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ADVANCING FINANCIAL RISK MODELING: VASICEK FRAMEWORK ENHANCED BY AGENTIC GENERATIVE AI

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ABSTRACT

This paper provides a comprehensive review of the Vasicek model and its applications in finance, categorizing the literature into four key areas: Vasicek model applications, Monte Carlo simulations, negative interest rates and risk, and deep learning for financial time series. To provide deeper insights, a synthesis chart and chronological analysis are included to highlight significant trends and contributions. Building upon this foundation, we employ Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) to generate synthetic future interest rate data. These generated projections are then integrated as inputs into the Vasicek model, dynamically adjusting its parameters with the support of AI-driven synthetic data. Additionally, we propose the use of publicly available financial information, gathered via public-facing large language models (LLMs) like ChatGPT, to assess whether the models project trends in line with real-world data. Specifically, we will query ChatGPT to analyze 50 key questions related to interest rates, risk management strategies, inflation, and economic indicators from institutions like the Federal Reserve and banks. Our approach also leverages publicly available information to refine model outputs, reducing reliance on assumptions and emphasizing the alignment of AI-generated noise with observable market behaviors. By integrating these real-world insights, we aim to ensure that our models remain both innovative and grounded in current economic realities. Ultimately, this framework combines advanced generative AI models, such as GANs and VAEs, with human oversight and economic data, providing a robust, adaptable, and forward-thinking approach to financial risk modeling.

Keywords: GANs, VAEs, Vasicek, GenAI, Financial Risk Modeling.

I. INTRODUCTION

The Vasicek model has long been a cornerstone in financial risk management and interest rate modeling, offering a stochastic framework for capturing the evolution of interest rates. Its applications extend across pricing fixed-income instruments, managing bond portfolios, and assessing risk. Despite its foundational role, traditional Vasicek modeling often relies on Monte Carlo simulations, which, while effective, are limited in their ability to adapt to complex and rapidly evolving market conditions.

Recent advancements in Generative AI (Gen AI) provide a promising avenue for enhancing the flexibility and accuracy of such financial models. Techniques like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) have demonstrated their capability to generate realistic synthetic data, offering new tools to address limitations in traditional modeling approaches. These methods enable dynamic parameterization of models like Vasicek, allowing them to better reflect market behaviors.

In our previous work, we demonstrated the use of GANs and VAEs to generate interest rate data and integrated these outputs into the Vasicek framework. This integration provided a pathway for more adaptive and robust interest rate simulations. Beyond this, we propose incorporating insights from publicly available information using large language models (LLMs) like ChatGPT. By querying these models with structured questions—such as those related to Federal Reserve policies, risk strategies, and economic trends—we aim to assess whether the outputs of our AI-driven models align with real-world data and expectations.

II. LITERATURE REVIEW

The Vasicek model has been widely used in finance for interest rate modeling and risk management [1]. This review paper organizes the literature into four categories and provides a synthesis of key findings. This paper organizes its contributions into four categories: Vasicek model applications, Monte Carlo simulations, the interplay of negative interest rates and risk, and the integration of deep learning for financial time series. By systematically analyzing these areas, we aim to bridge traditional financial models with cutting-edge Gen AI techniques, setting the stage for a more agentic and insightful approach to financial risk management. In table 1

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we have shown our prior work on which this work is build on. While in figure 1, 3 we have shown the synthesis of literature. Figure 2 shows traditional monte carlo paths.

Table 1: Build up on Prior Work

Ref	Contribution
[2]	Reviews Generative AI models and their potential applications in financial risk management, focusing on GPT and LLMs.
[3]	Explores the implementation of Generative AI for enhancing the robustness of the US financial and regulatory system.
[4]	Discusses the synergy between Generative AI and Big Data in the context of financial risk management and reviews recent developments in the field.
[5]	Links to the author's GitHub repository, where various resources on Generative AI and financial risk management are available.
[6]	Reviews the role of data engineering and data lakes in the implementation of Generative AI for financial risk management.
[7]	Analyzes how prompt engineering can be leveraged to improve financial market integrity and risk management through Generative AI.

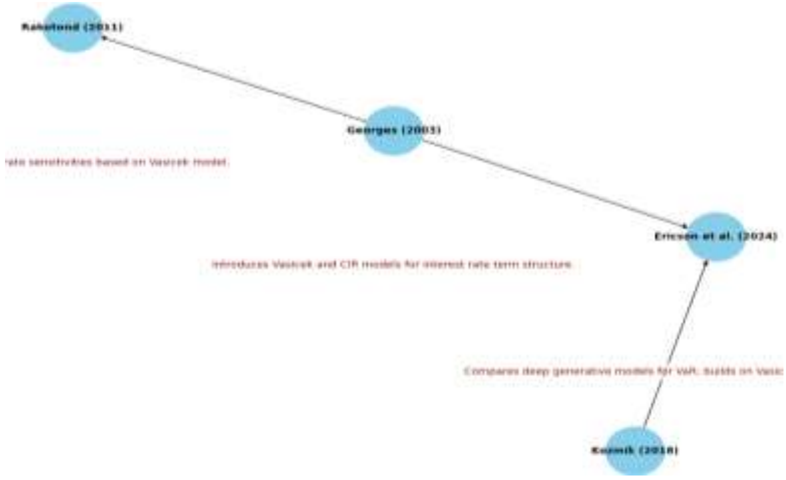

Figure 1: Connected Literature Review

Vaisec model has traditional used historical data, we have shown the past models have used sparse data in table 2 and table 3.

Table 2: Summary of Vasicek Model Applications

Ref	Contribution	Data Used	Innovative Contributions
[1]	Discusses the Vasicek and CIR models in the context of the expectation hypothesis of the interest rate term structure.	Historical interest rate data from global markets.	Novel comparison of Vasicek and CIR models with empirical data.
[8]	Provides an overview of the Vasicek interest rate model.	Literature-based analysis.	A comprehensive survey of the model's usage across multiple financial markets.
[9]	Introduces a new stochastic duration based on the Vasicek and CIR models.	Simulated datasets for testing assumptions.	Innovative approach to modeling stochastic duration within interest rate frameworks.
[10]	Analyzes interest rate sensitivities	Interest rate data	First attempt at integrating multiple

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	under the Vasicek and Cox-Ingersoll-Ross models.	from bond markets.	interest rate models to assess sensitivities.

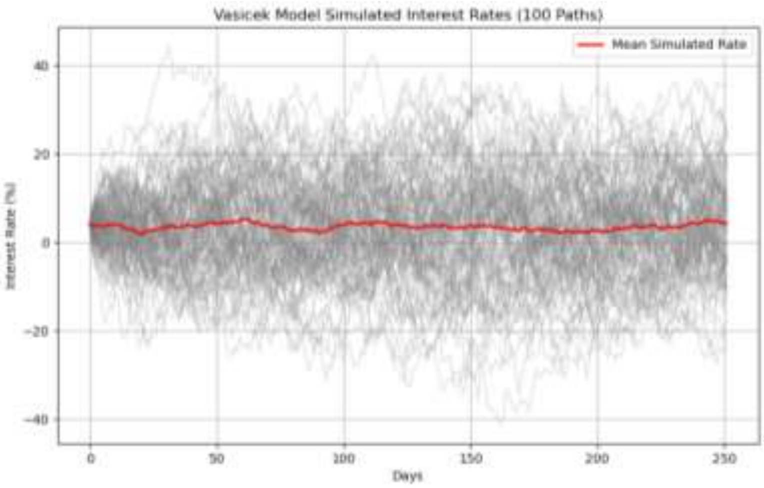

Figure 2: Monte Carlo Paths Generated by Traditional Model

Table 3: Monte Carlo Simulation Studies

Refere	Contribution	Data Used	Innovative Contributions
[11]	Applies Monte Carlo simulation to model Swiss Franc LIBOR using the Vasicek model.	Swiss Franc LIBOR rate data.	Unique application of Monte Carlo methods to foreign exchange interest rate modeling.
[12]	Focuses on parameter estimation for the Vasicek model using Monte Carlo simulation.	Simulated interest rate data.	First detailed Monte Carlo approach for parameter estimation of the Vasicek model.

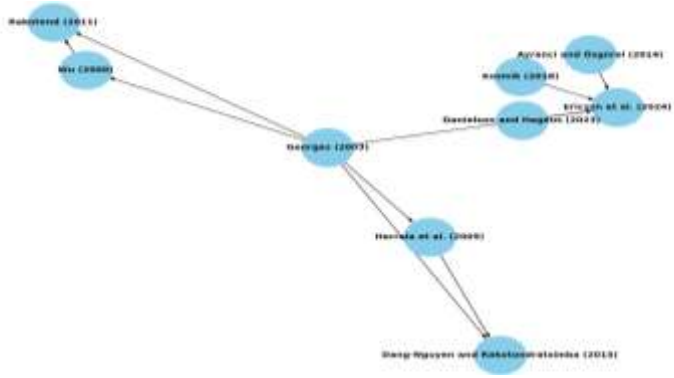

Figure 3: Synthesis of Citation and Literature Review

Table 4 shows Gaps in Vasicek modeling which we have addressed in this work.

Table 4: Gap Analysis in Vasicek Models

Gap	Description	Ref	Citation
Limited empirical validation	Lack of real-world data validation for model parameters.	[1]	Empirical tests are rare in most applications.
Integration with ML	Few studies explore combining machine learning techniques with the Vasicek model.	[1]	Model combinations are underexplored in practice.
Negative rates modeling	Limited research on handling negative interest rates effectively.	[13]	Few studies handle negative rates directly in Vasicek-type models.

III. BUILDING ON PAST WORK

Generative AI (GenAI) has increasingly found applications in various sectors, especially in financial risk management. The integration of large language models (LLMs) such as GPT models and Google Gemini is transforming methodologies in financial decision-making. Building on the extensive research by Joshi and colleagues, our proposed work leverages these advancements to further enhance financial risk modeling.

Joshi's research highlights the growing synergy between GenAI and financial risk management. In a recent study [2], the potential of GenAI models for improving financial risk analysis was explored. This paper emphasized the necessity for human oversight when fine-tuning financial risk models with proprietary datasets. The proposed work extends this concept by incorporating human oversight not only for model evaluation but also for validating outputs generated by VAEs, GANs, and Monte Carlo simulations.

Furthermore, Joshi's investigation into the robustness of US financial systems using GenAI models [3] demonstrates the potential of LLMs, such as ChatGPT-4 and Google Gemini, in improving regulatory compliance and assessing risk. Our framework aligns with these findings by integrating public-facing LLMs to query publicly available financial data. By analyzing 50 questions on interest rates, risk management strategies, and inflation trends, we aim to validate and refine the synthetic data generated by our generative models, ensuring alignment with real-world trends and expectations.

Moreover, Joshi's work on the synergy between GenAI and Big Data [4] underscores the importance of modern data platforms in optimizing AI-driven systems. Inspired by this, we propose to use synthetic data in conjunction with these platforms to feed the Vasicek model, dynamically adjusting its parameters based on AI-generated insights.

Finally, Joshi's research on prompt engineering [7] demonstrates how optimized prompts can improve the relevance and accuracy of AI-generated insights. Our proposed framework incorporates this by using carefully constructed queries to maximize the utility of public-facing LLMs like ChatGPT in validating model outputs and fine-tuning the noise introduced by generative methods. By doing so, we aim to bridge the gap between synthetic data generation and practical, real-world applications in financial risk modeling.

IV. PROPOSED AGENTIC GEN AI ARCHTECTURE

This paper proposes an agentic Generative AI (Gen AI) framework to enhance financial risk modeling by integrating traditional methods, such as the Vasicek model, with cutting-edge generative techniques and insights from publicly available data sources. In our approach to generating synthetic financial data for risk modeling, we leverage advanced Generative AI (Gen AI) techniques, specifically comparing Variational Autoencoders (VAE), Generative Adversarial Networks (GANs), and Monte Carlo methods. These models aim to simulate interest rate data and assess their efficacy in generating realistic financial behaviors that align with actual economic trends.

Our methodology involves generating future interest rate projections using GANs and VAEs. These projections are then integrated as inputs into the Vasicek model, allowing us to dynamically adjust the parameters based on AI-driven synthetic data. Furthermore, we plan to compare the outputs of these models to determine which method best represents market conditions.

To enhance the realism and relevance of our approach, we propose using publicly available information through public-facing large language models (LLMs) like ChatGPT. Specifically, we will query ChatGPT to gather insights from the Federal Reserve and banks by analyzing 50 questions related to interest rates, risk management strategies, inflation, and other economic indicators. By comparing the model outputs with this real-world data, we aim to assess whether our synthetic data aligns with actual trends and expectations.

In addition, we propose utilizing publicly available information to fine-tune model outputs, reducing reliance on assumptions and instead focusing on aligning AI-generated noise with observed market behaviors. By integrating real-world insights into the process, we ensure that the models remain grounded in current financial realities while maintaining the flexibility and adaptability of synthetic data generation.

Ultimately, our approach combines cutting-edge generative models with real-world insights, providing a robust framework for financial risk modeling that is both innovative and aligned with economic conditions.

The proposed approach involves the following key components:

1. Generating Synthetic Interest Rate Data

- We aim to utilize advanced Gen AI models, specifically Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs), to simulate future interest rate trajectories.
- These models will generate synthetic data representing realistic market behaviors, which will then be used as dynamic inputs for the Vasicek model to adjust key parameters such as mean reversion, volatility, and equilibrium rates.

2. Integrating Generative Models with Traditional Frameworks

- By incorporating AI-generated data into the Vasicek model, we propose dynamically adjusting model parameters, effectively blending traditional stochastic methods with AI-driven insights.
- This integration aims to simulate more robust and adaptive financial time series that reflect real-world complexities.

3. Leveraging Public Data Through Large Language Models

- We propose querying public-facing Large Language Models (LLMs) such as ChatGPT to gather insights from publicly available data, including reports from the Federal Reserve and banks.
- Specifically, we will analyze 50 questions related to interest rates, risk management strategies, inflation trends, and other economic indicators. These insights will serve to validate and fine-tune AI model outputs.

4. Comparative Analysis of Generative Models

- We will perform a comparative study of VAE, GAN, and Monte Carlo methods, evaluating their ability to simulate realistic financial behaviors and trends.
- This comparison will provide insights into the efficacy and limitations of each method in generating synthetic data for risk modeling.

5. Human Oversight and Feedback

- The final outputs of the generative models and the Vasicek model will be validated against real-world financial data, with human oversight ensuring accuracy and relevance.
- The proposed framework aims to combine generative AI methods, traditional models, and human expertise to produce a holistic and adaptable approach to financial risk modeling.

V. RESULTS AND DISCUSSION

We have shown the results through many charts in this section. Figure 4 and 5 shows a single path of the monteo Carlo Simulation for traditional Vasicek along with synthetic data. Figure 6 and 7 discuses the model implementation and the architecture. We observe that syn ethic data is rather less volatile than a randomly picked monte carlo path.

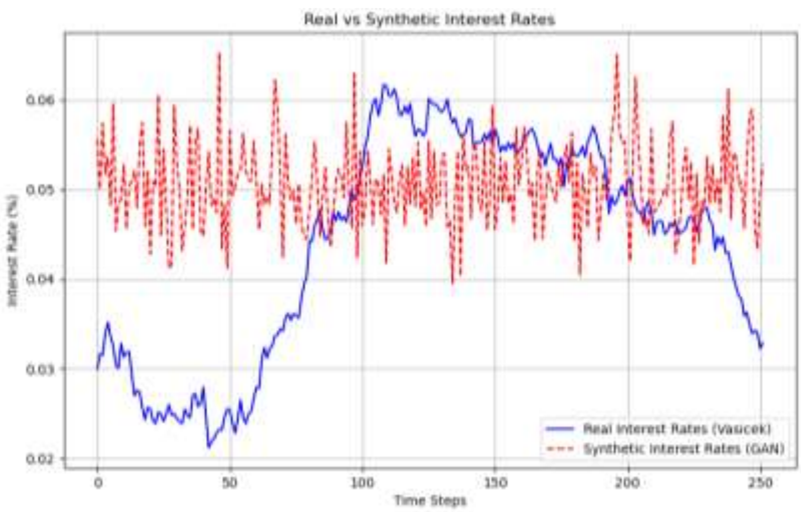

Figure 4: Real (single path) vs Synthetic for GANs

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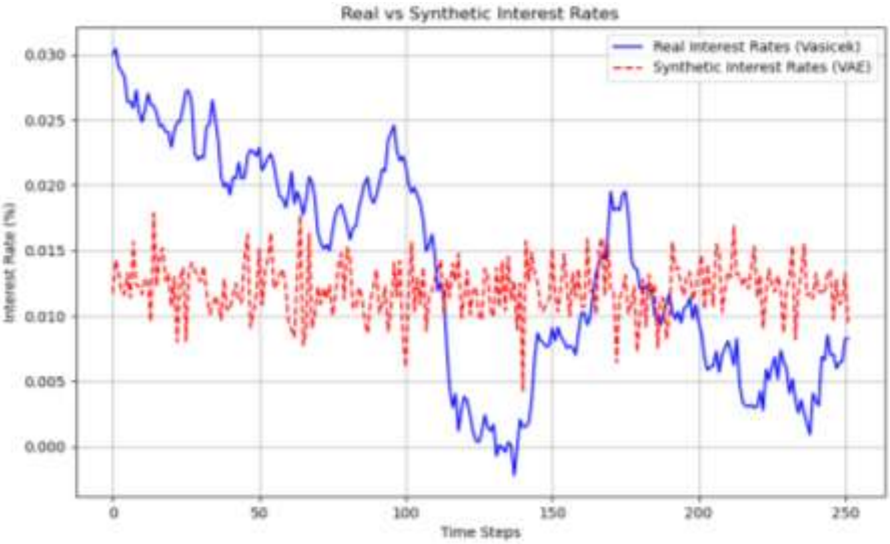

Figure 5: Real (single path) vs Synthetic for VAEs

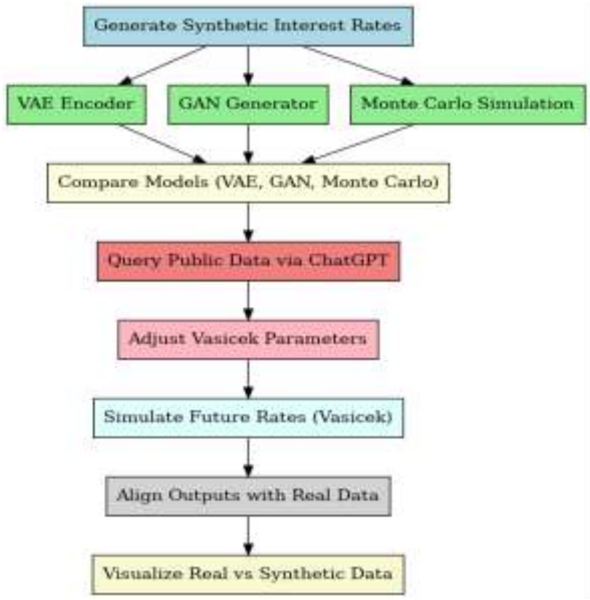

Figure 6: Model Implementation for Gen AI enhanced Vasicek

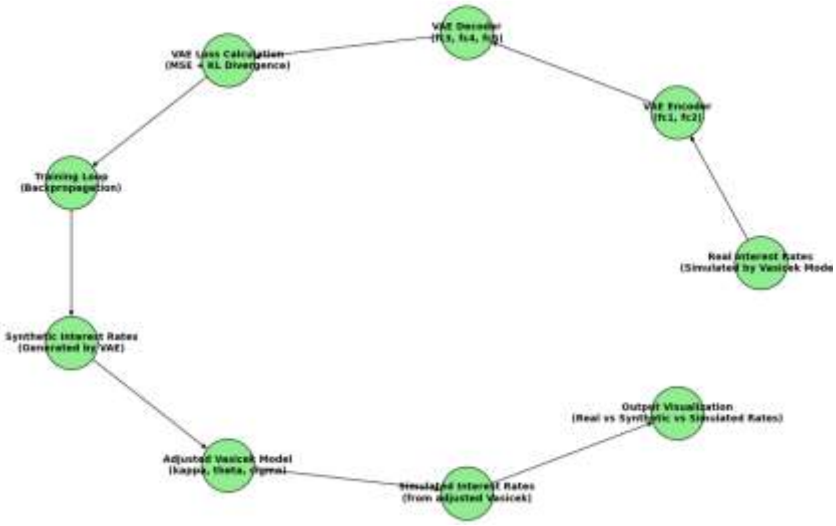

Figure 7: Architecture for the Model

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Below is extracted from the Python code to explain the model flow.

PSUEDO CODE

1. Define Vasicek model simulation function:

- Input: time step (dt), total time (T), kappa, theta, sigma, initial rate (r0)
- Initialize an array for rates with size N (number of time steps)
- Set initial rate (r0)
- For each time step:
- Calculate the change in rate (dr) using Vasicek model formula
- Update the rate array with the new value
- Return simulated interest rates

2. Define VAE Model (Encoder-Decoder architecture):

- Encoder:
- Fully connected layer to transform input to hidden representation
- Fully connected layer to output mean (mu) and log-variance (logvar)
- Reparameterization:
- Sample latent variable z from a normal distribution using mu and logvar
- Decoder:
- Fully connected layers to decode z and generate the reconstructed interest rate
- Output: Reconstructed rate, mu, logvar

3. Define VAE loss function:

- Calculate reconstruction loss (Mean Squared Error between real and predicted rates)
- Calculate KL divergence between learned distribution (mu, logvar) and unit Gaussian
- Return total loss as sum of reconstruction loss and KL divergence

4. Train VAE:

- For each epoch:
- Split real data into batches
- For each batch:
- Zero gradients
- Perform forward pass to get reconstructed rates, mu, logvar
- Calculate total loss
- Perform backpropagation to optimize VAE parameters
- Repeat for specified number of epochs

5. Generate synthetic data:

- Sample random latent variables from standard normal distribution
- Pass latent variables through decoder to generate synthetic interest rates
- Return synthetic rates

6. Simulate future rates with adjusted volatility:

- Input initial rate (r0), Vasicek parameters (kappa, theta), and volatility from VAE
- For each time step:
- Use adjusted volatility to calculate the rate change (dr)
- Update the rate array
- Return the simulated rates with adjusted volatility

VI. CONCLUSION

This review highlights the diverse applications of the Vasicek model in finance, from interest rate modeling to risk management and deep learning. Future research could explore the integration of machine learning techniques with traditional financial models. In conclusion, the integration of Generative AI (Gen AI) with traditional financial models, such as the Vasicek framework, holds significant promise for enhancing financial risk modeling. By leveraging advanced techniques like Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), this research has demonstrated the potential for more adaptive and accurate financial simulations. The incorporation of publicly available data, sourced from large language models (LLMs) like ChatGPT, further improves model outputs by aligning synthetic data with real-world financial trends and expectations.

The proposed approach not only enhances the flexibility of the Vasicek model but also reduces reliance on assumptions, ensuring that financial models better reflect current market dynamics. By combining AI-driven synthetic data with human oversight and economic data, we provide a more robust, innovative, and adaptable framework for financial risk management. This research paves the way for the continued evolution of financial modeling, offering more precise tools for assessing risks in an increasingly complex and unpredictable financial landscape. Ultimately, this fusion of generative AI with traditional financial theory represents a groundbreaking step toward improving decision-making and regulatory compliance in the financial industry.

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