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Yosuke Fukunishi
Graduate School of Economics, University of Tokyo

Haorong Qiu
Graduate School of Economics, University of Tokyo

Akihiko Takahashi
Graduate School of Economics, University of Tokyo

Fan Ye
Graduate School of Economics, University of Tokyo

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Generating the Term Structure of Interest Rates with Diffusion Models

Yosuke Fukunishi[1], Haorong Qiu[1], Akihiko Takahashi[1], and Fan Ye[1]

[1]Graduate School of Economics, University of Tokyo

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Abstract

This study introduces a novel generative modeling framework for simulating the term structure of interest rates. In recent years, generative models have achieved significant progress in image generation and are increasingly being applied to finance. To the best of our knowledge, this is the first study to apply a generative model—specifically, a diffusion model—to the term structure of interest rates. Furthermore, we extend the framework to incorporate conditional generation mechanisms and v-parameterization. The training dataset consists of spot yield curves constructed from daily overnight index swap (OIS) rates using cubic Hermite splines. As base conditioning variables, we use short-term interest rates and changes in consumer price indexes (CPIs). Empirical analysis covering the period from 2015 to 2025 demonstrates that our model successfully reproduces the level and shape of yield curves corresponding to historical macroeconomic conditions and short-term interest rate environments. Additionally, when incorporating further conditioning variables related to quantitative easing policies, monetary base, current account balances, and nominal gross domestic product (GDP), we find that the inclusion of quantitative easing indicator notably enhances the model's output relative to the base conditioning case. This suggests improved robustness and representational capacity under expanded conditioning.

Keywords: Machine Learning, Generative Models, Diffusion Models, Term Structure of Interest Rates, Yield Curve, Financial Time Series

1 Introduction

Generative models have experienced rapid growth in recent years, particularly within corporate environments over the past one to two years. However, their application in data-intensive domains—such as investment decision-making and risk management—remains in its early stages, though it holds considerable promise for future development. Against this backdrop, research into synthetic data generation in finance using generative models has begun to gain momentum. In this study, we focus on generating interest rate data—a topic that has received limited attention in prior research—and propose a method for constructing synthetic term structures of interest rates using diffusion models.

The foundation for the development of diffusion models was laid by Ho et al.[1], catalyzing rapid advancements in the field. For the implementation of synthetic data generation in this study, we incorporate two key technical innovations in diffusion modeling: conditional generation with cross-attention mechanisms and v-parameterization. The former was introduced by Rombach et al.[3], while the latter was proposed by Salimans and Ho[4]. These techniques have been widely adopted in the primary application areas of diffusion models, such as image and video generation.

Prior studies on synthetic data generation in finance using diffusion models include Chen et al. [5] , which targets multivariate time series, and Tanaka et al.[6], which transforms time series into images for conditional training. However, these studies primarily focus on stock price time series. To the best of our knowledge, no prior work has addressed the term structure of interest rates in the context of diffusion-based synthetic data generation. Moreover, among the studies in finance reviewed in this section, none appear to have explicitly implemented v-parameterization. Therefore, our work is also distinctive in its use of v-parameterization for synthetic data generation.

The remainder of this paper is organized as follows. Section 2 provides an overview of diffusion models and discusses their technical advancements. Section 3 introduces our proposed methodology for preparing yield curves as training data and conditional generation of the term structure of interest rates using diffusion models. In Section 4, we present the results of conditional generation based on conditioning data from specific historical periods, demonstrating that the inclusion of conditioning variables enables the model to produce yield curves that closely resemble historical scenarios. Finally, Section 5 concludes the paper by examining practical implications and potential applications, and by outlining directions for future research.

2 Diffusion Models

Diffusion models have emerged as a powerful class of generative frameworks, particularly effective in modeling complex data distributions through iterative denoising processes and their application to finance has also been proposed. The field of diffusion models has experienced significant growth since the publication of the Denoising Diffusion Probabilistic Model(DDPM) introduced by Ho et al.[1]. The following provides an overview of DDPM.

Let $\mathbf{x}_0 \in \mathbb{R}^d$ be a sample drawn from an unknown data distribution characterized by the probability density function $p(\mathbf{x})$. In the context of generative modeling, we aim to approximate $p(\mathbf{x})$ using a model $p_\theta(\mathbf{x})$, parameterized by θ and then generate new samples by sampling from $p_\theta(\mathbf{x})$.

Since DDPM has developed from diffusion models, it is defined as a latent variable model. In this context, let $\mathbf{x}_0$ represent sample data and assume latent variables $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T$ of the same dimension as the sample data.

An interesting aspect of DDPM lies in its formulation of the forward process, a Markov chain with Gaussian noise as follows:

$$\{\mathbf{x}_t\}_{t=1}^T, \quad \mathbf{x}_t = \sqrt{1-\beta_t}\mathbf{x}_{t-1} + \sqrt{\beta_t}\epsilon, \quad \epsilon \sim \mathcal{N}(0, I), \tag{1}$$

where $\mathcal{N}(\mu, \Sigma)$ denotes a normal distribution with mean μ and variance-covariance matrix Σ. In this explanation, the variance schedule$\beta_1 \dots \beta_t$ are treated as a hyperparameter and assumed to be set to known values, satisfying $0 < \beta_1 < \beta_2 < \dots < \beta_T < 1$.

Furthermore, by defining forward process as equation (1), when T is sufficiently large (e.g., $T = 1000$), $\mathbf{x}_T$ can be regarded as pure noise (i.e., $\mathbf{x}_T \sim \mathcal{N}(0, I)$).

According to Ho et al.[1], it is shown that the reverse process which traces the forward process in reverse order to progressively remove noises, is also a Markov chain with Gaussian transition probability and that the reverse process can be expressed as follows:

$$\{\mathbf{x}_t\}_{t=1}^{T}, \quad \mathbf{x}_{t-1} = \mu_\theta(\mathbf{x}_t, t)\mathbf{x}_t + \sqrt{\beta_t}\epsilon, \quad \epsilon \sim \mathcal{N}(0, I). \tag{2}$$

Then, given equation (2), we estimate $\mu_\theta(\mathbf{x}_t, t)$. This estimation can be performed by a neural network architecture such as U-Net, enabling the learning of the reverse process. As explained by Ho et al.[1], instead of estimating $\mu_\theta(\mathbf{x}_t, t)$,the reverse process can also be learned with a model that predicts the added noise $\epsilon_\theta(\mathbf{x}_t, t)$ given $\mathbf{x}_t$ and timestep t. This approach to learning the noise is referred to as *noise prediction.*

When performing sampling, we assume the initial value for the reverse process $\mathbf{x}_T \sim \mathcal{N}(0, I)$ so that $\mathbf{x}_T$ can be easily generated as a random vector. Then, by following the learned reverse process to progressively remove the noise, a sample can be obtained. This is the core idea behind DDPM.

Since the introduction of DDPM, theoretical advancements in diffusion models have included the unification with score-based models and the formulation of both the forward and reverse processes using continuous-time stochastic differential equations (SDEs),introduced by Song et al.[2]. Within this continuous-time SDE framework, the forward process in DDPM is represented as a stochastic process following the Ornstein-Uhlenbeck (OU) process, while the reverse process is expressed through an SDE derived from the relationship between the Kolmogorov forward and backward equations.

On the implementation side, one major advancement is conditional generation using cross-attention mechanisms, introduced by Rombach et al.[3], which enables image generation from words by connecting diffusion models with language models. Furthermore, to generate larger images more efficiently, techniques such as DDIM and *v-parameterization* proposed by Salimans and Ho[4]—both extensions of noise prediction—have been proposed and are now widely adopted in modern image generation frameworks, including Stable Diffusion v2.

3 Methodology

This paper aims to perform conditional generation of synthetic term structure of interest rate using a diffusion model. The procedure is outlined as follows:

- Step1: Obtain historical swap rates and construct yield curves using methods commonly applied in finance. Based on the constructed yield curves, we construct datasets of zero-rates at quarterly (0.25-year) intervals,which is applied for training data.
- Step2: Obtain the macro economic indicators as condition data to be applied during conditional learning.
- Step3: Prepare a diffusion model that supports conditional generation based on both training data and conditional data.
- Step4: Conduct training and perform conditional generation.

3.1 Data Preparation

3.1.1 Construction of Yield Curve and Interest Rate Dataset

In this study, we assume the simultaneous learning of interest rate data across multiple currencies and define the following requirements for the training interest rate dataset. The target currencies are Japanese Yen (JPY), US Dollar (USD), and British Pound (GBP). Furthermore, the interest rate targeted for training is chosen to be the zero rate used in the valuation of financial instruments, rather than the market-traded rate. Based on these requirements, the dataset is constructed through the following steps:

1. Time series data of OIS rates for each currency are obtained from Bloomberg. For details on the obtained OIS rates, see Appendix A. We collect data from 2010 to 2025. Due to differences in data availability across currencies, the starting dates of the datasets vary. However, in order to maximize the amount of data used for training, we do not align the starting dates and instead included all available data.

2. Since the obtained OIS rates correspond to instruments with annual interest payments, yearly tenor data is required to construct zero rates. However, due to missing market data for certain tenors, standard cubic spline interpolation is applied to generate interpolated OIS rate data for each currency.

3. Zero rates are constructed from the interpolated OIS rates using the bootstrap method for each currency. Additionally, following Healy[8], cubic Hermite spline interpolation is applied to the resulting zero rates. This yielded 120 data points per business day, with maturities ranging from 0.25 to 30 years for each currency.

4. The data for each currency are merged along the tenor axis to form a single training dataset. As a result, a dataset with the shape (11,185, 120) is created. where 11,185 represents the number of observations and 120 corresponds to the number of data points per observation.

3.1.2 Conditional Inputs

We use the following data as conditional inputs for yield curve generation:

Table 1: Condition Data

Data	Description	Update Frequency
Currency type	JPY = 1, USD = 2, GBP = 3	NA
Short-term interest rate	Overnight rate(JPY,GBP) or 1-week OIS rate (USD)	per Business day
Macroeconomic indicators	Inflation rates,and other indicators described in Appendix B	per Month

For details on the obtained condition data, see Appendix B. Although macroeconomic indicators are updated on a monthly basis, we use the indicators displayed on the Bloomberg or LSEG

Datasteram for a given business day directly to construct the dataset. Given that the dimension of the conditional features is X, we construct data with a shape of (11,185, X). Both short-term interest rate and macroeconomic indicators are publicly available and easily accessible, and are selected as conditioning variables ,which seems closely related to formation of the term structure of interest rates. The short-term interest rate is considered to have a direct impact on the short end of the yield curve. Among the components of macroeconomic indicators, inflation rates are regarded as influencing the determination of medium- to long-term interest rate levels and the shape of the yield curve.

3.2 Diffusion Model Setup

After preparation of the training data set, we conduct training using a diffusion model. For the implementation of the model, we refer to the standard diffusion model program utilized in the evaluation of a diffusion factor model in Chen et al.[5][7], and extend it by incorporating additional code to support conditional generation and the v parameterization technique for the estimation object. Although Chen et al.[5] proposes a model to learn latent factors, deploying neural networks defined in (18) of their article, we understand that the program code corresponds to a standard diffusion model implementation, using equation (7) in their paper as the objective function, as stated in Appendix D of Chen et al.[5]. The neural network architecture employed is the 2D U-Net framework, which is widely adopted in diffusion models, its architecture is as follows.
We reshape the data from a one-dimensional vector of length 120 into a two-dimensional matrix of size (10, 12). The resulting (10, 12) matrices are then processed using a 2D U-Net architecture consisting of two downsampling layers, one intermediate layer, and two upsampling layers. To implement conditional learning and sampling, we incorporate cross-attention layers into the intermediate stages of the U-Net framework according to Rombach et al. [3]. This adaptation enables the model to effectively utilize macro-level data—which strongly influences the shape of yield curves.

For the training hyperparameters, we use the cosine schedule for the beta schedule. The number of training steps is set to 1000, following the DDPM approach.

3.3 Model Training and Synthetic Yield Curve Generation

We train the model for 200 epochs using both interest rate data and conditional macroeconomic inputs. The training is carried out on a commercial GPU (Geforce 5070) and completed in approximately 30 minutes, demonstrating its practical feasibility. Synthetic yield curves are generated conditionally based on macroeconomic indicators using the trained model. The input conditional data must match the dimensionality of the features used during training. For example, if the model is trained with currency, short-term interest rates, and inflation rates as conditioning variables, then the scenarios should be provided as a array of shapes (1, 3). Each sample is generated in 1,000 time steps. The generation of 1,024 synthetic samples per condition takes approximately 90 seconds on the same GPU.

4 Results

This section discusses the analysis of the outputs generated by the trained model. To analyze the impact of conditioning data on generation, we train multiple models using different conditioning inputs and conduct a comparative analysis of their generated outputs. In this comparison, conditioning data from specific historical periods are used as inputs, and we also verify their consistency with the corresponding historical data.

4.1 Impact of Conditional Inputs

First, we choose a model conditioned on currency, short-term interest rates, and inflation rates as the baseline model for our experiment. To assess the impact of conditional input, we prepare three models that incrementally add each condition data. The description of each model is summarized in Table 2.

Figure 1 compares the yield curves generated by each model using the conditional data from April 2015 with the actual yield curve observed in April 2015. To align with the monthly historical data, 30 samples are generated. Each colored line represents the sampled yield curve. The results indicate that the model adapts effectively to different scenarios, producing curves that reflect the specified economic conditions.

Table 2: Definition of Models in figure 1

Model Name	Shape of Condition Inputs
CUR	(Currency)
ST Rate	(Currency , Short-Term interest Rates)
Baseline	(Currency , Short-Term interest Rates, Inflation Rates)

4.2 Empirical Comparison with Historical Data

To evaluate the accuracy of our baseline model, we compare synthetic yield curves generated under the conditions of a short-term interest rate and an inflation rate for a given historical month with the actual yield curves from that same period. Since short-term interest rates are available as daily data, we use the monthly average as an input condition. The number of generated samples is 30 samples, which is determined based on the number of days in each month. Given that there are three currencies, three comparisons are conducted for each month.

The comparison results for JPY interest rates are shown in Figure 2, those for USD interest rates are presented in Figure 3, and for GBP interest rates are in Figure 4. In Figures 2 through 4 , for better visual clarity, we calculate the mean and standard deviation of the generated yield curves under each condition, and visualize them using the mean ± 1 standard deviation bands. These are then compared with the corresponding mean and standard deviation of the historical yield curves.

This approach enabled us to clearly assess how closely the model could reproduce key characteristics of the yield curve, especially level, slope, and curvature, under specified macroeconomic conditions. While greater variance is observed during periods of extreme monetary policy (e.g., 2020), the generated curves generally capture the level, slope, and curvature of historical data. Focusing on the results for USD and GBP in 2025, it can be observed that the model is capable of reproducing not only normal yield curves but also inverted ones, confirming the model's ability to reproduce realistic yield curve shapes under standard macroeconomic conditions.

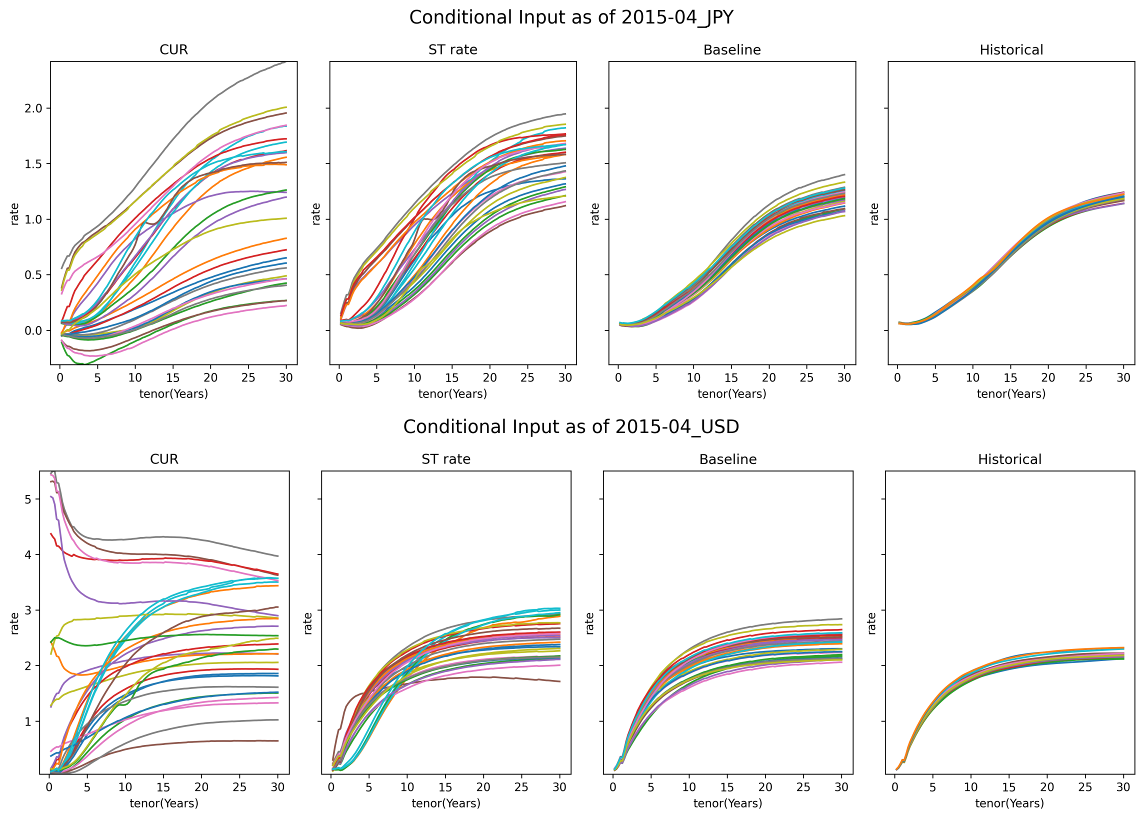

Figure 1: Comparison of generated and historical yield curves by adding conditions

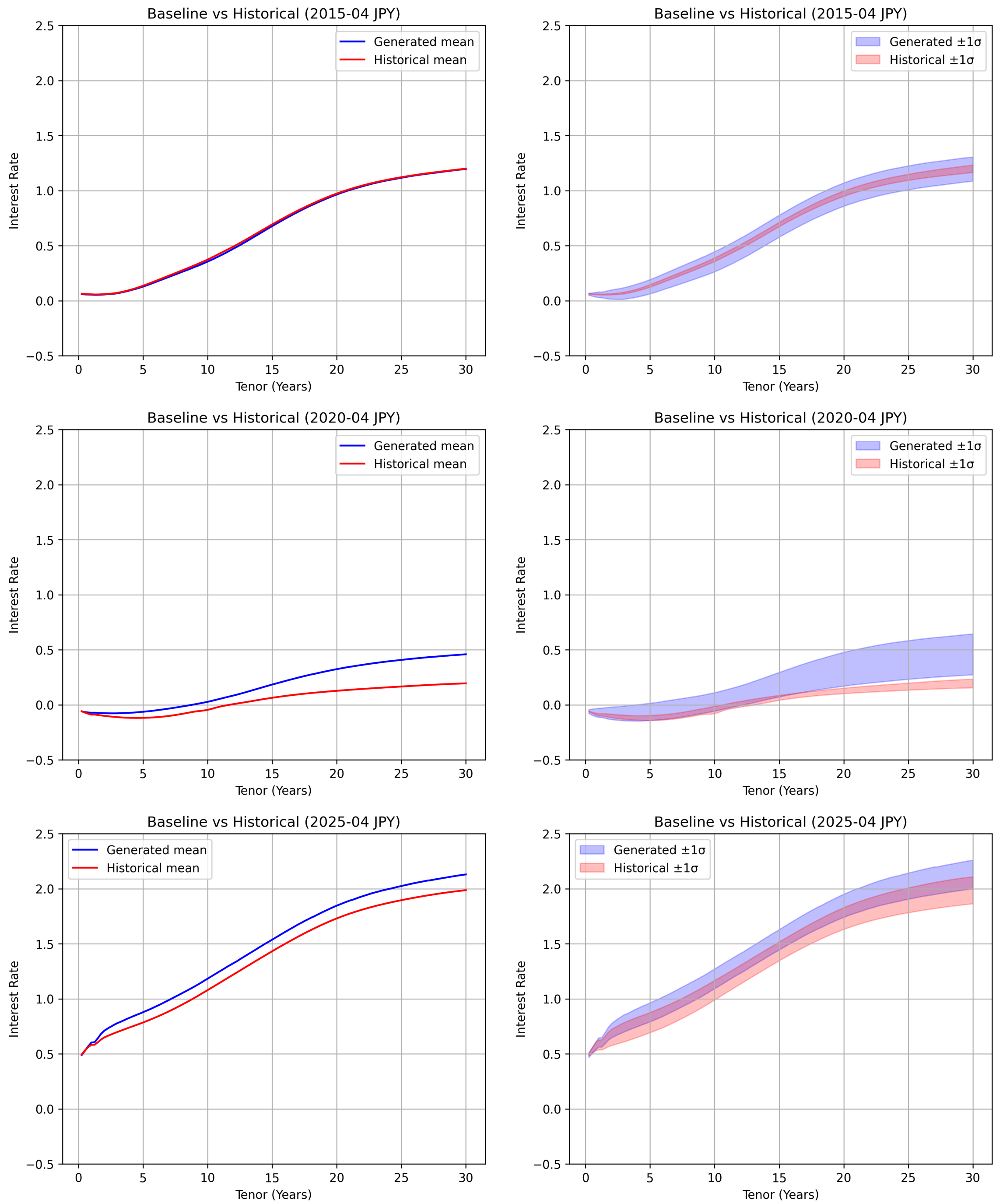

Figure 2: Comparison between generated sample and historical data: JPY

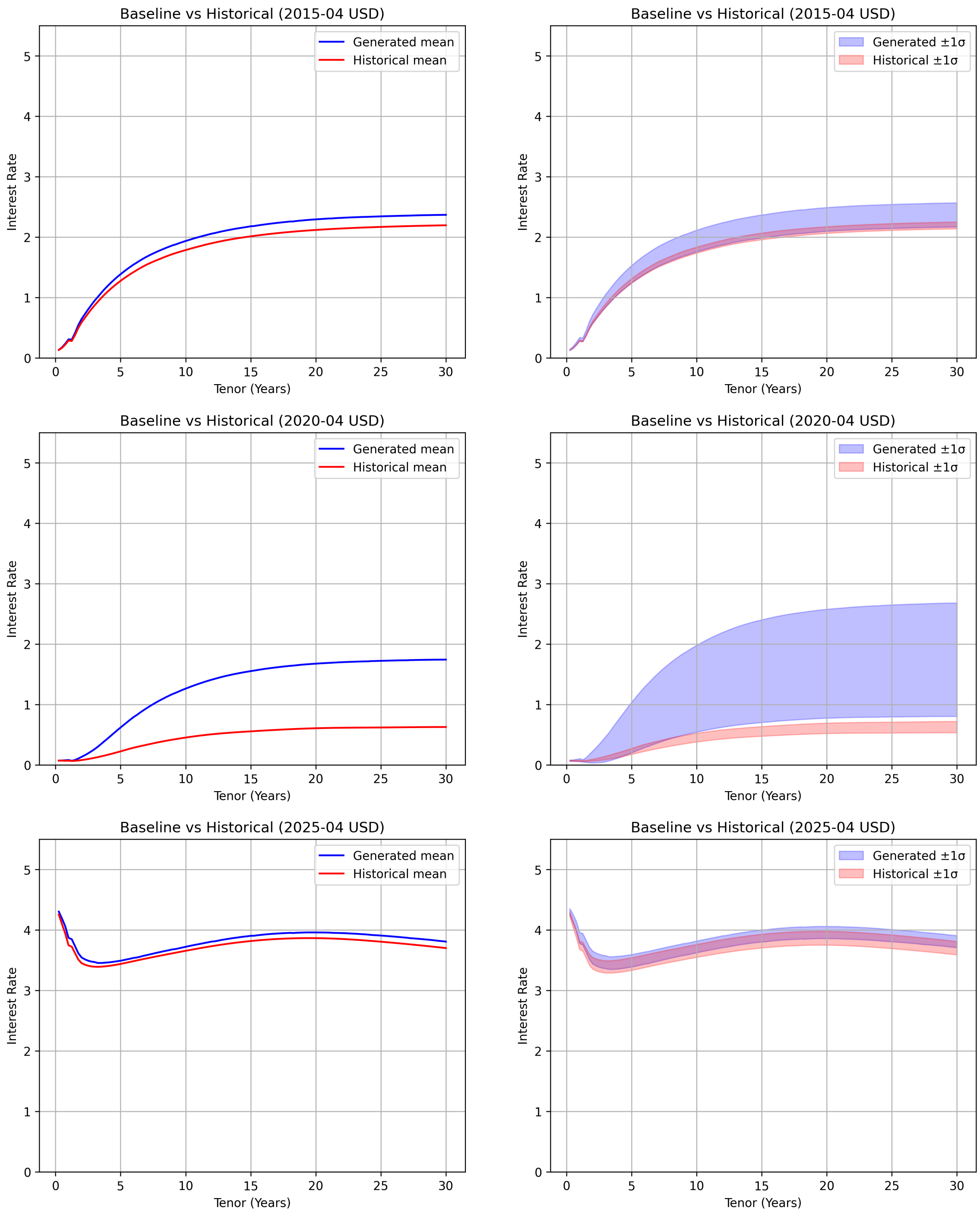

Figure 3: Comparison between generated sample and historical data: USD

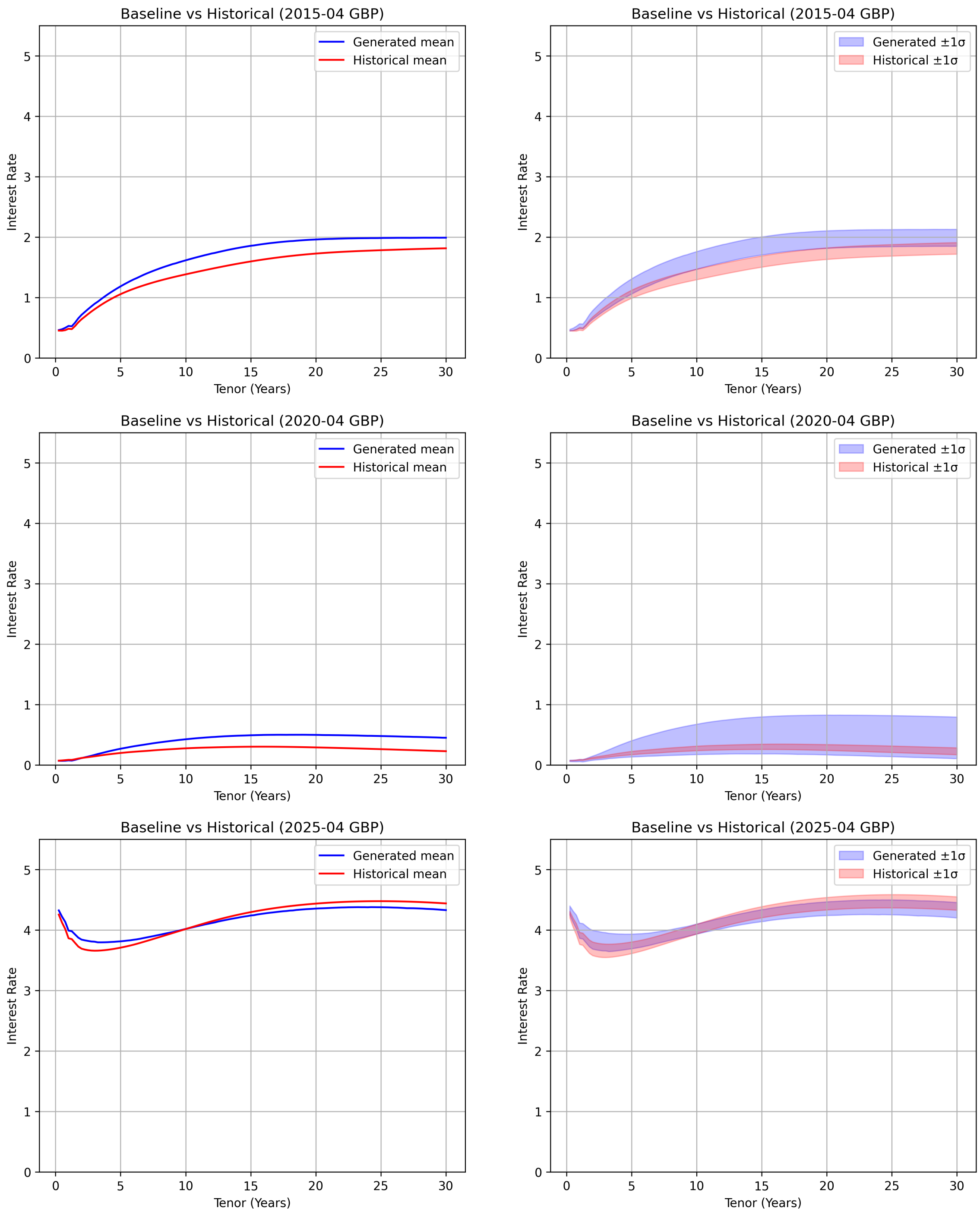

Figure 4: Comparison between generated sample and historical data: GBP

4.3 Further Analysis with Additional Macroeconomic Indicators

We further examine the incorporation of additional macroeconomic indicators into the baseline condition set(currency,short-term interest rates, and inflation rates) to capture broader structural features across different periods and market environments.

To better capture the extreme monetary policies in 2020, we introduce (i)the quantitative easing (QE) indicator specifically referring to the year-over-year (YoY) growth of the asset purchase amounts by each country's central bank, or proxy variables thereof. The exact definitions of the indicators are provided in Appendix B. For this dataset, we use LSEG Datastream and publicly available figures from each central bank as data sources.

In addition to the QE indicator, we consider indicators as follows: (ii) monetary base YoY growth, reflecting the intensity of monetary expansion, (iii) the current account balance to GDP ratio, and (iv) nominal GDP. Similarly to the QE indicator extension, these indicators are incorporated separately and simultaneously into the baseline condition set for model training and sample generation.

To assess the effect of these additional macro conditions, we evaluate the yield curves generated under the specified conditions by computing (i) the root mean square error (RMSE) between the generated and historical yield curves for each currency in representative months, and (ii) the maximum standard deviation (σ) across the samples generated, which reflects the dispersion and stability of the generation. The numerical results under different conditioning sets are summarized in Table 3 to Table 5. The results suggest that, for different time periods and currencies, augmenting the baseline conditioning set with an additional indicator that is relevant to the prevailing macro-financial environment can further improve the quality of the generated samples.

4.4 Enhancement with Additional Macro Economic Indicators as Conditions

As a result of RMSE comparison tests conducted with the addition of various macroeconomic indicators, it is found that the inclusion of the QE indicator and monetary base (QE+MB) for JPY and the inclusion of the QE indicator, the monetary base and the ratio of current account to GDP (QE + MB + CA% GDP) for USD and GBP is particularly effective in reproducing historical data. Based on this finding, an enhanced model is developed by adding these conditional data to the conditions of the baseline model and training it accordingly, followed by the generation of sample data.

Figures 5 to 7 present a graphical comparison between the generated samples and the historical data. The results generated by the enhanced model demonstrate superior reproducibility of historical data compared to those generated by other models. In particular, there is a significant improvement in reproducibility for the year 2020, which had been a challenge for the baseline model.

These findings indicate that the proposed method enhances the reproducibility of historical data by selecting and adding conditional models. In practical applications, depending on the intended use of synthetic data, different approaches may be considered: for cases requiring strict reproducibility of historical data, generation using the model with added conditional data is recommended; on the contrary, when a certain degree of flexibility in synthetic data is desirable, for example, in stress testing, generation using the baseline model may be more appropriate.

Table 3: RMSE and maximum standard deviation of generated yield curves under different conditioning sets (JPY). Values are reported as RMSE (basis points) with maximum standard deviation (percentage) in parentheses.

Conditions	2015-04	2020-04	2025-04
Historical	0.0 (0.03)	0.0 (0.04)	0.0 (0.12)
Baseline	1.1 (0.11)	16.1 (0.19)	10.9 (0.13)
Baseline+QE	0.7 (0.08)	9.2 (0.19)	1.8 (0.11)
Baseline+MB	3.2 (0.07)	2.7 (0.06)	2.9 (0.15)
Baseline+CA%GDP	0.5 (0.04)	2.5 (0.08)	10.8 (0.13)
Baseline+NOMGDP	3.1 (0.09)	10.4 (0.19)	11.4 (0.12)
Baseline+QE+MB	1.0 (0.07)	1.6 (0.05)	0.4 (0.10)
Baseline+QE+MB+CA%GDP	1.3 (0.06)	1.0 (0.05)	11.5 (0.13)
Baseline+QE+MB+NOMGDP	2.2 (0.08)	1.5 (0.06)	1.2 (0.11)
Baseline+QE+MB+CA%GDP+NOMGDP	2.5 (0.07)	0.5 (0.04)	4.6 (0.11)

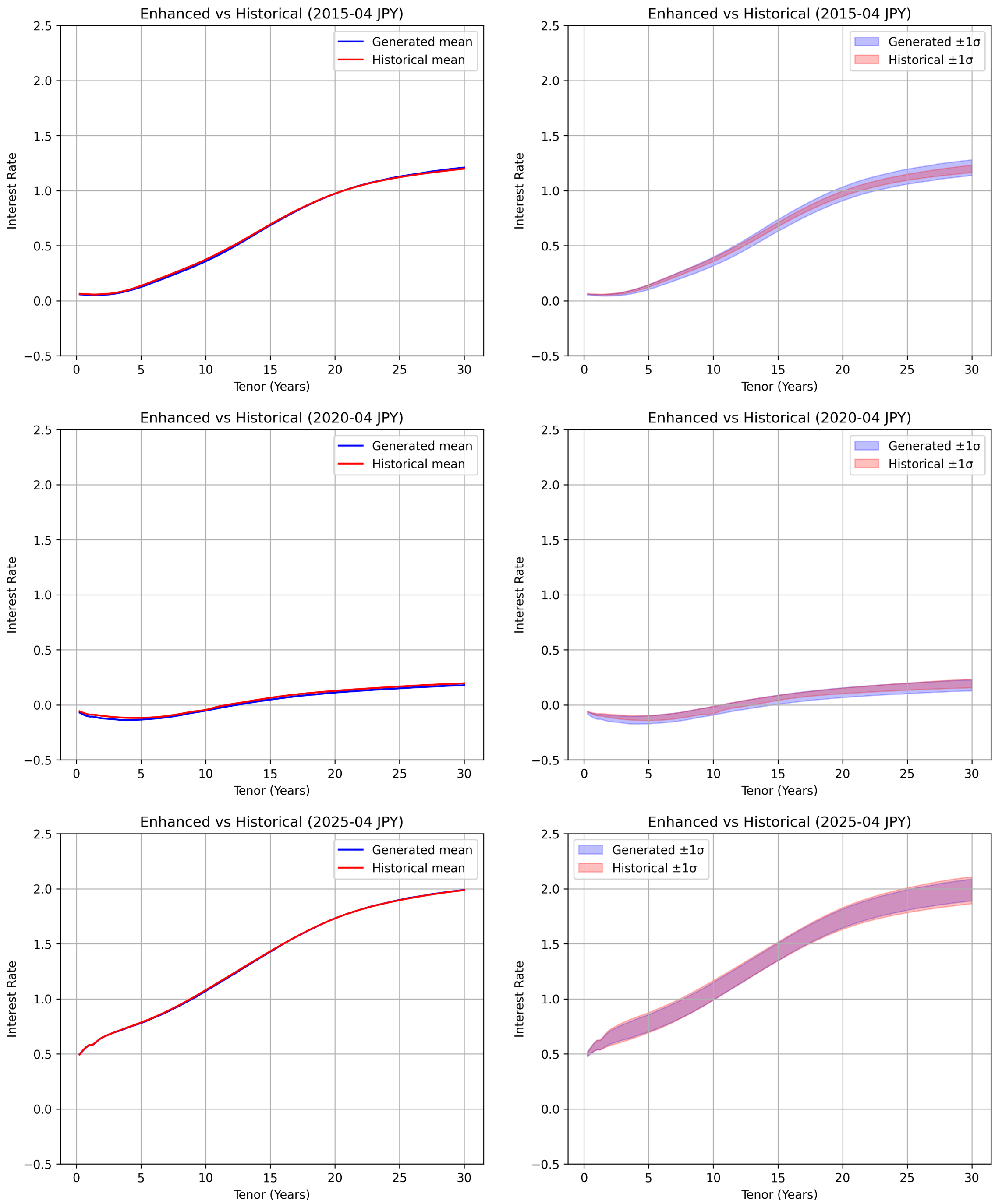

Figure 5: Enhancement with additional condition inputs: JPY

Table 4: RMSE and maximum standard deviation of generated yield curves under different conditioning sets (USD). Values are reported as RMSE (basis points) with maximum standard deviation (percentage) in parentheses.

Condition	2015-04	2020-04	2025-04
Historical	0.0 (0.06)	0.0 (0.09)	0.0 (0.11)
Baseline	15.2 (0.20)	89.6 (0.94)	8.7 (0.11)
Baseline+QE	15.3 (0.19)	1.9 (0.08)	4.9 (0.11)
Baseline+MB	9.7 (0.12)	33.1 (0.85)	6.0 (0.11)
Baseline+CA%GDP	13.4 (0.20)	207.7 (0.93)	9.1 (0.11)
Baseline+NOMGDP	14.3 (0.17)	45.8 (0.51)	7.0 (0.15)
Baseline+QE+MB	5.8 (0.11)	0.9 (0.07)	4.6 (0.10)
Baseline+QE+MB+CA%GDP	3.8 (0.10)	1.0 (0.08)	1.3 (0.10)
Baseline+QE+MB+NOMGDP	11.4 (0.14)	1.8 (0.09)	8.9 (0.13)
Baseline+QE+MB+CA%GDP+NOMGDP	9.1 (0.12)	1.0 (0.08)	8.5 (0.11)

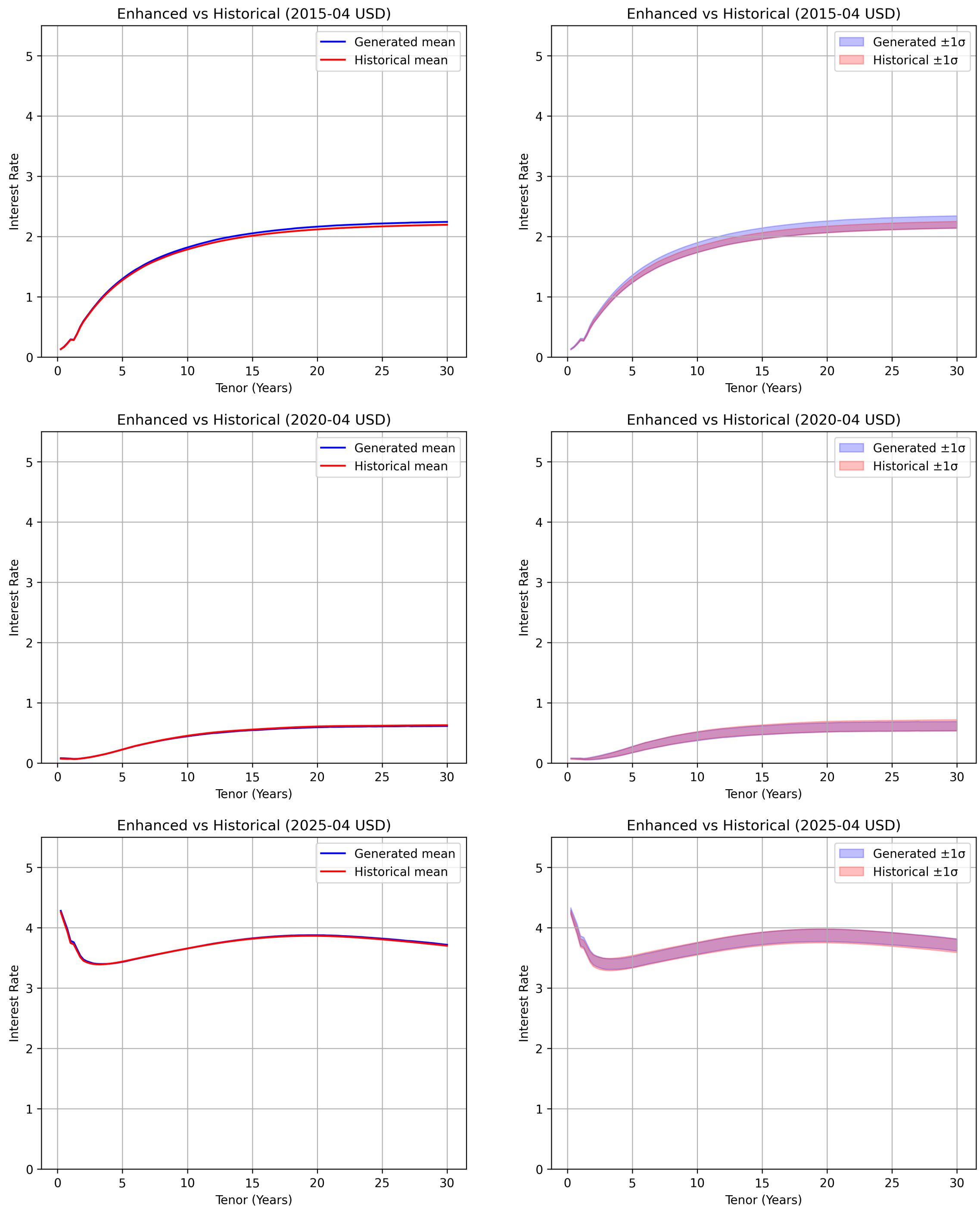

Figure 6: Enhancement with additional condition inputs: USD

Table 5: RMSE and maximum standard deviation of generated yield curves under different conditioning sets (GBP). Values are reported as RMSE (basis points) with maximum standard deviation (percentage) in parentheses.

Condition	2015-04	2020-04	2025-04
Historical	0.0 (0.10)	0.0 (0.06)	0.0 (0.11)
Baseline	20.5 (0.15)	17.3 (0.34)	8.8 (0.16)
Baseline+CA%GDP	22.8 (0.19)	1.5 (0.06)	7.0 (0.14)
Baseline+NOMGDP	18.7 (0.16)	23.5 (0.38)	13.2 (0.14)
Baseline+QE	20.4 (0.17)	0.4 (0.06)	2.3 (0.11)
Baseline+MB	11.3 (0.16)	32.4 (0.39)	11.4 (0.15)
Baseline+QE+MB	13.5 (0.16)	0.2 (0.06)	0.8 (0.10)
Baseline+QE+MB+CA%GDP	2.4 (0.15)	0.9 (0.05)	1.3 (0.10)
Baseline+QE+MB+NOMGDP	12.9 (0.16)	1.1 (0.05)	3.2 (0.10)
Baseline+QE+MB+CA%GDP+NOMGDP	4.4 (0.14)	1.4 (0.10)	2.6 (0.11)

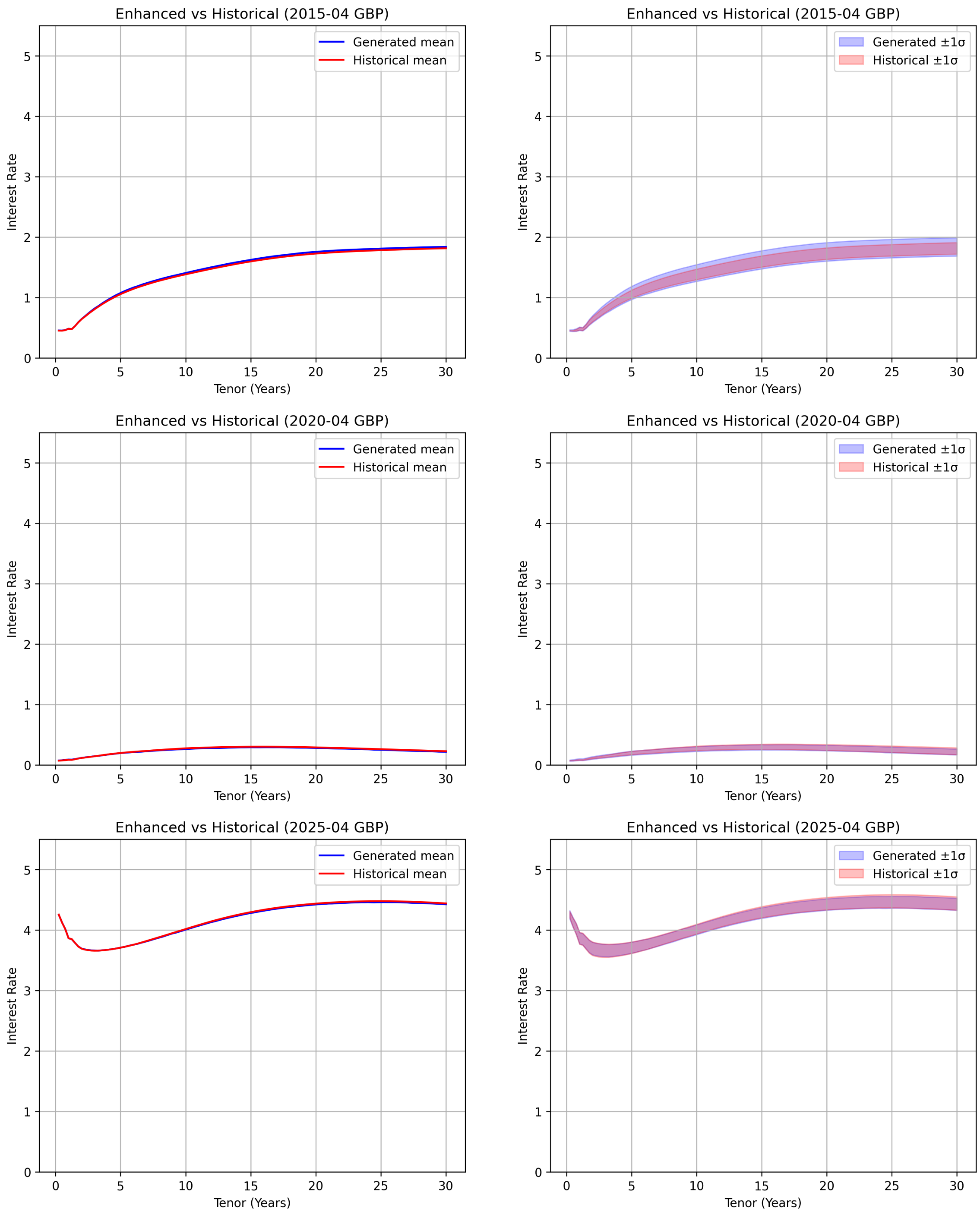

Figure 7: Enhancement with additional condition inputs: GBP

5 Conclusion

In this study, we proposed a conditional generative framework for synthesizing yield curves using diffusion models. To the best of our knowledge, this is the first application of diffusion models to the term structure of interest rates. By conditioning on macroeconomic indicators such as short-term interest rates and inflation, our model is able to generate realistic and historically consistent yield curves that reflect underlying economic environments.

This framework offers promising avenues for practical application. First, it can be utilized for scenario analysis: by specifying future economic scenarios and conditioning on the corresponding macroeconomic variables—predicted separately—the model can generate yield curves that support the formulation of bond investment strategies. Second, it can be applied to risk management: by conditioning on macroeconomic variables associated with stress scenarios, the model can simulate term structures to estimate potential losses and derive risk metrics. In both cases, the use of observable macroeconomic indicators and historical data as inputs enables intuitive and transparent analysis, which we consider a key advantage of the proposed approach. Third, as discussed in Section 4, when policy indicators such as quantitative easing metrics are used as conditioning variables, the model can be employed to assess the potential impact and effectiveness of policy measures prior to their implementation in actual markets. This opens up new possibilities for policy evaluation and macro-financial experimentation.

Future research will focus on expanding the set of conditioning variables to capture more nuanced economic scenarios, enhancing model robustness under extreme market conditions, and exploring practical applications in areas such as risk management, asset allocation and development of new interest rate-related financial products.

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Appendix A: List of obtained interest rate data

Table 6: Overview of Training Data:JPY

Tenor	Ticker	Start Date	End Date
3mo	JYSOC Curncy	2010/01/01	2025/07/02
6mo	JYSOF Curncy	2010/01/01	2025/07/02
9mo	JYSOI Curncy	2010/01/01	2025/07/02
1YR	JYSO1 Curncy	2010/01/01	2025/07/02
2YR	JYSO2 Curncy	2010/01/01	2025/07/02
3YR	JYSO3 Curncy	2010/01/01	2025/07/02
4YR	JYSO4 Curncy	2010/01/01	2025/07/02
5YR	JYSO5 Curncy	2010/01/01	2025/07/02
6YR	JYSO6 Curncy	2010/01/01	2025/07/02
7YR	JYSO7 Curncy	2010/01/01	2025/07/02
8YR	JYSO8 Curncy	2010/01/01	2025/07/02
9YR	JYSO9 Curncy	2010/01/01	2025/07/02
10YR	JYSO10 Curncy	2010/01/01	2025/07/02
11YR	JYSO11 Curncy	2011/02/01	2025/07/02
12YR	JYSO12 Curncy	2010/01/01	2025/07/02
15YR	JYSO15 Curncy	2010/01/01	2025/07/02
20YR	JYSO20 Curncy	2010/01/01	2025/07/02
25YR	JYSO25 Curncy	2010/01/01	2025/07/02
30YR	JYSO30 Curncy	2010/01/01	2025/07/02

Table 7: Overview of Training Data:USD

Tenor	Ticker	Start Date	End Date
3mo	USSOC Curncy	2012/10/01	2025/07/02
6mo	USSOF Curncy	2012/10/01	2025/07/02
9mo	USSOI Curncy	2012/10/01	2025/07/02
1YR	USSO1 Curncy	2012/10/01	2025/07/02
2YR	USSO2 Curncy	2012/10/01	2025/07/02
3YR	USSO3 Curncy	2012/10/01	2025/07/02
4YR	USSO4 Curncy	2012/10/01	2025/07/02
5YR	USSO5 Curncy	2012/10/01	2025/07/02
6YR	USSO6 Curncy	2012/10/01	2025/07/02
7YR	USSO7 Curncy	2012/10/01	2025/07/02
8YR	USSO8 Curncy	2012/10/01	2025/07/02
9YR	USSO9 Curncy	2012/10/01	2025/07/02
10YR	USSO10 Curncy	2012/10/01	2025/07/02
11YR	USSO11 Curncy	2024/07/22	2025/07/02

Tenor	Ticker	Start Date	End Date
12YR	USSO12 Curncy	2012/10/01	2025/07/02
15YR	USSO15 Curncy	2012/10/01	2025/07/02
20YR	USSO20 Curncy	2012/10/01	2025/07/02
25YR	USSO25 Curncy	2012/10/01	2025/07/02
30YR	USSO30 Curncy	2012/10/01	2025/07/02

Table 8: Overview of Training Data:GBP

Tenor	Ticker	Start Date	End Date
3mo	BPSWSC Curncy	2010/11/29	2025/07/09
6mo	BPSWSF Curncy	2010/11/29	2025/07/09
9mo	BPSWSI Curncy	2010/11/29	2025/07/09
1YR	BPSWS1 Curncy	2010/11/29	2025/07/09
2YR	BPSWS2 Curncy	2010/11/29	2025/07/09
3YR	BPSWS3 Curncy	2010/11/29	2025/07/09
4YR	BPSWS4 Curncy	2010/11/29	2025/07/09
5YR	BPSWS5 Curncy	2010/11/29	2025/07/09
6YR	BPSWS6 Curncy	2010/11/29	2025/07/09
7YR	BPSWS7 Curncy	2010/11/29	2025/07/09
8YR	BPSWS8 Curncy	2010/11/29	2025/07/09
9YR	BPSWS9 Curncy	2010/11/29	2025/07/09
10YR	BPSWS10 Curncy	2010/11/29	2025/07/09
12YR	BPSWS12 Curncy	2010/11/29	2025/07/09
15YR	BPSWS15 Curncy	2010/11/29	2025/07/09
20YR	BPSWS20 Curncy	2010/11/29	2025/07/09
25YR	BPSWS25 Curncy	2010/11/29	2025/07/09
30YR	BPSWS30 Curncy	2010/11/29	2025/07/09

Appendix B: List of obtained conditon data

Table 9: Overview of Training Data:USD

Indicator	Ticker	Detail	Transformation process
ST-rate	JYMUON Curncy	Overnight interest rate of JPY	None
ST-rate	USSO1Z Curncy	1week OIS rate of USD	None
ST-rate	SONIO/N Index	Overnight interest rate of GBP	None
Inflation rate	JNCPIYOY Index	CPI Index of Japan (yoy %)	None
Inflation rate	CPI YOY Index	CPI Index of U.S. (yoy %)	None
Inflation rate	UKRPCJYR Index	CPI Index of U.K. (yoy %)	None
QE Indicator	aJPBOJAGOVB[1]	Japan BOJ accounts, assets, Japan government bonds, JPY	Adjusted to yoy % terms
QE Indicator	aUSRHTBA[1 2]	U.S. Factors Affecting Reserve Balances of Depository Institutions, Reserve bank credit, Securities held	Adjusted to yoy % terms
QE Indicator	aGBBLTEA[1]	U.K. Holdings of gilts by the BOE asset purchase facility, GBP	Adjusted to yoy % terms
Monetary Base	JNMBYOY Index	Monetary Base of Japan(yoy %)	None
Monetary Base	ARDIMOYY Index	Monetary Base of U.S.(yoy %)	None
Monetary Base	UKMSM41Y Index	M4 Money Supply of U.K. (yoy %, sa)[3]	None
CA to GDP	EHCAJP Index	Current Account % GDP of Japan	None
CA to GDP	EHCAUS Index	Current Account % GDP of U.S.	None
CA to GDP	EHCAGB Index	Current Account % GDP of U.K.	None
Nominal GDP	ECOXJPS Index	Nominal GDP of Japan (USD bn)	Scaling(1/1,000)
Nominal GDP	GDP CUR$ Index	Nominal GDP of U.S. (USD bn)	Scaling(1/1,000)
Nominal GDP	ECOXUKS Indexy	Nominal GDP of U.K. (USD bn)	Scaling(1/1,000)

[1] Data from LSEG Datastream
[2] Missing values in the data sources are supplemented using publicly available data from central banks.
[3] Due to data availability issues, alternative data is used.