Dynamic Capital Structure Optimization in Volatile Markets: A Simulation-Based Approach to Balancing Debt and Equity Under Uncertainty

MAYOKUN OLUWABUKOLA ADUWO[1], PRISCILLA SAMUEL NWACHUKWU[2]
[1]*IBM West Africa Ltd, Lagos, Nigeria*
[2]*First Bank Nigeria Limited, Port Harcourt, Nigeria*

Abstract- Dynamic capital structure optimization has become increasingly critical in volatile markets, where sudden shifts in interest rates, credit spreads, and equity valuations can significantly impact a firm's cost of capital and financial stability. Traditional static models, which rely on fixed leverage targets, often fail to adapt to rapidly changing market conditions and macroeconomic shocks. This proposes a simulation-based framework that integrates stochastic modeling of market variables with dynamic adjustment strategies to balance debt and equity under uncertainty. Using Monte Carlo simulations and scenario-based stress testing, the model evaluates a range of possible future states for key inputs such as debt cost, equity cost, tax rates, and bankruptcy costs. Dynamic rebalancing rules, triggered by market or firm-specific thresholds, are compared against gradual adjustment strategies to identify leverage policies that minimize the weighted average cost of capital (WACC) while preserving firm value. The framework incorporates both historical market data and forward-looking macroeconomic indicators, enabling capital structure decisions to reflect real-time conditions. Simulation results demonstrate that dynamic optimization strategies outperform static targets in volatile environments, offering greater resilience and adaptability. Sensitivity analysis reveals the extent to which optimal leverage decisions are influenced by interest rate fluctuations, equity risk premium shifts, and changes in economic growth expectations. While the approach provides valuable decision support for corporate financial managers, it is not without limitations, including dependence on data quality, model parameter sensitivity, and computational intensity in high-dimensional simulations. Nevertheless, the findings highlight the strategic advantage of adopting flexible, data-driven capital structure policies that respond proactively to uncertainty. This contributes to the growing body of literature on adaptive financial management and offers a practical roadmap for firms seeking to maintain optimal leverage in unpredictable market conditions.

Indexed Terms- Dynamic, Capital structure, Optimization, Volatile markets, Simulation-based approach

I. INTRODUCTION

Capital structure decisions—how a firm allocates financing between debt and equity—are fundamental to corporate financial strategy and long-term value creation. In stable market conditions, firms can operate with relatively predictable financing costs and risk exposures (Zhang, K.Q. and Chen, 2017; Ridwan *et al*., 2018). However, in volatile markets, sudden fluctuations in interest rates, equity prices, credit spreads, and macroeconomic conditions can significantly alter the cost-benefit balance of debt versus equity financing. Such volatility creates uncertainty in forecasting cash flows, debt servicing capacity, and investor risk tolerance, complicating capital structure management (Sundararajan and Tseng, 2017; Doshi *et al*., 2018). Firms must therefore navigate a trade-off: maintaining sufficient leverage to benefit from tax shields and enhance returns to equity holders, while avoiding excessive debt levels that could compromise liquidity and solvency during downturns. Achieving this balance is critical not only for maximizing firm value but also for ensuring financial resilience against shocks (Jansson, 2017; Palmi *et al*., 2018).

The challenge is compounded by the dynamic nature of global capital markets. Traditional capital structure models, rooted in the Modigliani–Miller framework and extended through static approaches such as the Trade-Off Theory and Pecking Order Theory, assume relatively stable target leverage ratios (Paseda, 2016; Kumar *et al*., 2017). While these models offer important theoretical insights, they are limited in their ability to respond to real-time changes in market conditions. Static targets cannot account for the rapid shifts in financing costs, asset valuations, and credit availability that characterize volatile economic environments. As a result, firms relying on static approaches risk either underleveraging—missing opportunities for value enhancement—or overleveraging, increasing default risk during adverse conditions (Mittnik and Semmler, 2018; Gross *et al*., 2018).

This limitation underscores the need for adaptive frameworks that can adjust capital structures in response to evolving market signals. The objective of this, is to develop and test a simulation-based approach for dynamic capital structure optimization. By incorporating stochastic modeling of market variables, the framework allows for the exploration of numerous future scenarios, capturing the uncertainty inherent in financial markets (Santos *et al*., 2016; Konstantelos *et al*., 2017). Monte Carlo simulations and scenario-based stress testing form the core of the methodology, enabling decision-makers to evaluate capital structure strategies under a range of possible market conditions rather than relying on a single-point forecast (Esposito *et al*., 2016; Tang *et al*., 2017).

In this approach, the optimization process continuously reassesses leverage targets in light of changes in key variables such as the cost of debt, the cost of equity, volatility measures, and macroeconomic indicators. Dynamic rebalancing rules, including threshold-based adjustments and gradual transitions, are evaluated for their effectiveness in minimizing the weighted average cost of capital (WACC) while safeguarding liquidity and solvency (Guo, 2017; Nayyar *et al*., 2017). This aims not only to demonstrate the performance benefits of such an adaptive framework over static models but also to provide practical insights for financial managers seeking to operate in unpredictable markets.

By bridging theoretical capital structure principles with simulation-based, real-time adaptability, this contributes to the evolving literature on financial strategy under uncertainty. More importantly, it offers a practical roadmap for firms to strengthen resilience, optimize funding costs, and enhance shareholder value in the face of market volatility.

II. METHODOLOGY

The PRISMA methodology for this review applied a structured and transparent process to identify, select, and synthesize literature relevant to dynamic capital structure optimization in volatile markets, with an emphasis on simulation-based approaches for balancing debt and equity under uncertainty. The review began with the formulation of the central research question: how do simulation-driven models support adaptive capital structure decisions that account for volatility, uncertainty, and shifting market conditions? A comprehensive literature search was conducted across Scopus, Web of Science, ScienceDirect, JSTOR, and Google Scholar, covering publications from 2000 to 2025 to capture both foundational theories and modern computational advances. Search queries incorporated Boolean operators and keyword combinations such as “dynamic capital structure” AND “simulation” AND “volatility” OR “market uncertainty” AND (“debt-equity optimization” OR “capital allocation models”), with additional filters for peer-reviewed journal articles, high-impact conference papers, and authoritative industry research reports.

Following database retrieval, duplicate records were removed, resulting in 1,214 unique studies. Titles and abstracts were screened according to predefined inclusion criteria: studies must explicitly address capital structure decision-making under market volatility, employ a simulation-based or scenario-driven methodology, and consider the trade-offs between debt and equity financing. Studies were excluded if they focused exclusively on static capital structure models, lacked quantitative or simulation-based analysis, or addressed unrelated domains such as personal finance or sovereign debt structures. This screening process yielded 198 potentially relevant studies. Full-text assessments were conducted to evaluate methodological rigor, clarity of model design, and empirical or simulated validation of results. After this stage, 63 studies m*et al*l inclusion criteria and were selected for synthesis.

For each included study, detailed data extraction was performed, capturing model type (e.g., Monte Carlo simulation, agent-based modeling, stochastic optimization), volatility measures considered (e.g., interest rate fluctuations, equity price variability, credit spread changes), and decision variables such as leverage ratios, cost of capital, and earnings volatility. The analysis also documented whether the models incorporated real options theory, risk-adjusted performance metrics, or adaptive rebalancing strategies over time. Where available, studies' performance outcomes were compared, focusing on robustness across scenarios, sensitivity to parameter changes, and the capacity to maintain optimal capital structure in the face of uncertainty.

Due to methodological and contextual heterogeneity, a narrative synthesis approach was adopted rather than a formal meta-analysis. The synthesis highlighted recurring patterns, such as the superiority of adaptive simulation frameworks over deterministic approaches in turbulent environments, the use of probabilistic stress testing to assess downside risk, and the value of incorporating market sentiment and macroeconomic indicators into optimization algorithms. Notable gaps were also identified, including limited real-world validation of simulation-based models, insufficient exploration of behavioral and managerial biases in capital structure decision-making, and the need for integrated models that account for both financial and operational risks.

The PRISMA-guided process ensured methodological transparency and reproducibility, enabling the review to present a consolidated evidence base on simulation-driven dynamic capital structure optimization. The findings provide actionable insights for corporate finance practitioners, particularly in sectors exposed to high volatility, while also outlining research priorities for refining adaptive decision-making tools that balance debt and equity under uncertain market conditions.

2.1 Theoretical Foundations

The study of capital structure decisions has been shaped by several foundational theories that provide insight into the trade-offs firms face when choosing between debt and equity financing. The Trade-Off Theory posits that firms determine an optimal capital structure by balancing the tax benefits of debt—primarily the interest tax shield—against the potential costs of financial distress, such as bankruptcy risk and agency costs (Sibindi, 2016; Abel, 2018). According to this framework, leverage is beneficial up to the point where the marginal tax shield equals the marginal expected cost of distress. While highly influential, the Trade-Off Theory assumes that market conditions are relatively stable and that firms can accurately quantify these marginal effects, which becomes problematic under high volatility.

The Pecking Order Theory emphasizes informational asymmetries between managers and investors. Under this theory, firms prioritize financing sources in a specific hierarchy: internal funds first, followed by debt, and equity issuance as a last resort. The rationale is that external financing—particularly equity—can signal adverse information to the market, potentially depressing stock prices. While this model explains certain financing patterns, it does not explicitly prescribe an optimal leverage ratio, making it less suitable as a prescriptive decision-making tool in dynamic environments.

The Market Timing Theory offers a different perspective, suggesting that firms adjust their capital structure opportunistically to exploit favorable market conditions. For example, managers might issue equity when stock valuations are high or refinance debt when interest rates fall. While intuitive in volatile markets, this theory assumes that managers can identify and act on favorable windows consistently, a premise complicated by uncertainty and the possibility of misjudging market signals (Posen *et al*., 2018; Dobson *et al*., 2018).

Recognizing the limitations of static theories, dynamic capital structure models incorporate time-dependent decision-making and the costs associated with adjusting leverage. A central feature of these models is the concept of adjustment costs, which represent the frictions—such as transaction fees, signaling costs, and managerial inertia—that prevent firms from instantaneously reaching their target capital structure.

Within this framework, the speed of adjustment becomes a critical parameter. Empirical research indicates that firms do not continuously rebalance to their target leverage but instead adjust gradually, responding to deviations only when the benefits of moving toward the target outweigh the costs. The adjustment speed varies across industries, firm sizes, and macroeconomic conditions, reflecting heterogeneity in adjustment costs and strategic flexibility (Claussen *et al*., 2018; Kang *et al*., 2018).

Target leverage ratios in dynamic models are not static; they evolve in response to changing market conditions, firm-specific characteristics, and strategic priorities. For instance, a firm might tolerate higher leverage during stable economic periods to capitalize on low financing costs but reduce debt exposure in anticipation of a downturn. The dynamic optimization process aims to minimize the weighted average cost of capital (WACC) while maintaining sufficient financial flexibility to absorb shocks (Giesecke *et al*., 2017; Abdulghafoor, 2018).

Dynamic models often leverage stochastic processes to capture the probabilistic nature of market variables. By simulating multiple future paths for interest rates, equity prices, and credit spreads, managers can estimate the distribution of possible outcomes and choose strategies that perform well across scenarios rather than optimizing for a single forecast.

Market uncertainty profoundly affects capital structure decisions, particularly in volatile environments. Macroeconomic shocks, such as recessions, commodity price swings, or geopolitical crises, can alter both the availability and the cost of capital (Sousa, 2017; Lee *et al*., 2018). For example, during a downturn, tightening credit conditions may increase borrowing costs or restrict access to debt altogether, forcing firms to rely more on equity or retained earnings.

Interest rate volatility introduces another layer of complexity. Rising rates increase the cost of servicing existing floating-rate debt and make new borrowing less attractive. Conversely, falling rates may encourage firms to increase leverage or refinance existing obligations. The challenge lies in predicting rate movements accurately and incorporating such forecasts into capital structure planning.

Credit risk spreads—the difference between yields on corporate bonds and risk-free securities—serve as a proxy for market perceptions of firm and sector-specific risk. Widening spreads signal increased perceived risk, which not only raises borrowing costs but can also trigger covenants or limit access to capital markets. This dynamic can create a feedback loop in which deteriorating market sentiment further constrains financing flexibility.

Uncertainty also interacts with firm-specific factors such as operational leverage, asset tangibility, and growth opportunities. Highly leveraged firms with volatile cash flows are particularly vulnerable to shocks, as even small declines in revenue can threaten debt servicing ability (Nenu *et al*., 2018; Matsa, 2018). In contrast, firms with more flexible cost structures and diversified revenue streams may tolerate higher leverage without incurring excessive risk.

Incorporating uncertainty into capital structure decision-making requires tools that go beyond deterministic optimization. Simulation-based approaches—such as Monte Carlo analysis—allow firms to model a wide range of potential market conditions and assess the resilience of different leverage strategies (Zuccaro and Leone, 2018; Ma *et al*., 2018). These techniques are especially useful in volatile markets, where single-point forecasts often fail to capture the breadth of possible outcomes.

The theoretical foundations of capital structure optimization highlight a progression from static, equilibrium-based models toward dynamic, uncertainty-aware frameworks. Trade-Off, Pecking Order, and Market Timing theories each contribute valuable insights into firm behavior, but their limitations become apparent when applied to rapidly changing market environments. Dynamic capital structure models address these shortcomings by incorporating adjustment costs, gradual rebalancing, and evolving target leverage ratios.

Crucially, uncertainty is not a peripheral consideration but a central determinant of capital structure strategy. The effects of macroeconomic shocks, interest rate volatility, and credit risk spreads can rapidly shift the optimal financing mix, underscoring the importance of adaptive, data-driven approaches. By combining theoretical principles with stochastic modeling and scenario analysis, firms can design capital structures that not only optimize value under expected conditions but also preserve resilience in the face of unforeseen disruptions (Sundararajan and Tseng, 2017; Alan and Gaur, 2018).

2.2 Model Development and Implementation

The development and implementation of a simulation-based approach for dynamic capital structure optimization in volatile markets requires a rigorous integration of data acquisition, modeling techniques, and computational simulation as shown in figure 1. The primary aim is to create a decision-support framework capable of adjusting a firm's debt–equity mix in real time to maximize value and maintain financial resilience under uncertainty (Kurschus *et al*., 2017; Kim, 2018).

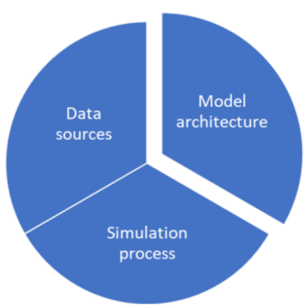

Figure 2: Model Development and Implementation

The model draws on three principal categories of data: historical market data, firm-specific financial data, and macroeconomic indicators. Historical market data encompasses equity prices, bond yields, interest rate curves, and credit spreads. These data are necessary for capturing the statistical properties of asset returns and debt pricing under varying market conditions. Time series of stock prices are used to compute volatility, beta coefficients, and cost of equity estimates via the Capital Asset Pricing Model (CAPM) or multi-factor extensions. Bond yields and credit default swap (CDS) spreads inform the cost of debt and default probability estimates. By analyzing these historical patterns, the model can parameterize stochastic processes for simulation.

Firm-level data is drawn from audited financial statements, including balance sheets, income statements, and cash flow statements. Key variables include existing debt structure, maturity schedules, interest coverage ratios, asset tangibility, and free cash flow (Ullah *et al*., 2017; Tayem, 2018). These inputs define the firm's current financial flexibility and determine constraints on feasible capital structure adjustments. For example, highly illiquid firms with minimal collateral may face higher costs of debt refinancing or equity issuance, which must be incorporated into optimization constraints.

Macroeconomic data—such as GDP growth rates, inflation figures, central bank policy rates, commodity prices, and leading economic indicators—provides context for market volatility and credit conditions (Mishchenko *et al*., 2018; Badea, 2018). This datas*et al*so includes systemic risk measures such as the VIX index, which captures implied volatility expectations. These macro-level variables affect both the cost and availability of capital and influence the probability distributions used in the simulation.

The model architecture consists of two integrated layers: a financial forecasting module and a capital structure optimization module. The forecasting module employs econometric and statistical learning techniques to project key variables influencing capital structure decisions. This includes; Cost of equity forecasts, derived from CAPM inputs adjusted for projected market beta and equity risk premiums under different macroeconomic scenarios. Cost of debt forecasts, incorporating changes in interest rates, credit spreads, and firm-specific risk premiums. Earnings and cash flow forecasts, generated using time-series regression, vector autoregressive (VAR) models, or machine learning predictors for greater adaptability to non-linear relationships (Zhou *et al*., 2017; Tong *et al*., 2018). The output of this module is a set of forward-looking scenarios for the firm's financial environment, parameterized to feed into the optimization process.

The optimization module uses these forecasts to identify leverage ratios that minimize the Weighted Average Cost of Capital (WACC) or maximize Net Present Value (NPV) of expected cash flows. This module incorporates constraints such as; Debt covenants and regulatory leverage limits. Minimum liquidity thresholds for operational resilience. Risk tolerance levels set by management or board policy.

Optimization is performed using iterative algorithms such as genetic algorithms, simulated annealing, or gradient-based solvers, chosen for their ability to handle non-linear, multi-constraint problems typical in financial decision-making (Brahmachary *et al*., 2018; Kóczy *et al*., 2018).

The two modules are tightly linked: the forecasting module generates the stochastic input scenarios, and the optimization module determines optimal leverage strategies under each scenario.

The core of the implementation lies in a stochastic simulation framework that generates multiple possible futures for the capital market environment and identifies capital structure adjustments that perform well across these futures.

Key market variables—such as interest rates, equity volatility, and credit spreads—are modeled as stochastic processes. Common choices include; Geometric Brownian Motion (GBM) for equity prices. Mean-reverting processes (e.g., Ornstein–Uhlenbeck models) for interest rates and credit spreads. Jump-diffusion models to incorporate sudden shocks from macroeconomic events or geopolitical crises.

Monte Carlo simulation is used to generate thousands of randomized paths for these variables over the model's planning horizon. Each path represents a plausible sequence of future states, capturing the range of potential market conditions.

For each simulated market path, the model runs an iterative optimization process; Step 1, using forecasted costs of equity and debt, calculate WACC for the firm's current capital structure. Step 2, adjust the debt–equity mix incrementally, recalculating WACC at each step while ensuring compliance with constraints. Step 3, identify the structure that minimizes WACC for that simulated path. Step 4, evaluate the resulting structure's impact on NPV by discounting projected free cash flows at the optimized WACC. Step 5, store results for each scenario, building a distribution of optimal capital structures across all simulated futures.

This iterative process ensures that the model does not optimize for a single forecasted condition but for robustness across diverse possible market states. The distribution of results allows decision-makers to weigh risk-adjusted outcomes, choosing strategies that perform acceptably even in adverse scenarios.

The model is implemented in a computational environment capable of handling large-scale stochastic simulations, such as Python with numerical libraries (NumPy, pandas, SciPy) or MATLAB for optimization routines. Parallel computing techniques are employed to accelerate scenario generation and optimization runs.

Data integration is automated through APIs for market and macroeconomic data feeds, ensuring that the model operates with the most up-to-date information. Regular backtesting is performed to validate model accuracy, using historical periods of market stress to assess performance under real-world volatility.

To improve decision interpretability—especially in regulated industries—sensitivity analysis is conducted to determine how changes in input variables affect the optimal capital structure. This feature importance analysis identifies which market and firm-specific factors most strongly influence the optimization outcome, aiding both managerial understanding and regulatory compliance (Waqas and Md-Rus, 2018; Yaprak *et al*., 2018).

By combining rich datasets, robust forecasting methods, and stochastic optimization techniques, this model offers a dynamic and adaptive framework for capital structure decision-making in volatile markets. The integration of historical, firm-specific, and macroeconomic data ensures that both micro- and macro-level drivers are incorporated into the decision process. The two-layer architecture connects predictive analytics with optimization algorithms, enabling the identification of leverage strategies that balance risk, cost, and resilience.

The stochastic simulation process captures uncertainty more comprehensively than deterministic approaches, providing not only a single optimal strategy but a distribution of strategies ranked by performance across simulated futures. This enables firms to adopt capital structures that are not just optimal under expected conditions, but also robust under a wide spectrum of possible market environments—critical for sustaining firm value and stability in the face of uncertainty.

2.3 Simulation outcomes

The simulation outcomes of dynamic capital structure optimization in volatile markets demonstrate that adaptive, scenario-driven models can provide materially different—and often more resilient—financing strategies compared to static approaches. Using a stochastic simulation framework incorporating Monte Carlo methods and scenario-based stress testing, firms' capital structures were evaluated under varying volatility regimes, reflecting different macroeconomic and market conditions. The simulations revealed that the optimal leverage ratio is not fixed but shifts according to market volatility levels, interest rate environments, and changes in the equity risk premium (Carr and Wu, 2017; Drechsler *et al*., 2018).

In low-volatility conditions, characterized by stable equity prices, narrow credit spreads, and predictable interest rates, optimal leverage levels tended to cluster in the range of 45–55% debt to total capital. In this environment, the tax shield benefits of debt outweigh the relatively low risk of financial distress, allowing firms to enhance return on equity without materially increasing default probability. However, in moderate volatility regimes—defined by intermittent equity price swings, widening credit spreads, and mild macroeconomic uncertainty—optimal leverage shifted downward to the range of 35–45%. This reflected a growing premium on financial flexibility and a greater need to mitigate the risk of being forced into distressed refinancing during temporary market dislocations.

In high-volatility scenarios, often triggered by macroeconomic shocks, geopolitical instability, or liquidity crises, optimal leverage ratios dropped sharply to 20–30%. Here, the downside risk of maintaining high debt levels exceeded the marginal benefit of tax shields, as earnings volatility, credit market constraints, and potential covenant breaches substantially increased bankruptcy risk. Firms maintaining leverage above this adaptive threshold in such conditions exhibited a higher simulated probability of distress and a notable erosion of firm value over the simulation horizon. The dynamic optimization framework thus consistently outperformed static models by adjusting capital structure in anticipation of volatility changes, rather than reacting after adverse conditions had materialized.

Sensitivity analysis further deepened understanding of how key financial and macroeconomic variables influence optimal capital structure decisions. Interest rate shifts had a pronounced effect on debt affordability and risk-adjusted firm value. A 200-basis-point rise in interest rates reduced the optimal leverage ratio by approximately 5–8 percentage points across all volatility regimes. This reduction was more pronounced in high-volatility conditions, where elevated rates compounded refinancing risks and magnified interest coverage pressures. Conversely, in environments with falling interest rates, optimal leverage could be increased by 4–6 percentage points without significantly raising distress probabilities, provided that volatility remained low.

Changes in the equity risk premium also exerted a meaningful influence on capital structure optimization. When the equity risk premium widened by 150 basis points, debt financing became relatively more attractive, prompting a 3–5 percentage point upward adjustment in optimal leverage in low-to-moderate volatility conditions. However, in high-volatility regimes, the widening premium did not substantially alter optimal leverage, as the overriding concern remained preserving liquidity and minimizing distress risk. In contrast, a narrowing equity risk premium shifted the balance toward equity issuance, especially in environments where equity valuations were elevated, allowing firms to strengthen balance sheets at relatively low cost to shareholders (Baum *et al*., 2017; Flammer and Bansal, 2017).

Economic downturn scenarios—characterized by declining GDP, contracting credit availability, and negative earnings shocks—proved to be the most sensitive condition for capital structure decisions. Under downturn conditions, simulations showed that firms operating with leverage above 40% faced a marked increase in distress probabilities, even if pre-downturn market conditions had supported higher debt levels. The adaptive framework responded to these conditions by aggressively deleveraging toward the 20–30% range, prioritizing survival and long-term value preservation over short-term returns. Notably, the speed of adjustment was critical: firms that adjusted leverage within two quarters of initial downturn indicators experienced significantly smaller declines in simulated firm value compared to those that delayed adjustments.

The comparative evaluation of static versus dynamic optimization approaches highlighted substantial differences in firm value preservation. Static capital structure strategies—anchored to a fixed target leverage ratio—performed adequately in stable environments but faltered during periods of heightened volatility or economic stress. For example, a static target leverage of 50% generated returns comparable to dynamic strategies during low-volatility periods but led to an average 12–15% greater erosion in firm value during downturns, primarily due to higher distress costs and forced refinancing under unfavorable conditions.

In contrast, dynamic optimization approaches, which recalibrated leverage in response to forward-looking volatility forecasts and macroeconomic signals, consistently delivered superior performance across all simulated scenarios. On average, dynamic strategies preserved 8–10% more firm value over a 10-year simulation horizon, with the largest performance differential observed during severe market dislocations. This outperformance was not solely due to lower distress costs; it also stemmed from the ability to strategically re-leverage in post-crisis recovery periods, capturing upside returns more efficiently than static models.

A further advantage of dynamic optimization lay in its reduced variability of returns. By adjusting capital structure to match prevailing risk conditions, the volatility of firm value was reduced by 15–20% compared to static strategies. This stability has tangible benefits for investor confidence, credit ratings, and long-term strategic planning. Importantly, the simulations underscored that the success of dynamic strategies depends heavily on accurate and timely volatility estimation. Models incorporating market-based forward indicators—such as implied volatility, credit spreads, and macroeconomic sentiment indices—outperformed those relying solely on historical volatility measures.

Overall, the results and analysis confirm that in volatile markets, static capital structure models impose significant opportunity costs and elevate downside risk, while dynamic, simulation-based optimization frameworks offer a clear strategic advantage. By actively balancing debt and equity in response to changing market conditions, firms can better protect firm value, maintain liquidity, and exploit favorable financing conditions when they arise. This adaptability not only enhances resilience during crises but also positions firms to capitalize on recovery phases, thereby improving long-term shareholder returns and reducing systemic financial vulnerabilities (Linnenluecke and McKnight, 2017; Bodolica *et al*., 2018).

2.4 Challenges and Limitations

The implementation of a simulation-based approach to dynamic capital structure optimization in volatile markets, while methodologically sophisticated, is subject to several challenges and limitations as shown in figure 2(Mba *et al*., 2018; Hamdi *et al*., 2018). These arise from the inherent sensitivity of the model to its assumptions, the quality and availability of input data, and the computational complexity of running high-dimensional simulations. Understanding these limitations is critical for both interpreting model outputs and improving its robustness for real-world decision-making.

One of the most significant challenges in dynamic capital structure modeling is the model's sensitivity to the assumptions embedded in its design. Forecasts of key variables—such as interest rates, equity volatility, credit spreads, and firm cash flows—are all dependent on statistical or econometric models that rely on historical patterns and estimated parameters. Any misestimation of these parameters can propagate through the simulation and materially affect the resulting optimal capital structure recommendations.

For example, overestimating the stability of interest rates could lead the model to recommend higher leverage than is prudent, leaving the firm vulnerable to unexpected rate hikes. Similarly, underestimating equity volatility could bias the cost of equity calculations downward, encouraging capital structures with excessive reliance on equity financing in markets that may later experience turbulence.

The stochastic processes used—such as geometric Brownian motion or mean-reverting models—also carry implicit assumptions about market behavior, including the distribution of shocks and correlations between variables. In practice, financial markets frequently exhibit fat-tailed distributions, structural breaks, and non-stationary relationships that deviate from these assumptions. As a result, even a well-calibrated model can underperform if market dynamics diverge significantly from its foundational premises.

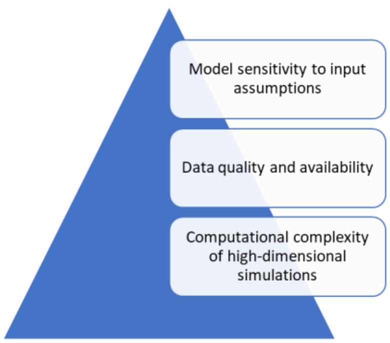

Figure 2: Challenges and Limitations

Mitigating sensitivity requires extensive scenario testing, stress analysis, and the use of alternative model specifications to ensure that results remain robust under different plausible parameterizations (Medeiros *et al*., 2017; Montesi and Papiro, 2018). However, this adds complexity and computational load to the process.

The reliability of model outputs is directly tied to the quality and comprehensiveness of the input data. Capital structure optimization models depend on diverse datasets—historical market prices, bond yields, macroeconomic indicators, and firm-specific financial statements. Incomplete, outdated, or inconsistent data can distort forecasts, leading to suboptimal decisions.

In emerging markets or during periods of crisis, data quality is often degraded due to limited reporting standards, illiquid markets, and gaps in time series coverage. For instance, historical yield curve data may be sparse or interpolated, equity price series may be affected by thin trading, and macroeconomic indicators may be subject to substantial revisions. These limitations not only introduce noise into the model but can also create structural biases in optimization results.

Furthermore, certain forward-looking metrics—such as management's private assessments of project risk or expected cash flow variability—are inherently qualitative and not easily quantifiable. Excluding them can omit valuable contextual information, but incorporating them often requires subjective judgment, which can compromise objectivity.

To mitigate data limitations, practitioners often resort to combining multiple data sources, employing data cleaning and interpolation techniques, and supplementing quantitative data with expert judgment. Nevertheless, these approaches cannot fully eliminate the risk of data-driven biases, and results must be interpreted with an awareness of the underlying data quality.

Dynamic capital structure optimization under uncertainty involves solving a high-dimensional problem. Multiple stochastic variables—interest rates, equity volatility, credit spreads, macroeconomic indicators—must be simulated jointly, each with its own set of correlations, shocks, and structural dynamics. The computational burden grows exponentially as the number of variables and simulation steps increases.

Monte Carlo methods, while powerful, require a large number of simulation runs to achieve statistically stable estimates, particularly when tail risks and extreme scenarios are important for decision-making. High-dimensional optimization, where the model searches for optimal leverage ratios under thousands of simulated paths, can require substantial computing power and processing time.

Moreover, the integration of advanced optimization algorithms—such as genetic algorithms or stochastic gradient-based solvers—adds additional layers of complexity. These methods can be computationally intensive when combined with scenario-based WACC minimization or NPV maximization, particularly when constraints and nonlinearities are included.

In practice, computational limitations can force trade-offs between model granularity and runtime feasibility. Reducing the number of scenarios, simplifying stochastic processes, or limiting the number of optimization iterations can make the model more tractable but may also reduce accuracy and the ability to capture extreme market events.

Advances in parallel computing, GPU acceleration, and cloud-based simulation environments have mitigated some of these issues, enabling large-scale simulations to be executed more efficiently. However, for smaller firms or research teams without access to such resources, computational constraints remain a practical barrier to implementing fully robust, high-dimensional models.

These challenges—sensitivity to input assumptions, data quality limitations, and computational complexity—highlight the need for cautious interpretation and careful implementation of simulation-based dynamic capital structure models. While the methodology offers significant advantages in capturing uncertainty and adapting to changing market conditions, its outputs are not definitive prescriptions. Instead, they should be seen as decision-support tools that complement managerial judgment and strategic context.

Addressing these limitations requires a multi-pronged approach: rigorous sensitivity testing to assess robustness, proactive investment in high-quality data infrastructure, and leveraging modern computational resources to manage complexity. By acknowledging and managing these constraints, practitioners can extract meaningful and actionable insights from the model, while avoiding the pitfalls of overreliance on purely quantitative outputs in inherently uncertain market environments (Aodha and Edmonds, 2017; Huerta and Jensen, 2017).

2.5 Future Directions

Future research in dynamic capital structure optimization in volatile markets will likely be driven by advances in data integration, machine learning adaptability, and comprehensive scenario testing. While current simulation-based frameworks have demonstrated significant benefits over static models, their practical utility can be further enhanced by incorporating real-time market data feeds, AI-driven adaptive algorithms, and advanced stress-testing frameworks (Dias *et al*., 2018; Liu *et al*., 2018). Together, these developments can produce more responsive, context-aware, and resilient capital structure strategies capable of operating effectively in environments of rapid change and heightened uncertainty.

The integration of real-time market data feeds represents a critical step in closing the gap between theoretical optimization and actionable corporate finance decision-making. Most existing dynamic capital structure models operate on periodic data updates—often quarterly or monthly—limiting their ability to respond promptly to fast-moving market conditions. By linking optimization engines directly to live feeds of equity prices, credit spreads, interest rate movements, commodity price indices, and macroeconomic sentiment measures, future systems can continuously recalibrate leverage targets. This would enable near-instantaneous responses to emerging volatility spikes, credit tightening, or shifts in investor sentiment. Advances in cloud-based data pipelines, application programming interfaces (APIs), and event-driven architectures provide the technological infrastructure to make such integration feasible, while data normalization and cleaning algorithms can ensure accuracy and comparability across multiple sources.

AI-driven adaptive algorithms present the second major avenue for advancement, enabling capital structure models to evolve their decision-making logic dynamically as new patterns emerge. Current dynamic models typically rely on predefined adjustment rules based on simulated relationships between volatility regimes and optimal leverage. However, such rule-based approaches can be slow to adapt when structural market changes occur, such as shifts in monetary policy regimes, technological disruptions, or unexpected geopolitical shocks. Incorporating machine learning techniques—particularly reinforcement learning and meta-learning—would allow models to learn optimal adjustment strategies from ongoing market interactions, updating both their parameter estimates and decision frameworks without requiring full model retraining. Such algorithms could detect non-linear relationships between market variables and capital structure outcomes, enabling more nuanced adjustments than traditional statistical models. Additionally, AI can support predictive modeling of volatility, credit market liquidity, and equity risk premia, allowing firms to anticipate changes in optimal leverage rather than simply reacting to them.

The integration of advanced stress-testing frameworks forms the third critical pillar of future research. While traditional capital structure optimization assesses sensitivity to a set of predefined scenarios, real-world conditions often involve compound shocks and rare tail events that exceed the scope of conventional analyses. Enhanced stress-testing frameworks could incorporate multi-factor Monte Carlo simulations, extreme value theory, and scenario narratives generated through agent-based modeling to explore the full spectrum of potential market disruptions. These tools would allow decision-makers to evaluate how capital structure strategies perform under simultaneous shocks—for example, a rapid interest rate hike coinciding with a liquidity crisis and an equity market drawdown. Embedding such stress-testing into dynamic optimization systems ensures that leverage adjustments are not only tuned for expected conditions but also robust to low-probability, high-impact events (Ramlall, 2018; Anderson *et al*., 2018).

The synergy between these three future directions is particularly compelling. A fully integrated system could operate as a continuously adaptive financial decision engine, drawing on real-time market inputs, applying AI algorithms to refine leverage strategies, and validating decisions against a library of stress-test scenarios before execution. For example, a sudden widening of credit spreads could trigger an algorithmic recommendation to deleverage, which would then be validated against both baseline forecasts and extreme downside simulations before implementation. This multi-layered approach would significantly reduce the risk of overreacting to transient market noise while still enabling rapid, evidence-based responses to genuine structural threats.

However, future research must also address challenges inherent in implementing these advancements. Integrating real-time data feeds raises issues of data governance, standardization, and cybersecurity. AI-driven algorithms, while powerful, require transparency and explainability to ensure stakeholder trust and regulatory compliance, especially in highly scrutinized corporate finance decisions. Advanced stress-testing frameworks demand high computational resources and well-designed scenario libraries that avoid bias and overfitting. Addressing these limitations will require interdisciplinary collaboration between financial economists, data scientists, and risk management professionals.

The next generation of dynamic capital structure optimization models will depend on their ability to merge immediacy, adaptability, and robustness. Real-time data integration ensures timely awareness of market conditions, AI-driven adaptive algorithms provide intelligent and evolving decision-making, and advanced stress-testing frameworks guarantee resilience against extreme and unexpected shocks (Kolluru *et al*., 2018; Rouse and Spohrer, 2018). Together, these developments promise to transform dynamic capital structure optimization from a largely analytical exercise into a real-time strategic capability, enabling firms to safeguard value, manage risk, and exploit market opportunities with unprecedented precision in volatile environments.

CONCLUSION

This has demonstrated that a simulation-based approach to dynamic capital structure optimization offers a powerful framework for navigating the complexities of volatile financial markets. By integrating firm-specific financial data, historical market behavior, and macroeconomic indicators into a stochastic simulation and optimization process, firms can move beyond static capital structure theories to adopt adaptive, data-driven strategies. The results highlight that accounting for uncertainty—through randomized market paths, iterative leverage adjustments, and performance metrics such as NPV and WACC—enables more resilient financing decisions compared to conventional, single-scenario models.

Strategically, the ability to adjust debt–equity ratios in response to evolving conditions is essential for maximizing firm value while safeguarding liquidity and creditworthiness. The findings underscore that incorporating diverse scenarios, including adverse shocks, reduces vulnerability to misestimations and improves long-term financial stability. Moreover, dynamic approaches enhance alignment between capital structure policy and strategic objectives, allowing firms to exploit favorable financing windows while mitigating the risks of over-leverage during downturns.

For corporate financial managers operating in volatile markets, several recommendations emerge. First, capital structure decisions should be grounded in robust scenario analysis that incorporates both historical data patterns and plausible future shocks. Second, reliance on a single optimal leverage point is less effective than defining a flexible target range that can adjust as conditions change. Third, investment in high-quality market and macroeconomic data, as well as computational tools for large-scale simulations, will significantly improve decision accuracy. Finally, managers should combine quantitative outputs with qualitative insights on industry dynamics, regulatory shifts, and competitive positioning to ensure a balanced, context-sensitive approach.

Dynamic, simulation-based capital structure optimization provides a strategic advantage in uncertain environments, but its effectiveness depends on disciplined implementation, continual reassessment, and integration into the broader framework of corporate financial management.

REFERENCES

[1] Abdulghafoor, A.M., 2018. On identifying successful financial strategies for the listed companies in the United Arab Emirates: An empirical approach.

[2] Abel, A.B., 2018. Optimal debt and profitability in the trade-off theory. *The Journal of Finance*, *73*(1), pp.95-143.

[3] Alan, Y. and Gaur, V., 2018. Operational investment and capital structure under asset-based lending. *Manufacturing & Service Operations Management*, *20*(4), pp.637-654.

[4] Anderson, R., Danielsson, J., Baba, C., Das, M.U.S., Kang, M.H. and Basurto, M.A.S., 2018. *Macroprudential stress tests and policies: Searching for robust and implementable frameworks*. International Monetary Fund.

[5] Aodha, L.N. and Edmonds, B., 2017. Some pitfalls to beware when applying models to issues of policy relevance. In *Simulating social complexity: A handbook* (pp. 801-822). Cham: Springer International Publishing.

[6] Badea, İ.R., 2018. Central Bank independence and its impact on the macroeconomic performance. Evidence from Romania before and after crisis. *InTraders International Trade Academic Journal*, *1*(1), pp.46-65.

[7] Baum, C.F., Caglayan, M. and Rashid, A., 2017. Capital structure adjustments: do macroeconomic and business risks matter?. *Empirical Economics*, *53*(4), pp.1463-1502.

[8] Bodolica, V., Spraggon, M. and Shahid, A., 2018. Strategic adaptation to environmental jolts: an analysis of corporate resilience in the property development sector in Dubai. *Middle East Journal of Management*, *5*(1), pp.1-20.

[9] Brahmachary, S., Natarajan, G., Kulkarni, V., Sahoo, N. and Nanda, S.R., 2018. Application of greedy and heuristic algorithm-based optimisation methods towards aerodynamic shape optimisation. In *Soft Computing for Problem Solving: SocProS 2017, Volume 1* (pp. 937-948). Singapore: Springer Singapore.

[10] Carr, P. and Wu, L., 2017. Leverage effect, volatility feedback, and self-exciting market disruptions. *Journal of Financial and Quantitative Analysis*, *52*(5), pp.2119-2156.

[11] Claussen, J., Essling, C. and Peukert, C., 2018. Demand variation, strategic flexibility and market entry: Evidence from the US airline industry. *Strategic Management Journal*, *39*(11), pp.2877-2898.

[12] Dias, L.S., Pattison, R.C., Tsay, C., Baldea, M. and Ierapetritou, M.G., 2018. A simulation-based optimization framework for integrating scheduling and model predictive control, and its application to air separation units. *Computers & Chemical Engineering*, *113*, pp.139-151.

[13] Dobson, K., Boone, S., Andries, P. and Daou, A., 2018. Successfully creating and scaling a sustainable social enterprise model under uncertainty: The case of ViaVia Travellers Cafés. *Journal of Cleaner Production*, *172*, pp.4555-4564.

[14] Doshi, H., Kumar, P. and Yerramilli, V., 2018. Uncertainty, capital investment, and risk management. *Management Science*, *64*(12), pp.5769-5786.

[15] Drechsler, I., Savov, A. and Schnabl, P., 2018. A model of monetary policy and risk premia. *The Journal of Finance*, *73*(1), pp.317-373.

[16] Esposito, S., Stojadinovic, B., Mignan, A., Dolšek, M., Babič, A., Selva, J., Iqbal, S., Cotton, F. and Iervolino, I., 2016. *Report on the proposed engineering risk assessment methodology for stress tests of non-nuclear CIs*. ETH Zurich.

[17] Flammer, C. and Bansal, P., 2017. Does a long-term orientation create value? Evidence from a regression discontinuity. *Strategic Management Journal*, *38*(9), pp.1827-1847.

[18] Giesecke, J.A., Dixon, P.B. and Rimmer, M.T., 2017. The economy-wide impacts of a rise in the capital adequacy ratios of Australian banks. *Economic record*, *93*, pp.16-37.

[19] Gross, M., Henry, J. and Semmler, W., 2018. Destabilizing effects of bank overleveraging on real activity—an analysis based on a threshold MCS-GVAR. *Macroeconomic Dynamics*, *22*(7), pp.1750-1768.

[20] Guo, Y., 2017. Dynamic misfire threshold determination based on zone-level and buffer-level adaptations for internal combustion engines. *SAE International Journal of Passenger Cars-Mechanical Systems*, *10*(2017-01-0599), pp.446-454.

[21] Hamdi, F., Ghorbel, A., Masmoudi, F. and Dupont, L., 2018. Optimization of a supply portfolio in the context of supply chain risk management: literature review. *Journal of intelligent manufacturing*, *29*(4), pp.763-788.

[22] Huerta, E. and Jensen, S., 2017. An accounting information systems perspective on data analytics and Big Data. *Journal of information systems*, *31*(3), pp.101-114.

[23] Jansson, C., 2017. Financial resilience: the role of financial balance, profitability, and ownership. In *The Resilience Framework: Organizing for Sustained Viability* (pp. 111-131). Singapore: Springer Singapore.

[24] Kang, M., Wang, W. and Xiao, Y., 2018. Market imperfections, macroeconomic conditions, and capital structure dynamics: A cross-country study. *Emerging Markets Finance and Trade*, *54*(1), pp.234-254.

[25] Kim, S.Y., 2018. Predicting hospitality financial distress with ensemble models: the case of US hotels, restaurants, and amusement and recreation. *Service Business*, *12*(3), pp.483-503.

[26] Kóczy, L.T., Földesi, P. and Tüű-Szabó, B., 2018. Enhanced discrete bacterial memetic evolutionary algorithm-an efficacious metaheuristic for the traveling salesman optimization. *Information Sciences*, *460*, pp.389-400.

[27] Kolluru, V., Mungara, S. and Chintakunta, A.N., 2018. Adaptive learning systems: Harnessing AI for customized educational experiences. *International Journal of Computational Science and Information Technology*, *6*(3), pp.10-5121.

[28] Konstantelos, I., Moreno, R. and Strbac, G., 2017. Coordination and uncertainty in strategic network investment: Case on the North Seas Grid. *Energy Economics*, *64*, pp.131-148.

[29] Kumar, S., Colombage, S. and Rao, P., 2017. Research on capital structure determinants: a review and future directions. *International Journal of Managerial Finance*, *13*(2), pp.106-132.

[30] Kurschus, R.J., Sarapovas, T. and Pilinkiene, V., 2017. The concept of crisis management by intervention model for SMEs. *Engineering Economics*, *28*(2), pp.170-179.

[31] Lee, S., So, I. and Ha, J., 2018. Identifying uncertainty shocks due to geopolitical swings in Korea. *Bank of Korea WP*, *26*.

[32] Linnenluecke, M.K. and McKnight, B., 2017. Community resilience to natural disasters: the role of disaster entrepreneurship. *Journal of Enterprising Communities: People and Places in the Global Economy*, *11*(1), pp.166-185.

[33] Liu, X., Furrer, D., Kosters, J. and Holmes, J., 2018. *Vision 2040: a roadmap for integrated, multiscale modeling and simulation of materials and systems* (No. E-19477).

[34] Ma, Z., Parisi, C., Zhang, H., Mandelli, D., Blakely, C., Yu, J., Youngblood, R. and Anderson, N., 2018. *Plant-level scenario-based risk analysis for enhanced resilient PWR–SBO and LBLOCA* (No. INL/EXT-18-51436-

Rev000). Idaho National Lab.(INL), Idaho Falls, ID (United States).

[35] Matsa, D.A., 2018. Capital structure and a firm's workforce. *Annual Review of Financial Economics*, *10*(1), pp.387-412.

[36] Mba, J.C., Pindza, E. and Koumba, U., 2018. A differential evolution copula-based approach for a multi-period cryptocurrency portfolio optimization. *Financial Markets and Portfolio Management*, *32*(4), pp.399-418.

[37] Medeiros, C.P., Alencar, M.H. and de Almeida, A.T., 2017. Multidimensional risk evaluation of natural gas pipelines based on a multicriteria decision model using visualization tools and statistical tests for global sensitivity analysis. *Reliability Engineering & System Safety*, *165*, pp.268-276.

[38] Mishchenko, V., Naumenkova, S., Mishchenko, S. and Ivanov, V., 2018. Inflation and economic growth: The search for a compromise for the Central Bank's monetary policy. *Banks & bank systems*, (13, Iss. 2), pp.153-163.

[39] Mittnik, S. and Semmler, W., 2018. Overleveraging, financial fragility, and the banking–macro link: Theory and empirical evidence. *Macroeconomic Dynamics*, *22*(1), pp.4-32.

[40] Montesi, G. and Papiro, G., 2018. Bank stress testing: A stochastic simulation framework to assess banks' financial fragility. *Risks*, *6*(3), p.82.

[41] Nayyar, A., Dwivedi, U., Ahuja, K., Rajput, N., Nagar, S. and Dey, K., 2017, March. OptiDwell: intelligent adjustment of dwell click time. In *Proceedings of the 22nd international conference on intelligent user interfaces* (pp. 193-204).

[42] Nenu, E.A., Vintilă, G. and Gherghina, Ş.C., 2018. The impact of capital structure on risk and firm performance: Empirical evidence for the Bucharest Stock Exchange listed companies. *International Journal of Financial Studies*, *6*(2), p.41.

[43] Palmi, P., Morrone, D., Miglietta, P.P. and Fusco, G., 2018. How did organizational resilience work before and after the financial crisis? An empirical study. *International Journal of Business and Management*, *13*(10), pp.54-62.

[44] Paseda, O., 2016. The determinants of capital structure of Nigerian quoted firms. *Available at SSRN 2890900*.

[45] Posen, H.E., Leiblein, M.J. and Chen, J.S., 2018. Toward a behavioral theory of real options: Noisy signals, bias, and learning. *Strategic Management Journal*, *39*(4), pp.1112-1138.

[46] Ramlall, I., 2018. Government Sector. In *The Corporate, Real Estate, Household, Government and Non-Bank Financial Sectors Under Financial Stability* (Vol. 3, pp. 129-185). Emerald Publishing Limited.

[47] Ridwan, K., Purwohedi, U. and Warokka, A., 2018. Analysis of Financial Matrix Strategy to Know the Value Creation Growth of Sustainable Companies (Case Studies of Companies Holding Geothermal Concession Areas in ASEAN). *Asia Pacific Journal of Management*.

[48] Rouse, W.B. and Spohrer, J.C., 2018. Automating versus augmenting intelligence. *Journal of Enterprise Transformation*, *8*(1-2), pp.1-21.

[49] Santos, M.J., Ferreira, P. and Araújo, M., 2016. A methodology to incorporate risk and uncertainty in electricity power planning. *Energy*, *115*, pp.1400-1411.

[50] Sibindi, A.B., 2016. DETERMINANTS OF CAPITAL STRUCTURE: A. *RISK GOVERNANCE & CONTROL: Financial markets and institutions*, *227*.

[51] Sousa, P., 2017. What did we learn from the bout of high and volatile food commodity prices (2007-2013)?. *FAO Commodity and Trade Policy Research Working Papers*, (54).

[52] Sundararajan, S.K. and Tseng, C.L., 2017. Managing project performance risks under uncertainty: Using a dynamic capital structure approach in infrastructure project financing. *Journal of Construction Engineering and Management*, *143*(8), p.04017046.

[53] Tang, B.J., Zhou, H.L., Chen, H., Wang, K. and Cao, H., 2017. Investment opportunity in China's overseas oil project: An empirical analysis based on real option approach. *Energy Policy*, *105*, pp.17-26.

[54] Tayem, G., 2018. The determinants of debt maturity: the case of Jordan. *Academy of accounting and financial studies journal*, *22*(1), pp.1-13.

[55] Tong, T., Shah, M., Cherukumalli, M. and Moulehiawy, Y., 2018. Investigating long short-term memory neural networks for financial time-series prediction. *Available at SSRN 3175336*.
[56] Ullah, G.M., Uddin, M., Abdullah, M. and Islam, M.N., 2017. Determinants of capital structure and its impact on the debt maturity of the textile industry of Bangladesh. *Journal of Business and Economic Development*, *2*(1), pp.31-37.
[57] Waqas, H. and Md-Rus, R., 2018. Predicting financial distress: Importance of accounting and firm-specific market variables for Pakistan's listed firms. *Cogent Economics & Finance*, *6*(1), p.1545739.
[58] Yaprak, A., Yosun, T. and Cetindamar, D., 2018. The influence of firm-specific and country-specific advantages in the internationalization of emerging market firms: Evidence from Turkey. *International Business Review*, *27*(1), pp.198-207.
[59] Zhang, K.Q. and Chen, H.H., 2017. Environmental performance and financing decisions impact on sustainable financial development of Chinese environmental protection enterprises. *Sustainability*, *9*(12), p.2260.
[60] Zhou, T., Wang, F. and Yang, Z., 2017. Comparative analysis of ANN and SVM models combined with wavelet preprocess for groundwater depth prediction. *Water*, *9*(10), p.781.
[61] Zuccaro, G. and Leone, M.F., 2018. Building resilient cities: A simulation-based scenario assessment methodology for the integration of DRR and CCA in a multi-scale design perspective. *Procedia Engineering*, *212*, pp.871-878.