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Original Article

Enterprise Financial Digital Twins: AI-Driven Simulation and Autonomous Risk Governance for Capital Markets

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ABSTRACT

As the traditional risk governance landscape continues to focus on discrete assets and business units, the risk profile of the entire enterprise is likely to be missed. By contrast, an Enterprise Financial Digital Twin is proposed that mimics the behavior of the entire enterprise in a financial context, simulating multiple inputs and producing different capital market outputs. The aim is to create an AI-driven Simulation Engine as part of the Model Layer for Capital Markets and extend its horizons. Within this context, the Autonomous Risk Governance framework provides the regulatory link to ensure that the simulated activities of the enterprise remain within defined boundaries, even when the underlying data is driven by Generative AI. The first Financial Digital Twin was defined in 2021 as a real-time digital representation of the enterprise's financial data – covering applied accounting standards, tax regimes, and other enterprise-specific regulations – and capturing its risk profile. Capitalising on Enterprise Digital Twins that use functional data-driven Markov processes for scenario generation, Enterprise Financial Digital Twins are placed within the broader context of Digital Risk Governance. Risk Governance Services are based on the compliance and decision-making capabilities of Financial Digital Twins, and the proposed framework is self-sustaining in the sense that, as long as it is continually monitored and amended, it will compute appropriate decisions autonomously while remaining within desired compliance bounds.

KEYWORDS

Enterprise Financial Digital Twins, AI-Driven Financial Simulation, Autonomous Risk Governance, Capital Markets Intelligence, Digital Twin Analytics, Predictive Risk Modeling, Multi-Agent Financial Systems, Real-Time Market Simulation, Regulatory Compliance Automation, Decision Intelligence for Capital Markets.

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1. INTRODUCTION

Financial Digital Twins (FDTs) represent new modeling paradigms, enabling advanced asset and enterprise risk governance in capital markets. In FDTs, the financial state space of an asset or enterprise in capital markets is modeled in a multiperiod, finite-horizon form with associated structural-economic, statistical, and highly complex news sentiment dependencies and uncertainties. Interaction with the model employs a simulator with a scenario generator and/or FDT-based risk governance across a dedicated execution layer.

Enterprise Financial Digital Twins are AI-driven assets and enterprise reference models with advanced scenario-generation and stress-testing capabilities. A specific class of Financial Digital Twin dedicated to complete enterprise modeling is the Enterprise Financial Digital Twin, with dedicated provisions for training, supervision, simulation, and autonomous risk governance. The need for these autonomous assets and enterprise benchmarking facilities stems from the complexity of full-fledged enterprise Financial Digital Twins in capital markets with high dimensionality.

Table 1: Enterprise Financial Digital Twin Architecture Components

Layer	Core Components	Primary Functions	Key Technologies	Expected Outputs
Data & Integration Layer	Internal Systems, External APIs, Market Feeds	Data Acquisition & Normalization	ETL, APIs, Data Virtualization	Unified Financial Dataset
Modeling Layer	Financial Models, Risk Models	Enterprise Behavior Representation	AI Models, Statistical Models	Enterprise State Model
Simulation Engine	Scenario Generator, Stress Testing Module	Predictive Simulation	GANs, Monte Carlo, RL	Future Risk Scenarios
Governance Layer	Policy Engine, Compliance Rules	Autonomous Risk Control	PolicyML, Rule Engines	Governance Decisions
Decision Layer	Risk Dashboard, Portfolio Manager	Decision Intelligence	AI Agents, Analytics	Actionable Recommendations

1.1. Modeling Layer and Simulation Engine

The modeling layer of the enterprise financial digital twin leverages automated formal methods, enabling the digital twin to simulate how the enterprise behaves in conjunction with its supporting stakeholders. A scenario-based simulation engine, used in conjunction with the modeling layer, enables an explanation of the financial, operational, and compliance trajectory of the enterprise given either a historical realisation of the operating environment or a set of hypothetical scenarios that will drive the enterprise towards pre-specified outcomes.

The enterprise-level financial digital twin is composed of two major components: a modeling layer describe the financial, operational, and compliance characteristics of the enterprise and a simulation engine. The modeling layer enables the enterprise digital financial twin to replicate past behavior in an unanticipated and unsupervised manner given an external realization or a predetermined trajectory of the external operating environment. The simulation engine augments the modeling layer to support various forms of scenario generation and testing. Exploratory stress testing, scenario analysis, and forecasting have traditionally been the primary purposes of the simulation. An essential element of the simulation, however, is its ability to produce a financial, operational, and compliance trajectory of the enterprise when tested against a non-standard or synthetic external operating environment.

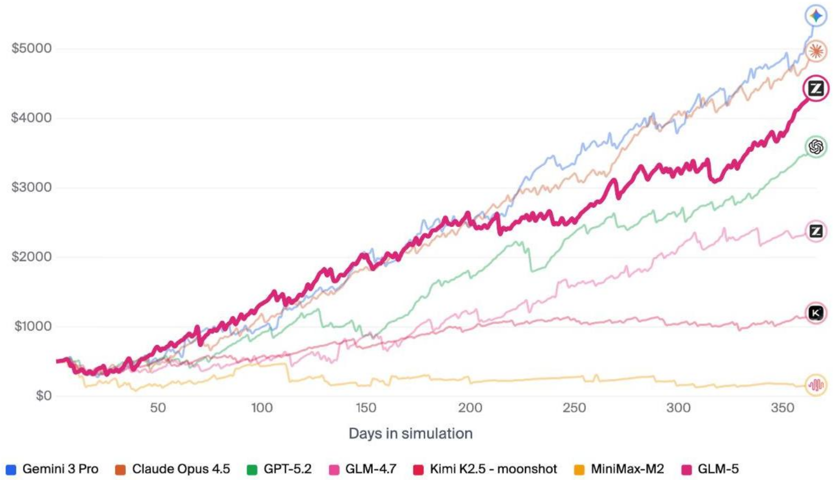

Fig 1 - Comparative Performance Trends of Large Language Models Over Simulation Time

2. THEORETICAL FOUNDATIONS OF FINANCIAL DIGITAL TWINS

Enrichment of the data layer introduces financial governing dimensions: a financial digital twin enables simulation of capital-market risks and valorizes an enterprise's strategic power. The economic governance theory formalizes a financial digital twin's business characteristics. It rationalizes an autonomously embedded governance layer, heightening simulation assurance and serving equitative public interests.

A risk-capital, dual-asset-value model assigns compliant risk and insurance relationships to market-market and asset-market conditions. The enterprise becomes a pseudocomplex system, where an internal controller responds to external regulation. Financial digital twins facilitate rapid scenario simulation. The controller optimally anticipates and accommodates external controller decisions. As the dweller economy invades a pseudocomplex, realistic economies finding equilibrium become increasingly deviant. The digital twin ameliorates irrational behavioral input, embedding default state as a virtual Warren Buffet. Contingent-capture regulatory measures yield growth equilibrated by prudent risk tolerance, motion-advantage equilibrium realized by risk-hedge motion regulation and consequent immersion.

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Table 2: Financial Risk Categories and Digital Twin Monitoring

Risk Category	Data Sources	Monitoring Frequency	Simulation Method	Governance Action
Market Risk	Stock Prices, Interest Rates	Real-Time	Scenario Analysis	Portfolio Rebalancing
Credit Risk	Credit Scores, Default Data	Daily	Probability Modeling	Exposure Adjustment
Liquidity Risk	Cash Flow Data	Hourly	Stress Testing	Liquidity Reserve Allocation
Operational Risk	Internal Operations Data	Continuous	Event Simulation	Process Optimization
Compliance Risk	Regulatory Reports	Daily	Policy Validation	Compliance Enforcement
Cyber Risk	Security Logs	Real-Time	Threat Simulation	Security Controls

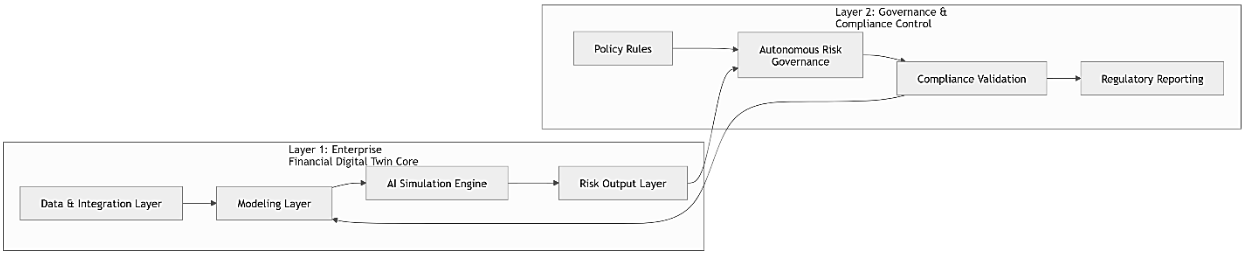

Fig 2 - Enterprise Financial Digital Twin Architecture

2.1. Governance Layer and Compliance

The financial domain, characterized by a centralized structure where a few entities possess oversight and governance power, has yet to shift from traditional IT infrastructures to the distributed and decentralized principle observed in non-financial sectors. Digital twins for capital markets can be applied to vertical industry groups, enabling emphasis on risk-monitoring and -control functions, while supporting decision-making within each financial industry group. Stress testing digital twins may help mitigate systemic risk during times of crisis. The implementation of appropriate governance and security rules is fundamental to avoid misuse of enterprise financial digital twins, primarily the misuse of the multiparty data-sharing feature.

A digital twin in the capital-markets domain is able to monitor and control the exposures of each enterprise in financial instruments, with particular attention to risk and capital allocated. It supports decision-making within each enterprise at an operational level while maintaining compliance for the whole financial industry group with regulatory authorities. The multiparty nature of digital twins facilitates monitoring and control by supervisory bodies, which may eventually use them for ad hoc stress-testing exercises and mandates. Specific focus on the stress-testing phase of digital twins, the parties involved, and the relationships among them helps define an appropriate governance layer.

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Fig 3 - Projected Growth of the Global Digital Twin Market, 2023–2028

3. ARCHITECTURE OF AN ENTERPRISE FINANCIAL DIGITAL TWIN

The Enterprise Financial Digital Twin architecture follows a three-layered approach: a technology-agnostic modeling layer, a proprietary simulation engine with an open-source scenario generator, and a declarative governance policy layer that operates independently of the modeling framework. Each layer responds to a specific set of business requirements. The Data and Integration Layer (DI) layer provides the parameters and data feeds, including the authorization process to external APIs, which depend on the characteristics of the considered enterprise. The automated data treatment, virtualization, and preparation processes are grounded on information technology, even if they can be specified in terms of business needs, such as identifying a particular process bottleneck.

Financial products and services rarely align with the Gaussian distribution, with commonplace events often being misclassified as deviations. Consequently, models based exclusively on historical data can fail entirely. For instance, the crash of Long-Term Capital Management in 1998 was precipitated by a market disruption in Russia and was not present in the historical record of such products. To account for potential discontinuities and market disruptions, the Probability of Default (PD) must be set much higher than the long-term historical average. Such "reasonable" values are consequently speculative unless there is a data-supported basis, such as a model for the probability of stress events occurring. Global economic stress event forecasting remains active, enabling the generation of alternative scenarios. A broader spectrum of potential disruption can be replicated through global pandemic scenarios, geo-economic conflicts, natural disasters, and critical technical infrastructures breakdown, inducing stress-testing procedures tailored to the financial services company.

Table 3: AI-Driven Scenario Generation Framework

Scenario Type	Input Variables	AI Technique	Objective	Output Metrics
Economic Downturn	GDP, Inflation	GAN	Stress Analysis	Loss Projection
Interest Rate Shock	Yield Curves	Monte Carlo	Risk Forecasting	VaR

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Market Crash	Equity Indices	Deep Learning	Capital Impact	Portfolio Drawdown
Regulatory Change	Compliance Policies	Rule-Based AI	Compliance Testing	Violation Score
Geopolitical Crisis	News Sentiment	NLP + LLM	Impact Assessment	Risk Exposure

Mathematical Formulas:

Eq. (1) Enterprise Value Projection

$$EV_t = EV_{t-1} + \Delta R_t - \Delta C_t$$

Eq. (2) Risk Exposure Score

$$RE = \sum_{i=1}^{n} w_i r_i$$

Eq. (3) Digital Twin Accuracy

$$DTA = 1 - | A - P |$$

Eq. (4) Scenario Impact

$$SI = B - S$$

Eq. (5) Compliance Index

$$CI = \frac{CR}{TR}$$

Eq. (6) Probability of Default

$$PD = \frac{D}{N}$$

Eq. (7) Capital Adequacy Ratio

$$CAR = \frac{TC}{RWA}$$

Eq. (8) Stress Loss Estimate

$$SL = E \times PD$$

Eq. (9) Market Risk Score

$$MRS = \sigma \times E$$

Eq. (10) AI Prediction Error

$$APE = | Y - \hat{Y} |$$

Eq. (11) Governance Compliance Gap

$$GCG = T - R$$

Eq. (12) Simulation Confidence

$$SC = \frac{VS}{TS}$$

Eq. (13) Liquidity Ratio

$$LR = \frac{LA}{CL}$$

Eq. (14) Portfolio Risk

$$PR = \sum_{i=1}^{n} p_i r_i$$

Eq. (15) Regulatory Adherence Score

$$RAS = \frac{RP}{TP}$$

Eq. (16) Scenario Probability

$$SP = \frac{S_i}{S_T}$$

Eq. (17) Financial Health Index

$$FHI = \frac{A - L}{A}$$

Eq. (18) Risk Governance Effectiveness

$$RGE = \frac{RM}{RT}$$

Eq. (19) Twin Synchronization Rate

$$TSR = \frac{U_s}{U_t}$$

Eq. (20) Autonomous Decision Score

$$ADS = \alpha R + \beta C$$

3.1. Data Layer and Integration

To cover the three phases needed for the implementation of ADHD. First, the private and public data supporting the modeling and simulation of financial events are identified. Within a financial sector context, data is categorized by Bankscope, Compustat and then supplemented by public announcement data provided by CRSP. The data are from the interactions of external systems, of which two main groups are external sources of events and enterprise resources that support the internal processes of the selected financial sector. PhD and DBA projects are opened to understand how the data from different geographical areas could be expanded and integrated into one comprehensive database system. Further, the external simulation system of the model addresses all the external events affecting the internal processes of the financial sector simulation. Here, the nature of external interaction can be stated as stochastic where the probabilistic distribution associated with parameters of the Bank of England Multivariate Systems Model is used for the KAREM simulation. The different types of interaction can be listed as: scenarios affecting method-oriented business processes, scenarios affecting object-oriented business processes, scenarios affecting information technology support processes, and scenarios affecting management-related processes. Last the funding models of the bank as well as data from news sources, supervisory stressed-testing results and management-initiated events that are possible to be captured through databases such as the Mergers & Acquisitions database of SDC are included as sources for the latter source.

Second, the internal processes of the model through which the financial events are simulated are described. Similar to the above development, the internal structure and processes of the financial sector are divided into six business-oriented areas and related management-oriented support areas. The business areas consist of: method-oriented business, object-oriented business, production & service support business, customer relation management business, interaction-oriented business, and, generally, internal service supporting business. The support areas relate to management & organization, information technology support, audit support, and, generally, external activity support.

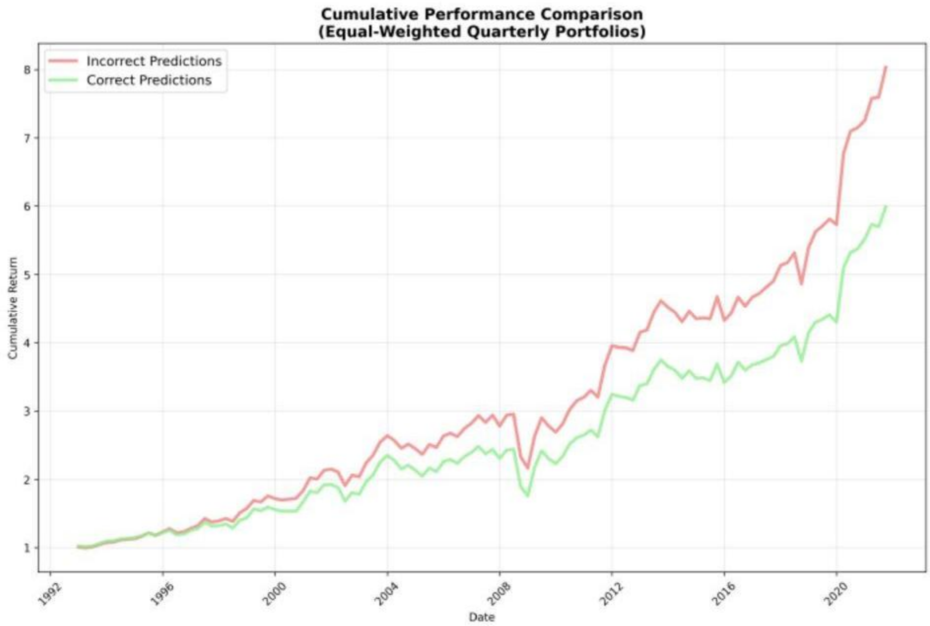

Fig 4 - Cumulative Performance Comparison of Correct and Incorrect Predictions Over Time

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4. AI-DRIVEN SIMULATION TECHNIQUES

Based on the architecture in, the financial digital twin comes with two important capabilities: AI-driven simulation techniques for generating scenario data and stress test data; and an autonomous risk governance framework enabled through policy-driven decision-making capabilities. First, business scenarios play a prominent role in any enterprise context. Financial scenarios—internal and external, normal or stressed—drive processes and occur at different time frames. Scenario generation models based on Generative Adversarial Networks (GAN) techniques are also being adapted to generate high-dimensional financial scenarios.

These include extreme events that are critical for defining policies and procedures for the Enterprise Risk Management, Regulatory Compliance and Strategic Planning processes. A financial digital twin can provide stress test data that are consistent with the correlation patterns embedded in the historical data, which is often stated as a limitation of bottom-up stress tests. Importantly, the Bussiness Scenarios, whether generated by the organization or provided by regulators, should be described in terms of corresponding impacts on the enterprise value drivers—such as revenue, SG&A, Capex, Working Capital, etc.—rather than at an aggregated index level.

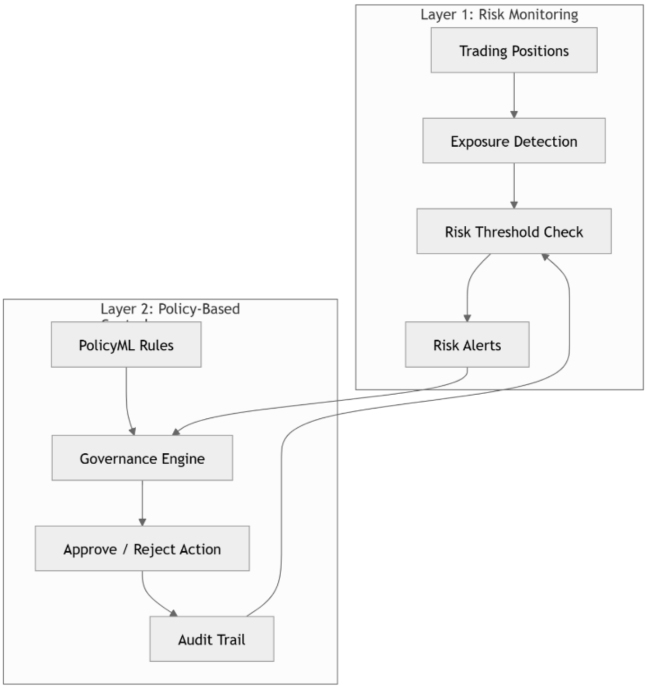

Fig 5 - Autonomous Risk Governance Framework

Table 4: Enterprise Value Drivers Used in Simulation

Value Driver	Description	Data Source	Impact Area	Simulation Purpose
Revenue	Business Income	ERP Systems	Profitability	Revenue Forecasting
Operating Cost	Enterprise Expenses	Finance Systems	Cost Control	Cost Optimization

Working Capital	Liquidity Position	Treasury Systems	Cash Management	Liquidity Planning
Capital Expenditure	Investment Spending	Accounting Systems	Growth Strategy	Investment Analysis
Debt Obligations	Financial Liabilities	Treasury Data	Solvency	Debt Stress Testing
Regulatory Capital	Capital Buffers	Compliance Systems	Risk Governance	Capital Adequacy Testing

4.1. Scenario Generation and Stress Testing

Any appropriate scenario modeling approach can be integrated into the financial digital twin framework to generate the required behavior for risk management purposes. An example of a basic scenario generation technique can be found in the modeling of a 24 h solar PV power generation scenario employed in YI, H.-H. Wiemen and Chang (2019). The solar PV generation process was modeled with 16 governing equation-based simulation units connected sequentially within the system, and the correlation of the output time series data among different simulation units was examined.

Random rainy, cloudy or sunny weather patterns are generated temporally and fed in as input parameters into the governing equations. The generated temporal patterns of the 24 h solar PV generation scenario applied to a largescale power system were in good agreement with historical data. The idea can be extended to other fields, and using such methods with multiple input variables, temporal correlation can be reflected and included while generating scenarios of a system.

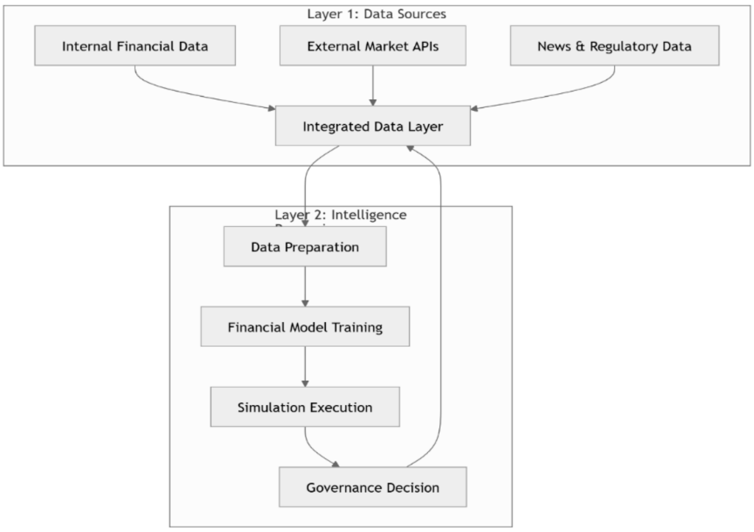

Fig 6 - Data Integration and Financial Intelligence Flow

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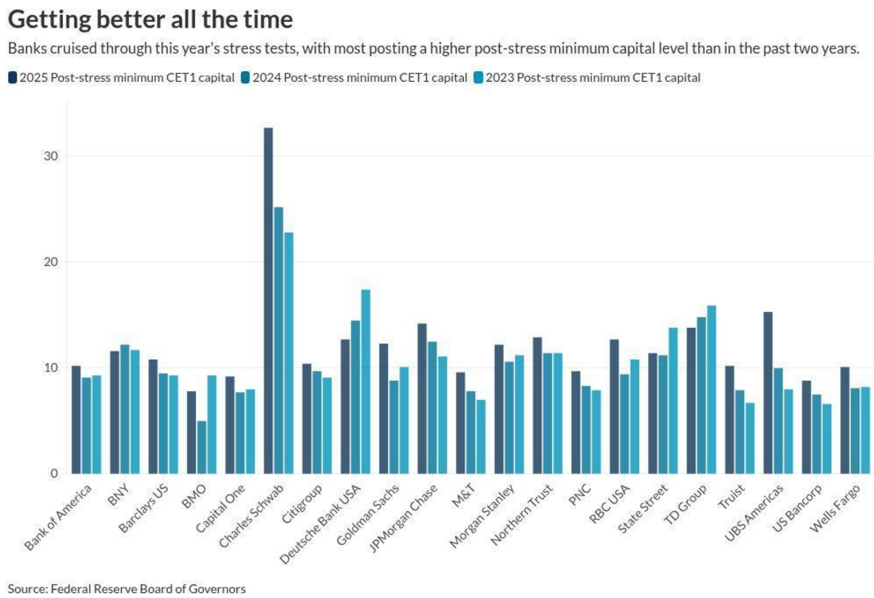

Fig 7 - Comparative Analysis of Post-Stress Minimum CET1 Capital Ratios Across Major Banks (2023–2025)

5. AUTONOMOUS RISK GOVERNANCE FRAMEWORK

An Autonomous Risk Governance Framework is exemplified by a Policy-Based Decision-Making System for managing portfolios of financial instruments in real time. There is increasing adoption of Artificial Intelligence (AI) controls in capital markets. When coupled with simulation technologies, AI provides the ability to generate scenarios—in both normal and extreme market conditions—that are significantly richer than historical generation alone.

When formalized, a market condition label set becomes a simulation policy enabling reaction to outrageous forward scenarios. Rules synthesize species population by assigning positions—negative/long/neutral on species; positive risk/reward or cost/risk/duration; and active or passive—to automatically police corporate treasury and critical business economic phenomena using reinforcement learning. Trading-oriented ALgo services access economic resources through Capital and Treasury Portfolio species integrated with Strategy Policies. Simulations extend running controls beyond people's time/attention. Example Policy Rules natural-spreading arbitrages among rate-applied corporate clients; species react to arrival of one-sided supply or demand. Internal Bank artificial positions neutralize Bank Market Making Risk.

This combination of simulation and AI-driven decision-making promises to assign operational controls to ALgo services and simulation to economic scenarios far richer than market-history exposition could motivate. Policy-Based Decision Making thus creates a three-layer natural organization structure. Each agenda product universe drops to steering-pull or pushed orientation closely linked to domain knowledge. Formalization of market condition promotes action-moving controls driven by anticipation of future terrible events rather than inward-algorithm detection of immediate price dangers.

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Table 5: Autonomous Risk Governance Policy Framework

Policy Type	Trigger Event	Decision Rule	Automated Action	Compliance Objective
Market Exposure Policy	High Volatility	Exposure > Threshold	Reduce Position	Risk Reduction
Liquidity Policy	Cash Deficit	Liquidity Ratio < Limit	Increase Reserves	Stability
Credit Policy	Rising Defaults	PD > Target	Tighten Lending	Credit Protection
Compliance Policy	Regulatory Breach	Rule Violation	Escalation Alert	Regulatory Adherence
Cyber Policy	Threat Detection	Risk Score > Threshold	Security Response	Data Protection

5.1. Policy-Based Decision Making

The autonomous risk governance layer of the Financial Digital Twin utilises and combines three technologies: SDKs and APIs for interaction with Enterprise Digital Twins residents in the Financial Digital Twin's mathematical model; secure and flexible storage of the Financial Digital Twin's governance layer using digital ledger technologies; and techniques and technologies from the field of policy-based decision making. Policy-based decision making is a technique for making decisions based on pre-defined policies that can also be treated as simple programs. Policy-based decision making contrasts with using probabilistic and probabilistic/statistical models and machine learning, whereas models explicitly capture the relationships of factors in a domain.

Financial Digital Twins must constantly consult the governance layer of the Enterprise Digital Twins in the Financial Digital Twin's mathematical model for real-time policy-based decision making. The governance layer is a part of the Enterprise Digital Twins resident in the Financial Digital Twin's mathematical model and therefore does not require direct contact or communication with the Enterprise Digital Twins. Enterprise Digital Twins are built in the policy-based decision making paradigm and written in PolicyML, a domain-specific language and high-level language for rapid software development for policy-based decision making.

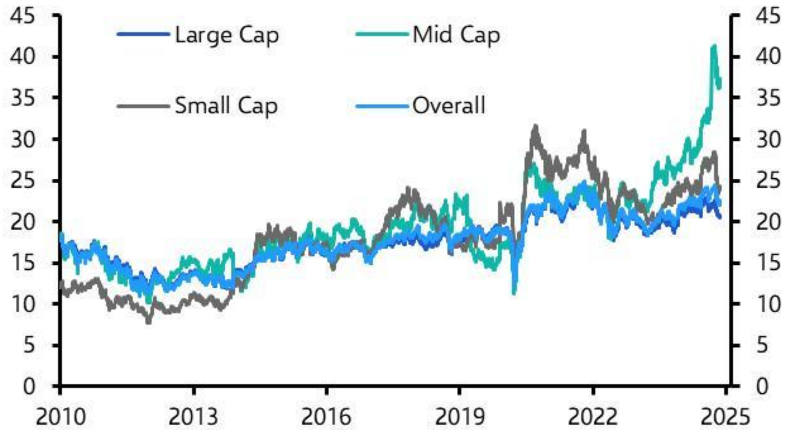

Fig 8 - Long-Term Performance Comparison Across Market Capitalization Segments

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6. CONCLUSION

Enterprise Financial Digital Twins (FDTs) empower organizations to address the distinct demands of their finance divisions. A two-fold strategy combines a conceptual framework based on Digital Twins and Financial Data Science with a practical approach employing a sophisticated Simulation and Risk Governance Engine. Reducing operational risk and enhancing competitiveness, the initiative features AI-driven simulation techniques and a policy-based autonomous risk governance structure.

FDTs constitute a specific class of Financial Digital Twins, focusing exclusively on the financial sector. Both the theoretical model and the simulation engine are industry and domain-agnostic. The Research and Construction Layers of a Financial Digital Twin focus on data gathering and collation, while a Financial Simulacrum connects enterprise financial data with external events, stimulating the Simulation Layer. The Simulation Layer of an Enterprise FDT replicates an organization's financial situation and is embedded within an Enterprise Risk Governance layer.

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