

Testing the Reliability of Technical Analysis Models for Short-term Prediction of Prices on the Financial Markets

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Abstract

The issue of successful investment has been addressed since the beginning of the financial markets. For investors and the academic community, there is a strong motivation to test the reliability of models for predicting the development of prices on these markets. Our goal is to determine which models are optimal for short-term predictions during periods of high market volatility, and what their reliability is. A number of studies indicate that methods of technical analysis are a suitable approach for their ability to be as effective as modern methods, user-friendliness, and their ability to be applied by basic software. The price prediction reliability for the first two weeks of March 2022 is tested on the case of copper based on three conventional forecasting strategies: a) linear regression, b) naive forecasting, and c) exponential smoothing, with the frequencies of data being the daily prices of the preceding month, the daily prices of the preceding three months, and the annual average monthly prices of the preceding 13 months. The results show that linear regression is the most suitable model with the frequency distribution of daily historical prices for the period of three months (MAPE = 4.16%) and average monthly data from the preceding year (MAPE = 4.37%). Predictions based on the daily frequency of data from the period of one previous month achieved the worst predictive results for all the models. The outcomes of this study, reflecting conditions of high market uncertainty, can help investors minimise risks and maximise returns. They demonstrate which method of technical analysis is suitable in terms of predictive power and the choice of data frequency under high market volatility.

Key words

financial market; copper price; volatility; prediction; technical analysis.

Cite as:

Kucher, R., Haskova, S., & Suler, P. (2024). Testing the Reliability of Technical Analysis Models for Short-Term Prediction of Prices on the Financial Markets. *Forum Scientiae Oeconomia*, 12(1), 42–64. https://doi.org/10.23762/FORUM_Scientiae_Oeconomica_12_1_42-64

Received: 21 January 2024

Revised: 23 April 2024

Accepted: 10 June 2024



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Introduction

Achieving maximum profit or outperforming the market have been investors' goals since the beginning of the financial markets. For this reason, predictive modelling is gaining increasing interest in the scientific community, especially among investors and analysts (Devriendt et al., 2021). Testing the predictive abilities of models is necessary for many reasons, such as verifying the reliability of the model, identifying the optimal model, or optimising investment decision-making strategies (Biecek & Burzykowski, 2021). From the perspective of rational decision-making by market participants, such testing is a strategic topic for educational institutions (Pietronudo et al., 2022).

Verifying the reliability of models becomes particularly important during periods of high market volatility. As an example of a volatile market from recent times, let us consider the period of the COVID-19 pandemic, which profoundly affected the global economy, especially investment activities (Kwilinski et al., 2023). The cause was a significant increase in uncertainty from external factors. In addition to uncertainty in the development of domestic and foreign markets, factors such as the possibility of lockdowns, inflation, interest rates, and consumer sentiment contributed to the uncertainty (Chernii et al., 2022). Another catalyst for volatility in capital markets was the Russia-Ukraine conflict, which inflated international energy prices, leading to an increase in commodity prices in importing countries' industries, affecting their economic outlook and increasing capital market volatility (Huang et al., 2023). It is evident that Russia, European financial markets, and global commodity markets are dynamically interconnected during times of conflict, with European stocks and Russian bonds acting as shock absorbers, and the conflict affecting yields and volatility between them in terms of short-term and long-term frequencies (Umar et al., 2022). The imposition of restrictions on access to SWIFT by some Russian banks resulted in a significant spillover of volatility from the rouble to other markets, with this effect diminishing after investors realised that the war would persist for a longer period (Lin & Wang, 2024).

Commodities are a prominent feature of the global economy. They constitute a significant component of income and prosperity, which is highly dependent on their prices both in the countries that produce them and in the countries that consume them. The price development of commodities is inseparably linked to transient shocks. Generally, the behaviour of asset prices in capital markets is uncertain and difficult to predict, especially during turbulent periods. At the same time, commodity price prediction is an important and challenging process, particularly in volatile markets.

Increased volatility presents a clear challenge to accurate forecasting due to the unpredictability and instability of the market environment, leading to research and the quest for the most effective predictive model that generates forecasts with the lowest percentage of errors (Gaytan et al., 2022).

A number of cited studies indicate that technical analysis might be such a model. Technical analysis includes the search for repetitive and predictable stock price patterns (Mustafa et al., 2022). Many studies have concluded that technical analysis is not a suitable tool for prediction (Goutte et al., 2023). On the other hand, a number of studies have suggested that technical analysis may not be a reliable tool for prediction (Thakkar & Chaudhari, 2021). There is also evidence supporting the effectiveness of simpler forms of technical analysis in generating predictive insights (Gradojevic et al., 2023). This has been confirmed by many researchers based on practical applications, such as Jin (2021), Anghel (2021), and Hudson and Urquhart (2019).

At the market level, the dominance of technical analysis is evident – the major real-time financial information agencies operating in the market such as Thomson Reuters consistently offer reliable,

comprehensive, and up-to-date information based on technical analysis (Picasso et al., 2019). Nti et al. (2020) prepared a systematic overview of 122 studies on the topic of forecasting the stock market that were published in academic journals between 2007 and 2018. The methods were divided into three categories – technical, fundamental and combined analysis. The results show that 66% of the studies were based on technical analysis, 23% on fundamental analysis, and 11% on combined analysis.

In addition to the question of choosing the proper technical analysis method, there is the question of selecting the amount and frequency of input data. How does this aspect affect the quality of prediction? In this context, we address two interrelated problems:

1. What basic model / models for modelling time series data are optimal for short-term predictions in the periods of high market volatility and what is their reliability?
2. Is the accuracy of the model influenced by the choice of frequency and the amount of data used?

From these perspectives, we test methods of technical analysis often used in practice, namely linear regression, naive forecast, and exponential smoothing, in terms of their ability to make short-term financial market predictions.

Tests of selected prediction models are carried out in the short-term view for the copper price development in the turbulent period of 1. – 14. March 2022, i.e. shortly after the outbreak of the Russian-Ukrainian conflict, which was preceded by the Covid-19 pandemic. Copper is among the precious metals, the price of which is strongly influenced by the uncertainty in world economic policy (Raza et al., 2023).

Model predictions of the copper price are carried out on the basis of historical data of three different frequency selections with the aim to confront the prediction with reality and, based on this comparison, to identify an adequate technical analysis model and such a frequency of data that can be generally used under specific conditions of high volatility in the precious metals market.

The outcomes of this study, reflecting conditions of high market uncertainty, can help investors minimize risks and maximize returns. They will demonstrate which technical analysis method is suitable in terms of predictive power and the choice of data frequency under high market volatility.

1. Literature review

What is the predicted development of a specific stock, ETF, currency, or derivative in the following minutes, hours or days? Is the so-called timing of the market possible? These are some of the most important current economic questions, which are addressed in practice by businesspeople, investors, and banks, and theoretically by current economic research.

Rouf et al., 2021 argue that forecasting short-term price development of stock and other marketable assets have undergone a revolution in recent years, which is related to the growing market capitalization of traded companies, technological development, and relatively easy access to the market. The authors thus claim that many analysts are developing new tools and techniques to forecast the future price movement and help with investment decisions. One of them is Vo-Van et al. (2022), who use Naive Bayesian classifier for short-term trading. The classifier is used for transforming daily time series of stock prices into a data frame using posterior probability functions. Inaba (2020) also points out the importance of specific region, type of the market and degree of globalization. Based on the analysis of data from 37 markets, the author correlates these determinants, emphasizing that the

forecasting methods must consider whether it is a developed or developing country. The influence of globalized markets within extensive research of the Tokyo stock market trading is confirmed by Yamamoto (2022), who examines the importance of technical analysis for foreign investors. While private and qualified domestic investors often opt for long-term investments based on fundamental analysis, foreign traders prefer using technical analysis for short-term trading. In terms of short-term trading, the influence of short-term interest rates is equally logical. Ysmailov (2021) confirms that high-interest rates in general are connected with the increasing temporary investments and declining cash volume. The dividend policy, which is theoretically important rather for long-term investors also plays a role in short-term speculations, although it might seem paradoxical. Driver et al. (2020) point out the investors' intense short-term pressure on companies regardless of long-term investment opportunities.

One of the highly topical areas of short-term investment research is the impact of social media sentiment. Li et al. (2021) use Granger causality test to quantify the impact of the social sentiment of Twitter and the volume of results generated by Google in order to forecast the development stock and cryptocurrency prices. According to the authors, the optimal model is a combination of the results provided by both networks. Khan et al. (2021) achieve 80.53% accuracy within Twitter. However, the authors point out to the importance of developing such algorithms, which would enable both effective work with large data volumes and removing the so-called social spam.

Another current area of short-term trading research is the effort to prevent stationary data. One of the possibilities is a relatively common use of neural networks and deep learning (Tashiro et al., 2019). This is not a new method, as the first attempts to use new technologies combined with artificial intelligence date back to the 1980s. Vachhani et al. (2020) provide an overview of machine learning algorithms; however, they are aware of the problems related to constant development of new methods. A similar comprehensive overview of the most frequently utilized machine learning methods is presented by Jiang (2021), who points to the rapid development of techniques, which is driven mainly by technological progress, as well as the necessity to consider new factors and growing volume of investments. According to Zhang (2022), the most efficient one is Extreme Learning Machine (ELM), a modified feedforward neural network with one hidden layer, with significantly increased learning speed. The author recommends using this method especially in a volatile period, when it shows high performance in the period of the so-called fluctuation. remarkable learning speed is suitable for high-volatility periods. Similarly, Nabipour et al. (2020) assess the efficiency of predictive models based on methods such as Random Forrest, Adaboost, XGBoost and other artificial neural networks. According to the authors, the best performance is achieved by the model based on Long short-term memory (LSTM) network. Most of the authors (Nabipour et al., 2020) further develop this research, analysing ten methods and complementing the LSTM network with recurrent neural network. This combination is considered highly efficient. They can base their assumptions on the research conducted by Lee et al. (2019), who conclude that these methods are more effective in times of shar market fluctuations, especially during financial crises, when they are able to detect effectively resistance levels. Wang et al. (2021) and Srivastava et al. (2021) propose a different machine learning model for analysing and forecasting financial time series based on the daily analysis of the performance of the international stock indexes. The authors also compare the outputs of machine learning and technical analysis to predict price movement in financial and capital markets.

In general, machine learning methods demonstrate relatively high levels of prediction accuracy, particularly when the appropriate network and data smoothing method are chosen. Hewmalage et al. (2021) note that there is a problem of a persisting relatively low application of these models in financial practice. According to the authors, for short-term trading, entrepreneurs need easily-applicable models established in the business platforms. Ayala et al. (2021) try to solve this problem by suggesting the use of both techniques - machine learning and technical analysis, combining a Linear model (LM), Artificial Neural Networks (ANN), Random Forrest, and support vector regression with technical analysis using the Triple Exponential Moving Average (TEMA) and Moving Average Convergence Divergence (MACD). Within the short-term investments Hašková et al. (2023) presents the predictive capabilities of a fuzzy multi-criteria evaluation system that operates on the basis of a non-fuzzy neural approach, but also one that is capable of implementing a learning paradigm and working with vague.

Despite the intensive efforts to apply new predictive methods based both on social networks sentiment analysis, neural networks and machine learning, technical analysis still holds the pre-eminent position in research and financial practice (Jin, 2021). It predominates within short-term trading, is robust, and forms the basis of short-term business strategies (Sermpinis et al., 2021). Technical indicators are better predictors than the fundamental indicators in the case of active intensive trading; their prediction performance is not affected by problematic data selection and processing and time changes (Wang et al., 2020). Predictions of stock return provided by technical indicators are statistically and economically significant; however, it is possible and feasible to further innovate and improve them (Dai et al., 2021). The authors form their opinion based on the examination of novel technical indicators in their research (Dai et al., 2020), combined with a two-phase probabilistic model defined by economic limitations.

Nevertheless, according to researchers, technical analysis has a lot of limitations. Hassanniakalager et al. (2021) correlate the method on the example of short-term currency trading with other predictive models, such as Vector Machine and dynamic Bayesian model averaging, which outperform technical analysis. At the same time, it is clear that technical analysis is not always suitable; according to Tan et al. (2020), its effectiveness depends on the area of research and type of business. The authors also point to the growth of transaction costs in short-term investments based on technical analysis and recommend combining with the Sentiment-Threshold method. Jin (2022) achieved similar results, analyzing the possibility of short-term five-minute cycle trading (intra-day) with gold as a commodity in the Shanghai Futures Exchange market. The author did not prove the effectiveness of this method compared to other business strategies. Strategies of short-term (spot) trading with other commodity (oil) is addressed by Nonejad (2021), who points to the instability of parameters and model uncertainty in the Bayesian approach. The author states that the statistical approach shows the highest effectiveness in short-term trading. In general, it is possible to use the method of commodity channels in the case of trading with oil or precious metals, although they are not always evaluated positively. Brogaard et al. (2019) criticized the methods for distorting prices, which impedes the companies to make decisions. However, according to Wena et al. (2019), channels can be used in selected markets. The authors highlight the substantial non-linear causality that exists between oil prices and the Chinese stock market.

Despite various studies on short-term business strategies based on machine learning or social network sentiment, technical analysis, supplemented by new indicators, such as tackling the problem of volatility (León-Castro et al., 2019) or static data, largely dominates the market. This problem was

addressed by Nonejad (2021) in another study on the function of dynamic averaging, declaring its effectiveness in economic predictive models.

The issue of Moving Average method (MA) draws the attention of many researchers. Ma, Yang and Su (2021) deal also with the appropriate application of this model in various situations, proving its highest effectiveness in volatile stock markets. The authors also point to the method's decreasing performance over time, warning about its detrimental effect when used for longer period. Similarly, Huang and Huang (2020) indeed, it has been confirmed that moving average (MA) strategies tend to experience diminished profitability when implemented through ETFs compared to when applied directly to the underlying indexes. The authors also test an investment horizon, declaring that the strategy is less effective in the long run than, for example, a buy-and-hold approach. Lin et al. (2021), who deal with an extensive comparison of both strategies, disagree with the above statement, claiming that the timing the momentum by incorporating the signals of the Moving Average enables achieving better performance by the application of the "buy and hold" strategy, including the often-discussed consideration of higher transaction costs in the case of the first variant. Almost the same conclusion was made by Hung and Lai (2022), who compare the efficiency of portfolios composed using Moving Average and "buy-and-hold" strategies. Aliu et al. (2022) used Vector Error Correction Model firstly to detect the effect that electricity prices maintain on the PX Index, secondaly to estimate forecasts using Facebook Prophet and Auto ARIMA Model.

High-frequency algorithmic trading is a unique method used for short-term trading in financial and capital markets. According to Vezeris et al. (2020), the financial practice uses mainly three dominant methods - MACD (oscillator), SMA (moving average) and PIVOT points (price transition), with the optimization of their setting being the key point. For this, the authors recommend ad-Backtest model, which appears to be the most efficient in terms of back testing. The variants method of autoregressive moving average (ARIMA) is also a subject to analyses in terms of this short-term trading; out of these variants, the most efficient one is DT-ARIMA (Zheng et al., 2021). Therefore, Huang et al. (2021) create more than 100 directed weighted stock exchange networks, in which they search for key nodes using the LeaderRank algorithm. The authors argue that an average clustering coefficient and global effectiveness rise sharply before and during a financial crisis and sharply decline after it, with only three largest shares having the major impact in the selected Chinese market. The current comparison of trading strategies based on technical analysis and PEGR indicator (Price to Earnings to Growth Ratio) is also surprisingly unique. While the technical approach dominates in the case of short-term investments, the Price to Earnings to Growth Ratio outperforms stochastic methods in the long run (Wang et al., 2020).

Short-term trading in financial and capital markets concerns stock, currencies, ETF and other instruments. Cryptocurrencies, which draw the attention of both businesspeople and economists, are also very popular, as Cohen (2021) points out. The author searches for optimal technical analysis using the comparison of three tools – relative strength index, moving average convergence divergence (MACD) and pivot reversals (PR), concluding that using MACD and PR methods in short-term trading significantly outperforms the "buy-and-hold" strategies; however, the relative strength index did not achieve the expected results. Yamani (2021) analyses the effectiveness of moving average, momentum and relative strength index, but through the prism of the economic crisis in 2008. The author concludes that such an important event causes a significant time deviation, which is reflected in the long run in the effectiveness of business strategies based on technical analysis. Zhang et al.

(2021) innovate the stochastic methods within trading with financial derivatives. They modify the oscillator using the probability approach, i.e., the second moment of risk-neutral variance implied by option prices to achieve higher prediction accuracy. Siddiqi (2019) improves stochastic stock predictive Black-Scholes, Heston, and Bates models for reliance on the fixed starting point. Hu and Jacobs (2020) further confirm the cross-sectional theory of stock option returns using a complex business model. The authors state that call option returns decrease (grow) with the volatility of underlying assets, despite the existence of option risk premium connected with the volatility and jump risk. Guo and Lin (2020) further verified these findings using the asymmetry property of S&P 500 index distribution.

Islam and Nguyen (2020) describe the current state of short-term business strategies research, favoring “newer” methods based on neural networks focused on static data processing. The authors create and correlate complex forecasting models using historical data on the stock gathered from Yahoo Finance. Comparisons of the autoregressive integrated moving average, artificial neural network and a stochastic geometric Brownian motion suggest higher efficiency of both static stochastic approaches. Ni et al. (2021) also use the stochastic oscillator to predict the asset development, but compare its performance with the effectiveness of business management. The authors further suggest using the fluctuations as a management quality indicator. Lin et al. (2020) propose a different correlation integrating the revaluation of intangible assets with stochastic technological limits in a dynamic stock model. They point out the risks consisting in the necessity to increase capital costs of new technologies.

Logically, researchers also verify the effectiveness of combined technical models, often based on the probability approach (Gavurova et al., 2017). In short-term trading, Lai et al. (2016) recommend the integration of averaging techniques and Bollinger Bands indicator, which are effectively used as the indicators of market entry and exit control, achieving better results than when using only one of the above methods. Huang and Martin (2018) applied Bollinger Bands to short-term leverage currency trading, declaring that USD Bollinger Bands optimized by the profit factor outperformed other strategies and generated the highest annual rate of return per risk unit with 68% prediction accuracy. They thus confirmed the results achieved by Coakley et al. (2016), who conducted complex empirical research on the profitability of technical analysis of foreign currency trading between 1996 and 2015. They confirmed the effectiveness of these forecasting methods, choosing Bollinger Bands supplemented by the relative strength index, which show the best performance. Gurrib et al. (2022) used a different combination based on Fibonacci retracement combined with price conflux strategies. They compare the model in various segments of short-term trading, stating that Fibonacci retracement captures the changes in energetic stock prices much better than the changes in the cryptocurrency exchange rates.

2. Methodology

This contribution evaluates the accuracy of commodity price prediction using three conventional forecasting strategies based on a) linear regression, b) naive forecasting, and c) exponential smoothing. The choice of these methods was influenced by these circumstances; these simple models are widely used in practice (Svetunkov et al., 2023), these simple practices have the ability to be as effective as advanced methods such as machine learning (Paldino et al., 2021; Funde & Damani, 2023), these simple practices are user-friendly and can be modeled in basic software (Ilic et al., 2021).

While linear regression, naive forecast, and simple exponential smoothing offer a comprehensive approach to forecasting in volatile market conditions, there are certainly other alternative methods available like Time series Decomposition, Machine learning models or State space Model and others (Jiménez-Navarro et al., 2023). Some alternative methods are more complex and require additional computational resources and expertise to implement effectively (Gill et al., 2022). In contrast, the chosen methods are relatively simple and easy to understand, making them more accessible and straightforward for analysis. Linear regression, naive forecast, and simple exponential smoothing offer clear and interpretable results, making it easier to understand the underlying drivers of the forecasts and communicate findings to stakeholders (Poongodi et al., 2020). Implementing and maintaining alternative approaches require additional resources, such as specialized software or computational power (Gill et al., 2024). The chosen methods are relatively resource-efficient and can be implemented with standard statistical software packages, minimizing the burden on resources. Thus, the decision to use specific forecasting methods involves a trade-off between complexity, performance, interpretability, and resource requirements.

Linear regression models are extensively utilized for price prediction of financial instruments and commodities in the field of finance (Sharaf et al., 2021). The method models the relationship between the variables and linear predictor functions in which the dataset estimates the parameters (Thamarai & Malarvizhi, 2020). The prerequisite for the model application is the existence of causality between the variables. Simple linear regression is suitable for modelling trends for data evenly distributed along the line (Apanovych & Prágr, 2023). It is described by the equation of the line (1):

$$Y = a + bX \quad (1)$$

In the context of linear regression, the dependent variable is denoted as Y, the independent variable as X, and the slope of the line as b.

A native model is one of the simplest predictive models. It assumes that future values will be the same as the most recent observed value, making it straightforward to implement and interpret. A naïve model serves as a baseline model against which the performance of more sophisticated methods can be compared (Vijh et al., 2020). This model assumes that the expected change in all forecasting points is zero and the last known value of the variable is thus used for the whole prediction horizon (Burghauserová et.al., 2023). For the time series with the linear trend, the model with proportional change (2) can be used:

$$F_{t+1} = X_t + p(X_{t+1} - X_t) \quad (2)$$

where p is a constant from the interval (0;1), F_{t+1} is the prediction for the period t+1, and X_t is the last known time series value (Díaz et al., 2020). The empirical research showed that the naïve model is applicable for many economic and financial time series (Atkins et al., 2018, Monahan, 2018).

The exponential smoothing model uses historical averages of the variable in the monitored period for predicting future behaviour of the given variable. It has ability to capture short-term fluctuations and smooth out random noise in the data. This method assigns exponentially decreasing weights to past observations, giving more weight to recent data points while still considering the entire historical

series. The main goal is to reduce fluctuations and identify the trend, which is otherwise imperceptible (Barrow et al., 2020). For non-seasonal models (3) it applies:

$$l_t = \alpha y_t + (1 - \alpha) l_{t-1} \quad (3)$$

where y_t represents the value of the series at a specific point in time (t), and l_t represents a component related to the level of the series. The smoothing coefficient α takes a value from the interval 0, 1 (Smyl, 2020).

To evaluate the accuracy of the models' predictions, methods of absolute error, or respectively mean absolute error (Abs Error), and Mean Absolute Percentage Error (MAPE) are used (Chicco et al., 2021). The Abs Error metric measures the average absolute value of the difference between the actual value and the predicted value for each point in the time series or for each observed value (4):

$$Abs\ Error = \frac{1}{n} \sum_{i=1}^n |x_i - \hat{x}| \quad (4)$$

where, the actual value of the quantity is denoted as x_i , for $i = 1 \dots n$, and its measured value is denoted as $\hat{x}$. If the absolute error is close to zero, the model has good predictive accuracy; conversely, the further the absolute error value, the lower the model accuracy.

MAPE is the most common metric used to evaluate the accuracy of a predictive model. It is especially useful in cases with outliers, as it does not penalize large errors in prediction as strongly (Koutsandreas et al., 2022). It measures the average percentage difference between actual and predicted values (5):

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{x_i - \hat{x}}{x_i} \right| \quad (5)$$

Models with a MAPE value below 10 % are considered very good, between 10 % and 20 % are good, between 20 % and 50 % are conditionally acceptable, and models with a MAPE value higher than 50 % are classified as falsely predicted (Kumar et al., 2020).

3. Data

Almost all predictive models need to specify the volume and frequency of the input data necessary for predicting future prices. The objective is to attain the highest level of accuracy achievable for an extended time horizon, emphasizing the importance of sustained predictive performance. In terms of the volume and frequency of the input data, commodity prices will be predicted from three perspectives: prediction based on the daily prices of the preceding month (22 input values), prediction on the basis of daily prices from the preceding three months (66 input values), and prediction on the basis of annual average monthly prices (13 input values). The methods will be applied for the given volume and frequency of data for a short-term 14-day price prediction in 1. – 14. March 2022, and their results will be compared with the actual real prices.

Price prediction will be tested on the case of copper, which was chosen for its specific properties used in industry and reflected by stock market investors. Unlike most other metals, copper is traded on both the London Metal Exchange (LME) and the New York Mercantile Exchange (NYMEX). While

the LME prices serve as a benchmark for over-the-counter (OTC) contracts, any deviations in price on the NYMEX are typically minimal. The demand for copper is experiencing rapid growth due to the expanding economies of China and India. These thriving economies require substantial amounts of copper to sustain their development, leading to an increase in prices (Ge & Tang, 2020).

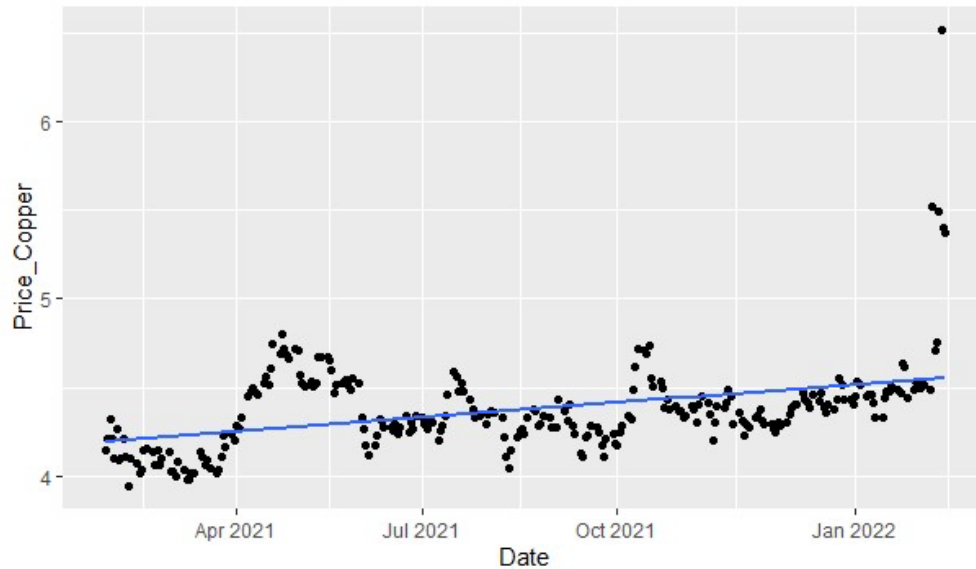


Figure 1. Daily closing prices of copper in USD/lb from 22/02/2021 – 28/02/2022

Source: Nasdaq (March, 2022), own processing in Rstudio using package „readxl”

Figure 1 shows the development of daily copper prices (in USD/lb) in the period 2/22/2021 - 2/28/2022. The data series shows a slightly increasing trend in the monitored period. Significant volatility in copper prices is recorded across the period February 2021 – December 2021 as part of the wave of the Covid-19 pandemic. The volatility during this period may stem from its status as a publicly traded commodity that is susceptible to rapid market reactions and sentiment (Xu, 2024). Regarding the development of copper prices after the outbreak of the Russian-Ukrainian conflict on February 24, 2022, a significant deviation from the counterfactual predictions was shown. Copper prices were consistently higher than expected (Khurshid et al., 2023).

Table 1. Descriptive statistics of the daily copper prices for the period 22 February 2021 – 28 February 2022

Variable	n	Mean	Sd	Median	Min	Max	Range	Skew	Kurtosis
Price Copper	273	4,37	0,25	4,34	3,94	6,52	2,57	3,19	20,7

Source: Own. Calculated in RStudio using package “psych”

Table 1 contains descriptive statistics of the daily copper price variable in USD/lb for the period 2/22/2021 to 2/28/2022. The variable contains 273 observations. The average value is \$4.37/lb with a price range of 2.57. The difference confirms the outliers in the data set that occur to the right of the

mean (Skew = 3.19); a positive kurtosis of 20.7 indicates a higher concentration of values around the mean than for a normal distribution.

The data was sourced from the Nasdaq (March, 2022). The copper prices prediction analyses for the dates 1 – 14 March 2022 is divided into three parts utilizing the data based on different frequencies. Table 2 contains the copper daily closing prices in USD/lb of the preceding month (1 – 28 February 2022 – 22 input values).

Table 2. Descriptive statistics of the copper prices for the period 1. February – 28. February 2022

Variable	n	Mean	Sd	Median	Min	Max	Range	Skew	Kurtosis
Price_Copper	22	4,79	0,53	4,53	4,44	6,52	2,08	1,79	2,54

Source: Own. Calculated in RStudio using package “psych”.

Table 3 contains the information on the copper daily closing prices in USD/lb of the preceding three months (1 December 2021 – 28 February 2022, 66 input values).

Table 3. Descriptive statistics of the copper prices for the period 1 December 2021 – 28 February 2022

Variable	n	Mean	Sd	Median	Min	Max	Range	Skew	Kurtosis
Price_Copper	66	4,52	0,36	4,44	4,23	6,52	2,29	3,44	13,3

Source: Own. Calculated in RStudio using package “psych”.

Table 4 contains the information on the copper annual average monthly prices in USD/lb of the preceding year (February 2021 – February 2022 13 input values).

Table 4. Descriptive statistics of the copper prices for the period February 2021 – February 2022

Variable	n	Mean	Sd	Median	Min	Max	Range	Skew	Kurtosis
Price_Copper	13	4,34	0,2	4,34	3,96	4,73	0,77	0,08	-0,32

Source: Own. Calculated in RStudio using package “psych”.

The variables include 22, 66 and 13 observations in total. The mean values are close to or equal to the median, suggesting that the datasets do not contain significantly outlier values; this is supported by the standard deviation values. Skewness greater than 1 in all cases indicates that the distribution is asymmetrical, slightly deviating from a normal distribution. The kurtosis of the distribution takes positive and negative values. A negative value indicates a flat distribution, while a positive value signals a narrow distribution with an elongated peak.

4. Research results

The prediction of copper price for 14 days in March 2022 using linear regression, naïve model, and simple exponential smoothing will be made from three perspectives in terms of the volume and frequency of the input data: 1) monthly prices from February 2022 (30 values), 2) monthly prices for three months, from December 2021 to February 2022 (90 values) and 3) data for one year from 12 average monthly prices from March 2021 to February 2022 (12 input values).

Results of a 14-day prediction for March 2022 based on daily values from 1 – 28 February 2022 are shown in Table 5. The method with the least % error of the day prediction is highlighted.

Table 5. Results of a 14-day forecast for March 2022 from daily prices of the preceding month February 2022

Day	Price March	Linear regression				Naive forecast				Exponential smoothing			
		Coefficient	ABS error	Error2	% Error	Coefficient	ABS error	Error2	% Error	Coefficient	ABS error	Error2	% Error
01.03.2022	4,587	5,281	0,695	0,483	15,15%	5,374	0,787	0,620	17,16%	5,581	0,995	0,989	21,69%
02.03.2022	4,656	5,319	0,664	0,440	14,25%	5,374	0,718	0,516	15,43%	5,626	0,970	0,941	20,84%
03.03.2022	4,772	5,357	0,586	0,343	12,27%	5,374	0,602	0,363	12,62%	5,670	0,899	0,808	18,83%
04.03.2022	4,929	5,395	0,466	0,217	9,46%	5,374	0,445	0,198	9,02%	5,715	0,786	0,617	15,94%
05.03.2022	4,892	5,433	0,541	0,293	11,06%	5,374	0,482	0,232	9,84%	5,759	0,867	0,752	17,72%
06.03.2022	4,868	5,471	0,603	0,363	12,38%	5,374	0,505	0,255	10,38%	5,804	0,935	0,875	19,21%
07.03.2022	4,731	5,509	0,778	0,605	16,44%	5,374	0,643	0,413	13,58%	5,848	1,117	1,248	23,61%
08.03.2022	4,710	5,547	0,837	0,701	17,77%	5,374	0,664	0,440	14,09%	5,893	1,183	1,399	25,11%
09.03.2022	4,573	5,585	1,012	1,025	22,14%	5,374	0,801	0,642	17,52%	5,937	1,365	1,862	29,85%
10.03.2022	4,640	5,623	0,983	0,967	21,20%	5,374	0,734	0,539	15,82%	5,982	1,342	1,802	28,93%
11.03.2022	4,626	5,661	1,035	1,072	22,38%	5,374	0,748	0,560	16,17%	6,026	1,401	1,962	30,28%
12.03.2022	4,597	5,699	1,102	1,215	23,97%	5,374	0,777	0,603	16,90%	6,071	1,474	2,172	32,06%
13.03.2022	4,578	5,737	1,159	1,344	25,33%	5,374	0,796	0,634	17,39%	6,115	1,538	2,365	33,59%
14.03.2022	4,525	5,775	1,250	1,562	27,62%	5,374	0,849	0,720	18,75%	6,160	1,635	2,672	36,13%
Average	4,691	5,528	0,837	0,759	17,96%	5,374	0,682	0,481	14,62%	5,870	1,179	1,462	25,27%

Source: Own.

Results of a 14-day prediction for March 2022 using monthly values from a period of three months from December 2021 to February 2022 (66 values) are shown in Table 6. The method with the least % error of the day prediction is highlighted.

Table 6. Results of a 14-day prediction for March 2022 from daily prices of the preceding months from December 2021 to February 2022

Day	Price March	Linear regression				Naive forecast				Exponential smoothing			
		Coefficient	ABS error	Error2	% Error	Coefficient	ABS error	Error2	% Error	Coefficient	ABS error	Error2	% Error
01.03.2022	4,587	4,815	0,229	0,052	4,99%	5,374	0,787	0,620	17,16%	5,820	1,233	1,521	26,892%
02.03.2022	4,656	4,822	0,167	0,028	3,58%	5,374	0,718	0,516	15,43%	5,950	1,295	1,676	27,81%
03.03.2022	4,772	4,829	0,058	0,003	1,22%	5,374	0,602	0,363	12,62%	6,080	1,309	1,713	27,43%
04.03.2022	4,929	4,837	0,092	0,009	1,88%	5,374	0,445	0,198	9,02%	6,211	1,282	1,642	26,00%
05.03.2022	4,892	4,844	0,048	0,002	0,99%	5,374	0,482	0,232	9,84%	6,341	1,449	2,098	29,61%
06.03.2022	4,868	4,851	0,018	0,000	0,36%	5,374	0,505	0,255	10,38%	6,471	1,603	2,568	32,92%
07.03.2022	4,731	4,858	0,127	0,016	2,68%	5,374	0,643	0,413	13,58%	6,601	1,870	3,498	39,53%
08.03.2022	4,710	4,865	0,155	0,024	3,29%	5,374	0,664	0,440	14,09%	6,731	2,021	4,086	42,92%
09.03.2022	4,573	4,872	0,299	0,090	6,55%	5,374	0,801	0,642	17,52%	6,862	2,289	5,240	50,06%
10.03.2022	4,640	4,879	0,240	0,057	5,16%	5,374	0,734	0,539	15,82%	6,992	2,352	5,533	50,70%
11.03.2022	4,626	4,886	0,261	0,068	5,63%	5,374	0,748	0,560	16,17%	7,122	2,497	6,233	53,97%
12.03.2022	4,597	4,893	0,296	0,088	6,45%	5,374	0,777	0,603	16,90%	7,252	2,655	7,051	57,77%
13.03.2022	4,578	4,900	0,323	0,104	7,05%	5,374	0,796	0,634	17,39%	7,382	2,805	7,867	61,28%
14.03.2022	4,525	4,907	0,382	0,146	8,45%	5,374	0,849	0,720	18,75%	7,513	2,988	8,926	66,02%
Average	4,691	4,861	0,193	0,049	4,16%	5,374	0,682	0,481	14,62%	6,666	1,975	4,261	42,35%

Source: Own.

Results of a 14-day prediction for March 2022 using one-year values with 13 average monthly prices from February 2021 to February 2022 (13 input values) are shown in Table 7. The method with the least % error of the day prediction is highlighted.

Table 7. Results of a 14-day prediction for March 2022 from average monthly prices from February 2021 to February 2022

Day	Price March	Linear regression				Naive forecast				Exponential smoothing			
		Coefficient	ABS error	Error2	% Error	Coefficient	ABS error	Error2	% Error	Coefficient	ABS error	Error2	% Error
01.03.2022	4,587	4,417	0,170	0,029	3,70%	5,374	0,787	0,620	17,16%	4,379	-0,208	0,043	-4,53%
02.03.2022	4,656	4,428	0,228	0,052	4,89%	5,374	0,718	0,516	15,43%	4,373	-0,283	0,080	-6,08%
03.03.2022	4,772	4,439	0,333	0,111	6,98%	5,374	0,602	0,363	12,62%	4,366	-0,405	0,164	-8,49%
04.03.2022	4,929	4,449	0,480	0,230	9,73%	5,374	0,445	0,198	9,02%	4,366	-0,563	0,317	-11,41%
05.03.2022	4,892	4,460	0,432	0,186	8,83%	5,374	0,482	0,232	9,84%	4,354	-0,538	0,289	-10,99%
06.03.2022	4,868	4,471	0,397	0,158	8,16%	5,374	0,505	0,255	10,38%	4,348	-0,520	0,271	-10,68%
07.03.2022	4,731	4,482	0,249	0,062	5,26%	5,374	0,643	0,413	13,58%	4,342	-0,389	0,151	-8,22%
08.03.2022	4,710	4,493	0,217	0,047	4,61%	5,374	0,664	0,440	14,09%	4,336	-0,374	0,140	-7,94%
09.03.2022	4,573	4,504	0,069	0,005	1,50%	5,374	0,801	0,642	17,52%	4,330	-0,243	0,059	-5,30%
10.03.2022	4,640	4,515	0,125	0,016	2,69%	5,374	0,734	0,539	15,82%	4,324	-0,316	0,100	-6,80%
11.03.2022	4,626	4,525	0,100	0,010	2,16%	5,374	0,748	0,560	16,17%	4,318	-0,308	0,095	-6,65%
12.03.2022	4,597	4,536	0,060	0,004	1,32%	5,374	0,777	0,603	16,90%	4,312	-0,285	0,081	-6,20%
13.03.2022	4,578	4,547	0,030	0,001	0,66%	5,374	0,796	0,634	17,39%	4,306	-0,272	0,074	-5,94%
14.03.2022	4,525	4,558	0,033	0,001	0,73%	5,374	0,849	0,720	18,75%	4,300	-0,225	0,051	-4,98%
Average	4,691	4,487	0,209	0,065	4,37%	5,374	0,682	0,481	14,62%	4,340	-0,352	0,137	-7,45%

Source: Own.

The first model prediction accuracy based on daily data from February 2022 significantly prefers the naïve model, with the MAPE value of 14.62% (Table 5). The second test of model prediction accuracy based on daily data from three months (December 2021 to February 2022) favors linear regression with the MAPE being 4.16% (Table 6). The third test based on the average monthly data from March 2021 to February 2022 favors linear regression with the MAPE of 4.37% (Table 7).

All models were used in a basic version and their extension would be possible using more sophisticated statistical models, however, this was not the goal of this research. For example, the naive method was used because the article only focused on one commodity. However, we realize that if an investor decides among several investment possibilities, it is more appropriate to use other, more robust models.

5. Discussion

The copper price prediction accuracy test was deliberately set in the turbulent period of March 2022. To understand the behavior of metal prices the insights into the economic consequences of the Covid-19 pandemic and the Russia-Ukraine war is helpful. The metal markets play a key role in the economic activities of countries, regions, companies or individuals. For that reason, measuring the volatility is the key interest for investors. Related to this is the choice of a suitable model to capture time series data and the choice of frequency data used. In this context, we examined questions:

1. What basic model / models for modelling time series data are optimal for short-term predictions in the periods of high market volatility and what their reliability is.

The paper tested the prediction ability of the most commonly applied models in practice - linear regression, exponential smoothing and naïve model. The prediction was analyzed using various frequency data that were compared with the reality, based on which we identified the optimal model applicable in the conditions of high market volatility for short-term copper price prediction. In the case of our research the simple linear regression with the frequency of daily historical prices of immediately preceding three months used for predicting 14-day prices for March 2022 is the most

suitable approach for predicting the copper prices. The linear regression model also proved to be applicable for the prediction using the frequency of average monthly data from the preceding year.

The similar view is held by Sagheer & Kotb (2019), who reminded that linear statistical methods have been solving the problem of prediction based on historical data for many years. Several models of non-linear time series have also been proposed, e.g. bilinear model or autoregressive conditional heteroscedastic model, which, however, compared to linear time series, are still in their infancy from the point of view of applicability in practice.

2. Is the model accuracy influenced by the choice of frequency and amount of data used?

Our results indicate a strong relationship between the prediction reliability and the frequency of the input data used. In other words, the accuracy of the predictions is significantly influenced by the amount of data available and how frequently it is collected. The quarterly framework of the daily data (the highest frequency and amount) and the 10 years framework of the average yearly data (the highest data amount) showed the best results when linear regression was applied. The worst predictive results within all models were measured when using monthly framework of the daily data (the lowest data amount).

This finding aligns with the conclusions drawn in previous studies conducted by Lyocsa et al. (2021), who statistically tested two data sets (low-frequency and high-frequency) to verify the prediction accuracy. They found that high-frequency data can make accurate short-term predictions for the maximum of one following month.

Linear regression is often identified as an optimal model for predicting prices in periods of high market volatility (Uras et al., 2020). Despite its simplicity, linear regression can be robust, especially when there is a linear relationship between the predictor variables and the target variable, a condition that often holds true for many financial time series data, particularly over short-term horizons (Wang et al., 2020). In periods of high volatility, simpler models may perform better than more complex ones because they are less prone to overfitting noisy data (Megaritis et al., 2021).

Generally, we can thus state that linear regression can predict the short-term future direction of precious metals' price development in turbulent environments. However, it is important to note that it may not always be the best model for all situations. In some cases, more sophisticated techniques such as machine learning algorithms or time series models may be necessary to capture the nonlinearities and complex dynamics present in volatile markets (Masini et al., 2021).

Conclusions

The issue of how to successfully invest in times of financial crises caused by war conflicts or the Covid-19 pandemic, has been addressed by investors and theoreticians since the beginning of financial markets. These periods bring about fundamental changes and significant capital spillovers, prompting the exploration of optimal approaches and models for short-term predictions amidst high market volatility. A number of cited studies indicate that technical analysis can be the right solution. Its advantages and disadvantages are summarized in the literary research, along with the overview of other most commonly used predictive methods and approaches, which are discussed as a better or equivalent alternative to technical analysis. Research based on testing the reliability of technical analysis results demonstrates its applicability for selected time series.

In line with the research objectives, a period of high market volatility and uncertainty, stemming from the Covid-19 pandemic and the Russian-Ukrainian war conflict in March 2022, was selected for analysis.

The paper employs commonly applied time series models – linear regression, exponential smoothing, and naïve model. The predictions of these models were analyzed using various frequency data and compared with actual outcomes to identify the optimal technical analysis model applicable in conditions of high market volatility.

The findings reveal that linear regression with daily historical prices for three months used for predicting 14-day prices for March 2022 yielded the most favorable results, with a Mean Absolute Percentage Error (MAPE) of 4.16%. Additionally, the model proved applicable for prediction using average monthly data from the preceding year, with a MAPE of 4.37%. However, predictions based on daily data from the preceding month were unsuccessful in all models, as the MAPE values were excessively high.

One significant feature of technical analysis is its widespread use in both research and practice within capital markets on a daily basis. The results of the study validate the appropriateness and effectiveness of employing this method for specific time series, supporting the conclusion that utilizing technical analysis is reasonably accurate and suitable.

The outcomes of this study, reflecting conditions of high market uncertainty, can be applied by investors to minimize risks and maximize returns. They will demonstrate which technical analysis method is suitable in terms of predictive power and the choice of data frequency under high market volatility, demonstrating the potential method and data frequency dominance. The results of the study can be generalized at least to cases where external factors cause volatility in the rare metals market.

It is crucial to acknowledge the limitations inherent in this study. Firstly, the research focuses primarily on the applicability of technical analysis within a specific timeframe and under specific market conditions, namely, the Covid-19 pandemic and the Russian-Ukrainian war conflict in March 2022. Therefore, the generalizability of the findings to other contexts may be limited. Additionally, the study utilizes selected time series models, and while these models are commonly applied in practice, there may be other approaches not explored in this research that could yield valuable insights.

Future research in this area could explore several avenues to enhance our understanding of the effectiveness of technical analysis and other predictive methods during periods of high market volatility. Firstly, investigating the robustness of the findings across different market conditions and timeframes could provide valuable insights into the generalizability of the results. Additionally, exploring the integration of multiple predictive methods, including technical analysis, fundamental analysis, and sentiment analysis, could lead to more accurate predictions and a comprehensive understanding of market dynamics.

Author Contributions: The article was compiled in cooperation with three authors: S.H., P.S., and R.K. S.H. provided guidance throughout the article, proceeding the parts of the abstract, introduction, methodology, data, research section with discussion, and conclusion. Additionally, she supervised the final consolidation and made changes according to reviewers' comments. P.S. contributed by creating sections focused on literature review, while R.K. participated in the preparation of methodological and research sections.

Funding: The article is supported by research fund IDUZO22003 from the Institute of Technology and Business in Ceske Budejovice.

Data Availability Statement: The data used in the article are based from secondary data collected from publicly available websites. All calculations performed are included in the text of the article. Further sharing is not restricted or limited in any way

Acknowledgements: Acknowledgments go primarily to the reviewers of the article, who made a significant contribution to improving the quality of the article. We also thank the Institute Board, which supports research activities.

Conflicts of Interest: The authors affirm no conflict of interest.

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