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The Informational Value of Technical Indicators in Forecasting Quoted Prices of a Government Bond: A Machine Learning Approach

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Abstract

In the context of increasing electronification and transparency in the secondary market for euro area government bonds, this study examines the informational value of technical indicators in predicting intraday quoted prices of the 10-year German government bond. Using a feedforward neural network based on 13 input datasets and two output variables, the paper aims to identify the technical indicators that contribute most to the model's predictive accuracy and efficiency under less-volatile market conditions. The results show that trend indicators, such as moving average convergence/divergence (MACD) and weighted moving average (WMA), and relative strength index (RSI), as the only momentum indicator among the remaining observed ones, allow the models to achieve lower forecast errors than those obtained with the input variable set that does not include technical indicators. On the other hand, Bollinger Bands (BB), as a volatility indicator, result in the worst predictive performance. The findings of the study extend the use of technical analysis beyond stock markets, where these indicators were initially developed, and enable the development of more efficient forecasting models in the government bond market.

Key words: technical analysis; machine learning; neural networks; government bonds

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Introduction

Government bonds form the foundation of the financial system. Governments use them to finance public spending, infrastructure projects, and economic stimulus measures, thereby playing a key role in maintaining economic stability and supporting financial infrastructure. Furthermore, banks use them as high-quality assets to meet regulatory requirements and to manage risks. In addition, due to their lower risk compared to other asset types, they are an attractive option for conservative and institutional investors.

The introduction of the MiFID II/MiFIR regulatory framework brought about a significant shift in the trading of government bonds in the euro area. These reforms encouraged a move of part of the trading from unregulated over-the-counter (OTC) markets to regulated trading venues. In parallel, the gradual electronification of the bond market, driven by the broader adoption of electronic trading platforms, further increased market efficiency. In addition, the introduction of stricter pre- and post-trade reporting requirements increased trading transparency. This progress in the bond market led to improvements in the development of the secondary market for government bonds, especially for highly liquid bonds.

According to the ICMA (2025) report, the three most liquid government bond issuers in the euro area are Italy, Germany, and France. Among them, German government bonds stand out, as instruments issued by a sovereign with the highest credit rating (AAA). Because of this high credit rating and the low risk associated with it, German government bonds serve as a benchmark for risk assessment. They are used to value instruments with similar maturities, especially those issued by entities with lower credit ratings. In addition, yields on these bonds are used to assess market expectations. Among German government bonds, those with a 10-year maturity play a special role. They represent a balance between short- and long-term bonds, and their yields are often monitored as signals of economic developments and reflections of market expectations regarding macroeconomic stability. All these characteristics make German 10-year government bonds a relevant object of scientific research. Moreover, the previously mentioned development of the secondary market in terms of electronification and transparency, which has led to higher efficiency of the secondary market, opens space for research on the market liquidity of selected bonds, in particular, to quoted prices that determine the bid-ask spread, which is a widely used indicator of illiquidity in the cost dimension of liquidity. Research on bond liquidity, primarily through the application of modern machine learning methods, has become prevalent in recent scientific literature (Muller et al., 2023; Cabrol et al., 2024) and represents a contemporary approach to analysing this segment of the financial market.

In general, the analysis of financial markets is based on three main categories of analytical methods: technical analysis, fundamental analysis, and quantitative analysis. Fundamental analysis studies which economic factors influence market trends (Cavalcante et al., 2016), while technical analysis examines price patterns and uses these patterns to predict future price movements (Borovkova & Tsiamas, 2019). In technical analysis, technical indicators (TIs) were introduced to analyse markets and better understand price patterns. Technical indicators, based on mathematical formulas that use historical prices or trading volume and heuristic rules within technical analysis, can generate buy (bullish) or sell (bearish) signals (Pricope, 2021). Apart from technical and fundamental analysis, quantitative analysis is fundamental to financial market analysis and offers a more comprehensive approach. It covers a wide range of methods, from basic descriptive statistics and statistical tests to optimisation and simulation procedures, through time series analysis, advanced econometric methods, and machine learning. In contrast to fundamental analysis, which primarily focuses on economic indicators, and technical indicators, which describe individual aspects of price movements, quantitative methods, such as machine learning methods, can simultaneously integrate information from multiple indicators, from historical prices and economic indicators to different technical indicators, identify complex relationships among them, and use the observed patterns to predict future movements in financial markets.

Based on the above, this paper links quantitative and technical analysis to examine the significance of individual technical indicators in improving the predictive accuracy of machine learning models for forecasting intraday quoted prices of the 10-year German government bond. Although technical indicators have been used for decades to develop simple trading strategies (Jiang, 2021), especially in the stock market for which they were initially developed, their value in designing such strategies is often questioned because of the lack of a strong theoretical basis and their weak adaptability to structural changes in financial markets. However, their informational value is emphasized when they are used as input variables in price prediction for financial markets using machine learning methods. Many previous studies that examine the use of machine learning methods for predicting prices in financial markets, especially stock prices, include technical indicators among the input variables.

Kumbure et al. (2022), in their literature review on the application of machine learning algorithms for predicting stock price movements, which covers 138 research articles published between 2000 and 2019, point out that, out of 2173 identified unique variables used in these studies, 1348 (62%) belong to the category of technical indicators. Additionally, Jiang (2021) conducted a literature review focusing on the use of deep learning (DL) methods for predicting stock price movements. Out of 124 analysed research articles, 46 included technical indicators as part of the input variable set. Moreover, the joint use of historical prices and technical indicators was present in 25% of the analysed articles. Earlier literature reviews by Bustos et al. (2020) and Henrique et al. (2019) also highlight technical indicators as the most common input variables in machine learning models. Furthermore, most studies use a combination of several technical indicators to predict market movements, which suggests that different indicators can complement each other and thus contribute to higher accuracy in forecasting future stock prices (Kumbure et al., 2022; Jiang, 2021; Henrique et al., 2019; Bustos & Pomares-Quimbaya, 2020).

While the above literature reviews indicate that the application of technical indicators in the stock market has been extensively studied, their application in the bond market is much less common. This can be explained, at least in part, by the significantly smaller number of studies that apply machine learning methods to the bond market compared with those focused on the stock market. Among the studies on the application of machine learning methods in the context of the bond market, Nunes et al. (2018) use moving averages (MAs) of yields to maturity on 2-, 5-, 10-, and 30-year bonds, with different rolling window lengths, in order to forecast the yield curve. Similarly, Müller et al. (2023) use the moving average of illiquidity as part of the set of independent variables to predict expected illiquidity of U.S. corporate bonds. Additionally, Kalinić Milićević (2025) shows that machine learning models exhibit statistically significant predictive superiority for modelling intraday quoted prices of a government bond when the input variable set includes technical indicators.

This paper extends the study by Kalinić Milićević (2025) by analysing the individual impact of the observed technical indicators on the predictive accuracy of a feedforward neural network-based machine learning model, which in that study was identified as the algorithm with the lowest forecast error. This research aims to identify the most informative technical indicators, initially developed for the stock market and here analysed in the context of the bond market, for forecasting the intraday bid and ask prices of the benchmark German government bond. Given the different characteristics of the stock and government bond markets, for example, in terms of volatility, the question arises about the value of individual technical indicators in a less volatile market, such as the government bond market, despite their popularity in research on the more volatile stock market. The purpose of the research is to identify the dominant technical indicators in the observed context of the government bond market and thus contribute to a more efficient handling of the high-dimensionality problem in machine learning models that can hurt the accuracy and generalisation of predictive models, especially when the number of observations is limited, as is the case for newly issued government bonds. Therefore, the research contributes to understanding the informational value of technical indicators in the bond market, a field that is much less explored in this context, and thus to the development of more efficient models with shorter training time.

The development of an efficient machine learning model to predict intraday quoted prices, and thus the bid-ask spread, would provide a wide range of market participants with valuable, timely information to make and improve trading decisions. For market makers, such a model would help them decide when and by how much to adjust their quotes to maintain competitive prices during stable market periods and to protect against potential losses during periods of increased market volatility. By adjusting their quoting strategies to market dynamics, market makers can reduce their exposure to adverse selection, increase profitability, and maintain a stable market presence, thereby potentially improving market liquidity and more efficiently discovering prices.

Furthermore, accurate intraday price prediction could benefit both institutional and retail investors. For institutional investors, who often manage large-volume transactions that can affect market prices and face difficulties finding counterparties for large trades, accurate prediction of quoted prices would allow them to identify optimal time intervals during the day when bid-ask spreads are narrower and price volatility is lower. This would enable them to execute orders gradually, in smaller parts, avoiding execution in unfavourable market conditions and without affecting market prices. On the other hand, retail investors, although they trade much smaller volumes, could use such predictions to improve their short-term trading decisions.

The research presented in this paper is divided into six chapters. After the Introduction, the Technical Analysis chapter follows, which presents the technical indicators used in the research. After the technical analysis chapter, the Methodology chapter describes the data and methodology used. This is followed by the Research Results and the Discussion chapters, in which the results are presented and analysed. The last chapter is the Conclusion, where the results are summarised, and recommendations for future research are given.

Technical analysis

Technical analysis (TA) is the process of analysing a security's historical prices to determine its future price movements. Technical analysts use technical indicators and candlestick pattern analysis to improve price movement forecasting. In line with this, many research papers use open, high, low, and close (OHLC) prices, trading volume, and technical indicators as input variables in prediction models. The methods used to develop these models vary by technical analysis approach: while studies that rely on technical indicators most often use regression methods, candlestick pattern analyses rely on image processing techniques (Li & Bastos, 2020). In this paper, the first of these two approaches is used, in which technical indicators serve as input variables in a machine learning regression model.

To provide an overview of the diversity of technical indicators used in technical analysis, Peng et al. (2021) presented a comprehensive review of 124 indicators, including those used in scientific literature published between 1999 and 2018 and those applied by market practitioners. However, despite the large number of existing technical indicators, according to the literature reviews by Kumbure et al. (2022), Peng et al. (2021), and Bustos and Pomares-Quimbaya (2020), specific indicators stand out for their frequent use in prior research. According to Kalinić Milićević (2025), these are: simple moving average (SMA), exponential moving average (EMA), weighted moving average (WMA), moving average convergence/divergence (MACD), relative strength index (RSI), stochastic oscillator %D, stochastic oscillator %K, momentum, Williams %R, commodity channel index (CCI), BIAS, Bollinger bands (BB), and accumulation/distribution oscillator (A/D oscillator). Additionally, these indicators, except for EMA, BIAS, and BB, are also included in the popular set of technical indicators presented in the study by Kara et al. (2011). Based on the above, the following sections present the theoretical framework for the technical indicators used in this research, which are drawn from the study by Kalinić Milićević (2025). Furthermore, since technical indicators can generally be classified into four basic categories, the selected indicators are presented within their corresponding categories.

Trend indicators

Trend is the primary element considered in technical analysis (Colby, 2003). Trend indicators indicate the direction of the price change for the observed security. Some well-known trend indicators include moving averages and MACD. Although there are several types of moving averages (Jansen, 2020), the three most commonly used are SMA, EMA, and WMA; in this paper, WMA is used.

WMA represents the average of prices from the previous n Periods, where the prices are assigned, weights corresponding to their indices within the n periods (Jansen, 2020). Formally, the WMA at the time t is defined by the following formula:

$$\boldsymbol{WMA(n)_t = \frac{2}{n(n+1)}\sum_{i=1}^{n} i \cdot P_{t-n+i},} \tag{1}$$

where P_{t-n+i} are the prices within the n periods preceding time t. A moving average defined in this way assigns higher weights to more recent data and lower importance to older data.

The next trend indicator is MACD, which shows the relationship between two moving averages of the security's price (Jansen, 2020; Colak & Koy, 2023). MACD is the difference between a short-term and a long-term exponential moving average (EMA). The number of periods used for the short-term and long-term moving averages is usually 12 and 26, respectively (Colby, 2003).

The MACD indicator consists of the following two components:

1. The MACD line, which represents the difference between the fast and the slow exponential moving averages:

   $$MACD_t = EMA(n1)_t - EMA(n2)_t, n2 > n1,$$

   where the exponential moving average at time t, for n periods, is calculated using the following formula:

   $$EMA(n)_t = \alpha P_t + (1-\alpha)EMA(n)_{t-1},$$

   where α is usually calculated using the formula $\alpha = \frac{2}{n+1}$ (Jansen, 2020; Lokhacheva et al., 2020; Singh et al., 2023)
2. The signal line, which is defined as the exponential moving average of the MACD over the previous 9 periods.

Based on the above, the indicator can be used in a trading strategy in two ways: (i) by using the main MACD line, or (ii) by observing the difference between the MACD line and the signal line. In this paper, MACD and the signal line are included as separate input variables in the machine learning model, allowing the model to learn and evaluate the relationship between these components on its own.

Momentum indicators

Momentum indicators measure the speed at which prices change over time. According to the literature reviews by Kumbure et al. (2022), Peng et al. (2021), and Bustos and Pomares-Quimbaya (2020), technical indicators from this category are the most frequently used indicators in previous research on the stock market. Among the indicators in this category, the most notable are RSI, the stochastic oscillators %D and %K, momentum, Williams %R indicator, and CCI.

One of the best-known momentum indicators is the RSI indicator (Colby, 2003). The RSI indicator is based on the calculation of average gains and average losses over a given time period. Higher values of the indicator (usually above 70) indicate that the security is overvalued, while lower values (usually below 30) indicate that it is undervalued. The following formula defines RSI:

$$\boldsymbol{RSI_t = 100 - \frac{100}{1 + \frac{EMA(n)_{DM^+}}{EMA(n)_{DM^-}}}} \tag{2}$$

where DM^+ i DM^- are gains and losses defined with $DM^+ = max\{P_t - P_{t-1}, 0\}, DM^- = min\{P_t - P_{t-1}, 0\}$ and $EMA(n)_{DM^+}, EMA(n)_{DM^-}$ Are the corresponding exponential moving averages over n Periods. A larger number of periods n Makes the indicator less sensitive to price changes, while a smaller number of periods makes it more sensitive. The default and often used value for n Is 14 (Colby, 2003).

The next momentum indicator is the stochastic oscillator, which compares a security's price with its price range over a selected period. The oscillator consists of two lines, %K and %D, which in the existing literature are not necessarily used together. Both lines are derived from the value. K, which indicates the position of the current price relative to the highest and lowest prices in the observed period. Formally, for a selected period length n, the value of K at time t is calculated using the following formula:

$$\boldsymbol{K(n)_t = 100 \cdot \frac{P_t - L_n}{H_n - L_n}}, \tag{3}$$

where P_t is the price at time t while $L_n = min\{P_{low,t-n}, \dots, P_{low,t}\}$ and $H_n = max\{P_{high,t-n}, \dots, P_{high,t}\}$ are the lowest and highest prices within the previous n periods. A value of 14 is often used for the number of periods n. From the calculated K values, the value of %K at time t is obtained by computing the simple moving average of K over the previous 3 periods, while the value of %D at time t is obtained by computing the simple moving average of %K, also over the previous 3 periods. After the %K and %D lines are calculated, the K value is omitted from further analysis.

The next indicator in this category is the momentum indicator, which has the same name as the current indicator category. This indicator measures the amount of price change within the observed period (Achelis, 2014). The indicator can be defined as a difference or a ratio, with the latter more commonly used to ensure comparable values over time (Colby, 2003). The momentum indicator at time t is calculated using the following formula:

$$\boldsymbol{Mom(n)_t = \frac{P_t}{P_{t-n}} \cdot 100}, \tag{4}$$

where P_t is the price of security in time t, while P_{t-n} is the price of security n periods before time t. The momentum indicator helps predict a trend change before it occurs, making it an important tool in technical analysis (Colby, 2003). When market prices start to rise, the indicator's value is usually high, but its growth slows as the market becomes overvalued and buying interest weakens. This indicates that the trend is losing strength, even if prices are still rising. A similar pattern appears during periods of falling prices. The indicator becomes less damaging before the price stops falling, which signals a decrease in selling pressure.

The next momentum indicator is Williams %R, also known as Williams percent range. The indicator is similar to the K value in the stochastic oscillator, but in this case, the smoothing with a simple moving average, which is used in the calculation of the %K and %D lines, is omitted. The formula for calculating the value of the indicator at time t is given by:

$$\boldsymbol{R(n)_t = \frac{P_n^{high} - P_t}{P_n^{high} - P_n^{low}}}, \tag{5}$$

where P_t is price of security in time t, while $P_n^{high} = max\{P_{t-n}, \dots, P_t\}$ and $P_n^{low} = min\{P_{t-n}, \dots, P_t\}$ are the highest and lowest price within period with lenght n. An interesting feature of this indicator is its ability to predict trend changes. Namely, the indicator reaches a local maximum (minimum) and then starts to fall (rise) several periods before the exact price change in the security (Achelis, 2014).

The last momentum indicator included in this paper is CCI. The CCI indicator measures the difference between the current typical price, calculated as the average of the current low, high, and closing prices, and the historical average price (Colby, 2003; Jansen, 2020). The value of the indicator at time t is calculated using the following formula:

$$\boldsymbol{CCI_t = \frac{\overline{P_t} - SMA(n)_t}{0.015 \sum_{t=i}^{T} |\overline{P_t} - SMA(n)_t| / T}}, \tag{6}$$

where $\overline{P_t}$ is the typical price of the security at time t, n is the number of periods, and T is the observed time period. The indicator values usually range between -100% and +100%. Values above +100% indicate the beginning of an upward trend, while values below -100% indicate the beginning of a new downward trend.

Volatility indicators

Volatility indicators measure how much a given variable, such as a security's price, fluctuates over a specific period of time. Compared with technical indicators from the first two categories, volatility indicators, along with indicators related to trading volume, are much less apparent in previous research. Since the bond market is generally less volatile than the stock market, this study includes only one technical indicator from the bond market. According to the set of technical indicators in Kalinić Milićević (2025), BB was selected as the representative of the volatility indicator category.

The BB (Bollinger bands) indicator analyzes the distance between the current typical price and the previous n typical prices (Borovkova & Tsiamas, 2019). The indicator is defined by three lines: the middle, upper, and lower line. The middle line corresponds to the simple moving average of typical prices over n periods. The price of the security is expected to move near the middle line (Nuij et al., 2014), but also within the bounds of the other two lines, the upper and lower line, which are based on the standard deviation of prices within the selected period n. Since standard deviation is a measure of volatility, the distance between the bands represented by the upper and lower line is expected to widen when the market is volatile and to narrow when the market becomes more stable (Achelis, 2014). The following expressions formally define these three lines:

$$\boldsymbol{Middle_t = SMA(n)_t}, \tag{7}$$

$$\boldsymbol{Upper_t = Middle_t + d\sigma}, \tag{8}$$

$$\boldsymbol{Lower_t = Middle_t - d\sigma}, \tag{9}$$

where $\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_{t-n+i} - Middle_{t-n+i})}$ is the standard deviation of typical prices over n periods and d is the number of standard deviations used to define the distance between the median line and the two boundary lines.

The technical indicators presented above will be used individually as input variables in the machine learning models, along with the available historical data.

In the next chapter, the procedure for constructing the database used in the empirical analysis is described, along with the methodological framework implemented in this research.

Methodology

Data

The empirical analysis in this study is based on a time series of historical data for a German government bond with a 10-year maturity. The bond was issued on 5 July 2024 with a maturity of 10 years. The historical time series includes data at a 5-minute frequency within trading days during the first month of trading. More precisely, the dataset covers the period from 5 July to 31 July 2024. For each trading day in the observed period, historical data were collected from 9:00 to 17:30 at 5-minute intervals, yielding a total of 1957 observations.

The data were collected from the Refinitiv platform and include the following input variables for the model: OHLC bid prices, OHLC ask prices, the mid price, the yields associated with the bid, ask, and mid prices at the end of each five-minute interval, as well as variables related to the number of changes in the bid price and the ask price in each five-minute interval. The labels of these variables at time $t, t \in \{1,2,\ldots,1957\}$ are as follows: $bid_t^{open}, bid_t^{high}, bid_t^{low}, bid_t^{close}, ask_t^{open}, ask_t^{high}, ask_t^{low}, ask_t^{close}, mid_t, yield_t^{bid}$, $yield_t^{ask}, yield_t^{mid}, mov_t^{bid}, mov_t^{ask}$.

For each time *t,* the following two target variables are defined:

$$\boldsymbol{bid_t = bid_{t+1}^{close}}, \tag{10}$$

$$\boldsymbol{ask_t = ask_{t+1}^{close}}. \tag{11}$$

In addition to the above initial variables, the dataset also includes lagged variables and the variable $hour_t$ which carries information about the hour of the day to provide the machine learning model with additional information for recognising patterns over time. In more detail, for each target variable bid_t i ask_t In more detail, for each target variable, three time lags were determined by performing partial autocorrelation analysis (PAC). They were found to be statistically significantly related to the corresponding target variable at the 1% significance level. The values of the obtained lags are 38, 76, and 104, while the corresponding variables are denoted respectively by $bid_t^{38}, bid_t^{76}, bid_t^{104}, ask_t^{38}, ask_t^{76}, ask_t^{104}$.

The choice of these input variables is based on the criterion of data availability at the intraday level. Although other variables could affect quoted prices, they do not change at the intraday level and are therefore not included in this study. Potentially, information on macroeconomic announcements available at the intraday level could also be included in the set of input variables, but this is left as a direction for future research.

The constructed set of 21 input variables was individually extended with the selected technical indicators to create datasets for evaluating the importance of each technical indicator in improving the predictive accuracy of the constructed model for forecasting intraday quoted prices of the observed government bond. Table 1 lists the generated datasets. The first column contains the dataset name, while the second column lists the input variables included in the dataset, along with the initial input variables described above. The third column contains the parameter values for the technical indicator under consideration. Based on the analysis carried out in Kalinić Milićević (2025), which resulted in superior model performance on the input variable set that contained technical indicators with pre-specified, widely used parameter values, compared with models applied to the set with technical indicators whose parameters were set using PAC analysis, this study also considers technical indicators with pre-specified (default) parameters.

Table 1

Input variable sets

Name of the set	Additional input variables	Parameters
wma_38	$WMA_{38}^{bid}, WMA_{38}^{ask}$	*n* = 38
wma_76	$WMA_{76}^{bid}, WMA_{76}^{ask}$	*n* =76
wma_104	$WMA_{104}^{bid}, WMA_{104}^{ask}$	*n* = 104
wma_38_76_104	$WMA_{38}^{bid}, WMA_{38}^{ask}, WMA_{76}^{bid},$ $WMA_{76}^{ask}, WMA_{104}^{bid}, WMA_{104}^{ask}$	*n* = 38, *n* =76, *n* = 104
macd	$MACD^{bid}, MACD^{ask},$ $MACD_{signal}^{bid}, MACD_{signal}^{ask}$	$\boldsymbol{n_1} = \mathbf{12},$ $\boldsymbol{n_2} = \mathbf{26}$
rsi	RSI^{bid}, RSI^{ask}	*n* = 14
stoch d	D^{bid}, D^{ask}	*k* = 3
stoch k	K^{bid}, K^{ask}	*n* = 14
mom	Mom^{bid}, Mom^{ask}	*n* = 12
CCI	CCI^{bid}, CCI^{ask}	*n* = 20
Williams R	R^{bid}, R^{ask}	*n* = 14
BB	$\boldsymbol{Middle^{bid}}, \boldsymbol{Middle^{ask}}, \boldsymbol{Upper^{bid}},$ $\boldsymbol{Upper^{ask}}, \boldsymbol{Lower^{bid}}, \boldsymbol{Lower^{ask}}$	*n* = 20

Source: Author's work.

Model performance was evaluated on each dataset presented in Table 1, as well as on the initial input variable set, which consists of 21 variables without technical indicators.

The following section presents the methodological framework implemented in the research. It includes a brief description of the feedforward neural network as the machine learning method used in the study, along with details on training and testing the model.

Feed Forward Neural Network

Feedforward neural networks (FFNNs) are one of the three main groups of neural networks. The other two are recurrent neural networks (RNNs) and convolutional neural networks (CNNs). According to Dixon et al. (2020), neural networks (NNs) can in general be defined as a nonlinear mapping $F(x)$ in a high-dimensional input space, implemented through hierarchically organised layers of abstraction. A feedforward neural network consists of three types of layers in its architecture: an input layer, one or more hidden layers, and an output layer. If a neural network has more than one hidden layer, it is called a deep neural network (DNN).

The process of transforming input data into output data starts in the input layer, which passes the data to the hidden layers, and ends in the output layer, where the obtained result is compared with the expected output for the input data. The hidden and output layers consist of neurons. The size of the network can be described by its depth, measured by the number of hidden layers, and its width, measured by the number of neurons per layer. Neurons consist of an aggregation function and an activation function (Jiang, 2021). The aggregation function computes a linear combination of the input data, assigning weights to each input and including a bias term. In contrast, depending on its type, the activation function applies a nonlinear transformation, enabling the network to learn nonlinear relationships. The weights assigned to the input data, along with the bias, form the neural network's parameters. These parameters are determined during the training process, where the goal is to optimise prediction performance by accurately estimating the weights. The neural network's parameters are updated during training using optimisation algorithms that minimise the cost function. Two popular optimisation algorithms are stochastic gradient descent (SGD) and adaptive moment estimation (Adam). The cost function is usually tied to the type of output, which depends on the machine learning problem, such as regression or classification. For example, in regression problems, the mean squared error (MSE) or the root mean squared error (RMSE) is commonly used as the cost function.

While the weights and biases are the parameters of the neural network learned from the input data during training, the number of neurons and hidden layers, as well as the type of activation function and optimization algorithm, are the neural network's hyperparameters. These hyperparameters can be viewed as configuration settings that define how the network is trained. Their precise choice affects the neural network's final predictive performance.

Neural networks, even simpler ones such as feedforward neural networks, tend to overfit. This means the network parameters adapt too much to the training data, reducing their ability to generalise and make accurate predictions on the test data. The best protection against overfitting is to train the neural network on a large dataset (Jansen, 2020). As an alternative or in addition to this, regularisation techniques such as early stopping or dropout can be used. Early stopping refers to stopping training when the network's performance stops improving, whereas setting a dropout rate means randomly dropping a fraction of neurons with a given probability. Randomly switching off some neurons during propagation prevents individual neurons from becoming too specialised in specific patterns in the data (James et al., 2021). The possibility of using early stopping and setting the dropout rate introduces two additional hyperparameters for the neural network, which can be tuned to achieve better predictive performance on data other than the training data.

The selected hyperparameters of the feedforward neural network, which include the number of neurons, the number of hidden layers, the activation function, the dropout rate, the batch size, the type of optimisation algorithm, and its learning rate, were optimised using the Optuna algorithm (Akiba et al., 2019) for hyperparameter optimisation, separately for each of the observed input variable sets. The chosen level of optimisation complexity, determined by the number of hyperparameters optimised, is justified by the aim of achieving the best possible model performance on the observed datasets, thereby enabling relevant empirical conclusions. For each dataset, the hyperparameters were optimised by evaluating the model over 300 hyperparameter combinations, with a maximum of 500 epochs per combination. The optimal number of neurons was determined from the set $\{4,5,6,\ldots,64\}$, number of hidden layers from the set $\{1,2,3\}$, activation function from the set $\{ReLu, LeakyReLU, Tanh\}$, batch size from the set $\{2,16,32,64\}$, optimisation algorithm from the set $\{SGD, Adam\}$, learning rate from segment $[10^{-5}, 10^{-1}]$ and drop out rate from segment $[0.1, 0.5]$. The procedure for training and testing the model is described in the following subsection.

Training and testing the model

For each of the 13 constructed datasets, a feedforward neural network model was trained and tested. To evaluate model performance, the observed datasets were divided into three parts: a training set, a validation set, and a test set. The training set covers the period from 8 July 2024 to 21 July 2024; the validation set, from 22 July 2024 to 24 July 2024; and the test set, from 25 July 2024 to 31 July 2024. Although the initial observation period starts on 5 July 2024 (Friday), the data from that day were excluded from the training set, because they were used to calculate lagged variables and technical indicators for the following working day, i.e., 8 July 2024 (Monday). Furthermore, the training and validation sets were used for hyperparameter optimisation. Afterward, the model with the resulting hyperparameters was trained on the period from 8 July 2024 to 24 July 2024 and evaluated on the test set.

During model training and hyperparameter optimisation, the mean squared error was used as the measure of model accuracy. Additionally, the results report the coefficient of determination (R^2) and the mean absolute percentage error (MAPE).

Results

Using the methodological approach described above, feedforward neural network models were trained and tested on 13 datasets. The predictive performance of the models on the training and test sets for each dataset is presented in Table 2.

According to the results in Table 2, models based on only 5 of the 12 datasets with technical indicators have lower MSE on the test set than the model based on the input variable set without technical indicators. The technical indicators whose individual inclusion in the input variable set, together with the initial variables, contributed to lower forecast errors of the corresponding models on the test set, compared with the error achieved by the model based on the initial input variables without technical indicators, are $RSI, WMA(104), MACD, WMA(76), WMA(38)$. Table 3 shows that these technical indicators also perform better when the MSE values are examined for each quoted price.

The results indicate that the individual inclusion of the analysed trend indicators, which are the most widely used in stock market research, was also successful for intraday forecasts of the quoted prices of the government bond. Including all three moving averages simultaneously resulted in slightly worse model performance on the test set. It can be observed that the model's performance on the training set, when all three moving averages are included, is better than, for example, when only the moving average with $n = 76$, is included. However, the relationship between the performance of these two models on the test set is reversed, indicating that the model trained on the data with three moving averages overfits. Furthermore, among momentum indicators, only RSI is informative in the observed context. On the other hand, including BB as a volatility indicator resulted in the highest forecast error on the test set.

Table 2

Results of training and testing of FFNN models

	Train set				Test set			
Set	**MSE**	**R2**	**MAPE**	**Rank MSE**	**MSE**	**R2**	**MAPE**	**Rank MSE**
wma_38	0,00154	0,9920	0,0262	5	0,02283	0,8532	0,1167	**5**
wma_76	0,00158	0,9918	0,0267	8	0,02235	0,8563	0,1163	**4**
wma_104	0,00141	0,9927	0,0246	1	0,02040	0,8688	0,1099	**2**
wma_38_76_104	0,00156	0,9920	0,0263	6	0,02381	0,8469	0,1183	7
macd	0,00162	0,9916	0,0274	10	0,02106	0,8646	0,1133	**3**
rsi	0,00149	0,9923	0,0265	3	0,00506	0,9675	0,0588	**1**
stoch d	0,00152	0,9921	0,026	4	0,02505	0,8389	0,121	8
stoch k	0,00156	0,9919	0,0258	7	0,02639	0,8303	0,1248	9
mom	0,00175	0,9910	0,0287	12	0,02949	0,8104	0,1335	11
CCI	0,00159	0,9918	0,0269	9	0,03021	0,8057	0,1341	12
Williams R	0,00164	0,9915	0,0272	11	0,02932	0,8115	0,1315	10
BB	0,00184	0,9905	0,029	13	0,04290	0,7241	0,1597	13
Initial (w/o TI)	0,00144	0,9926	0,025	2	0,02376	0,8472	0,1189	6

Source: Author's work.

Table 3

Test results of the models, separately for each quoted price

	MSE on the test set	
Set	**BID**	**ASK**
rsi	0,00489	0,00523
wma_104	0,02001	0,02079
macd	0,02115	0,02096
wma_76	0,02198	0,02272
wma_38	0,02246	0,02319
wma_38_76_104	0,02347	0,02415
stoch d	0,02467	0,02542
stock k	0,02617	0,02662
Williams R	0,02885	0,02978
mom	0,029	0,02999
CCI	0,02993	0,0305
BB	0,04223	0,04356
Initial (w/o TI)	0,02333	0,02418

Source: Author's work

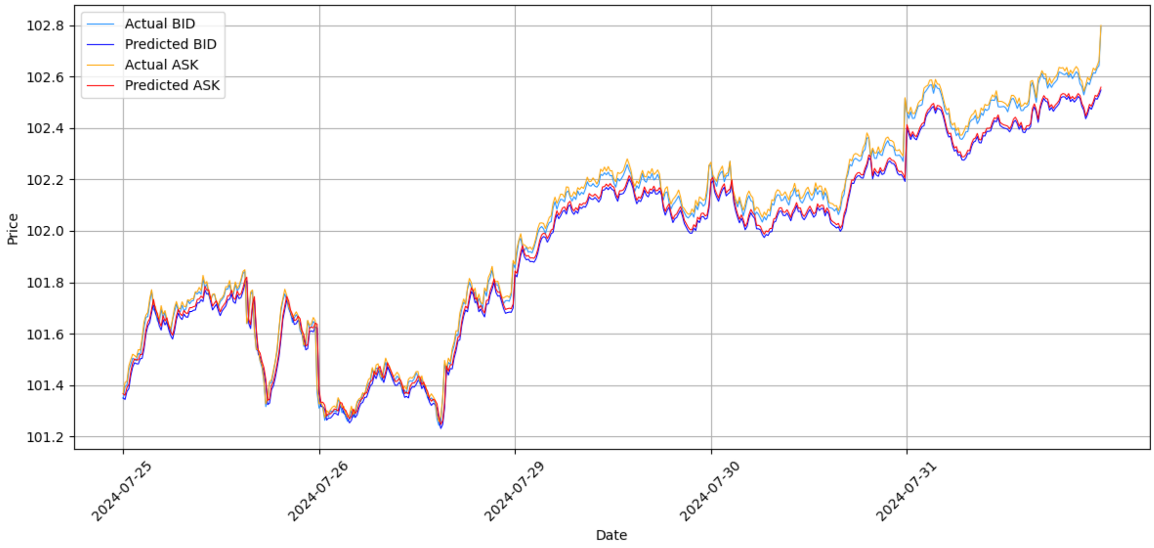
To assess the model's acceptability, MAPE values were reported as an additional measure of model accuracy.

Looking at the MAPE values, all models have MAPEs below 10% on the training set, which, according to Lewis (1982), indicates highly accurate forecasts on this set. However, when observing the MAPE values on the test set, only the model ranked 1 has an MAPE below 10% and thus retains the status of a model with highly accurate forecasts on the test set as well. According to Lewis (1982), models with MAPE values between 10% and 20% fall into a lower category and are considered to have good forecasts. Since the top-ranked model clearly differs from the remaining models in terms of the MAPE accuracy measure, it is interesting to compare its predictions with those of the model with the highest forecast error and with those of the model that excludes technical indicators.

Based on the above, the graphical representation of the relationship between the actual values of the target variables in the test set and those predicted by the models with the lowest and highest forecast error, as well as by the model based on the initial set of input variables (without technical indicators), is shown in Figures 1–3.

Figure 1

Graphical representation of bid and ask prices predicted by the model with the lowest forecast error, based on the dataset that includes RSI

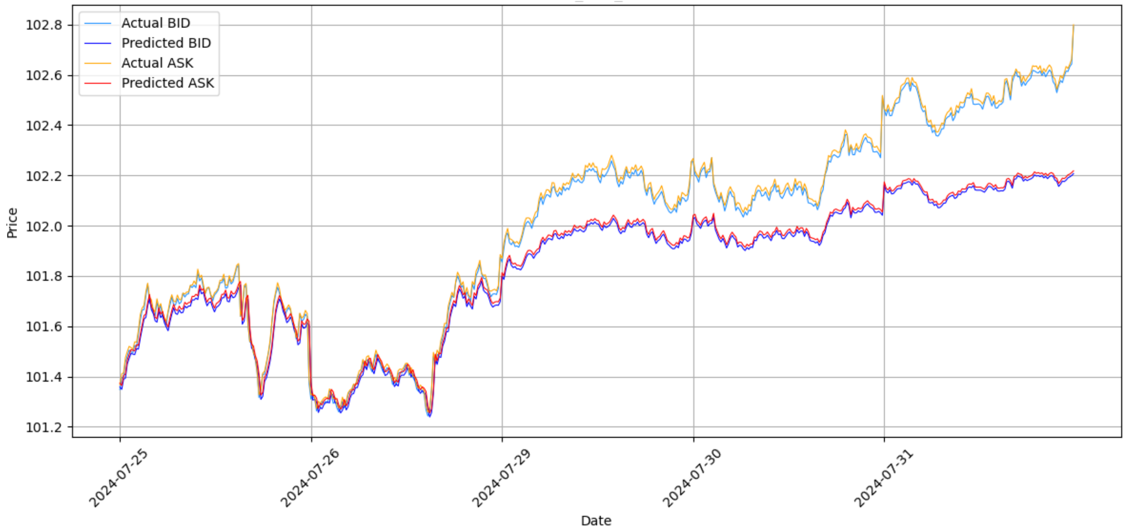


Source: Author’s illustration.

From the graphical representations, it can be observed that the highlighted models perform similarly in the initial part of the test set. However, differences in prediction accuracy are evident around midday on the first trading day (25 July 2025). However, the predictive capacity of the models in the second part of the test set highlights the difference in their performance. It can be observed that the model that had access to the values of the RSI technical indicator has fewer forecast errors in the relatively later part of the test set than the model that did not have access to the values of technical indicators, and especially than the model that had access to the value of the volatility indicator. This feature of the top-ranked model, based on the RSI technical indicator, enabled it to achieve an MAPE below 10% and a coefficient of determination (R^2) above 0.95 across the entire test set. On the other hand, none of the remaining models tested over the same period achieved a MAPE value below 10% or an R^2 value higher than 0.87.

Figure 2

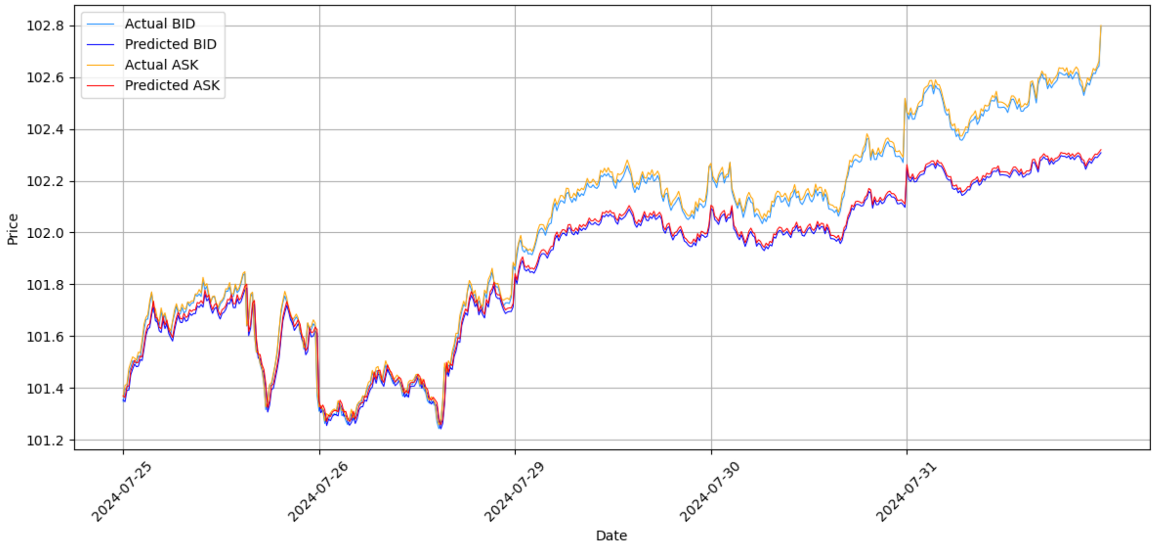
Graphical representation of bid and ask prices predicted by the model with the highest forecast error, based on the dataset that includes BB



Source: Author's illustration.

Figure 3

Graphical representation of bid and ask prices predicted by the model based on the initial dataset without technical indicators



Source: Author's illustration.

Based on the above, it can be concluded that the performance of the constructed models deteriorates as new data move further away from the period during which the models were trained, which is, in fact, a fundamental problem of forecasting in the context of financial markets. This is particularly pronounced in the government bond market, which is characterised by changes in bond liquidity and the volatility of their prices over the life of the financial instrument, i.e., from issuance to maturity. Consequently, the patterns that the model learns in one period of the bond's life, primarily when they are based on a homogeneous set of variables, do not necessarily have to apply to the remaining periods. Therefore, depending on the forecasting frequency, it is often necessary to include additional external (macroeconomic and market) and internal (coupons, duration, etc.) factors that may affect the bond's market behaviour, which makes forecasting in the context of bonds considerably more challenging than forecasting stocks. The lower the forecasting frequency, the more potentially influential variables there are, but the dataset is often limited in size. On the other hand, the higher the forecasting frequency, the fewer potentially influential variables are available, but the more data are available. The results of the analysis in this paper, which is based on an intraday context, show that including the RSI technical indicator enabled the model to forecast quoted prices most accurately over the following 515 time points, compared with other models, corresponding to a period of 5 trading days. However, even this best model's performance begins to deteriorate after the first two trading days, corresponding to 206 time points. Thus, in the intraday context, the model covers a numerically significant number of time points, whereas, in terms of elapsed time, this corresponds to two trading days.

In conclusion, trend indicators and RSI, as a momentum indicator, proved to be informative for intraday prediction of the selected German government bond's quoted prices, even at the beginning of trading, when historical data are limited. On the other hand, when examine the performance of the model based on the input variable set that includes the BB indicator, either on the training set or on the test set, where in both cases this model has the highest rank value, indicating its weakest capacity in this forecasting problem, it can be concluded that the volatility indicator, in this government bond context, does not have the informational value that may have been observed in studies related to the stock market, presumably due to its inclusion in a large number of such studies.

Discussion

Based on the conducted research and the results of the empirical analysis, it can be concluded that the technical indicators which, according to the literature reviews by Kumbure et al. (2022), Peng et al. (2021), and Bustos and Pomares-Quimbaya (2020), proved to be important in the context of the stock market due to their frequent use in previous studies, did not all show the same informational importance for predicting intraday quoted prices in the examined context of government bonds. BB, as a volatility indicator, resulted in the model with the lowest predictive accuracy. This highlights the reduced importance of volatility monitoring in the secondary market for government bonds, especially at the intraday level, compared with its potential importance in the much more volatile stock market. Among momentum indicators, RSI showed the highest informational value. In contrast, momentum, the stochastic oscillators %D and %K, Williams %R, and CCI resulted in inferior model performance, even worse than the model that does not include technical indicators. From this, it can be concluded that in a less volatile context, the ratio of average losses to average gains carries more valuable information than observing the position of the current price within a given interval (as is the case with the stochastic oscillators and Williams %R), or relative to a certain average (as is the case with CCI). Additionally, momentum, a relatively simple indicator that compares the current price with a previous period's price, ranked among the three models with the highest forecast error. Finally, trend indicators proved valuable for predicting quoted prices. Among them, the moving average over 104 periods, corresponding to one trading day, is superior to those over fewer periods. This further emphasises the importance of a longer observation horizon to capture better the underlying stable market patterns characteristic of the government bond market.

Conclusion

The analysis of the informational importance of technical indicators in the government bond market, in the context of intraday quoted prices for the benchmark 10-year German government bond, highlights the importance of selecting technical indicators in a relatively stable, less volatile market, in contrast to their widespread use in the more volatile stock market. The results justify the prior use of trend indicators in the bond market, showing that indicators such as MACD and WMA (especially with a longer rolling window) have informational value for machine learning models, even outside the traditional stock market framework. Their ability to smooth the potential impact of short-term fluctuations makes them suitable for forecasting quoted prices in more stable markets, such as the secondary market for government bonds.

On the other hand, most momentum indicators showed limited informational capacity in the observed context. The only indicator from this category that enabled the machine learning model to achieve superior performance compared with all other models included in the analysis is RSI. In the observed context, the ratio of average losses to average gains captured by the RSI indicator proved to be more informative than other momentum indicators that position the current price within an interval or relative to an average price over a given period. Finally, BB, as a volatility indicator, performed worst in the German government bond market, indicating its limited applicability in a more stable market environment.

The contribution of this study lies in identifying the technical indicators with the highest informational value in a less volatile government bond market. This enables more efficient selection of input variables, reduced dimensionality, and improved efficiency of machine learning models. Although this extends the use of technical analysis beyond the stock market, future research should investigate methods for adapting the parameters of technical indicators calibrated initially for the stock market to extract as much useful information as possible for accurately predicting future movements in government bond prices. Future research should also consider including information from other factors, both external and internal, such as macroeconomic announcements and, for example, the time to the next coupon payment, while accounting for the constraints imposed by the availability of intraday data.

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