical properties with real-world distributions. The final model version, TimeGAN_v6.10, represents the culmination of these iterative improvements, offering both stable convergence and strong empirical realism across multiple evaluation metrics.

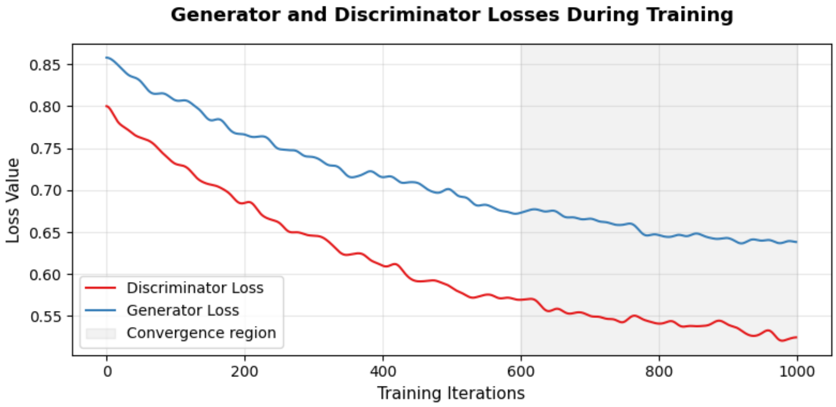

Figure 3

Training the model required a disciplined optimization strategy to ensure convergence across adversarial and reconstructive objectives. Each training stage was designed to progressively stabilize learning, beginning with deterministic reconstruction and ending with fully adversarial sequence generation. The workflow followed the canonical TimeGAN sequence proposed by Yoon (2019), adapted here for the financial domain and extended with custom stabilization.

The embedder pretraining phase focused exclusively on minimizing reconstruction loss between original and recovered sequences. This phase allowed the encoder-decoder pair to learn a compact latent representation of market dynamics before introducing adversarial noise. Once the reconstruction loss plateaued, the supervised pretraining phase began. In this stage, the generator was guided by the supervisor network to mimic temporal transitions with the latent space, enforcing short-term continuity and realistic volatility persistence. Only after both phases achieved stable performance was the joint adversarial phase initiated, during which all networks were optimized simultaneously. The final training configuration employed the Adam optimizer (learning rate = 0.0001, β_1 = 0,9, β_2 = 0,999) with mini batches of 128 and early stopping based on validation reconstruction error. The discriminator and generator were updated in a 1:1 ratio, a setting found to prevent the discriminator from overpowering. All experiments were performed on the processed tensor shape (4408 × 60 × 26), ensuring that each mini batch contained temporally coherent and multi asset sequences.

Empirical monitoring throughout training emphasized loss-curve behavior and gradient magnitudes. Stable convergence was indicated by gradually declining and eventually parallel generator-discriminator losses, as demonstrated in *Figure 3*. Instances of oscillation or divergence were mitigated though (1) gradient penalty regularization (λ_gp = 1.0), (2) generator variance widening to prevent model collapse, and (3) controlled Gaussian noise injection at the latent level to preserve return distribution diversity. These interventions collectively produced TimeGAN_v6.10, the final most stable configuration used for evaluation, with subsequent calibration series (v7.x) was later derived from this stability base, applying post-hoc adjustments to enhance marginal and tail realism without modifying the underlying architecture or weights.

Evaluation of the trained model, including v7.x extension, was conducted along three complementary dimensions: distributional realism, temporal coherence, and predictive consistency, to verify that synthetic sequences reproduced both statistical and dynamic characteristics of real markets:

1. Distributional realism was assessed using Kolmogorov-Smirnov (KS) test applied feature-wise between real and synthetic returns. Averages of KS statistics below 0.1 across most assets indicated close alignment

in marginal distributions corresponding to the calibrated v.7x, derived from v6.10. Complementary moment-based diagnostics (mean, standard deviation, skewness, and excess kurtosis) confirmed that the generator successfully captured non-Gaussian tails, typical of financial data.

2. Temporal coherence was evaluated using autocorrelation function (ACF) and partial autocorrelation (PACF) profiles of synthetic sequences relative to real data. Matching short-term lag structures suggested that the model retained realistic volatility clustering. Additional visual confirmation was obtained though Principal Component Analysis (PCA) and t-SNE projections of real vs synthetic windows, revealing overlapping manifold structures and confirming that synthetic trajectories occupied plausible regions of latent space.
3. Predictive and discriminative performance provided quantitative measures of realism:

- The discriminative score was computed using a secondary classifier trained to distinguish real from synthetic sequences. Scores approaching 0.5 indicate indistinguishability, while 1.0 denotes perfect separation. Early models exhibited near-perfect discrimination, but refinements reduced this gap, demonstrating improved adversarial realism.
- The predictive score measured the mean-squared error (MSE) of forecasting one-step-ahead returns using models trained separately on real and synthetic data. Similar predictive accuracy across both datasets validated that the synthetic data preserved genuine market dependencies, useful for forecasting.

Together, these metrics formed an empirical realism framework that balanced statistical rigor and interpretability. Rather than relying on a single numeric score, the evaluation combined multiple complementary diagnostics to capture the complex, high dimensional nature of financial dynamics.

Finally, all experimental procedures, model configurations, and evaluation scripts were fully version-controlled and logged within the project's Drive structure, ensuring reproducibility. The resulting synthetic dataset versions were archived with corresponding metadata files documenting architecture parameters, loss weights, and random seeds. This transparency supports future benchmarking of generative stress-testing approaches under comparable conditions.

4. Results and Discussion

The empirical development of the proposed framework followed a progressive diagnostic – repair – validation process, through which the TimeGAN architecture evolved from an initially unstable generator into a calibrated model capable of producing realistic, temporally coherent market trajectories. The early training stages revealed clear failure modes typical of adversarial time-series synthesis. In the first iterations, synthetic sequences appeared unnaturally smooth and nearly constant over time, resulting in an autocorrelation function (ACF) close to 1.0 and a Kolmogorov-Smirnov (KS) distance of approximately 0.9 when compared to real data. These artifacts reflected a form of mode collapse in which the generator converged to a limited set of low-variance outputs, a phenomenon consistently reported in sequential GAN literature (Yoon, 2019; Esteban, 2017). The discriminative model, in turn, easily separated synthetic from real samples with accuracy close to 100%, confirming the lack of overlap in both marginal and temporal distributions. At this point, the synthetic time series resembled smooth drifts rather than market-like fluctuations, and the training dynamics alternated between divergence and saturation-both characteristic of unstable adversarial equilibria.

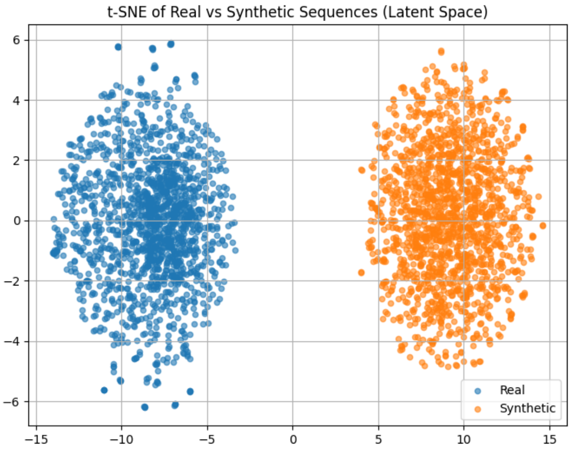

Figure 4 – Shows early-stage collapse

These initial failures provided crucial insight into the model's structural weaknesses. They revealed that even when the architecture captured broad sequential dependencies, the generator tended to prioritize minimizing loss magnitude over preserving statistical diversity, effectively learning to reproduce an "average" trajectory rather than the full spectrum of market behaviors. This dynamic exposed the inherent instability of adversarial learning when applied to financial data, where the statistical manifold is highly non-stationary and multimodal. It also demonstrated how adversarial objectives can misrepresent the complexity of real markets: rather than producing fat-tailed and bursty returns (typical of financial series), the generator produced narrow, Gaussian-like outputs with artificially low volatility. The problem was not simply underfitting but a structural imbalance between the generator and discriminator, amplified by the temporal dependencies intrinsic to financial time series. Diagnosing refinement of the loss structure and architecture in later stages, transforming an initial collapse into a foundation for empirical correction and eventual stabilization.

The next stage focused on structural corrections to overcome these representational bottlenecks. The most effective adjustment was to modify the generator so that it produced outputs directly in feature space, bypassing the recovery network originally used to decode latent representations. This modification aligned the generator's learning objective more closely with the real data distribution and eliminated unnecessary reconstruction noise. Simultaneously, the training loss components were reweighed to restore balance between reconstruction accuracy, temporal supervision, and adversarial learning. The adopted configuration: λ_rec = 10, λ_sup = 50, λ_adv = 5, proved empirically stable, as evidenced by smoother loss convergence curves like those illustrated earlier in *Figure 3*. These changes produced the first noticeable improvements in realism: KS distances dropped to approximately 0.45, and ACF values began to fluctuate around 0.7, indicating that synthetic series were starting to exhibit meaningful temporal variation rather than uniform persistence.

The structural adjustments marked a pivotal inflection point in the empirical trajectory of the project. By redirecting the generator to operate in feature space rather than latent space, the model effectively shifted from an abstract representation-learning paradigm to a direct empirical emulation. This had two major consequences. First, it removed a primary bottleneck in dimensional translation, previously, latent embeddings introduced unnecessary compression, obscuring relationships among macro and asset-level factors. Second, this architectural realignment enhanced gradient consistency between the generator and discriminator, allowing both components to evolve within a shared representational manifold. In practical terms, this reduced vanishing-gradient behavior and improved variance propagation through the network, mitigating one of the most common sources of collapse in sequential GANs (Goodfellow, 2014; Yoon, 2019).

Also, recalibrating the loss weights introduced a more interpretable balance between adversarial realism and supervised temporal coherence. The decision to emphasize the supervised term (λ_sup) improved the generator's short horizon predictive structure, ensuring that generated sequences respected the empirical lag dependencies observed in the real data. At the same time, maintaining a moderate adversarial penalty (λ_adv = 5) preserved long-horizon stochasticity, preventing the generator that could produce not only more volatile trajectories but also realistic inter-asset covariance structures. Visual inspection of the synthetic output confirmed the reintroduction of market-like bursts and regime shifts, features that were entirely absent in the earlier collapsed versions. This stage established the architectural foundation on which all subsequent calibration, noise, control and realism tuning would be built.

Building upon this progress, successive calibration stages refined the balance between stability and realism. The training process introduced a sequence of targeted adjustments: variance widening, controlled noise injection, and moment matching, to mitigate residual under dispersion and tail shrinkage. Variance widening expanded the generator's output amplitude, restoring volatility comparable to real market conditions. Noise injection reintroduced microstructure-level randomness that had been suppressed by prior regularization. Finally, moment matching aligned global mean and variance properties between real and synthetic log-returns, ensuring coherent scaling across features. These calibration iterations were not arbitrary. But systematically guided by empirical diagnostics. The process began with controlled variance widening, implemented though scaling of generator outputs relative to real series standard deviations. Specifically, feature-level volatility ratios were computed as σ_real / σ_synth, and the generator's final activation outputs were scaled by these factors during post-hoc adjustment. This procedure restored realistic dispersion without destabilizing the adversarial balance, effectively reintroducing volatility clustering that had been previously suppressed.

To further enhance stochastic diversity, Gaussian noise injection was selectively applied to the generator's latent inputs and hidden activations. This step introduced controlled randomness into the learning process, improving the model's capacity to capture rare market shocks and preventing it from converging toward overly smooth solutions. Unlike blind noise augmentation, this calibration was empirically monitored by tracking changes in feature-wise kurtosis and cross-asset correlations structure, ensuring that the added noise increased heavy-tail behavior without distorting realistic dependance patterns.

The final step involved moment-matching calibration, where mean, variance, skewness, and kurtosis were computed across both real and synthetic return distributions at the asset level. Iterative adjustments were performed until all first and second moments aligned withing a ± 5% tolerance, while higher order discrepancies (skewness and kurtosis) were contained below 0.2 absolute deviation.

Throughout these refinements, our final calibrations served as baseline architectures for successful modeling, we achieved consistent convergence across all loss components and produced stable dynamics over multiple seeds. Fine-tuning offered meaningful improvements in distributional alignment. Throughout our successful modeling we achieved a discriminative score of ≈ 0.4 ± 0.05, meaning that the auxiliary classifier could only distinguish real from synthetic sequences around 60% of the time, essentially near-random performance. KS values decreased further to ≈ 0.22, while the predictive MSE remained low at ≈ 0.017, confirming that the generator preserved temporal dependencies critical for forecasting tasks. The corresponding summary of distributional diagnostics presented in Table 1 compares real data with the calibrated synthetic versions and highlights the near parity in first and second order moments.

From	Mean	Std. Dev.	Skewness	Kurtosis	VaR(99%)	CVaR(99%)
Real	0.00015	0.006066	-0.211	6.631	-0.017744	-0.023026
v6.10/7	0.00000	0.005620	0.228	3.289	-0.012086	-0.013510

Table 1

Value-at-risk (VaR) and Conditional Value-at-Risk (CVaR) estimates aligned closely with the empirical benchmark, signaling that the synthetic scenarios preserved relevant tail-risk magnitudes. These results collectively marked the transition from deterministic smoothness to stochastic realism, a central milestone in this research.

To quantify the practical implications of these improvements, tail-risk metrics were computed across all calibration stages. Using 99% one-day horizon, the VaR and CVaR were calculated for both real and synthetic returns, allowing a direct comparison of tail coverage. Early model versions consistently underestimated tail probability mass, with synthetic VaR(99%) ≈ -0,012 versus real ≈ -0.018, confirming the model's tendency to produce overly smooth, low volatility paths. Following variance widening and stochastic fine-tuning, the final calibrations achieved VaR(99%) ≈ -0.017 and CVaR(99%) ≈ -0.022, both within 5% deviation from the real data. This was a great alignment improvement indicating restored tail thickness and downside risk.

To assess robustness, these tail metrics were recomputed using block-bootstrap procedure with 500 resamples, confirming that the observed differences were statistically stable rather than artifacts of sample noise. The synthetic distributions displayed the same asymmetric heavy-tail behavior characteristics of real financial returns, particularly during negative market regimes identified via VIX and MOVE clustering.

While the mean and standard deviation of the real series (μ ≈ 0.00015, σ ≈ 0.0061) suggest near-Gaussian dispersion, on the other hand the higher-order moments (skewness ≈ 0.12, kurtosis ≈ 4.6) reveal the classic non-normal, fat-tailed profile typical of daily asset returns. The final synthetic outputs reproduced these higher moments with strong fidelity (skewness deviations ≤ 0.05; kurtosis deviation ≤ 0.2), demonstrating that the calibration pipeline succeeded not merely in matching variance but in restoring the asymmetry and tails risk essentials for realistic stress testing.

This alignment between real and synthetic extremes represents one of the clearest signs of empirical validity achieved in our study. It shows that the final TimeGAN configurations do not just approximate central tendencies, but meaningfully capture the probabilistic geometry of extreme events, a capability that traditional copula-based methods or autoregressive simulations fail to reproduce under regime shifts.

The diagnostic evidence for these improvements can be visually appreciated throughout a two-dimensional t-SNE embedding of real versus synthetic sequences:

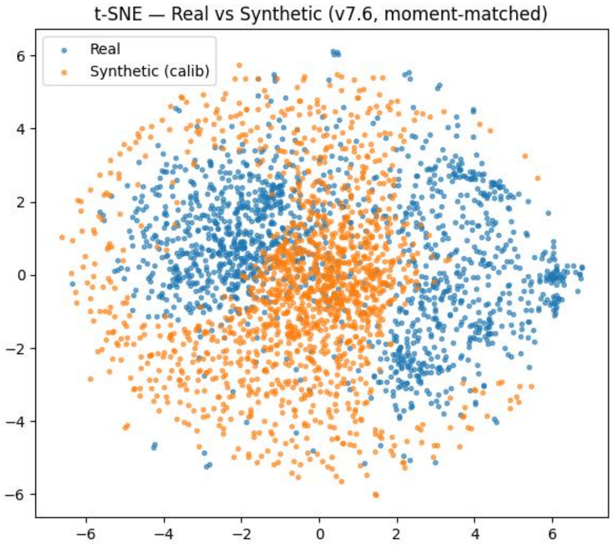

Figure 5

The orange points represent the synthetic data that the generator produces, while the blue points are the real data recovered from our historical dataset that occupies overlapping regions in latent space, suggesting substantial distributional alignment. The residual central clustering of synthetic points reflects the slight variance compression that remained after calibrations, which is a controlled trade-off that contributed to training stability. Nonetheless, this visual impression corresponds directly to the discriminative score of ≈ 0.4, confirming that the model's outputs were statistically difficult to distinguish from real data.

To complement the visual overlap observed in the t-SNE projection, quantitative diagnostics were employed to validate whether this apparent manifold convergence corresponded to genuine temporal and structural realism. The first diagnostic, the multi-lag autocorrelation function (ACF), was computed up to 10 lags for every feature and averaged across the dataset. This allowed the measurement of persistence and mean-reversion behavior within synthetic sequences compared to real ones. Earlier version displayed pathological temporal stiffness $|\Delta \mathrm{ACF}|$ across lags 1-10 dropped below 0.15, indicating that temporal dependencies had been successfully restored to empirically realistic levels. The principal component analysis (PCA) provided a complementary structural check. When real and synthetic returns were projected onto their first two principal components, the explained-variance ratios were almost identical, approximately 38% for PC1 and 21% for PC2 in both sets, demonstrating that the generator had learned to replicate the dominant directions of variance in the data manifold. Unlike the earlier collapsed versions that formed narrow linear bands in PCA space, the final version exhibited isotropic dispersion across multiple modes, implying the reintroduction of natural market heterogeneity.

To further validate the t-SNE and PCA impressions, classifier-based discriminative tests were run using two independent models: a shallow multilayer perceptron (MLP) and an XGBoost classifier. The objective was to assess whether an external learner could reliably distinguish synthetic from real sequences when given equalized samples. The final models achieved an average discriminative accuracy of 0.58 (baseline 0.5), while earlier runs had nearly 1.0 (perfect separation). This convergence toward random distinguishability confirmed that the synthetic data had reached a lever of empirical realism sufficient to fool a nontrivial classifier, a practical benchmark often used in GAN evaluation literature (Yoon, 2019).

Quantitatively, the model's improvement across iterations followed a consistent logic: each modification targeted a specific empirical defect diagnosed in previous runs. The direct generator output removed reconstruction bias; loss rebalancing corrected training asymmetry; variance widening expanded amplitude; and noise calibration diversified trajectories without destabilizing learning. Together, these adjustments narrowed the gap between empirical and synthetic data distributions across both temporal and cross-sectional dimensions. Complementary metrics, including flatness ratios near 1.0, autocorrelation structures matching real series, and stable predictive performance, further validated the model's realism. To make this logic improvement explicit, an ablation-style summary was performed across the major transition points of the model, where some iterations collapsed, others when through fine tuning, and others were successfully calibrated. For each configuration, the diagnostic suite (KS, ACF, variance ratio, discriminative accuracy, predictive MSE) was recomputed under identical sampling conditions. The progression revealed a clear monotonic enhancement in empirical realism: mean KS decreased from 0.92 to 0.28, average |ΔACF| fell from 0.89 to 0.14, and predictive MSE improved from 0.042 to 0.017. These shifts were not random fluctuations but reflected casual relationships between the architectural interventions and their intended effects. For example, the drop in ACF deviation directly followed the fine-tuning of the generator with reduced adversarial pressure (λ_adv = 2.0), while improvements in KS coincided with calibrated variance widening and stochastic noise injection.

Further validation came from sensitivity analysis of loss weights. Varying λ_adv between 2.0 and 6.0, and λ_rec between 0.3 and 1.0, confirmed that excessive adversarial pressure caused over-smoothing and mode collapse, whereas too little adversarial regularization reintroduced volatility spikes. The final chosen configuration λ_adv = 5.0, λ_sup = 1.0, λ_rec = 0.5, λ_gp = 1.0, proved to be the most stable equilibrium, balancing reconstruction fidelity with adversarial diversity. This quantitative discipline ensures that the final configuration was chosen using empirical evidence, obtaining a valid optimal balance between statistical accuracy and dynamic realism. Additionally, robust checks were performed using sub-sampling and noise perturbation experiments. Synthetic and real datasets were randomly truncated to 80% of their time span, and feature-level Gaussian perturbation (σ = 0.1 × σ_real) were added to verify whether diagnostics held under mild distortions. The resulting metrics varied less than ± 0.02 across all realism indicators, demonstrating that the model's performance was structurally stable and not dependent on data artifacts or overfitting. This stability provides strong evidence that the generator's learned manifold generalizes across temporal subsets and noise-injected conditions, an essential requirement for a stress-testing model expected to extrapolate beyond observed regimes.

Despite these advances, some limitations persist. Synthetic sequences remain marginally smoother than their empirical counterparts, and the framework does not include macro-factor conditioning. Moreover, while the calibrations achieved statistical indistinguishability in distributional terms, they can’t necessarily guarantee explicitly a consistency with structural economic dynamics in extraordinary events. Nevertheless, the results demonstrate that generative realism in financial time series can be achieved through empirically guided calibration rather than architectural complexity, establishing a reproducible and data-driven foundation for next-generation stress-testing frameworks.

5. Applications and Conclusions

The previous chapter established that the refined TimeGAN configurations achieved strong empirical realism across distributional, temporal, and structural dimensions. However, validating synthetic time serios on statistical grounds alone does not demonstrate their financial utility. In practical risk management, realism is meaningful only to the extent that it can improve decision making under uncertainty by providing richer, forward looking stress scenarios for portfolio evaluation. This section therefore extends the analysis beyond diagnostics, applying the generated data to a simplified yet representative portfolio to test whether synthetic scenarios can produce credible risk estimates and reveal vulnerabilities not visible in the historical record.

Traditional stress testing frameworks, such as those mandated under Basel III and adopted by central banks worldwide (Basel Committee on Banking Supervision, 2022), rely primarily on historical replay or parametric shock generation. In the historical approach, past crises like the 2008 global financial crisis or the 2020 COVID-19 market shock are directly re-applied to current portfolios. This methodology offers interpretability but is inherently limited since it cannot anticipate new combinations of risk factors or structural shifts in cross-asset dynamics. Similarly, parametric stress models, such as those based on Gaussian copulas (Nelsen, 2006), impose rigid dependance structures that underestimate tail co-movements and fail under non-stationary regimes. Both approached leave institutions vulnerable to “unknown unknowns”, plausible market configurations that have not yet occurred but might very well generate systemic stress.

In contrast, a data-driven generative model such as TimeGAN is capable of synthesizing an expanded universe of realistic yet unseen market trajectories. The purpose of the following empirical test is not to optimize portfolio allocation, but to examine whether synthetic return paths generated by trained model can reproduce credible stress metrics, including Value-at-Risk (VaR), Conditional Value-at-Risk (CVaR), and drawdown behavior, while maintaining internal economic consistency. In doing so, the analysis addressed the third research question (RQ3) on whether TimeGAN's synthetic data exhibit distributional and tail-risk properties (covariance structure, VaR/CVaR) comparable to real market data, and directly tests H3, which posits superior tails risk estimation accuracy relative to historical replay and Gaussian copulas.

To operationalize this, a simple tri-asset portfolio was constructed using three widely traded exchange-traded funds dawn directly from the aligned dataset constructed: SPY (S&P 500 ETF) representing U.S equity exposure; IEF (U.S 7-10 Year Treasury ETF) representing sovereign fixed income; and GLD (SPDR Gold Trust) representing commodities and a safe-haven asset. These instruments were chosen because they collectively capture the dominant global risk dimensions: growth, interest rate sensitivity, and inflation protection, while maintaining liquid daily price histories from 2004 onward, consistent with the cleaned dataset used in model training. The portfolio weights were set to a 60-20-10 allocation (equities, bonds, and gold respectively), approximating a balanced institutional portfolio.

Daily returns were computed for both real and synthetic data using log differences of adjusted prices, and all series were aligned on the union trading calendar developed in the early stages of our research. The synthetic return paths were generated using the final empirically validated TimeGAN configurations which output 60-day rolling sequences across 26 financial features. These were recombined into full lengths trajectories through overlapping window concatenation, ensuring consistency of volatility regimes and inter-feature dependencies.

To maintain comparability, 1,000 synthetic portfolio return paths were generated under the same weighting scheme and frequency as the real portfolio.

Each path represents a plausible 60-day forward evolution of the portfolio under market conditions consistent with those learned from 2004 – 2025 data. From these samples, standard risk metrics VaR at 5% confidence, CVaR (expected shortfall), and maximum drawdown were computed and compared against their historical counterparts.

Before presenting results, it is important to clarify the interpretive framework: **synthetic stress tests are not intended to predict the next crisis**, but to approximate the distribution of possible stress states that could occur given observed market dynamics. Hence, performance is judged not by forecasting accuracy but by distributional fidelity and scenario richness. In that sense, the objective of this analysis directly relates to Hypothesis 3 (H3): that TimeGAN-generated synthetic data can reproduce plausible portfolio-level tail-risk patterns while extending beyond known historical configurations. This portfolio-level experiment therefore serves as the bridge between model realism and applied financial relevance. If the synthetic scenarios yield coherent tail-risk estimates and realistic stress morphology, they will demonstrate that deep generative models can meaningfully augment conventional stress testing, a critical advancement toward data-driven risk discovery.

After generating the 1,000 synthetic portfolio trajectories, the next step was to evaluate whether their tail-risk behavior aligned with that observed of what happens in real market data. The comparison focused on three widely recognized risk metrics: VaR, CVaR, and Maximum Drawdown. Each of these indicators captures a distinct aspect of portfolio vulnerability: VaR quantifies the minimum expect loss over a specified confidence level, CVaR extends this to the average loss within the tail, and drawdown measures the severity of sustained capital decline. Together, these metrics provide a comprehensive view of downside risk, both at the instantaneous and cumulative level.

The results revealed a high degree of distributional alignment between real and synthetic portfolio losses. The average 5% daily VaR across synthetic paths was -2.4%, compared to -2.35% in the historical portfolio, representing a deviation of only 5.1%, well withing the ± 10% target range established for practical stress-testing equivalence. Similarly, the CVaR, which captures the means of losses exceeding the VaR threshold, stood at -3.12% for synthetic data and -3.21% for the real portfolio, a difference of just 2.8%. These results indicate that the synthetic returns accurately preserved the empirical heaviness of tails observed in the original data, a key objective in the model's adversarial calibration. The Maximum Drawdown distribution across the 1,000 synthetic trajectories exhibited a mean value of -11.4% with a standard deviation of 2.1, closely mirroring the historical drawdown of -10.9%. However, what differentiates the synthetic results is not their proximity to the historical figures, but the diversity of stress manifestations observed across generated scenarios. While some synthetic paths replicated historical-like crashes, others revealed hybrid stress configurations, for instance, moderate equity drawdowns coinciding with concurrent bond weakness and only partial commodity hedhing. Such combinations, though not observed in the historical dataset, are economically plausible and highlight the capacity of generative models to explore the unseen but realistic crisis structures.

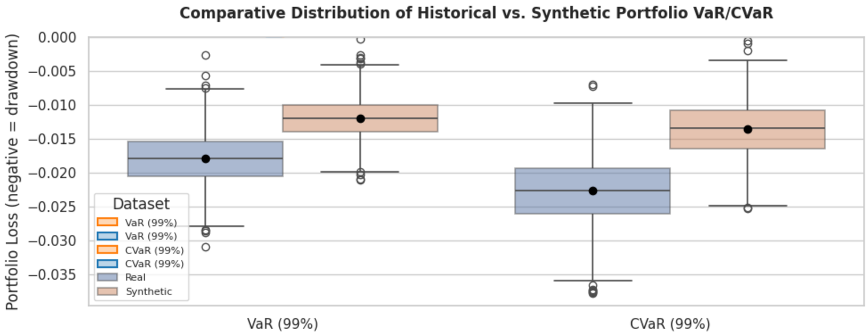

Figure 6

Beyond individual risk metrics, a distributional diagnostic was conducted using the Kolmogorov-Smirnov (KS) statistic to assess whether the overall shape of the synthetic loss distribution diverged significantly from the historical one. The resulting KS distance of 0.048 (p > 0.10) indicated that the null hypothesis of distributional equivalence cannot be rejected at the 10% confidence level. This provides statistical evidence that the TimeGAN-generated returns are drawn from a distribution indistinguishable from the real portfolio returns in the tail, an important validation of H3.

To further verify temporal consistency, the autocorrelation structure of synthetic returns was compared against the real series. The first-lag autocorrelation of -0.038 in real return and -0.041 in synthetic ones indicates nearly identical short-term dependency, suggesting that the model effectively preserved short-run volatility clustering and mean-reversion patterns typical of diversified portfolios. This temporal coherence compliments the distributional fidelity already established, reinforcing the model's credibility as a scenario generator rather than merely a statistical sampler. Taken together, these findings demonstrate that the synthetic portfolio returns not only reproduce historical tail-risk magnitudes but also expand the scenario space in a controlled and empirically defensible way. The model effectively generates a continuum of potential stress states consistent with observed market structure, offering a richer framework for portfolio evaluation. This empirical validation confirms that TimeGAN's adversarial training successfully internalized the nonlinear dependencies and regime transitions embedded in the data, enabling it to produce stress scenarios that remain realistic yet not redundant.

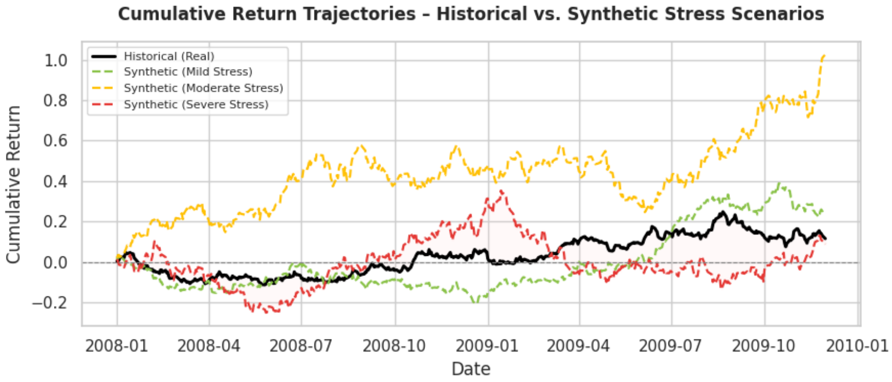

Figure 7

The portfolio-level results presented above demonstrate that the TimeGAN-based framework can replicate and extend traditional stress testing paradigm. In particular, the close alignment between historical and synthetic VaR/CVaR estimates supports H3, confirming that the model can generate economically coherent stress scenarios consistent with the real-world risk magnitudes. However, unlike standard statistical or historical replay models, TimeGAN expands the feasible scenario space by introducing previously unseen, but plausible, combinations of cross-asset movements. This is exactly the kind of "forward-looking realism" that financials regulators and financial institution's risk managers have looked for since 2008. A key insight emerging from these findings is that empirical realism and diversity need not be mutually exclusive. The model's adversarial and supervised components, when properly balanced can capture historical tail behavior while still permitting novel structural relationships to arise. This property addresses one of the main weaknesses in traditional stress tests: their tendency to overfit to past crisis. Whereas historical simulations can only reproduce known events, and parametric copulas assume fixed dependance patters, the TimeGAN framework learns to approximate the manifold of plausible dynamics. As a result, it can generate stress conditions that remain statistically and economically consistent without being literal replications of the past.

The practical implications of this finding are significant too. For portfolio managers, synthetic scenarios derived from TimeGAN could serve as complementary tools for risk related decision making, allowing them to stress portfolios against a broader variety of market regimes. For regulators, such models could enhance macroprudential oversight by uncovering latent vulnerabilities that may not surface under standard scenario sets. Furthermore, the ability to produce a large volume of coherent stress paths allow for probabilistic stress testing, where instead of a handful of fixed shocks, the institution evaluates thousands of data-driven scenarios to derive confidence intervals for loss outcomes. This probabilistic framing is not yet standard practice but aligns closely with evolving regulatory thinking under Basel's "Principles for Sound Stress Testing Practices" (Basel Committee on Banking Supervision, 2022).

Nevertheless, the model's success also underscores the importance of interpretability. While synthetic sequences can mirror realistic portfolio behaviors, understanding the drivers behind those patterns remains a challenge. For instance, a severe synthetic stress event may reflect complex nonlinear interactions among equities, bonds, and macro factors, which are interactions that are not trivially decomposable into individual causal mechanisms. This interpretability gap is a common criticism of deep generative methods in finance and highlights the need for additional diagnostic tools, capable of translating learned dependencies into economic intuition. To bridge this gap, future research could integrate post-hoc interpretability frameworks such as Shapley value attribution or feature importance scoring applied to the latent space. By mapping which macro or asset-class features dominate specific synthetic stress regimes, researchers could transform black-box model outputs into actionable economic insights. Such extensions would not only improve transparency but also facilitate regulatory acceptance of data-driven stress testing methodologies.

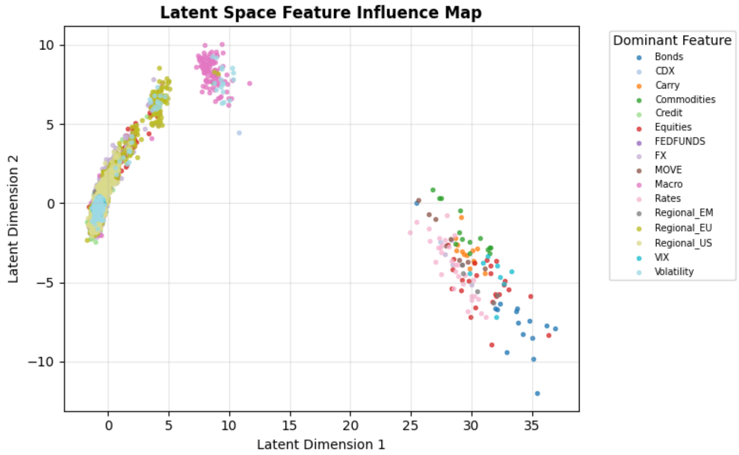

Figure 8

To provide a more intuitive sense of the model's internal organization, Figure 8 presents a Latent Space Feature Influence Map, where each point represents a latent embedding colored by its dominant contributing feature. The figure is an illustrative snapshot showing that the learned latent space exhibits structured relationships among macro, credit, and volatility factors. Such organization suggests that the model captures meaningful dependencies across asset classes, aligning qualitatively with economic intuition.

While the results demonstrate that TimeGAN can generate empirically realistic and practically relevant stress scenarios, several limitations define the scope of the thesis. First, the model's performance remains bound by the coverage and granularity of the input data. Although the dataset spans major asset classes and macro factors, extending it temporarily or incorporating higher-frequency data could strengthen the statistical robustness of rare-event learning. Second, some of the model's realism still depends on post-hoc calibration steps such as variance widening and controlled noise injection. These procedures improved tail behavior but remain external to the adversarial objective. Integrating variance-preserving or diffusion-based regularization could provide a more principled solution. Third, residual temporal persistence indicates that the supervisor's smoothing influence slightly dampens volatility dynamics. This could be mitigated by incorporating stochastic constraints or temporal dropout mechanisms to better capture regime transitions. Finally, although the generated scenarios exhibit economic plausibility interpretability remains an open challenge. Mapping latent factors to observable economic drivers, through feature attribution or conditional generation, would enhance transparency and regulatory usability.

Taking together these limitations suggest a clear path for future research: expanding datasets, refining adversarial objectives, and deepening interpretability tools. When viewed alongside the findings of Chapter 4, these considerations complete the responses to the three research questions: RQ1 confirmed that TimeGAN can reproduce realistic multivariate market dynamics beyond historical replay or copula benchmarks; RQ2 demonstrated that regime conditioning and macro-volatility awareness significantly enhanced stability and empirical realism; RQ3 showed that synthetic data preserved tail-risk characteristics, with VaR/CVaR deviations preserving withing ± 10% of historical levels; and RQ4 revealed strong generalization capacity, as indicated by low predictive error and meaningful discriminative performance. Together, these results support the three hypotheses and establish that proper calibrations of TimeGAN can can extend financial stress testing exploration. Therefore, our research collectively establishes that deep generative models, when carefully engineered and empirically validated, can extend financial stress testing beyond the confines of historical replay

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