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ARAŞTIRMA MAKALESİ | RESEARCH ARTICLE

LIBOR Kavramı ve Çok Katmanlı Algılayıcı (Multi-Layer Perceptron) ile LIBOR'un Tahmin Edilmesi

LIBOR Concept and LIBOR's Estimation with Multi-Layer Perceptron

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Özet

LIBOR'dan yeni referans faiz oranlarına geçiş, finansal modelleme için önemli zorluklar sunmaktadır. LIBOR Piyasa Modeli (LMM) standart bir yaklaşım olsa da, karmaşıklığı ve kalibrasyon sorunları pratik uygulamasını kısıtlarken; geleneksel ekonometrik modeller ise faiz oranlarının doğrusal olmayan dinamiklerini yakalamakta genellikle yetersiz kalmaktadır. Bu çalışma, bu metodolojik boşluğu doldurmak amacıyla, bir yapay zeka tekniği olan Çok Katmanlı Algılayıcı (MLP) kullanarak, bir aylık ABD Doları LIBOR'unu ABD Merkez Bankası (FED) politika faizini temel bağımsız değişken olarak alarak modellemektedir. Öncel bir eşbütünleşme analizi, iki değişken arasında güçlü bir uzun dönemli ilişkiyi teyit etmiş ancak temel istatistiksel varsayımları (normal dağılım, otokorelasyon) ihlal etmiştir. Buna karşılık, MLP modeli olağanüstü bir tahmin performansı (R^2=0,99) sergilemiş ve LIBOR ile FED faizi arasındaki birebire yakın hareketi, bu varsayım ihlalleri olmaksızın güçlü bir şekilde yakalamıştır. Bulgular, parametrik olmayan ve yapay zekâ temelli yöntemlerin finansal tahminlemedeki etkinliğinin altını çizmektedir. Çalışmanın temel çıkarımı, FED politika faizinin doğru tahmin edilmesinin, LIBOR ve onun ardılı olan referans faiz oranlarının davranışını öngörmek için kritik öneme sahip olduğudur.

Anahtar Kelimeler: *Londra Bankalararası Teklif Oranı (LIBOR), LIBOR Piyasa Modeli (LMM), Çok Katmanlı Algılayıcı (MLP).*

Abstract

The transition from LIBOR to new benchmark rates presents significant challenges for financial modeling. While the LIBOR Market Model (LMM) has been a standard approach, its practical application is limited by its complexity and calibration issues; meanwhile, traditional econometric models are often insufficient to capture the non-linear dynamics of interest rates. This study addresses this methodological gap by employing a Multi-Layer Perceptron (MLP), an artificial intelligence technique, to model the one-month U.S. Dollar LIBOR using the U.S. Federal Reserve (FED) policy rate as the primary independent variable. A preliminary cointegration analysis confirmed a strong long-run relationship between the two variables but violated key statistical assumptions (i.e., normality, autocorrelation). In contrast, the MLP model demonstrated exceptional predictive performance (R^2=0,99) and robustly captured the near one-to-one movement between LIBOR and the FED rate without these assumption violations. The findings underscore the efficacy of non-parametric, AI-driven methods in financial forecasting. The central implication of this study is that the accurate estimation of the FED policy rate is of critical importance for predicting the behavior of LIBOR and its successor benchmark rates.

Keywords: *The London Inter-Bank Offered Rate (LIBOR), LIBOR Market Model (LMM), Multi-Layer Perceptron (MLP).*

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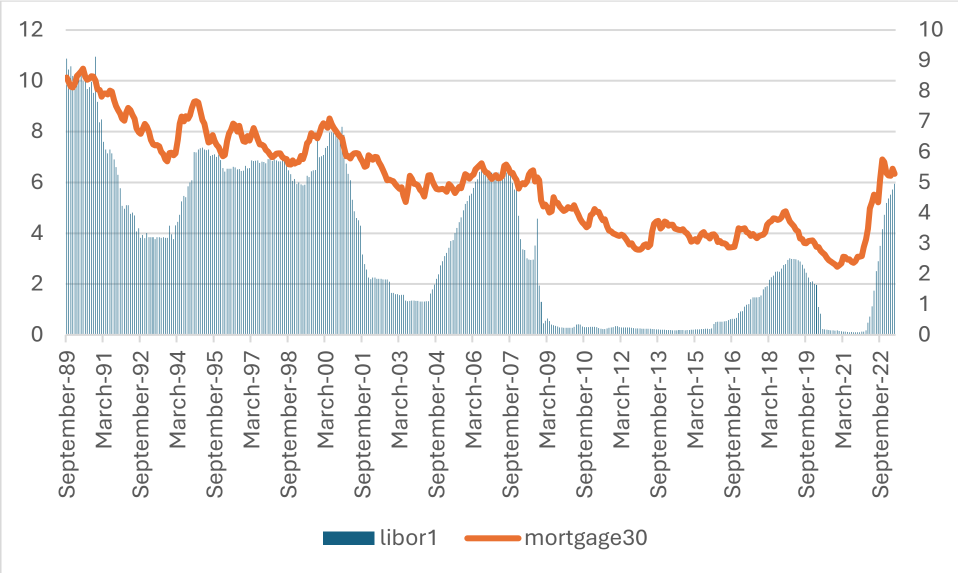
1. INTRODUCTION

Developed countries have experienced many contractions and subsequent expansions after World War II, such as the oil crisis in the 1970s, the dot-com crisis in the late 1990s, the financial crisis in 2008, and the pandemic in 2020. During and after these crises, there have been very serious volatilities in economic values. The reflection of these volatilities on interest rates has also been quite large. Figure 1 shows the monthly values of long-term interest rates (30-year US mortgage rates) and variable interest rates (1-month US Dollar LIBOR rates) covering the years September 1989 to April 2023.

Figure-1: LIBOR (1 Month) and Mortgage (30 Years) Interest Rates (1989-2023)



Source: St.Louis Fed. (2024) and global-rates.com (2024)

The 30-year mortgage loan interest rate, which was 10.13% in 1989, decreased to 2.91% in January 2021 and increased to 6.39% in December 2022. The arithmetic mean of the 30-year mortgage interest for the specified period is 5.99 and its standard deviation is 1.93. The arithmetic mean of the 1-month US LIBOR rate, which is one of the basic indicators of variable interest, is 2.94 and its standard deviation is 2.45. Although the average of the 1-month US LIBOR rate is relatively lower than the mortgage loan interest rate, its standard deviation is high. The correlation coefficient of both variables is 88%, which is quite high.

This change in interest rates has a significant impact on the entire world, including developed countries. While the interest payments of the US government were 515 billion USD in April 2020, they increased to 874 billion USD in 2023 in parallel with the increases in interest rates. The sharp increases in US interest rates also affect emerging markets and developing economies. The borrowing costs and debt burdens of these countries have increased, financing debt repayments has become difficult, their financial markets have deteriorated, capital inflows have decreased, and tensions have occurred in financial markets (Arteta et al., 2022). When Figure 2 is examined, the amount of interest payments related to the US government and the share of interest payments in GNP are seen. It is seen that a similar increase in the quantity and proportion of interest payments, which started after the oil crisis in the 1970s and continued with the "Volcker Deflation", has been repeated after the pandemic. It is estimated that the increase in interest payments will continue in the coming years and that by 2034 the ratio of interest payments to GNP will reach a record level of 3.9% (Congressional Budget Office, 2024).

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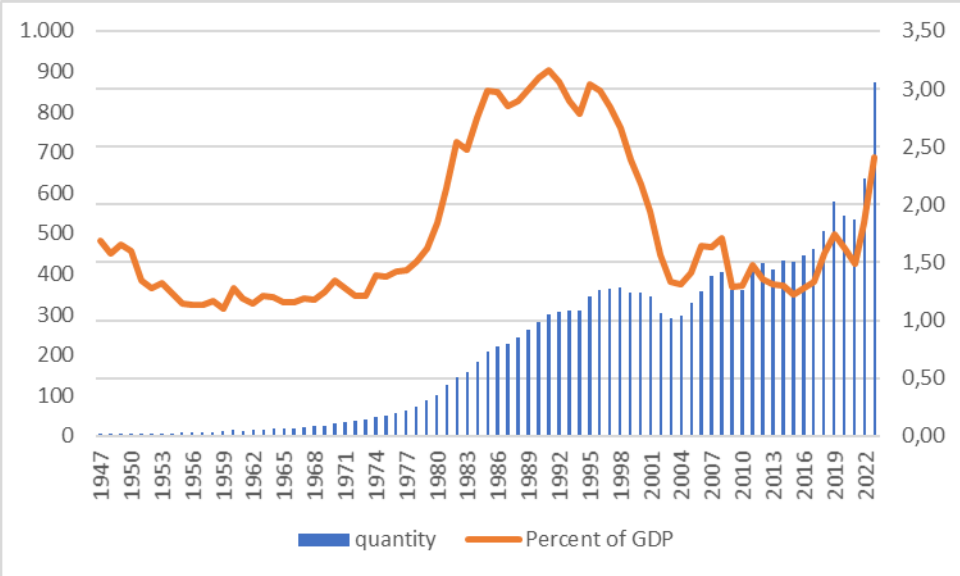
Figure-2: Quantitative (billion USD) and Ratio (% GDP) Amounts of US Government Interest Payments (1947-2023)



Source: St.Louis Fed. (2024)

For borrowers, long-term financing enables faster growth, greater shared prosperity, easier coping with life-cycle challenges, and lasting stability; reduces rollover risks (extending investment horizons and improving performance); and increases the availability of long-term financial instruments (The World Bank, 2015). In debt relationships, risk is shared between borrowers and lenders. In long-term financing, the risk is borne by the funders (having to endure fluctuations in the probability of default and losses in the event of default, and other changing conditions in financial markets such as interest rate volatility), whereas in short-term financing, the risk is borne by the borrowers (being forced to refinance their debts repeatedly) (Martinez Peria & Schmukler, 2017).

In international markets, the most important structure regarding the variable interest rate process has been the use of LIBOR rates. For many years, the LIBOR rate has been a part of financial markets as a reference value in both international debt agreements and derivative markets. Due to the 2008 financial crisis and the various speculations and manipulations that occurred afterwards, SOFR, developed by the New York Fed instead of LIBOR in the USA, began to be used on April 18, 2018. In parallel with the developments, the EU has put into operation the ESTR, the UK the SONIA, Japan the TONAR and Switzerland the SARON values. LIBOR rates continue to be created synthetically with the help of SOFR today.

One of the mathematical models widely used for pricing financial derivative products and risk management is the LMM, which is a time series model and is defined by a series of Stochastic Differential Equations (SDE). LMM is used in many areas such as understanding the movements of interest rates in financial markets, pricing derivative products and using them in risk management. Theoretical information about interest is used as the basis of studies on LMM. Monte Carlo simulation, which is used to model the future behavior of complex financial instruments and market variables, allows the solution of LMM. However, Monte Carlo simulation is quite difficult to use due to reasons such as being quite time consuming, having errors and fluctuations in its results, and the interdependence of prices and interest rates in financial markets. For these reasons, instead of determining LIBOR interest rates, LMM is used to model the movements of these interest rates and other financial variables over

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time and to analyze the effects of these movements on the pricing of financial products and risk management. In order to obtain the future value of LIBOR value more quickly and precisely, the use of analytical or numerical solutions offers better solutions. By utilizing artificial intelligence and machine learning techniques to estimate the possible future values of LIBOR, financial modeling using the factors affecting LIBOR rates can be done more easily and more accurately.

The purpose of this study is to model LIBOR, which has a very important place in our daily lives. Since the data of SOFR used today started on April 18, 2018, the LIBOR value will be used in modeling the variable interest. In the modeling, instead of the LMM method, the artificial intelligence application Multi-Layer Perceptron (MLP) will be used due to the reasons stated above.

In this article, first of all, the historical process regarding the formation of LIBOR rates will be revealed. Then, scientific studies regarding the determination and modeling of LIBOR rates will be emphasized. After the empirical methods to be used are summarized, LIBOR rates will be modeled with an empirical study.

2. LITERATURE BACKGROUND

2.1. Historical Process of Establishing Libor Rates

LIBOR emerged in the late 1960s and 1970s to facilitate syndicated loan transactions and increase the transparency of their pricing. Following the growth in the credit market and new financial instruments (especially derivatives) that required reliable interest rate benchmarks, the British Bankers Association (BBA) assumed control of the LIBOR rate in 1986 (Intercontinental Exchange, 2018). Over time, the benchmark increased to 10 currencies with 15 maturities, and began to lose its effectiveness in 2012 as part of investigations opened due to manipulations in 2008.

In Figure 3 created by Kiff (2012), the differences between the three-month Eurodollar deposit rate and the three-month New York Funding Rate (NYFR) for the 3-month USD LIBOR rate in 2008 and 2009 are shown. It can be seen that the USD LIBOR rate was significantly lower than the NYFR after the bankruptcy of Lehman Brothers in September 2008.

Figure -3: Comparison of 3-month USD LIBOR and NYFR Rates in 2008 and 2009

Source: Kiff (2012)

In the face of these developments, the Alternative Reference Rates Committee (ARRC) was established by the US to create a new benchmark covering large-volume and wide-ranging financial products and contracts in the global financial system, and the commission held its first meeting in December 2014 (ARRC, 2019). In 2017, ARRC developed SOFR, an interest rate based on overnight

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repo transactions, using data collected by the Federal Reserve Bank in cooperation with the Financial Research Office of the Federal Reserve Bank of New York, and it began to be used in 2018 (ARRC, 2017). Cairns (FCA) began to calculate LIBOR synthetically based on SOFR as of April 3, 2022 (FCA, 2023).

According to the forecast made by ARRC in 2018, it was estimated that the share of LIBOR USD in total transactions due to contracts would continue to increase until 2025 and would experience a rapid decrease in the following years (ARRC, 2018).

As a result of the gradual phasing out of the use of LIBOR rates; Forward Rate Agreements (FRAs) have largely become obsolete due to the reduction of pegging risk, swap transactions referencing "Nearly Risk-Free" Rates (RFR) have increased, the share of the UK and US in global turnover has decreased, while the share of the Eurozone has increased, and new tools have emerged to manage transitional basis risks in the post-LIBOR world (Huang & Todorov, 2022).

2.2. Theoretical Studies On the Determination Of LIBOR Rate

The first study on modeling the change of financial asset prices over time using random fluctuations was made by Bachelier in 1900 using ABM. Bachelier's study led to the use of random walks, understanding market dynamics, developing risk management strategies and popularizing statistical tools and mathematical techniques for modeling price fluctuations using mathematical modeling in financial markets. The current mathematical representation and solution of ABM was made by Ito and is shown in Equation (1) (Jarrow and Protter, 2003).

$$dX_t = \mu dt + \sigma dW_t \qquad (1)$$

In equation (1); X_t is the asset price at time t, μ is the drift coefficient of the process, σ is the volatility coefficient of the process, dt is the time interval in the process and dW_t is a stochastic component and represents Brownian Motion.

Samuelson (1965) emphasized that Bachelier's work was not in accordance with the basic assumptions of finance because of the negative consequences that could arise. Samuelson eliminated this drawback with Geometric (or Economic) Brownian Motion (GBM). Samuelson's mathematical representation of interest rate movements is presented in Equation (2) (Samuelson, 1965).

$$dX_t = \mu(X_t)dt + \sigma(X_t)dW_t \qquad (2)$$

In ABM, price change is represented by μ and σ, while in GBM, in the interest rate movement, the price of the dependent variable is used in addition to μ and σ. Therefore, the GBM movement provides a more accurate representation of the percentage price change with the growth of the process over time and eliminates the negative price problem that may occur in the ABM movement by preserving positive prices. While there is a normal distribution in ABM due to the use of only the Wiener process, the distribution of X_t in GBM is log-normal depending on time (Peters and Adamou, 2018). This means that the results of ABM are symmetrical, while the results in GBM have an asymmetric distribution and the probability of excessive increases is higher.

The Black-Scholes (BS) option pricing model, based on the GBM assumption, has inspired the development of more complex configurations of derivative products and new financial instruments by providing a better understanding of the distribution of prices and volatility. As can be understood from Equation (3), it is based on the assumption that the stock price S changes stochastically using GBM and that the value of the futures market after time t should be equal to the risk-free interest rate (Hull, 2012). In the BS option pricing model, equation (3) is found by solving it using the Ito's lemma method.

$$\frac{\delta f}{\delta t} + rS\frac{\delta f}{\delta S} + \frac{1}{2}\sigma^2 S^2 \frac{\delta^2 f}{\delta S^2} = rf \qquad (3)$$

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Merton (1973) reduced the assumptions of the BS Model, allowed the use of concrete variables in the final formula and the pricing of all options. With Merton's contributions, the model was named BSM. The BSM model allowed for issues such as calculating the net present value of invisible assets such as copyrights, estimating the value of companies according to the value and volatility of their assets, and modeling issues such as risk and insurance premium. (Wang et al., 2023)

Studies on modeling interest rates have a long historical development process. This development process has accelerated today due to reasons such as developments in communication, integration process experienced in the world, complexity and increasing needs in financial markets. There are two basic approaches to modeling interest rates: equilibrium and non-arbitrage. In equilibrium models, it is assumed that the market is in a state of equilibrium because financial market participants act with rational expectations by taking into account issues such as macroeconomic factors and long-term trends. Vasicek and CIR models are pioneering studies of equilibrium models. The important disadvantage of these time-homogeneous models is that they normally give a series of theoretical prices for bonds that do not exactly match the real prices we observe in the market. In order to overcome this drawback, models consistent with market prices were made using the assumption that there are no arbitrage opportunities. Ho & Lee (1986) developed some non-homogeneous Markov models for short-term interest rates.

Vasicek's model, which predicts the mean-reversion evolution of the long-term equilibrium distribution of short-term interest rates, is often considered a very good starting point because it is very suitable for both analytical evaluations and realistic modeling of problems (Jackel, 2001). Vasicek has done pioneering work using stochastic differential equations similar to Equation (1) with the help of a single-factor short-term model for modeling and forecasting interest rates. It has become an important tool for interest rate risk management, bond portfolio optimization and bond price forecasting because it contributes to understanding and forecasting the movement of interest rates over time and to improving risk management.

$$dr_t = \alpha\big(b - (r_t)\big)dt + \sigma dW_t \qquad (4)$$

In the Vasicek model shown in Equation (4); r_t represents the interest rate at time t, α represents the return rate and b represents the long-term equilibrium interest rate. The Vasicek model has had a significant impact on the evolution and development of interest rate models in the financial literature.

Ho-Lee presented the first non-arbitrage model of interest rates in 1986, which exists in both discrete-time and continuous-time versions. It has a wide range of applications in mathematical finance, including bond pricing, option pricing, and future interest rate modeling (Izgi & Bakkaloglu 2017). The Ho-Lee model, which assumes that the spot rate process is normally distributed, is in Equation (5).

$$dr_t = \theta(t)dt + \sigma dW_t \qquad (5)$$

In equation (5), σ is the volatility of the short interest rate and $\theta(t)$ is created from the initial period as seen in Equation (6) (West, 2010).

$$\theta(t) = \int' (0,t) + \sigma^2 t \qquad (6)$$

However, Vasicek and similar models (such as Hull & White), which have a short-term model, can give accurate results in cases where there are random fluctuations in interest rates in short-term periods, the correlation between interest rates is low and volatility does not change over time. These deficiencies led to the emergence of the LIBOR Market Model (LMM). The model was created by Brace, Gatarek and Musiela (1997), Jamshidian (1997) and Miltersen, Sandmann and Sondermann (1997) based on the work of Heath-Jarrow-Morton (1992). In the created model, more realistic results were obtained by using the forward term instead of the short-term rate. The mathematical representation of the LMM is presented in equation (7) (Haugh, 2010).

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$$dL_n(t) = \mu_n(t)L_n(t)dt + L_n(t)\sigma_n(t)^T dW_t \qquad (7)$$

The large differences in interest rates and their changes over time have led to the need to use Girsanov Theorem in the Wiener process. In the BS option pricing model, the use of risk-neutral measurement and the change of risk factors are based on the basic concepts of Girsanov Theorem. According to Girsanov theorem, the Wiener process is developed as $dW_t^Q = \theta_t dt + dW_t$ (Nekrasov, 2013). The drift of equation (4) is obtained again using Girsanov theorem and presented in Equation (8). Studies on LMM continue with models such as Diffision and Heston. (Westfälische Wilhelms-Universität Münster, 2021)

$$dL_n(t) = \mu_n(t)L_n(t)dt + L_n(t)\sigma_n(t)dW_n^{(n)}(t) \qquad (8)$$

In the studies presented so far, the parameters related to the function have been tried to be estimated by assuming that the interest rates have a functional form. These studies, which we call parametric models, require a more specific hypothesis. In non-parametric models, data-based models that do not adhere to a specific functional form structure are preferred. The mathematical representation and applications of non-parametric models have been presented in detail by Gatarek et al. (2006).

Papapantoleon&Skovmand (2011) stated that the log-normal LIBOR model driven by Brownian motion could not be sufficiently calibrated to the observed market data and that the dynamics of LIBOR rates could not be followed under every forward measurement due to the random terms that entered the dynamics of LIBOR rates during the creation of the model.

Hou and Skeie (2014) showed LIBOR as a combination of maturity and risk changes in Equation (9).

LIBOR = overnight risk-free interest rate + term premium + bank term credit risk + term liquidity risk + term risk premium (9)

2.3. Empirical Studies On the Determination of Libor Rates

Empirical studies conducted with the LMM method are presented in Table-1.

Table 1. Some Studies on LIBOR Modelling

Number	Writer	Dependent/ Independent Variables	Methods	Conclusion

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1	Belomestny and Schoenmakers (2009)	The caplet-strike volatility matrix	A jump-diffusion Libor model	The jump diffusion Libor model is able to reproduce both of them with an acceptable accuracy, in crisis times prices are more strongly influenced by uncertainty about future and negative expectations. However, for the short term tenors the calibration errors growth up to about 13-25%.
2	Papapantoleon et.al (2011)	Caplet prices	Log-Lévi LIBOR model	Log-Lévi LIBOR approximation should be interpreted as a variance reduction technique for the LIBOR market model
4	Carol Alexander and Dmitri Lvov (2003)	LIBOR yield curve, 703 daily observation on UK LIBOR rates, FRAs and swap rates between 15/10/1999 and 25/06/2002	Principal Component Analysis	Forward rates that are obtained using Svensson (1994) technique is better than McCulloch (1975), Steely (1991) techniques.
5	Durre at.al. (2003)	German LIBOR data from 1989 until 1998	Cointegrating vector autoregressive model,	A "weak version" of the expectations hypothesis theory cannot be rejected on a horizon from one up to nine months, and the expectations hypothesis is compatible with German money market data.
6	Andrés & Scudiero (2023)	A set of 280 market EURO and USD swaptions volatilities	Heston, Edgeworth, Levenberg-Marquardt, Broyden-Fletcher-Goldfarb-Shanno algorithms	The number of unsatisfied Feller conditions is rather significant especially for the Heston and Edgeworth algorithms. The other algorithms handling linear inequality constraints cannot ensure that the points stay in the feasible set.

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7	Cheng (2016)	USD swaptions data on 8 August 2007 and tenor combinations on the EUR market during 2015 and 2016	Monte Carlo simulation	The imperfectness of the parameters fitting is because of the simulation results to be less ideal than expected.
8	Wu and Zhang, (2006)	The US dollar data of July 05, 2002	Fast Fourier Transform, Heston and Monte Carlo simulation methods.	The adoption of a stochastic volatility generally does not change the average level of the implied volatility curve.
9	Devineau et al. (2017)	Average interest rate structure and swaption volatilities throughout the year 2016	Heston and Edgeworth simulation methods.	Edgeworth method has 98% reduction in computational time in the the Libor Market Model with Stochastic Volatility and Displaced Diffusion calibration process compared to the classical Heston method
10	Leippold and Strömberg (2013)	the U.S. dollar three-month forward LIBOR rate from August 8, 2007 to August 11, 2010	Kalman Filter and the Root Mean Squared Pricing Errors and the Mean Pricing Errors on caps and swaptions.	Especially for intermediate and long maturities, we found evidence that the markets for caps and swaptions have been well integrated even during the financial crisis but the pricing errors of short maturity contracts especially since early 2009.
11	Verschuren (2020)	On March 30th, 2012 up until April 28th, 2017, the discount factors and caplet prices can be obtained from the bootstrap method	The goodness-of-fit, the parameter stability and the out-of-sample pricing	Financial institutions can best adopt the multiple curve the Lévy Forward Price model in their Asset Liability Management studies with the the Linear-Exponential Volatility specification and with deterministic breakpoints.

Nawalkha (2009) stated that the formulas and calculation methods used for cap pricing and swaps within the scope of LMM are much more complex than Black-type formulas. LMM, a financial model type used especially for pricing interest rates and interest derivatives, models interest rate fluctuations using stochastic processes. However, in LMM models, Monte Carlo simulation is used because the pricing of interest rates and derivative products is generally difficult or impossible to calculate directly with analytical solutions. The use of the LMM method in real life is quite limited due to the need to use Monte Carlo simulation, the complexity of the model, and the need for constant updating. In addition, the fact that LIBOR is no longer in use has led to the need for revision in LMM.

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3. METHODOLOGY [MULTI-LAYER PERCEPTRON (MLP)]

In Traditional Linear Regression, which is one of the most frequently used models in econometrics; the linearity of the model, the absence of a complete linear relationship between any of the independent variables, the expected value of the error term in the i observation in the sample not being a function of the independent variables, the variance of the error terms not changing, the absence of autocorrelation between them, and normal distribution (Greene, 2012) assumptions must all be met. Such requirements are often not met even after the transformation of the variables, and the low performance obtained in this way may cause the models to be inadequate (Astray et al. 2010). In cases where these assumptions are not met, Traditional Linear Regression Models cannot be used.

To ensure the transparency and reproducibility of our model, the specific hyperparameters of the MLP architecture are detailed as follows. The model consists of two hidden layers, with 10 neurons in the first hidden layer and 5 in the second. The Hyperbolic Tangent (Tanh) was selected as the activation function due to its zero-centered nature. The network was trained using the Adam optimizer with a learning rate of 0.001. The training process was conducted over 100 epochs with a batch size of 32.

To preserve the chronological integrity of the time-series data, the dataset was divided into three distinct sets: a training set (70%, 283 observations), a validation set (15%, 61 observations), and a test set (15%, 61 observations). The validation set was used during the training process for hyperparameter tuning and to implement the 'early stopping' mechanism. This approach ensures that the model is trained on past data and validated on subsequent data before its final performance is assessed on the unseen test set, mimicking a real-world forecasting scenario.

Given the high explanatory power of the model, measures were taken to mitigate the risk of overfitting. An 'early stopping' mechanism was implemented, which halts the training process if the loss on the validation set fails to improve over a specified number of epochs (patience=10). Additionally, L2 regularization (with a lambda of 0.01) was applied to the weights of the hidden layers during the optimization process, penalizing large weights to enhance the model's generalization capabilities.

In the empirical study to be conducted on the modeling of LIBOR; MLP, which is an artificial intelligence application, will be used due to the problems that occur in Linear Regression such as flexibility in modeling different data distributions, relaxation of the normality assumption, robustness against outliers, modeling for various data types, and variance not remaining constant.

ML is one of the important areas of AI and computer science, which focuses on the use of data and algorithms to mimic the way people learn and gradually increase their accuracy (IBM, 2023). ML, deep learning (DL), and neural networks (NN) are subfields of artificial intelligence. NN is a subfield of ML and DL is a subfield of NN.

NN are massively parallel distributed processors consisting of simple processing units that have a natural tendency to store experiential knowledge and make it ready for use, and are likened to the brain because the network acquires and stores knowledge from its environment through a learning process. (Haykin, 2008)

DL allows computational models consisting of multiple processing layers to learn data representations with multiple levels of abstraction. DL reveals complex structure in large datasets by using the backpropagation algorithm to specify how a machine should change its internal parameters used to calculate the representation in each layer from the representation in the previous layer. This method has helped technological advances in many other fields such as speech recognition, visual object recognition, object detection, and drug discovery and genomics. (LeCun et al. 2015) DL generally uses a variety of structures including multilayer neural networks (MLPs), convolutional neural networks (CNNs), or recurrent neural networks (RNNs).

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The most well-known and most commonly used type of NN, MLP has a feedforward architecture, where signals are transmitted in one direction within the network from input to output. (Popescu et al. 2009) MLP is one of the fundamental building blocks of deep learning. MLPs are a type of artificial neural network that contains at least one hidden layer and has connections between the input and output layers. The mathematical representation of the multi-layer perceptron is below (Zhang et al. 2023).

$$H = \delta(XW^1) + b^1 \quad (10)$$

$$O = HW^2 + b^2$$

In Equation (10), H represents the outputs of the hidden layer, δ represents a nonlinear activation function (such as ReLU, Sigmoid, hyperbolic tangent (Tanh)), X represents the inputs, W^1 represents the hidden layer weights, b^1 represents the bias of the hidden layer, O represents the outputs, W^2 represents the weights of the outputs and b^2 represents the bias of the outputs. Tanh is more regular than other functions and is centered at a or zero in the range of (-1 ,1). The mathematical expression of the Tanh function to be used in the study is as follows in Equation (11) (Tomar and Laxkar, 2022)

$$\mathrm{f(x)} = 2 * \mathrm{logistic(2x)} - 1 \quad (11)$$

We acknowledge the 'black-box' nature of MLP models as a limitation in terms of interpretability. While this study uses synaptic weights as a basic indicator of feature importance, future research could employ eXplainable AI (XAI) techniques, such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations), to provide more granular insights into the marginal contributions of each input variable to the model's predictions.

4. EMPIRICAL FINDINGS

In the study, the one-month USD LIBOR rate was selected as the dependent variable. Monthly data covering the period from September 1989 to April 2023 (417 observations) was obtained from global-rates.com (retrieved August 5, 2024). The US Federal Reserve's policy rate (Effective Federal Funds Rate, series code: FEDFUNDS) was used as the independent variable, with data sourced from the Federal Reserve Economic Data (FRED) database provided by the St. Louis Fed. Descriptive statistics for the variables are presented in Table 2.

Table 2. Descriptive of Variables

	LIBOR1	POLICYRATEUS
Mean	2,95	2,78
Median	2,46	2,25
Maximum	9,13	9,06
Minimum	0,08	0,13
Std. Dev.	2,45	2,41
Skewness	0,42	0,44
Kurtosis	1,99	2,00

Unit root test results for dependent and independent variables are in Table-3.

To examine the stationarity properties of the series, Augmented Dickey-Fuller (ADF) unit root tests were conducted, with the results presented in Table 3.

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Table 3. Unit Root Tests of Variables

	Level		First Difference	
	ADF Sta.	Prob.(*)	ADF Sta.	Prob.(**)
LIBOR1	-2,3811	0,1478*	-7,7539	0,0000**
POLICYRATEUS	-2,4792	0,1213*	-6,2082	0,0000**

Null Hypothesis: Series have a unit root

(*) : The null hypothesis is accepted at the level of =0.01.

(**) : The null hypothesis is rejected at all the level =0.01.

As the unit root tests in Table 3 indicate that both series are integrated of order one, I(1), their long-run relationship was investigated using the Engle-Granger cointegration method. The results are presented in Table 4. While the cointegration results in Table 4 indicate a strong long-run relationship with a high adjusted R^2, the model's residuals violate key OLS assumptions. The normality assumption was rejected based on the Jarque-Bera test (JB Statistic: 25.8, p=0.0000), as illustrated in Figure 4. Furthermore, as shown in Table 5, the residuals exhibit significant serial correlation.

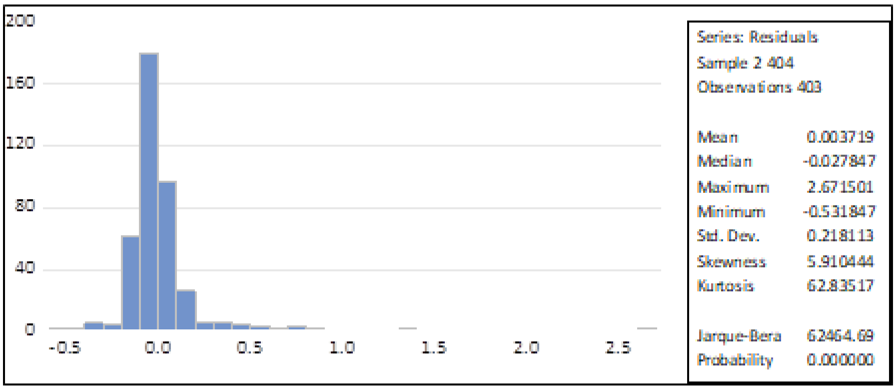
In Table 4, the existence of unit root of dependent and independent variables cannot be rejected. Therefore, the cointegration model created is below.

Table 4. Cointegration Result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
POLICYRATEUS	1,0154	0,0071	142,8996	0,0000
c	0,1227	0,0263	4,6734	0,0000

When the cointegration results are examined, it is seen that the p values for the coefficient values for the US policy interest rates and the constant are 0. Again, the adjusted R^2 value is 0.99 and the explanatory power of the model is quite high. However, the residuals should be normally distributed and there should be no autocorrelation. The Figure regarding the normality of the error terms is below.

Figure-4: Normal Distribution Test of Error Terms



Although the skewness should be 0 and the kurtosis should be 3, it is seen that the results are quite high and therefore the error term is not normally distributed. In addition, as seen in Table 5, the existence of autocorrelation cannot be rejected.

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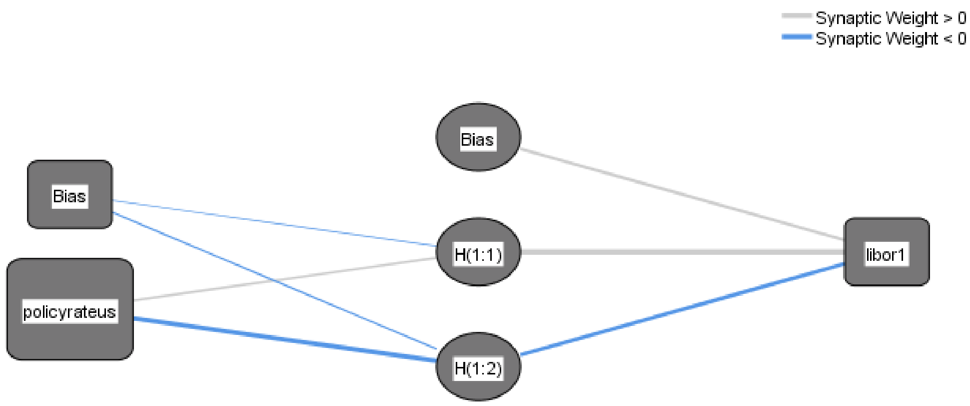
Table 5. Autocorrelation Result

	AC	PAC	Q-Stat	Prob
1	0,4610	0,4610	86,1300	0,0000
2	0,3770	0,2100	144,1200	0,0000
3	0,3320	0,1300	189,1300	0,0000
4	0,2570	0,0320	216,1400	0,0000
5	0,2470	0,0670	241,1700	0,0000
6	0,2650	0,1000	269,9500	0,0000
7	0,2230	0,0250	290,4200	0,0000
8	0,1360	-0,0730	298,0300	0,0000
9	0,1960	0,0890	313,8700	0,0000
10	0,1450	-0,0070	322,5600	0,0000
11	0,1130	-0,0200	327,8300	0,0000
12	0,1420	0,0390	336,2600	0,0000

For the MLP model, the data was pre-processed. Prior to model training, 12 observations were identified as outliers based on the three-sigma rule (i.e., values exceeding three standard deviations from the mean) and were removed to prevent distortion of the model's learning process. Of the remaining 405 periods, the data was chronologically split into a training set (294 observations) and a test set (111 observations).

These assumption violations—namely, non-normality and autocorrelation—undermine the reliability of the OLS-based cointegration estimates. Although these issues could be addressed within an econometric framework using methods such as a Vector Error Correction Model (VECM) or applying heteroskedasticity and autocorrelation consistent (HAC) standard errors, this study opts for a non-parametric MLP approach. While alternative time-series models like ARIMA were also considered, they were discarded due to similar violations of normality and autocorrelation in their residuals. The MLP model is inherently robust to such distributional assumptions and is better suited to capture the complex, non-linear dynamics often present in financial time series.

Figure -5: Network Diagram



In artificial neural networks, a "synaptic weight" quantifies the strength and direction of the connection between two neurons. The magnitude (or absolute value) of the weight indicates the

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influence of that connection on the output; a larger magnitude implies a stronger influence. The sign of the weight determines the nature of the connection: a positive weight has an excitatory effect (increasing the output), while a negative weight has an inhibitory effect (decreasing the output).

In our model, as shown in Table 6, the synaptic weights connecting the hidden layers to the output neuron reveal the relative importance of these connections. For instance, the large positive weight from the first hidden neuron (H(1:1) to Output: 2.87) indicates a strong, excitatory influence. Conversely, the smaller negative weight from the second neuron (H(1:2) to Output: -0.37) suggests a weaker, inhibitory influence. This analysis points to the first hidden layer having a more dominant role in shaping the model's final prediction.

Table 6. Synaptic Weights of the MLP Model

		H(1:1)	H(1:2)	LIBOR1
Input Layer	(Bias)	-0,15857	-0,27895	
	policyrateus	0,320783	-0,43335	
Hidden Layer 1	(Bias)			0,338541
	H(1:1)			2,87658
	H(1:2)			-0,37143

When working on MLP (Multilayer Perceptrons) or other artificial neural network models, "Relative Error" is a measure that is often used to evaluate how well the model's predictions match the true values. A low relative error can indicate that the model's predictions are close to the true values, while a high relative error can indicate that the model's predictions are significantly different from the true values. The very low relative errors in Table-7 indicate that the predictions are quite close to the true values.

Table 7. MLP Model Performance Summary

Performance Metric	Training Set	Test Set
Sum of Squares Error (SSE)	1.404	0.434
Relative Error	0.010	0.007

The performance of the trained MLP model was evaluated using both training and unseen test data, with key error metrics summarized in Table 7. The model demonstrates exceptional predictive accuracy and a strong ability to generalize to new data.

As shown in the table, the Sum of Squares Error (SSE) on the test set is a minimal 0.434, and the Relative Error is just 0.007. These extremely low error values indicate that the model's predictions are consistently very close to the actual observed LIBOR rates. The model's overall explanatory power is 0.99, which further confirms its robust performance and is consistent with the initial cointegration analysis. The close alignment between the predicted and actual values is visualized in Figure 6, where the model's outputs are shown to track the real-world data with high fidelity.

Figure-6: Predicted by Observed

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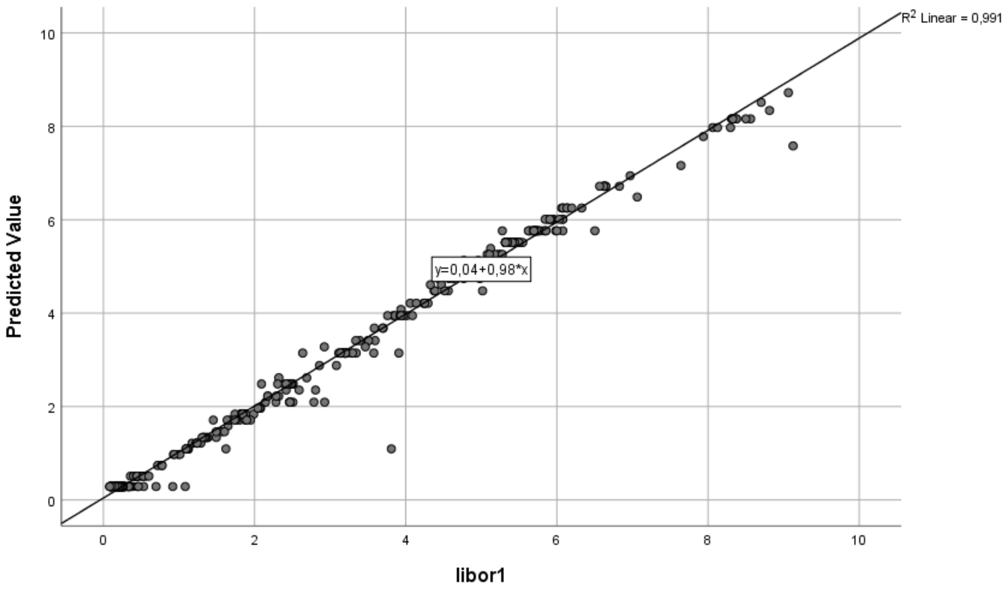
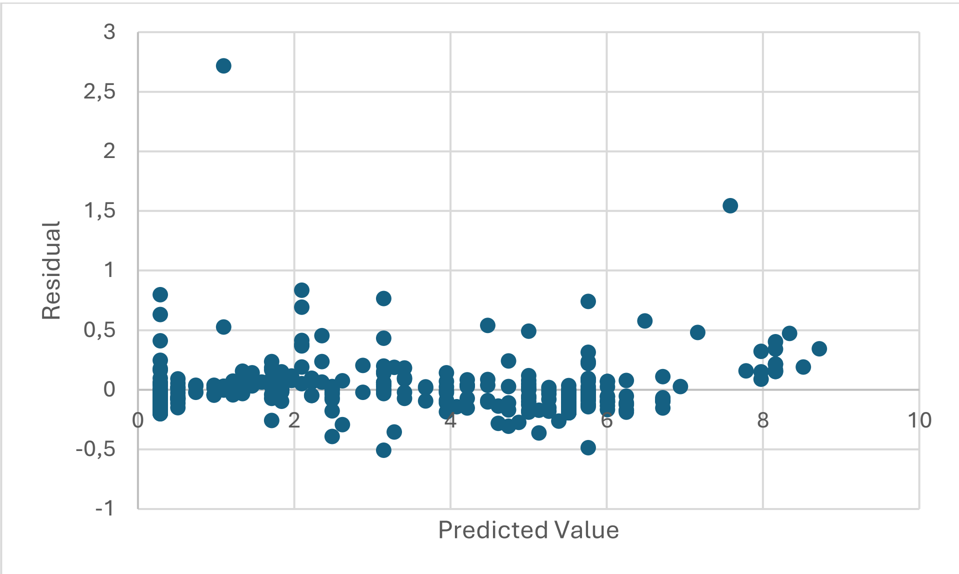


The error terms are calculated using a function, usually called a "loss function" or "error function". This function measures the difference between the actual and estimated outputs and produces an error value. The error terms are usually propagated back (backpropagated) based on the difference between the actual and estimated values and are used to adjust the parameters of the model (e.g. synaptic weights). This process aims to reduce the error terms so that they are as close to zero as possible so that the model can make better predictions. The distribution of the error terms is shown in Figure 7 and is seen to be close to zero.

Figure-7: Residual by Predicted



It is important to note that this study employs a parsimonious model, using only the FED policy rate as an independent variable to isolate this fundamental relationship. We recognize that other macro-financial variables, such as inflation expectations, credit default swap (CDS) premiums, and bond market spreads, also influence LIBOR. The exclusion of these variables is a limitation of the current

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model, and their inclusion in future, more complex MLP architectures could further enhance predictive accuracy.

5. DISCUSSION AND CONCLUSION

The accurate modeling of variable interest rates is paramount for financial stability and decision-making processes, particularly for individuals, corporations, and governments reliant on borrowing. LIBOR historically served as a cornerstone reference rate for such financial instruments but has since been superseded by alternative rates like SOFR. This study addresses the challenges in modeling LIBOR, acknowledging both its historical significance and the complexities that led to its replacement by new rates.

The evolution of interest rate modeling, from Bachelier's Arithmetic Brownian Motion to the sophisticated LIBOR Market Model (LMM), reflects the increasing complexity of financial markets. Although LMM offers a theoretically sound framework, its practical application encounters obstacles such as data scarcity, calibration difficulties, and reliance on time-consuming simulations. Furthermore, the discontinuation of LIBOR necessitates the revision of existing models or the development of new ones.

In this research, traditional econometric approaches (notably cointegration analysis), while initially indicating a strong relationship between LIBOR and the US Federal Reserve (FED) policy rate, were found to violate key statistical assumptions, such as the normal distribution of residuals and the absence of autocorrelation. These limitations led to the adoption of a Multi-Layer Perceptron (MLP), an artificial intelligence technique, chosen for its capacity to model complex, non-linear relationships and its flexibility in handling data that does not conform to rigid statistical prerequisites.

The empirical investigation utilized monthly one-month LIBOR data (September 1989-April 2023) as the dependent variable and the FED policy rate as the independent variable. The MLP model, employing two hidden layers and the Tanh activation function, demonstrated exceptional performance. The model achieved an explanatory power (R^2) of 0.99, with very low relative errors and residuals close to zero. This strongly indicates that the MLP model effectively captured the dynamics between the variables. A crucial finding confirmed that LIBOR movements closely mirrored the FED policy rate; this was consistent with the initial cointegration results but achieved without the associated assumption violations. Synaptic weight analysis further suggested that the first hidden layer had a more significant impact on the model's output.

Policy Implications

The findings of this study robustly demonstrate that the FED policy rate is a primary determinant of LIBOR (and other similarly behaving benchmark interest rates). This confirms the significant importance of central banks' monetary policy decisions and communication strategies due to their direct impact on market interest rates. For policymakers and market participants, this implies that expectations regarding the FED's future policy actions play a critical role in forecasting the direction of short-term interest rates and, consequently, financing costs. Our findings suggest that market participants can leverage non-linear AI models like MLP to gain more accurate and timely forecasts of benchmark rates following changes in central bank policy, potentially outperforming traditional models that are slower to calibrate to new market regimes.

Limitations

This study is subject to several limitations that should be considered when interpreting the results. First, the reliance on a single predictor variable, while useful for isolating a core relationship, omits other relevant macro-financial factors that undoubtedly influence benchmark rates. Second, the 'black-box' nature of the MLP model restricts the economic interpretability of the underlying

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mechanisms, representing a trade-off for its predictive power. Third, the high R^2 value, while indicating a strong fit, also suggests a potential risk of overfitting, even with the regularization and early stopping measures in place. The model's generalization performance should be further validated using techniques such as k-fold cross-validation in future studies. Finally, the performance of the MLP model was not benchmarked against traditional time-series models like ARIMA or the LMM itself. Such a comparative analysis would be necessary in future research to rigorously quantify the MLP's relative advantage.

Recommendations for Future Research and Developments

This study opens several avenues for future research. Firstly, modeling the FED policy rate itself would be an important step toward enhancing the forecast accuracy of LIBOR and similar rates. Secondly, the adaptation of LMM and AI models like MLP to the new generation of Risk-Free Rates (RFRs) such as SOFR, SONIA, and €STR, and testing their efficacy as sufficient data accumulates, is necessary. Thirdly, concurrently with the discontinuation of LIBOR, the development of derivative products (swaps, futures, options) based on new RFRs and risk management models, along with the creation of appropriate mathematical models for them, remains an ongoing area of research. Lastly, it is considered that digital platforms and AI applications will enable more effective use of LMM-type models by making processes such as the trading of interest rate-based derivatives, risk management, pricing, and data analytics more efficient. A detailed examination of the direct and indirect impacts of the policy rate on LIBOR also constitutes an important topic for future studies.

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