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Predicted Future Development of Imperfect Complementary Goods – Copper and Zinc Until 2030

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Abstract
The objective of the paper was to evaluate the mutual relationship of copper and zinc prices between 2011 and 2021 and to predict their future prices until the year 2030. For this purpose, the following methods were used: regression of neural structures in TIBCO's Statistica software, version 13.0, time-series smoothing by means of multilayer perceptron network, graphical representation, Pearson correlation coefficient, and logical judgment. According to the prediction, the copper price will decrease slightly compared to the preceding years. In 2026, it is expected to stabilize at USD 610/t until the year 2030. Zinc price is expected to increase slightly until the end of the year 2030 when the resulting predicted price is USD 410/t. Pearson correlation coefficient of copper and zinc achieves the approximate value of 0.65. The results thus confirm the fact that these commodities are not perfect complements. First, the mutual relationship of the two commodities indicates that the price of zinc is pushed up mainly by the copper price. On the contrary, the copper price is pushed down by the price of zinc. There is a price convergence between the two commodities. The future development of copper and zinc prices is not subject to unpredictable events, such as a political situation or the aforementioned COVID-19 pandemic. Such a long-term prediction might thus not provide an objective result.

Keywords
Commodity market, copper and zinc, neural networks, price prediction, complementary goods

Introduction

There are growing concerns about future copper supplies. As the largest producer of copper, Chile also has the largest copper reserves in the world (Espinoza, Soulier, 2016); therefore, it retains its potential to be a key factor in future supplies. This paper examines some of the most relevant resources and technological challenges that may occur as a result of the accelerated development of the projects concerning copper mining in brownfields and greenfields in Chile until the year 2035, regardless of economic, regulatory, and environmental constraints.

Although copper has been used for ages by humankind, more than 95 % of copper has been mined since 1900, and more than half of copper mining and smelting has been done in the last quarter-century. According to the estimates, the copper deposits will be depleted within 25 – 60 years. Consensus has been reached on the issue of resource depletion. The recognition of the fact that resources are not infinite while the Earth is, enhances the idea (Zhang et al., 2017) that the vision of continuous economic growth is not sustainable over time (Urbancová et al., 2020; Cihelková et al., 2020). The supply and demand for mineral resources are balanced in general, with a slight surplus, which means the stability of the international mineral commodities market. These resources (especially iron ore and copper ore) are rich and have great potential, and the scope of their development and use will grow gradually. Until the end of the year 2014, the reserve production ratio of iron, copper, bauxite, lead, zinc ores, and potassium salt was 95 years, 42 years, 100 years, 17 years, 37 years, or 170 years. Apart from lead ores, all five other types have a production reserve ratio exceeding 20 years, which indicates a high degree of guaranteed resources. If recycled metals are used, the supply of six global mineral products will exceed demand in the next 20 years. Between 2015-2035, the supply of iron ore, refined copper, zinc, and potassium salt will exceed their demand. It is assumed that there is no problem with the supply-side of bulk mineral products, such as iron ore; however, there can be some local or structural scarcity due to geopolitics, monopoly control, resource nationalization, and trade frictions (Zhaozhi et al., 2016; Koplyay et al., 2018).

The portfolio management analysis shows the importance of precious metals assets in terms of the advantages of portfolio diversification and hedging purposes, especially in the long run (Mensi et al., 2021; Masood et al., 2017). The need for such resources is growing. Their extraction is extremely energy-intensive and represents one of the major contributors to global CO2 emissions. Kasych, Rowland, and Yakovenko (2019) focused on analyzing the growth rate of production in the mining industry and evaluating the increase in emissions associated with increasing production. The ecological consequences should be considered due to the increasing public interest in well-being issues connected with industrial impact on the environment (Krzymowski, 2020; Mishchuk & Grishnova, 2015; Tvaronavičienė et al., 2021; Zielińska, 2020), influencing the steep development of appropriate advanced technologies and knowledge management systems (Kumar & Kumar, 2019; Lewandowska et al., 2021; Oliinyk et al., 2021; Shuyan & Fabus, 2019; Petruf et al., 2015; Turisová et al., 2021; Melnikova et al., 2016; Rajbhandari et al., 2022). In connection with this, Rousek (2019) created a comprehensive overview of the destruction of products that are environmentally friendly and thus do not leave an ecological footprint in the form of CO2. With the growing copper demand, the decrease in the quality of copper ore and automatic increase in energy consumption to ensure copper mining is expected. From the long-term and global perspective, we differentiate between the supply and demand sides of various minerals by means of linear programming (Tokimatsu et al., 2017).

Priester et al. (2019) provided information about the grades of nine metals: copper, gold, iron, lead, manganese, nickel, PGM, tin, and zinc. The authors analyze the implications of possible development of ore grades from which these metals are extracted. It is thus necessary to precisely analyze the purchase price of such concentrates purchased by smelters from mining companies, except for the price of copper. The evaluation of copper concentrates is the priority task for miners or traders who monitor the processes, including market prices of copper and other precious metals, such as gold, silver, and also price discounts or coefficients that usually represent the major part of the revenues from negotiations concerning concentrates, smelting or refining (Vochozka and Horák, 2019).

Daw (2017) proposes a new additional criticality indicator that complements the two models of the European Commission and considers the upstream market of the material as well as its downstream processing in the economy. Market fundamentals (physical supply and demand) explain the fluctuations in commodity prices (Guzmán et al., 2018; Bilan et al., 2017), especially in the medium and long term. However, following the recent price boom, there has been a certain disagreement on the role of the fundamental factors, such as liquidity or money supply in key countries and regions, commodity financialization, and mainly financial speculations (Sinicakova and Gavurova, 2017; Gavurova et al., 2017).

Indonesia is a country rich in natural resources, especially mineral ores. Since 2017, the mining sector has been contributing an average of 10 % to Indonesia's GDP, which accounts for approx. 33.2 % of the exports. Mining and the mineral industry thus naturally play an important role in the economic growth of the country. The Indonesian government introduced the policy of export banning as a complement to the current mining law in order to increase the country's income from its mineral wealth. This policy bans the export of crude mineral ore except for coal, copper, iron ore, lead, and zinc. Tui et al. (2021) also state that such ores must be fully processed and refined before being exported.

About 25 % of all global copper production is used for extracting brass. Brass is used mainly for wrought products, with the greatest ductility achieved in the case of 32% zinc content. Due to their excellent properties, copper and zinc alloys are widely used as industrial materials. In the case of perfect complements, mutual replacement of the goods X and Y is impossible, as no price change can change the X and Y relationship. On the basis of brass price and volume of its production, it can be concluded that they are probably imperfect complements. As for complements, the commodity markets interact in terms of their price and production volume. Base metals show significant seasonal fluctuations in supply and small seasonal fluctuations in demand, which makes the analysis easier. They are easy to store, with the storage costs not exceeding 5 % of their value pa (Geman et al., 2013). If the demand and supply sides are influenced by both markets, the markets are sensitive to each other (what happens in one market influences what happens in the other market). Demand shocks may influence the price for up to 15 years, while the effects of minerals supply shock last for up to 5 years (Struermer, 2018). Individuals derive benefits by consuming two marketed commodities and a non-market commodity. The non-market commodity influences the relative demand for marketed commodities by functioning as a complement to one of the marketed commodities. By means of a new approach to the identification, Santra (2021) shows that price fluctuations are primarily driven by demand, not by supply shocks. Geman et al. (2016) introduced a new concept of the distances between two commodity markets through quantities, which takes into account the basic financial and economic indicators.

This article aims to evaluate the mutual development of copper and zinc prices between 2011 and 2021 and to predict the future development of the price of both commodities on the basis of this relationship. The article first aims to determine the relationship between the prices of both metals. As follows from the above, they should be complementary goods. Therefore, the following research questions can be formulated:

RQ1: Are copper and zinc perfect complements, imperfect complements, or indifferent goods?

RQ2: What was the development of copper price between 2011 and 2021?

RQ3: What was the development of zinc price between 2011 and 2021?

RQ4: What will be the development of copper prices between 2021 and 2030?

RQ5: What will be the development of zinc price between 2021 and 2030 depending on copper price?

Literary research

The current high volatility of one commodity can influence the future volatility of some other one. Barbaglia et al. (2020) studied volatility spillover among a large number of commodities using the VAR (Vector autoregressive) model and proposed the t-lasso method for obtaining a large VAR. The authors show the existence of volatility spillover between energy and biofuels and between energy and agricultural commodities. Good predictive performance of t-lasso is useful, especially for achieving more accurate volatility predictions only for short-term financial investors. Wang and Wei (2017) used the VAR model to examine the relationship between exchange rates, economic growth, and foreign direct investment. This method, however, is not suitable for the purposes of this article. The theory of storage in relation to commodities provides two predictions, including the volume of the commodity held in inventory. When inventory is low (i.e., if there is a shortage), spot prices exceed the futures prices, and the volatility of spot prices exceeds the volatility of futures prices. These predictions were tested by Geman et al. (2013) for six fundamental metals traded on London Metal Exchange (aluminum, copper, lead, nickel, tin, and zinc). The results showed that Working's Theory of storage and its two key predictions related to prices and volatility are validated for six fundamental metals.

The interdependence of commodity and stock markets is a fundamental issue when building portfolios and trading using more assets marketed in two different markets. The study analyzed the structure of commodity and stock market interdependence using the random matrix theory and network analysis. The results presented by Kim et al. (2011) show that stock and commodity markets need to be treated as completely separate asset classes. Commodity prices can be predicted based on the information about various markets by determining long-term models of commodity prices balance in various markets. Lutzenberger et al. (2017) classified metals into portfolios by one or two specific characteristics and examined whether the average returns of such portfolios differ significantly. The unique sample of 30 metals over a sample period of 24 years (from January 1990 to December 2013) and found that value (5 or 6 years) and momentum (2 – 6 months) can significantly contribute to predicting the return of a wide range of metals. The basic variables specific to metals, such as production, inventory, consumption, secondary production, country concentration, or reserves, can predict expected return in some cases when taking into account economically interpretable transformations. Roy et al. (2021) used monthly data for a period of more than 30 years and found that the exchange rate is determined by commodity prices, and Australian indices of basic metals highly correlate with the country's exchange rate. The phenomenon of financialization has changed the behavior and structure of the interdependence of commodities and general stock markets. It is commonly perceived that the increase in offsets is due to distressed investors who sold both assets during the 2007-

2009 financial crisis. For this reason, it is important to pay attention to the protection of investors' finances and interests (Polishchuk et al. 2019) and the findings of the comprehensive risk assessment including data on financial losses (Kelemen et al. 2020). Oil and copper show a significant response to the changes in stock market risks, while aluminum or wheat do not react to them. Adams et al. (2015) suppose that the commodities with the highest investment inflows will be the most sensitive to stock market risk. Stock market response to commodity price shocks can be non-linear or asymmetric. A study by Badamvaanchig et al. (2021) deals with asymmetric linkages by applying non-linear autoregressive distributed lag (NARDL) models between January 2007 and December 2018. The results provide clear evidence of the existence of long-term asymmetric linkages between stock prices and commodity prices. The analysis proves the existence of a positive relationship between copper price and stock price in the case of a positive copper price shock but not a defined relationship in the case of a negative copper price shock.

Research by Ding et al. (2020) showed that responses to other commodity market shocks could be predicted by cross-market commodity prices using long-term equilibrium models. The prices of liquid commodities (oil and metals) can be predicted only on the basis of various market prices. The metals and oil market is connected with other commodity markets and the global commodity index. Warell (2018) carried out a quantitative analysis using monthly data from January 2003 and June 2017 and performed both statistical tests for structural breaks and a reduced price regression of the most important factors for iron ore prices in the given period. It shows that to determine long-term impacts on prices, more complex data on the influence of iron ore supply are necessary. To conclude, similar to the findings, the single most important impact on the iron ore price during the entire commodity boom, both in the long run and in the short run, stems from GDP growth in China. According to Vrbka (2016), the development of GDP itself can also be predicted using ANN, so there is a certain coherence in the possibility of using ANN to estimate the development of the value of commodities affecting a country's GDP. In connection with both methods, Vochozka (2016) dealt with determining which of these statistical methods provides better results.

The development of freight rates has also had a significant impact on the iron ore price in the commodities boom; however, to a smaller extent. Shaikh et al. (2020) analyzed the relationship between the prices of export commodities and the fluctuation of the AUD/USD exchange rate using a time-varying parameter model. The empirical findings show that the year 2018–2019 was the year of investors' fear. By convention, the stock index and implied volatility are negatively linked: the decrease in the stock index increases the level of the implied volatility index. Purpose market volatility is subject to good or bad news as well as the responses to fake news and policy changes. The paper considers the impacts of the recent COVID-19 pandemic on the global stock market, commodities, and FX market, as measured by the investors' fear index. The authors use regression models based on time series and bring evidence of unprecedented reactions on stock, commodity, and FX markets in the wave of COVID-19. In the context of global pandemic and security crises, the provision of critical raw materials is also a question of the security of critical infrastructure for the functioning of a green and sustainable national economy (Kelemen, Jevčák 2018; Hudáková et al. 2019; Gavurova et al. 2021).

In recent years, there have been developed many new approaches and technologies to predict stock prices. One of them is the method of artificial neural networks (Horák, Krulický, 2019), which have a number of advantages compared to conventional methods. The paper's objective is to compare the method of exponential smoothing of time series and time series using artificial neural networks as tools to predict the future development of stock prices. Experts have found that artificial neural networks show better results than conventional statistical methods. However, in this case, the result was different; the question is why. It can be due to the possible turbulent stock price development.

Ly and Die (2021) apply recurrent neural networks for predicting time series using the RNN methods, specifically for predicting cotton and oil prices. Their experiment shows how to combine new machine learning techniques with conventional approaches successfully. Averaging predictions made by two types of models provide better results in comparison with both methods. Compared to ARIMA and LSTM, RMSE (Root Mean Squared Error average prediction of cotton price was by 0.21 or 21.49 % lower. The author agrees with using neural networks for predicting copper and zinc time series. The study by Serpen and Gao (2014) presents computational and message complexity analysis for a multilayer neural network, which is implemented in fully distributed and parallel form across a wireless sensor network. The paper presents the limits and results of an empirical study on the time, space, and complex aspects of wireless sensor networks and a design of multilayer perceptron neural networks. The ANN method is currently widely used for economic predictions. For example, Krulický and Rowland (2019) used ANN to predict the development of the company's performance. The aim of the paper by Suler, Rowland, and Krulicky (2021) is to predict the development of the export of the Czech Republic to the People's Republic of China using ANN (artificial neural networks). Based on the past data, ANN with the best predictive ability is generated. For this purpose, three experiments are carried out. The first, second, and third experiments consist in generating ANN for predicting the development of the exports based on time series. The generated ANN are MLP neural networks and regression time series. MLP networks turn out to be more effective for predicting the future development of exports. They are also able to predict possible extremes. The results show a significant decrease (over 10 %). MLP networks are able to capture the trend of the whole time series as well as the majority of local extremes. MLP networks can also be applied to search for seasonal data fluctuations (Vrbka et al., 2019). On the other hand, Horak and Machova (2019) turned to the development and prediction of exports of the People's Republic of China to the United States. The prediction was performed using regressive time series analysis and ANN. Subsequently, the achieved results were compared. Vochozka (2018) examined a regressive analysis of palladium price movements on the New York Stock Exchange by comparing two statistical tools. The curve provided by the method of least squares using negative exponential smoothing showed the best characteristics of all linear regressions; all retained structures of neural networks were applied in practice. In terms of the performance of the correlation coefficient, only the neural networks that do not reflect any difference remain. Rowland, Suler, and Vochozka (2019) also dealt with the accuracy of development prediction using regression analysis and ANN. According to Vochozka et al. (2018), Artificial intelligence and ANN are increasingly entering the economy and participating in its management in many of its sub-areas.

The use of similarities by means of a panel estimate of new volatility models leads to excellent out-of-sample risk prediction compared to predictions provided by existing models and conventional practices that do not include volatility similarities. Bollerslav et al. (2018) show that under empirically realistic assumptions, the risk models show a value close to 0.5 % of the total wealth per year compared to the static risk model. By compiling time series models for quantiles, flexible distribution is created for which the quantiles can be easily calculated by means of the parametrized transformation of parametric distribution. Hothorn, Möst, and Bühlmann (2018) show that it is an extremely flexible framework because any continuous distribution can be presented as a transformation of a random variable with any continuous distribution.

Kurumatami (2020) examined agricultural commodities and their future prices. The author proposed a method of predicting time series for future prices of agricultural products and determined criteria for evaluating the predicted time series in terms of statistical characteristics. Agricultural commodity prices are highly seasonal, and conventional methods, such as autoregressive integrated moving average (ARIMA) and Box Jenkins, turned out to be not very suitable for predicting. Alipour, Khodayar, and Jafari (2019) assessed various methods of predicting within econometrics and financial management. They applied methods such as ARIMA, TGARCH, and stochastic differential equations in time series predicting monthly copper prices. The efficiency of such approaches was also tested in predicting the time series of monthly copper prices from the year 1987 to the end of the year 2014. The results show that better predictions are achieved by the average of about one thousand runs using Stochastic Differential Equations (SDE). There were calculated MAPE ARIMA and TIGARCH of 20.90 %, or 54.36 %, by using SDE. The predictive power of the TGARCH model was extremely low and unacceptable. Therefore, if there is no complex method for predicting available, the SDE model is a good, promising method for predicting copper prices. The study by Olofsson (2021) tries to analyze this correlation quantitatively. The study uses the analysis of time series and ARIMA models to analyze the covariance of the exploration permit application submitted to the Mining Inspectorate of Sweden and the average annual prices of copper, lead, zinc, silver, and gold in the period 2000-2018. The article did not show any significant covariance between most prices of minerals and submitted applications. Formal Bayesian inference on quantiles is challenging because the approach to both quantile function and probability is necessary. Griffin, and Mitrodima (2020) propose a flexible Bayesian time-varying transformation model, which enables the direct calculation of probability and quantile functions. The usefulness of the model is illustrated using MCMC methods. The model is defined for a finite number of quantiles. This method thus does not appear to be useful.

Brenes et al. (2020) aim to determine an equation that would enable the estimate of the monthly stock prices of Netflix, Inc. The individual estimated beta coefficients for the model were significant both for the basic coefficient and for the correlation coefficient, whose values achieved 57.8122, or 0.0333.

The most suitable methods for the purpose of the paper appear to be time-series of multilayer perceptron networks and time series smoothing.

Data and methods

The data for the analysis are available on the web pages of the London Stock Exchange (www.londonstockexchange.com [online]. [cit. 2021-11-10]). The information about the exchange rate and price of one ton of copper and zinc in USD are used for the analysis. The time interval for which the data are available, the daily closing price of one ounce of copper and zinc in the period 17 December 2011 – 3 September 2021.

Figure 1 provides a better picture of the examined time series.

Figure 1 Development of copper and zinc prices between 2011-2021

Regression will be performed using neural structures in the TIBCO's Statistica software, version 13.0. For RQ1, the independent variable is copper price; zinc price is a dependent variable.

Then we will proceed analogously to smooth the copper and zinc time series (RQ2 and RQ3).

Multilayer perceptron networks (MLP) are generated to smooth copper and zinc time series. The dependent variable is the price of copper and zinc. The independent variable is perceived by the software as the number of days from 1 December 2011.

The time series are randomly divided into three datasets – training, testing, and validation. The first dataset contains 70 % of the input data. The training dataset is used to generate the neural structures. The remaining two datasets contain 15 % of the input data each. Both groups are used to verify the reliability of the generated neural structure. Descriptive characteristics of the data are presented in Table 1.

Table 1 Characteristics of the dataset

Samples	Data statistics	
	Copper	Zinc
Minimum (Training)	291.9000	96.1000
Maximum (Training)	797.5000	251.7000
Mean (Training)	432.7518	155.6049
Standard deviation (Training)	86.7793	42.5841
Minimum (Testing)	294.6500	97.0500
Maximum (Testing)	783.6500	252.1000
Mean (Testing)	438.8626	156.8772
Standard deviation (Testing)	94.9268	42.5300
Minimum (Validation)	296.6000	97.9000
Maximum (Validation)	787.2500	250.2000
Mean (Validation)	435.5529	157.7604
Standard deviation (Validation)	15.1288	52.6865
Minimum (Overall)	291.9000	96.1000
Maximum (Overall)	797.5000	252.1000
Mean (Overall)	434.0881	156.1189
Standard deviation (Overall)	88.6619	42.6060

Source: Authors.

We will generate 10,000 neural networks for each research question. Based on the calculation, 5 artificial neural networks with the best characteristics will be retained for each situation.

The hidden layer of MLP will contain 2-8 neurons. For the multilayer perceptron network, the following activation function in the hidden layer and the output layer are considered:

- Linear,
- Logistic,
- Atanh,
- Exponential,
- Sine.

Other settings remain default (according to ANN – automated neural networks). If needed, the weights of the individual neurons are iterated using the ONN (own neural networks). The output for RQ1 will be a scatter plot representing the actual relationship between copper and zinc and the modeled relationship of copper and tin according to the five retained neural networks. For RQ2 and RQ3, the output is five models smoothing the time series of the prices of metals under review and five smoothed time series for each metal.

The retained neural networks from RQ2 are saved in the PMML format. To predict the future development of copper prices until the year 2030, the neural networks are imported back into the Statistica software, trading days are assigned, and the future values of zinc and copper until the year 2030 are calculated. This provides the answer to RQ4. The result is a line graph of copper prices prediction until the year 2030.

The result of the prediction of RQ4 is used along with the time (trading days until the year 2030) as a predictor for estimating the future zinc prices, which provides the answer to RQ5.

Results

Relationship between zinc and copper prices

Table 2 shows the 5 best structures generated by the neural networks for the relationship between the copper and zinc regression model.

Table 2 Retained neural structures – regression model of zinc and copper prices

Index	Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 1-4-1	0.651206	0.671615	0.633969	521.9116	495.6603	549.0451	BFGS 206	SOS	Logistic	Exponential
2	MLP 1-5-1	0.654334	0.675768	0.635830	518.2111	490.6713	546.9260	BFGS 220	SOS	Logistic	Exponential
3	MLP 1-6-1	0.655649	0.673956	0.634478	516.6503	493.2385	548.4001	BFGS 239	SOS	Tanh	Sine
4	MLP 1-7-1	0.657751	0.679114	0.638952	514.1677	486.6383	542.8535	BFGS 387	SOS	Logistic	Logistic
5	MLP 1-7-1	0.656847	0.674923	0.636074	515.2266	492.2418	546.6629	BFGS 1370	SOS	Logistic	Identity

Source: Authors.

The second column contains the names of the networks and their characteristics. Each network has one input; the hidden layer contains 4-7 neurons and only 1 output neuron. The third, fourth, and fifth columns show the performance of each retained structure, with all networks achieving the performance of 63-68 %, which can be considered a worse performance. The sixth, seventh and eighth columns contain training, testing, and validation errors ranging from 487 to 549, which indicates that the number of errors is rather high. A different version of the BFGS training algorithm was used for each network for network training. The error function (Column 10) was SOS for all networks. For the hidden layer (column 11), the logistic and logistic tangent activation functions were used. For the activation of the output layer (column 12), exponential, sine, logistic, and identity were used.

Figure 2 shows 5.MLP network marked with different colors. Blue dots represent the actual zinc price.

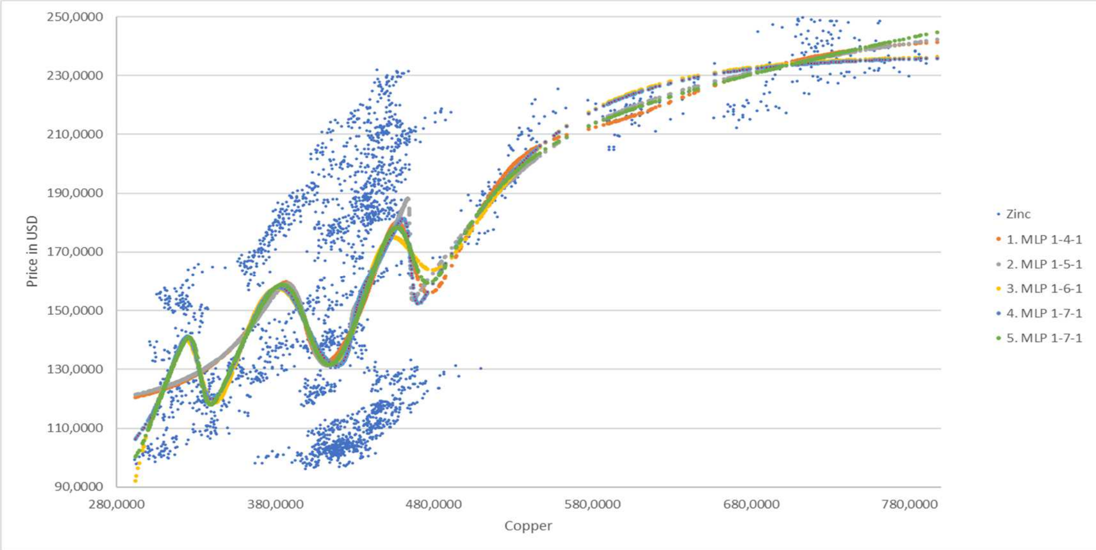


Figure 2 Regression models of copper and zinc prices relationships

Each of the structures follows the same trajectory with slight deviations. However, the course of the networks does not correspond to the actual zinc price (marked by blue dots); in an ideal case, the dots representing the models would overlap the initial data. The performance of the network is thus low.

Copper price

Table 3 shows 5 structures with the best characteristics generated by the neural networks for smoothing copper price time series.

Table 3 Retained neural networks - copper

Index	Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 1-7-1	0.975611	0.974015	0.975723	181.3793	230.7840	199.8800	BFGS 152	SOS	Logistic	Exponential
2	MLP 1-6-1	0.973971	0.974981	0.974713	193.3506	222.7492	207.2147	BFGS 333	SOS	Tanh	Exponential
3	MLP 1-8-1	0.975637	0.973911	0.975288	181.1553	232.1463	203.1942	BFGS 239	SOS	Logistic	Logistic
4	MLP 1-7-1	0.976322	0.974391	0.974933	176.0979	227.9512	206.3609	BFGS 206	SOS	Tanh	Logistic
5	MLP 1-8-1	0.975119	0.975647	0.975998	184.9329	216.7222	197.6899	BFGS 1475	SOS	Logistic	Exponential

Source: Authors.

The second column contains the names of the networks and their characteristics. Each of the networks contains one input; the hidden layers contain 6-8 neurons. The output neuron is one in the case of all networks; it is the copper price. The third, fourth, and fifth columns show the performance of the retained structures, with all networks achieving a performance of about 97 %, which can be considered a good performance. The sixth, seventh, and eighth columns present training, testing, and validation errors ranging from 176 to 232, which means that the number of errors is lower than in Table 2. A different version of the training algorithm BFGS (column 9) was used for network training. The error function presented in column 10 was SOS. For the hidden layer in column 11, logistic and logistic tangent activation functions were used. The exponential and logistic function activated the output layer in column 12. The performance can be considered more successful than in the previous case.

Figure 3 shows the basic characteristics representing the smoothed time series of copper in the given period and for retained networks.

Figure 3 Smoothed time series of copper price in the years 2011 – 2021

The red curve in Figure 3 represents the actual price of copper. It can be seen that the other networks marked with different colors do not copy the actual price. The red curve would follow all MLP networks if the performance was ideal. The figure shows price fluctuations represented by local minimums and maximums. Between the years 2011 and 2014, copper prices ranged from 380 to 480 USD/t. In the next years, until 2019, the copper price also ranged between 380 and 480 USD/t, with an increase starting at the beginning of 2020, when the price was 380 USD/t at the beginning 580 USD/t at the end of the year. The increase continued until 2021, achieving the price of 580 USD/t at the beginning of the year and 780 USD/t at the end of the year.

Figure 4 shows the most successful model, which will be used for the calculation within RQ5. The smoothed network with the best performance is 2. MLP.

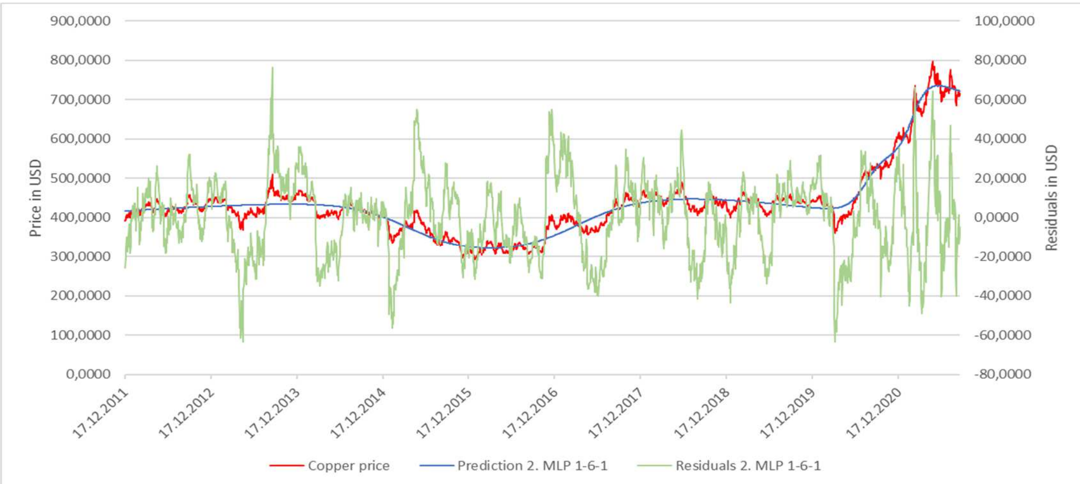


Figure 4 Comparison of the actual course of copper price and the most suitable smoothed time series, residuals

The residuals are presented on axis y in different orders. Residuals indicate the difference between the actual price and the model. In an ideal case, residuals should be zero and should be situated on axis x. The higher values of the residuals, the less precise the model is. This model thus does not show good results.

Development of zinc price

Table 5 shows the 5 best structures generated by the neural networks to smooth the zinc price time series.

Table 4 Retained neural networks - zinc

Index	Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
1	MLP 1-7-1	0.985808	0.985766	0.985183	25.51471	25.67840	27.02238	BFGS 332	SOS	Logistic	Identity
2	MLP 1-8-1	0.983885	0.983562	0.984355	28.94358	29.52305	28.51503	BFGS 312	SOS	Tanh	Exponential
3	MLP 1-8-1	0.984917	0.984318	0.985647	27.10680	28.17703	26.18435	BFGS 999	SOS	Logistic	Identity
4	MLP 1-6-1	0.985566	0.984911	0.985974	25.94950	27.28049	25.59879	BFGS 484	SOS	Logistic	Identity
5	MLP 1-7-1	0.984762	0.984477	0.985199	27.38617	28.01094	27.04899	BFGS 367	SOS	Tanh	Tanh

Source: Authors.

The second column contains the names of the networks and their characteristics; each of the networks has one input, the hidden layer contains 6 – 8 neurons, and one output neuron in each network – zinc price. The third, fourth, and fifth column present the performance of the retained structure, with all networks achieving approx. 98 %, which can be considered successful. The sixth, seventh, and eighth columns contain training, testing, and validation errors (26 – 30); it can be seen that the number of errors is the lowest of all tables. A different variant of the training algorithm BFGS presented in column 9 was used for network training. The error function (column 10) used for all networks was SOS. The activation function of the hidden layer in column 11 was logistic and logistic tangent; the activation function of the output layer (column 12) was exponential, logistic tangent, and identity. The network performance can be considered nearly ideal.

Figure 5 shows the smoothed time series of zinc prices between 2011 and 2021.

Figure 5 Smoothed time series of zinc prices in the period 2011 – 2021

The red curve represents the actual zinc price and other color networks smooth the actual zinc price time series. The performance is almost ideal. The figure shows price fluctuations expressed by local minimums and maximums. Zinc price grew from the year 2011 (100 USD/t) until the year 2014, achieving the value of 150 USD/t. In 2015, the price decreased to 100 USD/t, starting to grow again in 2016 (190 USD/t). In 2017, the development was unstable, with the price being 170 USD/t at the beginning of the year, increasing to 230 USD/t, and finally decreasing to 170 USD/t at the end of the year. In 2019, the price decreased slowly, achieving the value of 140 USD/t at the end of the year. In 2020 and 2021, the price achieved the value of 250 USD/t.

Figure 6 shows the predicted copper price until the year 2030 using the four most successful networks. The fifth structure generated nonsensical results, as it obviously suffered from overfitting.

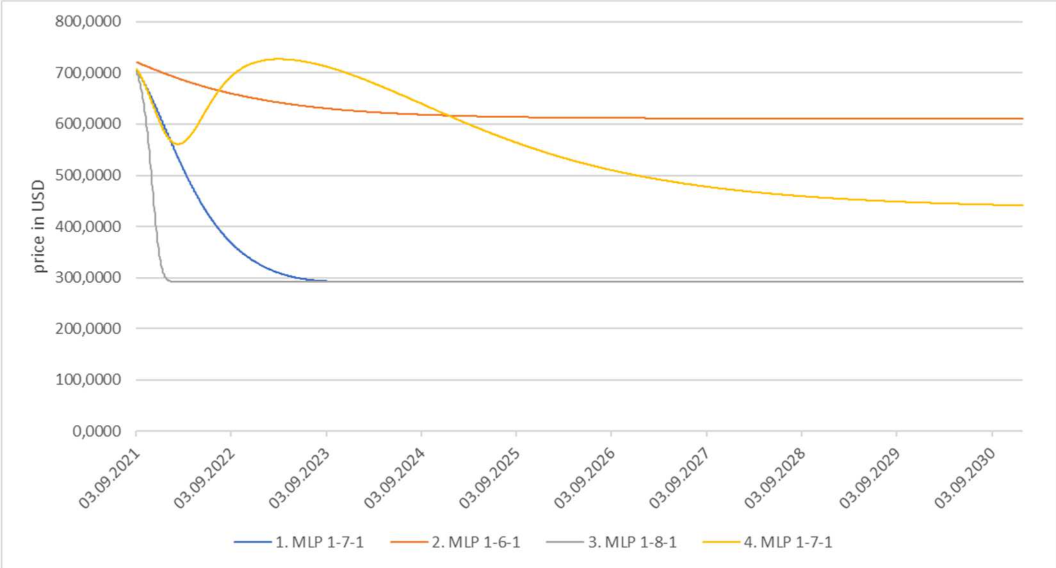


Figure 6 Predicted copper prices until 2030 using the four most successful networks

The blue curve representing the network 1.MPL showed the value of 700 USD/t in 2021. According to the prediction, its value will decrease slowly until 2023, stabilizing at the value of 300 USD/t until the year 2030. The red curve representing the network 2.MPL showed the value of 700 USD/t in 2021; according to the prediction, there will be a slight decrease by 90 USD/t and stabilization at the value of 610 USD/t in the year 2027 (until the year 2030). The grey curve of the 3.MPL network shows the value of 700 USD/t in 2021. The prediction expects it to fall sharply until the end of the year 2021, stabilizing at the value of 300 USD/t at the beginning of the year 2022 until the year 2030. The yellow curve of 4.MLP showed the value of 700 USD/t in 2021. According to the prediction, it will decrease slightly in the year 2022, achieving the value of 570 USD/t. This will be followed by a decrease until the year 2023 (up to 720 USD/t) and another decrease in the next years. The price is expected to be unstable, with the expected value of 720 USD/t in the year 2023 to 520 USD in the year 2030.

Figure 7 shows the zinc price in 2021 – 2030, dependent on the copper price predicted using the four most successful structures. The fifth structure showed nonsensical results, as it obviously suffered from overfitting.

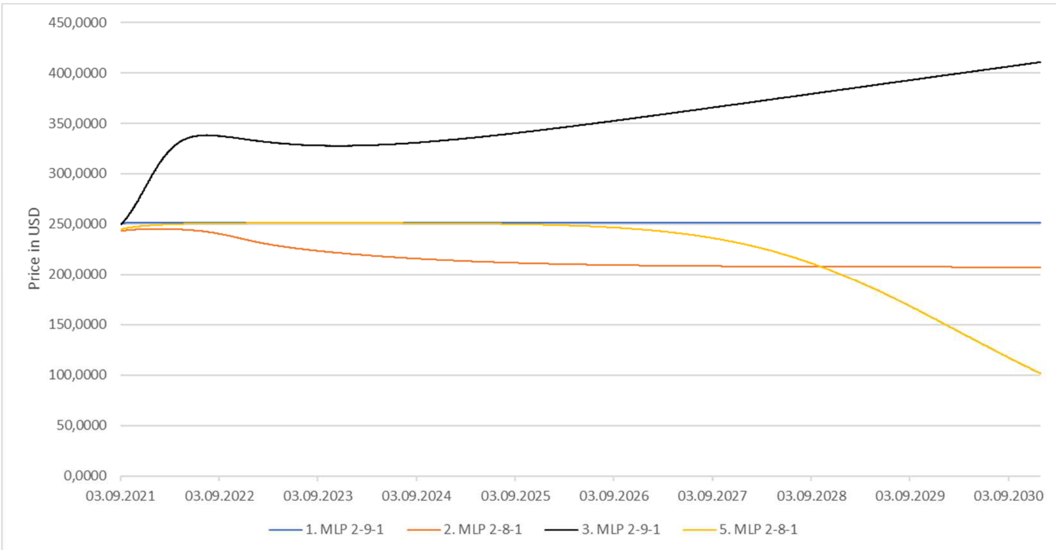


Figure 7 Predicted zinc price in dependence on copper price until 2030

The blue curve of 1.MLP shows the constant price of 250 USD/t from 2021 to 2030. The orange curve of 2.MLP shows the value of 240 USD/t in the year 2021, with a tendency slightly decreasing trend until the year 2030, with the price achieving the value of 210 USD/t. The black curve of the network 3.MPL shows the value of 250 USD/t in 2021, with a subsequent increase until the year 2022, achieving the value of 340 USD/t. In the next years, the value decreases slightly to the value of 330 USD/t, which is followed by a slight decrease in 2024 until the year 2030, achieving the value of 410 UDS/t. The yellow curve of 5.MLP shows the same value of 250 USD/t from the year 2021 to the year 2026, which is followed by a decrease to 100 USD/t in 2030.

Discussion of results

RQ1: Are copper and zinc perfect complements, imperfect complements, or indifferent goods?

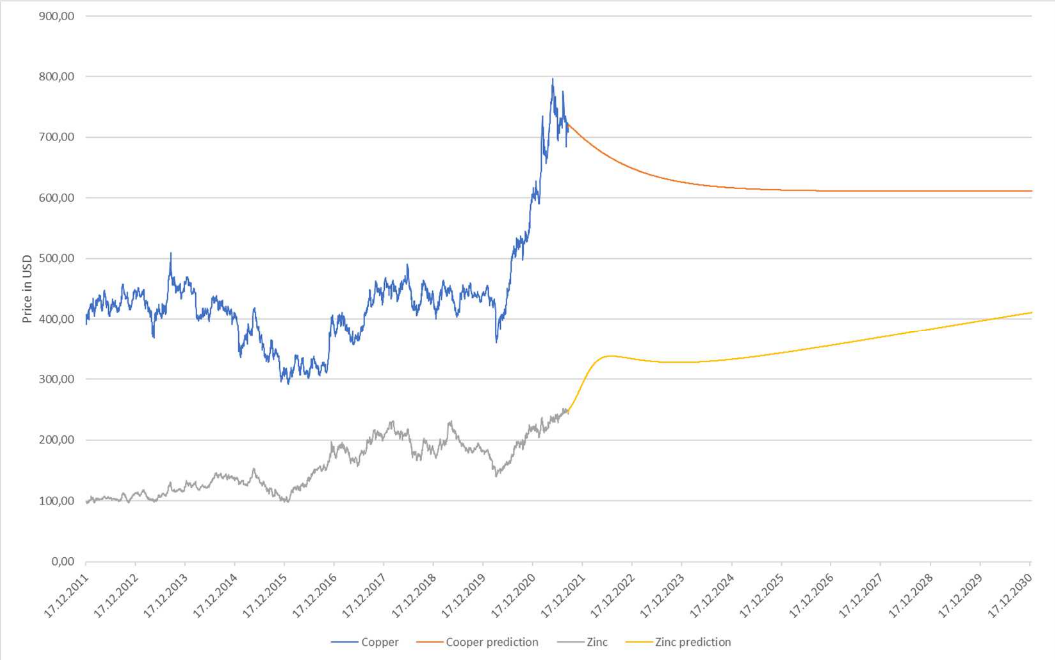
The results presented in Table 2 suggest that zinc and copper prices show the interdependence of 65 % on average. Pearson correlation coefficient is approx. 0.65. It can thus be stated that the dependence was confirmed. If the value was 1, it would mean a perfect interdependence of zinc and copper prices. Hutson et al. (2021) argue that asymptotic tests are most valid in all cases, which is due to their robust type I errors in general. The authors show that the robust permutation test of the Pearson correlation coefficient does not control type I error in abnormal settings when two variables could be dependent but uncorrelated. The value of $\rho_c = 1$ indicates a perfect agreement, while $\rho_c = 0$ indicates a lack of agreement. The value of 0.65 confirms the dependence but is not the perfect one. Both metals are used industrially both in alloys and separately. The results thus prove that these commodities are not perfect complements, but they can still be considered complements. How do such imperfect complements behave? Firstly, the production volume of one type of goods should influence the production volume of the other goods. This applies to the potential risk related to mining and price between both commodities' markets. However, the interdependence of both commodities should not be ignored.

RQ2: What was the development of copper price between 2011 and 2021?

Figure 3 is a graphical illustration of the copper price development. From the year 2011, the price fluctuated around 400 USD/t and decreased gradually in the next years until 2016. According to Zhaozhi et al. (2016), this is due to the demand for iron ore, which will gradually reach its peak around the year 2015-2016. After the year 2016, the price increased up to the value of 460 – 480 USD/t. In the last decades, metal exchanges have been more and more integrated with the international financial markets, which means that speculators, banks, financial groups, investors, hedge funds, and other actors are gaining an increasingly important role. The important role of financial speculations is partly because the fundamentals, in general, were not able to explain price fluctuations successfully and short-selling is possible in many mineral markets. Howeer, Guzman et al. (2018) rule this argument out because many mineral commodities are not traded on stock markets, yet they show a similar or even greater price increase than the commodities that are traded on stock markets. At the end of the year 2019, there can be seen a significant decrease to 370 USD/t. From the beginning of the year 2020, the price shows a fast increase up to the value of 790 USD/t. This is naturally caused by the COVID-19 pandemic. As Shaikh et al. (2021) describe, all stock markets show an unexpected price increase, which means that investors' fears grew as a result of the outbreak of the COVID-19 pandemic in China.

RQ3: What was the development of zinc price between 2011 and 2021?

More detailed information on the development of zinc price is presented in Table 5 and Figure 5. Zinc price rose from 2011 to the end of the year 2014, when it achieved its maximum (160 USD/ t). Subsequently, the price decreased to the value of 100 USD/t, and in 2016, it started to increase to 190 USD/t. In 2017, the price development was unstable; at the beginning of the year, the price was 170 USD/t, grew subsequently to the value of 230 USD/t, and fell to 170 USD/t at the end of the year. In 2018, the price grew slightly to 200 USD/t and then decreased again to 170 USD/t, which was followed by an increase to 230 USD/t. In 2019, the price decreased slowly, reaching 140 USD/t at the end of the year, while in 2020 and 2021, it increased to 250 USD/t. It shall be noted that in 2020 and 2021 increased due to the ongoing COVID-19 pandemic**.**



Graph 1 Current time series of copper and zinc prices ad their prediction until 2030

This is a long-term machine prediction. High prediction accuracy thus cannot be expected. We are more interested in the trend of the time series curve. It is thus not possible to capture possible fluctuations. Rather, the prediction in the current environment is addressed. The software evaluated 2.MLP as the best network for predicting copper price (see the red curve in Graph 6). According to the prediction, copper price is expected to decrease slightly from 720 USD/t in 2022 to 610 USD/t in 2026 and is expected to stabilize at this value until the year 2030. In general, Guzman et al. (2018) consider three effects of financial speculations in commodities, which may potentially influence prices: herd behavior, rational speculative bubbles, and arbitrage between spot and futures prices. All these facts suggest that the effect of financial speculations on commodity prices may exist in certain periods only and may not be permanent. As for copper, the author explicitly mentions the case of market manipulations in the year 1995, also known as the Sumitomo copper affair. However, this paper does not deal with the manipulation of this type due to the lack of empirical evidence. In fact, they suggest that a significant part of copper price movements is due to macroeconomic factors. There are three main macroeconomics that play a relevant role: liquidity (mainly in the USA and to a lower extent in the EU; not in China in the monitored period). In the light of these results, the future development of copper prices is very likely to be determined by the physical demand from China or other developing countries and largely also by the decisions of the central banks of the USA, Europe, and (possibly) China on the liquidity in the markets and sometimes (or rather under specific conditions) on the number of financial investments (and speculations) in minerals. Vochozka (2018) argues that the predictions made by neural networks are more accurate for the first three months than for the rest of the monitored period (two years).

RQ5: What will be the development of zinc price between 2021 and 2030 depending on copper price?

The answer to this research question can be seen in the graph in Figure 8, which shows the best prediction of copper and zinc price from the retained MLP structures. According to the prediction, copper price is expected to be 250 USD/t at the end of the year 2021 and to grow slightly in the year 2023 to the value of 320 USD/t. In the next years, the value is expected to grow slightly, approx. by 10 USD/t per year and to achieve the value of 410 USD/t in 2030. The result is a copper development trend since it is not possible to make accurate machine predictions for such a long period.

What is very important is the relationship of both variables in the prediction. Copper price should rather decrease in the given period; zinc price should increase. Given that these are partial complements, several partial conclusions can be drawn. First of all, the mutual relationship of both commodities says that the copper price mainly pushes up the zinc price. On the contrary, copper price is pushed down by zinc price. Both commodity prices are mutually converging. However, they are unlikely to be at the same level in the near future. If the production of both metals decreases due to more difficult mining of both metal ores, their prices will converge significantly faster.

If there is a fluctuation in one of the markets under review (either in the volume of production or commodity price), such a fluctuation is reflected in the other market. This is evidenced mainly by the development of both commodity prices in the years 2013 - 2021.

An interesting starting point for manufacturers is the search for substitutes of both metals, some other metallic and non-metallic materials. In such a case, the interdependence of the two complements would be even weaker. This would eliminate the risk transferred from one market to another.

Conclusion

The objective of the paper was to evaluate the mutual relationship between copper and zinc prices between 2011 and 2021 and to predict their future prices until 2030. The objective of the paper was achieved by means of regression of neural structures in the TIBCO's Statistica software, version 13.0, time-series smoothing by means of multilayer perceptron network, graphical representation, and logical judgment. According to the prediction, copper price is expected to decrease slightly compared to the past years and stabilize at the value of 610 USD/t in 2026 until the year 2030. Zinc price is expected to increase slightly until the year 2030, where the resulting prediction value is 410 USD/t.

Copper price and zinc price show interdependence of approx. 65 % on average. Ge et al. (2019), in accordance with the theory of consumption of stock market complement, consumers will consume the basic products, and at the same time, they will consume complements – products in the relevant industry, which are centered around the product platform. In industries oriented on platform products, the more complements, the higher the value of the platform is. Pearson correlation coefficient was approx. 0.65. The result thus confirms the fact that the commodities are not perfect complements. Nguyen et al. (2019) state that although revenues show slight and statistically significant correlations, jump correlations between the commodities differ significantly. Especially energy, metals, and grains show the same jump correlations, while the jumps of meat and soft commodities do not correlate. This also applies to revenues where energy, metals, and grains show much higher correlations (by 0.43-0.51) compared to 0.08-0.20 in the remaining two sectors. The mutual relationship of both commodities indicates that zinc price is pushed up especially by copper price, while the copper price is pushed down by zinc price. The prices of both commodities converge. However, if the production volume of both metals declines due to the more difficult mining of both metal ores, their prices will converge significantly faster.

According to Skapa (2018), investments in commodities have become a new topic for private investors in recent years. Private investors are trying to spread their investments across a much wider range of investments than in the past. They are looking for new sources of return and better diversification of investment risk (Táncošová & Slaný, 2004).

The future development of copper and zinc prices is not affected by unpredictable events, such as political situations, market restrictions, or the aforementioned COVID-19 pandemic. Therefore, we concluded that the prediction is an estimate rather than a determinative indicator of the future situation. Another fact we want to point out is that such long-term predictions may not provide an objective result. Although the most suitable retained structures of MLP networks are applied, they are adjusted for market fluctuations observed in both current and past prices.

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