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THE INFLUENCE OF WORLD OIL PRICES ON THE CHINESE YUAN EXCHANGE RATE

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Abstract. This article aims to find out if and if any influence the evolution of oil price on the world market influences the value of the Chinese currency. Data, which we used for analysis, is available on the World Bank website. The analysis uses data about the Chinese Yuan (CNY) to the US Dollar (USD). The second series of data is the Brent crude oil price expressed in US Dollars per barrel. The time interval for which data will be available is the daily closing value of both variables, beginning on September 1, 2014, and ending on August 30, 2019. To accomplish our research aim, we must conduct an experiment. Therefore, the experiment assumes a uniform procedure with a gradual change of one parameter, namely the delay of the CNY / USD time series. Regression is performed using neural structures. We generate 10,000 neural networks for every single experiment combination (time delay, set of independent variables). As a result, we perform 10 calculations and get ten different outputs. From each experiment, we always preserve 5 artificial neural networks that show the best aspects. It could be estimated that fluctuations in oil prices on world markets would affect the CNY / USD price; however, it was not clear to what extent. Based on this paper, we demonstrate that such influence exists; it can be identified at an interval of 1.97% to 9.57%. This is a very significant influence, even regarding the importance of the raw material.

Keywords: world oil price; Chinese Yuan; exchange rate; artificial neural networks; price development, time series

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JEL Classifications: C22, C45, F31

Additional disciplines: political sciences; energetics and thermoenergetics; informatics

1. Introduction

The influence of oil price on the Chinese Yuan has received a great pact of consideration in recent years. Decades ago, empirical research showed noxious relationship between oil price shocks and gross domestic product. However, recent studies stated a diverse relation between oil price shocks and macroeconomy depending on the economic status of a country (Iwayemi, Eowowe 2011).

Important role represents world oil price directly or indirectly influencing the Exchange rate (Vochozka et al. 2020). The effect can be either negative or positive. Although China produces oil, the country is dependent heavily on imported oil because the demand of the commodity is higher than domestic production (Strakova, Kalinova 2020).

The researcher investigates the influence of world oil prices on the Chinese Yuan Exchange rate, and reviewed literatures mainly from web of science that are related to the topic.

2. Literature review

Every country has differences in earning which are cohered to different macroeconomic and microeconomic determinants (Valaskova, 2021). Time series predictions can be used for exchange rate analysis (Machova, Marecek, 2019). Based on the analysis, it is clear that the public sector and the national economy are appreciable importance (Rousek, 2020; Halaskova et al., 2021). In addition, according to Ginevicius (2020) and Kocisova et al. (2018) economic development represents for countries own competitiveness influenced by various factors. The importance of the macro- and microeconomic determinants working together we see in the major economies across the world. According to Valaskova (2021) paper factors such as behaviour of managers, comparing the influence of similar factors across countries detect the critical intentions management of earnings. Their own companies, and others, which are based there, influence every country. Liquidity and quality of reported earnings are significantly emphasised on companies due to macroeconomic conditions (Durana, 2021; Onuferova, Cabinova 2018; Belas et al. 2018). In addition, according to Kharroubi (2021) and Krajčík (2022) rapid developments in science and technology are essential ingredients of globalization, which provides diverse workforce a reality in present day organization. Market development is influenced in individual economic cycles with the support of state and government decisions (Valaskova et al., 2021; Filipova et al., 2016; Dvorsky et al., 2021). For the survival of organizations in the global market is the adoption of a global approach (Kharroubi at al., 2021; Gavurova, 2012; Fedorko et al. 2018; Masood et al., 2019). Despite optimistic forecasts for 2021 (5% for global economic growth) according to World Economic Situation and Prospects by United Nations (2021) predicts only 4,7% global economic growth, which will primarily offset the losses incurred in 2020 (Durana et al., 2021).

In mid-2014, the crude oil price began to decrease considerably, and this sharp fall in the crude oil price had an appreciable impact on the world economy and international trade. In mid-2014, world oil prices experienced a sharp decrease, which had a very great impact on global trade (Smelc, 2020). According to Sultonov (2017), consequential results exhibited relevant changes in dynamic conditional correlation and causality relationship among commodity and foreign exchange markets during the period of the crude oil price decrease.

China dominates the largest world markets (Krulicky, Brabenec, 2020). The changing oil prices as of late has arose simultaneously with a quick extension of Chinese export. The stock market of China shows an earlier instability in the series of prices (Dias et al., 2020a; Dias et al., 2020b). China and Indonesia form the bottom of the ranking in diversity and inclusion, where they show the development of an economy with a wide range of workforces (Kharroub, 2021) countries at the bottom of diversity and inclusion rankings include China and Indonesia, have large emerging economies with a substantial local labour supply. The outcomes Suggest a steady relationship and yields somewhat positive qualities at the cost of oil and variable coefficients for cost intensity, alongside the normal negative flexibility for the genuine conversion scale (Faria et al., 2009).

Apart from the United States, oil trading is influenced by a consolidated change in oil price and exchange rate. Especially, for the world's biggest oil importer, China (Machova, Marecek, 2020). Siyao et al. (2019) believed that any minor instabilities in oil price essentially affect China's oil importation, but in oil exporting countries like

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Azerbaijan and Kazakhstan whose economies depend on oil, the macroeconomic indicators like currency, GDP severely depend on the oil factor. Humbatoya and Hajiyew (2019) inferred that daily oil production and consumption have less effect on the formation of the world oil prices. In contrast to that, Rangasamy (2017) revealed that inflation is drove by a change in oil prices in South Africa. In addition, in Russia, an investigation of the Russian Ruble (RUB) and the US Dollar (USD) demonstrated that the USD/RUB exchange rate was influenced by the adjustments in oil price in the study-periods. The impact of oil cost on the USD/RUB conversion scale was more grounded after the 2008 world financial crisis. This affirms the speculation that the Russian Economy indicates manifestations of the Dutch Disease in 2008 as suggested by Bilan et al. (2018). Law (2018) found that in a case of large appreciation in oil price, there was a depreciation of exchange rate in Thailand. According to Valaskova (2021) political and financial conditions appear to be exceedingly important. Current macroeconomic conditions worsen the competitive position of companies and enlarge the compulsion on financial managers (Durana, 2021).

There is a unanimous agreement, that oil prices influence farming costs through exchange rate. Authorities should consider the importance of cross-sectional differences according to Valaskova (2021). A challenge in energy security in China can easily spillover to maintaining food security, alternatively putting pressure on the country's economy. Ma et al. (2015) demonstrated that farming costs are not fundamentally influenced by the sudden changes in oil prices. Reliably, farming costs are unbiased to changes in oil prices over the long haul. Considering the macro-level aspects, legal and regulatory systems help mitigate opportunistic managerial behaviour (Valaskova et al., 2021; Evteeva et al., 2019; Tende, Obumneke, 2014).

Brahmasrene et al. (2014) shared similar views and supported exchange rate shock has a substantial adverse effect on crude oil prices while the impulse response of the exchange rate variable to a crude oil price shock was statistically insignificant, the impact of extreme price volatility in June 2008 on exchange rates was substantial. Hasanov et al. (2017) accepted that world oil prices are deniably a major leading force behind exchange rate and suggested that productivity is another major player. Amano and Norden (1998) in 1998 were not certain in their findings. They pointed that oil prices may have been the dominant cause of obstinate exchange rate shocks because they found even relation between oil price shocks and the US currency exchange rate. (Das, Dutta 2019) shared similar view with (Baghestani, Toledo, 2019). They stated that oil price has a huge impact on both, exchange and interest rate. Huang and Feng (2007), after examining the scale to which oil price shock affect the Chinese RMB exchange rate, proposed that there was an insignificant appreciation of the future exchange rate. In addition, Milani (2008) alleged that the effect of oil price shocks is minimal as pronounced by agents. The research stated that oil prices affect the economy through a supplementary channel, which is the formation of agents' beliefs. Milani supported the claim with the implied responses of oil price fluctuations in the 1970s compared with 2008.

Over the years, whenever there is a change in commodity price information, the exchange rate of non-commodity currencies strongly influence price changes (Vochozka et al., 2021). While many researchers undoubtedly believe that oil prices occupy high position in the macroeconomic pursuits. Some other researchers do not believe the notion that oil price shocks influence macroeconomic activities. Barsky and Kilian (2004) alleged that a primary cause for the constant acceptance of the oil shock supposition was acuity that explained the US recession in the 1970s and since then the topic become popular to date. In general, oil prices represent a relevant position in global economic system. Escobedo and Madrigal (2013) investigated the dependence between oil and wheat prices. Using time series data, they concluded that there is both short-term and long-term relationship between the two commodities. Chen and Chen (2007) revealed that oil prices not only have been the dominant source of exchange rate but can also have substantial predicting power of future exchange rates.

Since the financial crisis in 2007/2008, there has been an increase in uncertainty (Mulacova, 2012) and global oil prices are the most important determinant of currency exchange rates, and the Chenese Yuan is not an exception. A stable world oil price minimizes exchange rate fluctuations and uncertainty in the Chinese yuan. Fluctuation in oil prices as a significant energy asset influences all parts of the economy (Vochozka et al., 2020). Based on the literatures reviewed, the influence of world oil price on the Chinese Yuan exchange rate is significant and requires further investigation. From the literatures reviewed, it can be inferring that oil price and Exchange rate are correlated because it can be seen that a change in world oil price is accompanied by a season of fluctuations in Exchange rate value of currencies. This conclusion agrees with all researchers who believed a correlation between oil prices and exchange rate, particularly with Qiang et al. (2019) that concluded the impact level relies upon the overall level of every nation influenced by oil price.

The goal of the allowance is to find out whether and what impact the advancement of oil prices on the world market have on the value of Chinese currency.

3. Data and methods

The works of Chen and Chen (2007), Qiang et al. (2019) or Vochozka et al. (2020) clearly indicate the existence of correlation among the oil price based on data from world market and the value of CNY. However, the question is whether its influence is significant enough to be identified and measured. The detailed analysis of the main objective of the contribution results in two research questions:

1. Is there a relation among the oil price on the world market and the value of CNY?
2. Can such a relation be identified and measured?

For the analysis, we used data, which are available on the World Bank websites. For the analysis, the information about CNY and USD exchange rate. The second time series will be represented by Brent oil price in USD per barrel. The use of USD value for calculating the price of CNY and oil eliminates the shift that could occur by the fluctuation of USD value. These data are also available on the website of World Bank. The time interval for which the data are available is the daily closing value of both variables starting from 1 September 2014 until 30 August 2019. The descriptive data characteristics are given in Table 1.

Table 1. Date set characteristics

Samples	Brent in USD/barrel Input variable	CNY/USD Output variable (target)
Minimum (Training)	27.8800	0.139600
Maximum (Training)	102.7900	0.163600
Average (Training)	58.5614	0.152175
Standard deviation (Training)	12.9949	0.006092
Minimum (Testing)	30.5000	0.139800
Maximum (Testing)	100.2000	0.163600
Average (Testing)	61.7022	0.152119
Standard deviation (Testing)	12.2878	0.006461
Minimum (Validation)	31.5500	0.139600
Maximum (Validation)	102.7700	0.163600
Average (Validation)	59.8710	0.152370
Standard deviation (Validation)	18.2674	0.009356
Minimum (Overall)	27.8800	0.139600
Maximum (Overall)	102.7900	0.163600
Average (Overall)	59.2272	0.152196

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Standard deviation (Overall)	13.1782	0.006168

Source: Authors

Figure 1 shows a graphical representation of chosen statistical characteristics of the CNY/USD exchange rate development including the histogram of the entry data.

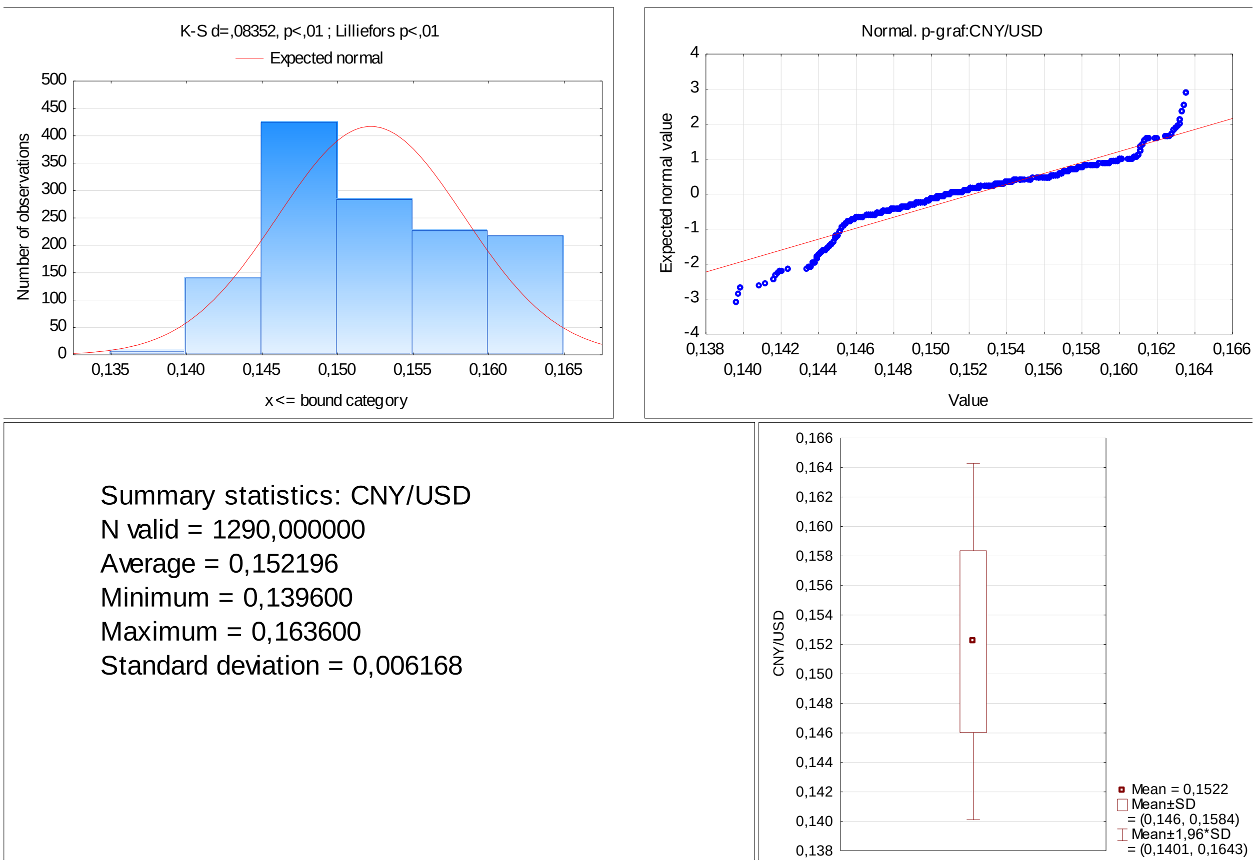

Figure 1. Graph of basic statistical characteristics of CNY/USD

Source: Authors.

Figure 2 shows the same characteristics as the first for the second time series, i. e. Brent oil prices in USD per barrel.

An interesting fact is that unlike the Brent in USD/barrel, the CNY/USD histogram does correspond to standard distribution. For data processing, DELL´s Statistica software, will be used version 12.

For better understanding the course of both inspected time series, Figure 3 is included, demonstrating in one combined graph the course of both time series. The blue line represents the course of CNY/USD, while the red one represents Brent in USD/barrel. Axis X represents time. Due to the software used, it is necessary to explain that this is time on days when the software marks 1 January 1900 as the beginning of the axis. This means that the first day of the monitored period, that is, 1 September 2014 is the 41,883rd day from the beginning of the defined

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time axis. On the left side of the axis, the value of CNY/USD is marked, while the left side shows the price of Brent in USD/barrel. It may appear at first sight that there is a certain match in the course of both time series, although the lag is not steady but changes over time. An interesting period is between the 4,268th and the 42,900th day, when the course of the data is inverse to the previous period.

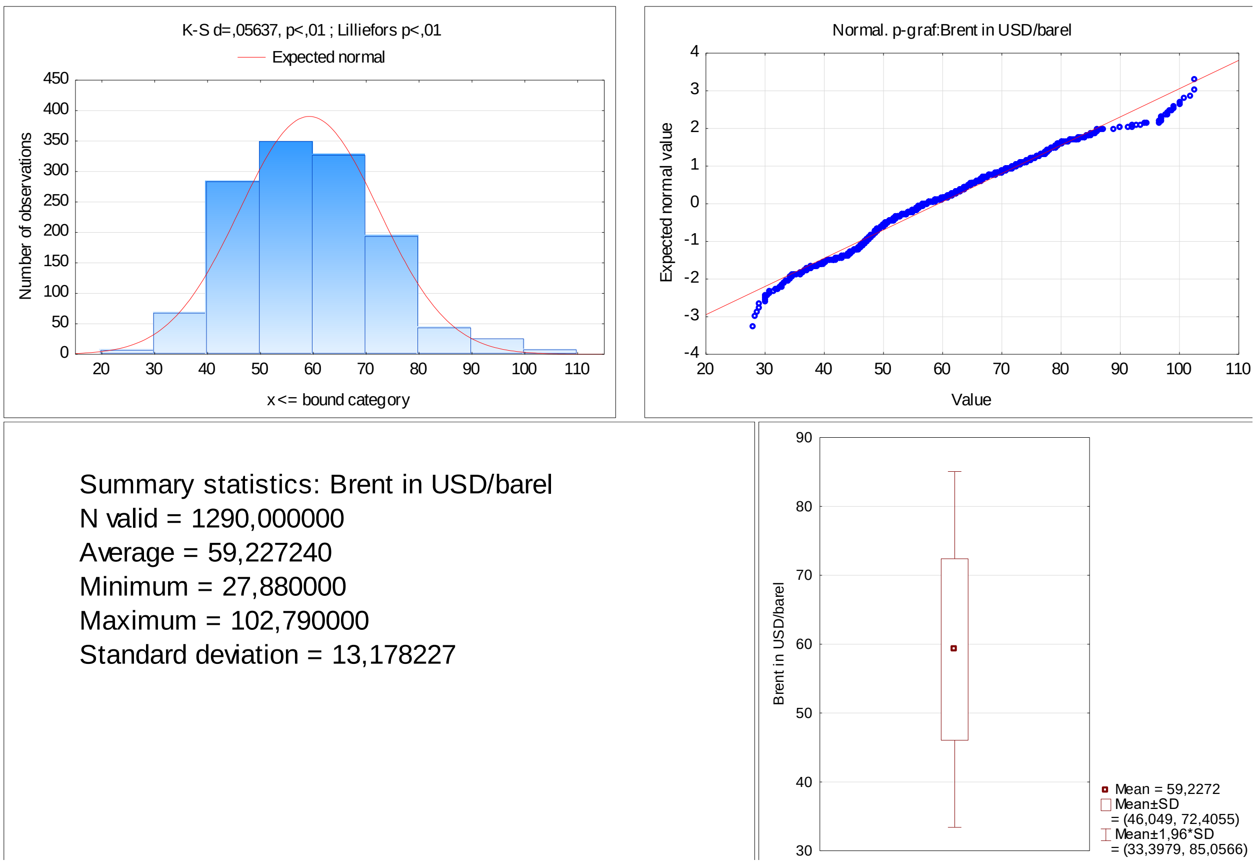

Figure 2. Graph of basic statistical characteristics for Brent oil price per barrel

Source: Authors

It is important to be aware of the fact that even if there is a relation among Brent in in USD/barrel and CNY/USD, it does not have to be identifiable immediately. It can happen that the changes in the world oil price will affect the value of CNY only after a few days. To achieve the objective of this research, an experiment has to be carried out.

The time lag can only be determined heuristically. Therefore, the experiment will assume a unified procedure with a gradual change of one parameter – time lag of the time series CNY/USD. The assumptions will be as follows:

1. The change in CNY/USD will show on the same day. In such a case, CNY/USD would not react to the price of Brent in USD/barrel but to the causes leading to the change of price of Brent in USD/barrel.
2. The change in CNY/USD will show one day after the adjustment in the price of Brent in USD/barrel.
3. The change in CNY/USD will show 5 days after the adjustment in the price of Brent in USD/barrel.

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4. The change in CNY/USD will show 10 days after the adjustment in the price of Brent in USD/barrel.
5. The change in CNY/USD will show 30 days after the adjustment in the price of Brent in USD/barrel.

Since we do not investigate the time lag after each day, the real time lag is a risk which will also be estimated in the result. Despite this risk, the estimation will be close to reality. Moreover, the time lag does not occur constantly during the monitored period. In such a case, it would not be realistic to obtain an accurately result. However, this accuracy is not the objective of this contribution.

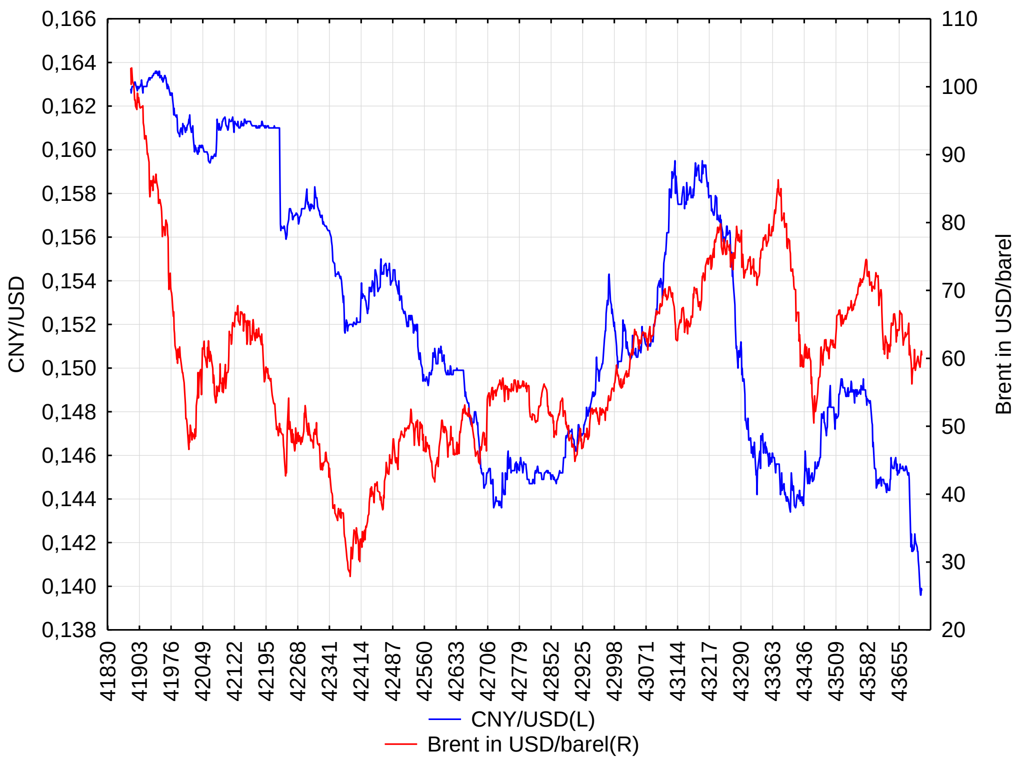

Figure 3. Development of CNY/USD and Brent in USD/barrel

Source: Authors.

It is important to be aware of the fact that even if there is a relation among Brent in in USD/barrel and CNY/USD, it does not have to be identifiable immediately. It can happen that the changes in the world oil price will affect the value of CNY only after a few days. To achieve the objective of this research, an experiment has to be carried out.

The time lag can only be determined heuristically. Therefore, the experiment will assume a unified procedure with a gradual change of one parameter – time lag of the time series CNY/USD. The assumptions will be as follows:

6. The change in CNY/USD will show on the same day. In such a case, CNY/USD would not react to the price of Brent in USD/barrel but to the causes leading to the change of price of Brent in USD/barrel.
7. The change in CNY/USD will show one day after the adjustment in the price of Brent in USD/barrel.
8. The change in CNY/USD will show 5 days after the adjustment in the price of Brent in USD/barrel.
9. The change in CNY/USD will show 10 days after the adjustment in the price of Brent in USD/barrel.

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10. The change in CNY/USD will show 30 days after the adjustment in the price of Brent in USD/barrel. Since we do not investigate the time lag after each day, the real time lag is a risk which will also be estimated in the result. Despite this risk, the estimation will be close to reality. Moreover, the time lag does not occur constantly during the monitored period. In such a case, it would not be realistic to obtain an accurately result. However, this accuracy is not the objective of this contribution.

Regression will be performed by using neural structures in the Statistica software. We will generate multilayer perceptron networks (ML) and radial basis function networks (RBF). The dependent variable will be CNY/USD. The experiment will assume two sets of independent variables:

1. Brent in USD/barrel (continuous variable): in this case, we will only measure the relationship of the two variables with a preordained time lag. This will provide an answer to the research question 1: if there is a relation between the oil price in the world market and the value of CNY.
2. Brent in USD/barrel and date (continuous variable): in this case, if the answer to the first research question is yes, the influence of Brent in USD/barrel on CNY will be measured. This will provide the respond to the research question 2.

The time series will be randomly divided into three datasets – Training, Testing, and Validation. The first set will contain 70% of the input data. Based on the Training dataset and neural structures will be generated. The remaining two datasets will each consist 15% of the input information. Both sets will be used for the verification of the identified neural structure trustworthiness. A total of 10,000 neural networks will be generated for each experiment (time lag, set of independent variables). As a result of 10 calculations carried out, ten various outcomes will be obtained. From each experiment, 5 artificial neural networks with the best characteristics* will be preserved. The first results shall provide the answers to the research question 1, while the other set of outputs shall provide the answers to the research question 2. It may appear logical to carry out all five experiments in the defined time lag, and then to carry out only the calculation for the identified most precise time lag in the case of the second test of independent variables. If the results are correct, the assumption will prove to be right. Therefore, it is recommended to carry out the calculations for all defined time lags also in the case of the second set of independent variables. If the same time lag is identified as the most precise one in both different sets of independent variables, the result, as well as the methodology and assumption, will be validated.

The MLP hidden layers will contain 2–8 neurons in the case of first set of independent variables, and 3–9 neurons in the case of the second set. In the case of radial basis function, the hidden layer will always consist of the minimum of 21 neurons and the maximum of 30 neurons. For the multilayer perceptron network, the following distribution function will be considered in the output and hidden layers:

- Linear,
- Logistic,
- Atanh,
- Exponential,
- Sinus.

Other settings will remain default (according to the ANN tool – automated neural networks). If necessary, the weights of the individual neurons will be reiterated using the ONN tool (own neural networks). However, it shall be stated that the improvement of ANN using this tool is a coincidence rather than an exact process with a well-predictable outcome.

* We will use the method of least squares. The generation of networks will be terminated if there is no improvement, i. e. if there is no decrease in the sum of the squares. We will thus keep the neural structures whose sum of residual squares to the actual development of CNY/USD will be as low as possible (zero in ideal case).

Finally, the results of both groups of retained neural networks will be compared.

3. Results

Dependence of CNY/USD on Brent in USD/barrel

Based on the procedure specified above, a total of 10,000 neural networks were generated for each predefined time lag. Out of these networks, 5 with the best parameters were preserved. Table 2 appears the overview for the data without time lag.

Table 2. Overview of retained neural networks in experiment without time lag considered

Network	Training perf.	Test. perf.	Valid. perf.	Training error	Testing error	Validation error	Training algorithm	Error function	Activation of hidden layer	Output activation function
RBF 1-24-1	0.412751	0.372668	0.511868	0.000015	0.000018	0.000014	RBFT	Sum of squares	Gaussian	Identity
RBF 1-29-1	0.402858	0.411735	0.501684	0.000016	0.000017	0.000015	RBFT	Sum of squares	Gaussian	Identity
RBF 1-27-1	0.421069	0.363556	0.501947	0.000015	0.000018	0.000015	RBFT	Sum of squares	Gaussian	Identity
RBF 1-29-1	0.416481	0.331440	0.505133	0.000015	0.000019	0.000015	RBFT	Sum of squares	Gaussian	Identity
RBF 1-25-1	0.403294	0.314854	0.501389	0.000016	0.000019	0.000015	RBFT	Sum of squares	Gaussian	Identity

Source: Authors.

There are only RBF networks. The input layer contains only one variable – Brent in USD/barrel (continuous variable). This is represented by one neuron in the input layer. In the hidden layer the neural networks contain between 24 and 29 neurons. The output layer contains logically one neuron and one output variable – CNY/USD. For all networks, RBFT training algorithm was applied. For the activation of the neurons in the hidden layer, Gaussian curve was used, while the neurons of the output layer were activated using the Identity function (for further details, see Table 2). All retained neural networks used method of least squares as an error function. The performance is given by the correlation coefficient, which achieves the values between more than 0.37 and more than 0.51 across the retained neural networks.

Table 3 shows retained neural networks for 1-day time lag.

Table 3. Overview of retained neural networks for the experiment with 1-day lag

Network	Training perf.	Test. perf.	Valid. perf.	Training error	Testing error	Validation error	Training algorithm	Error function	Activation of hidden layer	Output activation layer
RBF 1-25-1	0.367709	0.265241	0.423495	0.000016	0.000019	0.000017	RBFT	Sum of squares	Gaussian	Identity
RBF 1-27-1	0.412785	0.344563	0.432329	0.000015	0.000018	0.000017	RBFT	Sum of squares	Gaussian	Identity
RBF 1-25-1	0.434149	0.292056	0.427362	0.000015	0.000019	0.000017	RBFT	Sum of squares	Gaussian	Identity
RBF 1-30-1	0.448699	0.321214	0.421693	0.000015	0.000018	0.000017	RBFT	Sum of squares	Gaussian	Identity
RBF 1-26-1	0.411882	0.336311	0.431904	0.000015	0.000018	0.000017	RBFT	Sum of squares	Gaussian	Identity

Source: Authors.

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The table shows that the networks retained are only the RBF networks. In the hidden layer the neural networks contain 25–30 neurons. The output layer logically includes one neuron and one output variable – CNY/USD. For all networks, RBFT training algorithm was applied. The neural structures used Gaussian curve for the activation of the hidden layer of neurons. Identity feature has been applied to activate the output layer. As an error function, the sum of the least squares was used by all maintained neural structures. The performance is given by the correlation coefficient, which achieves the values between more than 0.26 and more than 0.44 across the retained neural networks and the datasets.

Table 4 shows the retained neural networks for 5-day time lag.

Table 4. Overview of retained neural networks for experiment with 5-day lag

Network	Training perf.	Test. perf.	Valid. perf.	Training error	Testing error	Validation error	Training algorithm	Error function	Activation of hidden layer	Output activation function
RBF 1-28-1	0.359699	0.428676	0.462018	0.000016	0.000018	0.000017	RBFT	Sum of squares	Gaussian	Identity
RBF 1-21-1	0.375812	0.449748	0.483160	0.000015	0.000018	0.000016	RBFT	Sum of squares	Gaussian	Identity
RBF 1-23-1	0.383388	0.387543	0.459824	0.000015	0.000019	0.000017	RBFT	Sum of squares	Gaussian	Identity
RBF 1-25-1	0.369094	0.448173	0.468541	0.000015	0.000018	0.000016	RBFT	Sum of squares	Gaussian	Identity
RBF 1-21-1	0.344893	0.422891	0.459610	0.000016	0.000018	0.000017	RBFT	Sum of squares	Gaussian	Identity

Source: Authors.

Even in this case, the RBF networks show the main characteristics. In the hidden layer the neural networks include 21–28 neurons. RBFT training algorithm was applied for all networks. The neural structures used Gaussian curve for the activation of the hidden layer of neurons. For the activation of the output layer, the Identity function was used. All retained neural structures used the sum of least squares as an error function. The values of the correlation coefficient are between nearly 0.36 and more than 0.48 across neural networks and datasets and thus its performance is determined.

Table 5 shows the retained neural networks for the data with 10-day lag.

Table 5. Overview of retained neural networks for experiment with 10-day lag

Network	Training perf.	Test. perf.	Valid. perf.	Training error	Testing error	Validation error	Training algorithm	Error function	Activation of hidden layer	Output activation function
RBF 1-23-1	0.422277	0.289404	0.411383	0.000015	0.000018	0.000017	RBFT	Sum of squares	Gaussian	Identity
RBF 1-22-1	0.449527	0.335184	0.421136	0.000015	0.000018	0.000017	RBFT	Sum of squares	Gaussian	Identity
RBF 1-25-1	0.446497	0.281631	0.413589	0.000015	0.000018	0.000017	RBFT	Sum of squares	Gaussian	Identity
RBF 1-28-1	0.450363	0.285487	0.417970	0.000014	0.000018	0.000017	RBFT	Sum of squares	Gaussian	Identity
RBF 1-21-1	0.412808	0.271661	0.417731	0.000015	0.000018	0.000017	RBFT	Sum of squares	Gaussian	Identity

Source: Authors

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In addition, in this case, only the RBF networks showed the best characteristics. The neural networks contain between 21 and 28 neurons in the hidden layer. The output layer logically contains only one neuron and one output variable, i. e. CNY/USD. For all networks, was applied RBFT training algorithm. The neural structures used Gaussian curve for the activation of the hidden layer of neurons. For the activation of the output layer, was used the Identity function. All retained neural structures used the sum of least squares as an error function. The performance is given by the correlation coefficient achieving the values of between more than 0.28 and more than 0.45 across the preserved neural networks and datasets.

Table 6 contains the retained networks for the first set of variables with a 30-day lag.

Table 6. Overview of retained neural networks for experiment with 30-day lag

Network	Training perf.	Test. perf.	Valid. perf.	Training error	Testing error	Validation error	Training algorithm	Error function	Activation of hidden layer	Output activation function
RBF 1-29-1	0,504936	0,417204	0,469858	0,000013	0,000015	0,000015	RBFT	Sum of squares	Gaussian	Identity
RBF 1-25-1	0,492835	0,402539	0,467906	0,000013	0,000016	0,000015	RBFT	Sum of squares	Gaussian	Identity
RBF 1-28-1	0,491749	0,426946	0,474171	0,000013	0,000015	0,000015	RBFT	Sum of squares	Gaussian	Identity
RBF 1-24-1	0,503934	0,421252	0,477249	0,000013	0,000015	0,000015	RBFT	Sum of squares	Gaussian	Identity
RBF 1-27-1	0,515606	0,481461	0,468058	0,000013	0,000014	0,000015	RBFT	Sum of squares	Gaussian	Identity

Source: Authors

The table shows that there are only RBF networks. In the hidden layer, the neural networks contain 24–29 neurons. For all networks, was applied RBFT training algorithm. Neural structures used Gaussian curve for the activation of the hidden layer of neurons, while for the activation of the output layer, was used the Identity function. All retained neural structures used the sum of least squares as an error. The performance is appeared by the correlation coefficient achieving the values of between above 0.40 and above 0.51 across all the retained neural networks and datasets.

The best results are shown by the neural networks with the highest performance (= with the highest correlation coefficient), which, in ideal case, is identical in the training, testing, and validation datasets, and with the smallest error. All maintained neural networks are affected by minimal error. The highest performance in all datasets is achieved in two cases – without any time lag and with a 30-day lag, or the differences between them are minimal, with slightly better results achieved in the case of the networks representing a 30-day lag. This could be explained by the fact that the time lag is probably between 0 and 30 days. At the same time, it can be stated that the time lag does not have to be constant within the interval. More detailed characteristics of the maintained neural networks for the dataset with a 30-day lag are given in the text below.

Table 7 shows the performance of the individual data sets by specific neural networks.

Table 7. Correlation coefficients of individual datasets

Network	CNY/USD Training	CNY/USD Testing	CNY/USD Validation
1.RBF 1-29-1	0.504936	0.417204	0.469858
2.RBF 1-25-1	0.492835	0.402539	0.467906
3.RBF 1-28-1	0.491749	0.426946	0.474171
4.RBF 1-24-1	0.503934	0.421252	0.477249
5.RBF 1-27-1	0.515606	0.481461	0.468058

Source: Authors

It results from the table that the performance of all retained neural structures is approximately the same. Minor differences do not have a significant impact on the performance of the individual networks. The value of the correlation coefficient in all training datasets is at the interval of more than 0.49 to more than 0.51. The correlation coefficient of the testing datasets achieves the values of between above 0.40 and above 0.48 for all neural networks. The correlation coefficient of the validation datasets of all neural networks is about 0.47. To choose the most appropriate neural structure, a more detailed analysis of the results acquired must be carried out. Table 8 shows the basic statistical characteristics of the individual datasets for all neural structures.

Table 8. Statistics of individual datasets by retained neural structures

Statistics	1.RBF 1-29-1	2.RBF 1-25-1	3.RBF 1-28-1	4.RBF 1-24-1	5.RBF 1-27-1
Minimal prediction (Training)	0.14318	0.14680	0.14586	0.14487	0.14386
Maximal prediction (Training)	0.16677	0.16676	0.16564	0.16341	0.16400
Minimal prediction (Testing)	0.14683	0.14680	0.14594	0.14620	0.14510
Maximal prediction (Testing)	0.16676	0.16675	0.16496	0.16336	0.16400
Minimal prediction (Validation)	0.14625	0.14683	0.14599	0.14798	0.14671
Maximal prediction (Validation)	0.16669	0.16676	0.16534	0.16341	0.16400
Minimal residuals (Training)	-0.01463	-0.01658	-0.01601	-0.01592	-0.01620
Maximal residuals (Training)	0.01449	0.01460	0.01280	0.01310	0.01403
Minimal residuals (Testing)	-0.01449	-0.01406	-0.01344	-0.01425	-0.01405
Maximal residua (Testing)	0.01227	0.01228	0.01082	0.01312	0.01202
Minimal residuals (Validation)	-0.01255	-0.01428	-0.01317	-0.01454	-0.01483
Maximal residuals (Validation)	0.01485	0.01246	0.01521	0.01308	0.01258
Minimal standard residua (Training)	-4.01689	-4.51769	-4.35931	-4.36985	-4.48091
Maximal standard residuals (Training)	3.97793	3.97692	3.48442	3.59497	3.88114
Minimal standard residuals (Testing)	-3.68314	-3.54739	-3.44145	-3.62991	-3.71718
Maximal standard residuals (Testing)	3.11746	3.09997	2.76965	3.34226	3.17966
Minimal standard residuals (Validation)	-3.25771	-3.70885	-3.44086	-3.80729	-3.84626
Maximal standard residuals (Validation)	3.85619	3.23586	3.97297	3.42616	3.26253

Source: Authors.

The individual characteristics of the neural networks should be horizontally the same (minimum, maximum, residuals, etc.) in ideal case. In the case of equal values, the differences are minimal. Basically, minimal differences are also in the case of residuals characteristics. However, we are not able to specify which of the retained neural networks show the best results. Figure 4 shows a line graph that indicates the actual development of CNY/USD in dependence on Brent in USD/barrel, and the regression curve by individual retained time series.

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The graph clearly shows that all retained neural networks can forecast the basic development trend of CNY/USD but are not able to make a reliable prediction of local minimum and maximum.

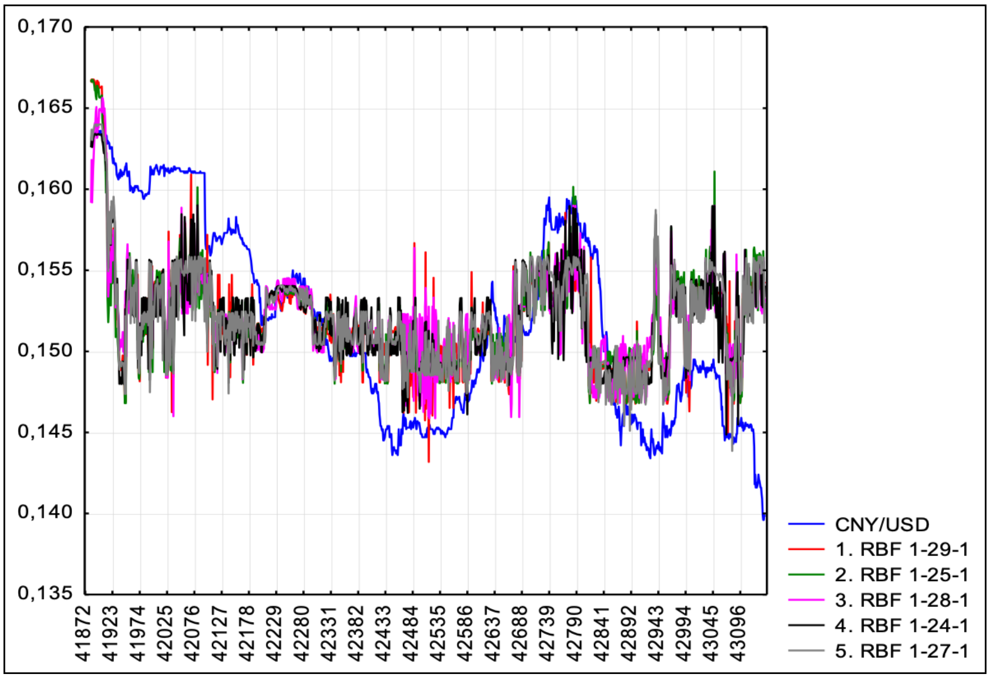

Figure 4. Line graph – development of CNY/USD in dependence on Brent in USD/barrel in the monitored period
Source: Authors.

It can thus be summarized those better results (only slightly) are achieved by the neural networks created with a 30-day lag. However, it cannot be specified which of these networks is able to describe the CNY/USD and Brent in USD/barrel relationship best. This can be since the obvious time lag is not steady in the monitored period. The result is thus not conclusive.

Dependence of CNY/USD on Brent in USD/barrel

Another set of results was generated based on the procedure specified above. In this case, the independent variables are Brent in USD/barrel and time in the form of a date. In each case, these are 5 most successful networks retained from the original 10,000 generated neural networks. Table 9 shows the survey of neural networks without any time lag.

Table 9. Overview of retained neural networks without time lag

Network	Training perf.	Test. perf.	Valid. perf.	Training error	Testing error	Validation error	Training algorithm	Error function	Activation of hidden layer	Output activation function
MLP 2-9-1	0.991104	0.992567	0.988662	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 600	Sum of squares	Logistic	Exponential
MLP 2-9-1	0.989826	0.991889	0.988722	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 579	Sum of squares	Logistic	Tanh
MLP 2-8-1	0.990183	0.991887	0.988570	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 252	Sum of squares	Logistic	Identity
MLP 2-9-1	0.989606	0.991624	0.988597	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 313	Sum of squares	Logistic	Sinus
MLP 2-7-1	0.989353	0.991952	0.988617	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 531	Sum of squares	Logistic	Logistic

Source: Authors.

The best results were achieved by the MLP networks. The input layer contains two variables. In the hidden layer the neural networks contain 7–9 neurons. The output layer contains only one neuron and one output variable – CNY/USD. For all networks, BFGS training algorithm was applied, a different variant in each case. The neural networks used the logistic function for the activation of the hidden layer of neurons, while for the activation of the output layer, the exponential, hyperbolic tangent, Identity, and Sinus functions were used (for more details, see Table 9). All maintained neural networks used the sum of least squares as an error function.

Table 10 shows the retained neural networks with 1-day lag.

Tabulka 10. Overview of retained neural networks with 1-day lag

Network	Training perf.	Test. perf.	Valid. perf.	Training error	Testing error	Validation error	Training algorithm	Error function	Activation of hidden layer	Output activation function
MLP 2-8-1	0.990150	0.991327	0.990797	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 451	Sum of squares	Logistic	Logistic
MLP 2-9-1	0.989899	0.991714	0.990755	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 407	Sum of squares	Logistic	Identity
MLP 2-9-1	0.990384	0.992272	0.990605	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 247	Sum of squares	Logistic	Logistic
MLP 2-8-1	0.989811	0.990394	0.990614	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 296	Sum of squares	Tanh	Logistic
MLP 2-9-1	0.990456	0.992254	0.991117	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 198	Sum of squares	Logistic	Tanh

Source: Authors

The best characteristics were shown by the MLP networks. The input layer contains two variables. The neural networks contain between 8 and 9 neurons in the hidden layer. For all networks, the Quasi-Newton training algorithm (BFGS) was applied, a different variant for each case. The neural networks used the logistic function and the function of the hyperbolic tangent for the activation of the hidden layer, while for the activation of the output layer, logistic, Identity and hyperbolic tangent were used. As an error function, the sum of least squares was used for all retained neural networks.

The overview of retained neural networks for a 5-day lag is shown in Table 11.

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Table 11. Overview of retained neural networks with 5-day lag

Network	Training perf.	Test. perf.	Valid. perf.	Training error	Testing error	Validation error	Training algorithm	Error function	Activation of hidden layer	Output activation function
MLP 2-9-1	0,990174	0,992059	0,990862	0,000000	0,000000	0,000000	BFGS (Quasi-Newton) 365	Sum of squares	Tanh	Exponential
MLP 2-9-1	0.990077	0.992352	0.991139	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 455	Sum of squares	Tanh	Logistic
MLP 2-9-1	0.990033	0.992092	0.990955	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 513	Sum of squares	Tanh	Exponential
MLP 2-9-1	0.990486	0.992449	0.990874	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 587	Sum of squares	Tanh	Tanh
MLP 2-9-1	0.987757	0.991094	0.990796	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 309	Sum of squares	Tanh	Identity

Source: Authors

In this case, only the MLP networks showed the best characteristics. In the hidden layer of all neural networks contained 9 neurons. The output layer contains one neuron and one variable – CNY/USD. For all networks, Quasi-Newton training algorithm was applied (a different variant in each case). For the activation of the hidden layer, all neural structures used the function of hyperbolic tangent, while for the activation of the output layer, exponential, hyperbolic tangent, and Identity functions were used. As an error function, all retained neural structures used the sum of least squares.

Table 12 shows the retained neural networks for a 10-day lag.

Table 12. Overview of retained neural networks with 10-day lag

Network	Training perf.	Test. perf.	Valid. perf.	Training perf.	Testing error	Validation error	Training algorithm	Error function	Activation of hidden layer	Output activation function
MLP 2-9-1	0.991655	0.990138	0.991282	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 408	Sum of squares	Tanh	Logistic
MLP 2-8-1	0.991058	0.990685	0.991387	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 539	Sum of squares	Logistic	Logistic
MLP 2-9-1	0.990482	0.990920	0.991438	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 492	Sum of squares	Logistic	Logistic
MLP 2-8-1	0.990527	0.990200	0.990750	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 528	Sum of squares	Logistic	Identity
MLP 2-8-1	0.990662	0.990455	0.991091	0.000000	0.000000	0.000000	BFGS (Quasi-Newton) 287	Sum of squares	Tanh	Logistic

Source: Authors.

Only the MLP networks showed the best characteristics. The input layer contained two variables. In the hidden layer the neural networks contain 8–9 neurons, while the output layer contains only one neuron and one output variable – CNY/USD. For all networks, was applied the Quasi-Newton training algorithm (BFGS, a different variant for each case). The neural structures used the function of hyperbolic tangent and the logistic function for the activation of the hidden layer, while for the activation of the output layer, logistic and Identity functions were used (for more details, see Table 12). As an error function, all maintained neural structures used the sum of the least squares.

The last calculation was carried out for the time lag of 30 days (for more details, see Table 13).

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Table 13. Overview of retained neural networks with 30-day lag

Network	Training perf.	Test. perf.	Valid. perf.	Training error	Testing error	Validation error	Training algorithm	Error function	Activation of hidden layer	Activation of the output layer
MLP 2-8-1	0,988006	0,988878	0,990756	0,000000	0,000000	0,000000	BFGS (Quasi-Newton) 443	Sum of squares	Tanh	Logistic
MLP 2-8-1	0,989739	0,990934	0,991442	0,000000	0,000000	0,000000	BFGS (Quasi-Newton) 394	Sum of squares	Logistic	Logistic
MLP 2-8-1	0,989014	0,989250	0,990487	0,000000	0,000000	0,000000	BFGS (Quasi-Newton) 586	Sum of squares	Tanh	Logistic
MLP 2-8-1	0,986828	0,988465	0,990590	0,000000	0,000000	0,000000	BFGS (Quasi-Newton) 385	Sum of squares	Logistic	Tanh
MLP 2-9-1	0,988719	0,989029	0,990966	0,000000	0,000000	0,000000	BFGS (Quasi-Newton) 825	Sum of squares	Logistic	Identity

Source: Authors.

The best characteristics were shown by the MLP networks. The input layer contains two variables. In the hidden layer the neural networks contain 8–9 neurons. For all networks, BFGS training algorithm was applied (a different variant in each case). The neural structures used the function of hyperbolic tangent and logistic function for the activation of the hidden layer, while for the activation of the output layer, the logistic, were used Identity and hyperbolic tangent functions. All retained neural networks used the sum of least squares as an error function.

In the case of the second set of results of the second variant of the experiment (that is, when considering the influence of time and Brent in USD/barrel), the results are significantly more positive. The performance of all retained networks is always above 0.98 in terms of the correlation, which indicates almost direct dependence. The involvement of the time factor brought a new dimension, and it can thus be inferred that the development of CNY/USD can be estimated and forecast very well. However, the question is what the influence of Brent in USD/barrel on CNY/USD is. When comparing the results by the time lag, it can be determined that the best characteristics show the retained networks with a 10-day lag. In the text below, we will thus focus on this set of retained neural networks.

The values of the correlation coefficients indicating the performance of the individual retained networks for a 10-day lag and the datasets of each day network data by specific neural networks are shown in Table 14.

Table 14. Correlation coefficients of individual datasets

Network	CNY/USD Training	CNY/USD Testing	CNY/USD Validation
1.MLP 2-9-1	0.991655	0.990138	0.991282
2.MLP 2-8-1	0.991058	0.990685	0.991387
3.MLP 2-9-1	0.990482	0.990920	0.991438
4.MLP 2-8-1	0.990527	0.990200	0.990750
5.MLP 2-8-1	0.990662	0.990455	0.991091

Source: Authors.

It results from the table that the differences in the performance of the retained neural structures are almost imperceptible. The value of the correlation coefficient for all datasets is above 0.99. This indicates that all neural structures are applicable. Only the first and second retained neural networks (1. MLP 2-9-1 and 2. MLP 2-8-1) appear to be slightly more successful. A more detailed analysis of the results must be carried out to choose the most suitable neural structure. Table 15 shows the basic statistical characteristics of the individual dataset for all neural structures.

Table 15. Statistics of individual datasets by retained neural structures

Statistics	1.MLP 2-9-1	2.MLP 2-8-1	3.MLP 2-9-1	4.MLP 2-8-1	5.MLP 2-8-1
Minimal prediction (Training)	0.14184	0.14184	0.14108	0.14185	0.14208
Maximum prediction (Training)	0.16309	0.16329	0.16312	0.16341	0.16360
Minimal prediction (Testing)	0.14206	0.14195	0.14080	0.14198	0.14225
Maximum prediction (Testing)	0.16309	0.16329	0.16312	0.16333	0.16360
Minimal prediction (Validation)	0.14204	0.14197	0.14097	0.14201	0.14225
Maximum prediction (Validation)	0.16297	0.16321	0.16311	0.16325	0.16360
Minimal residuals (Training)	-0.00238	-0.00277	-0.00273	-0.00237	-0.00256
Maximal residuals (Training)	0.00292	0.00284	0.00313	0.00295	0.00274
Minimal residuals (Testing)	-0.00250	-0.00227	-0.00238	-0.00235	-0.00257
Maximal residua (Testing)	0.00219	0.00212	0.00195	0.00222	0.00198
Minimal residuals (Validation)	-0.00244	-0.00237	-0.00209	-0.00241	-0.00265
Maximal residuals (Validation)	0.00253	0.00182	0.00269	0.00192	0.00185
Minimal standard residua (Training)	-4.32935	-4.86063	-4.64482	-4.03999	-4.40338
Maximal standard residuals (Training)	5.30592	4.99714	5.32968	5.03172	4.70718
Minimal standard residuals (Testing)	-4.02335	-3.74685	-3.98543	-3.77010	-4.17833
Maximal standard residuals (Testing)	3.52278	3.49366	3.26677	3.55779	3.21478
Minimal standard residuals (Validation)	-4.13663	-4.01196	-3.56650	-3.93748	-4.43330
Maximal standard residuals (Validation)	4.27570	3.07970	4.57933	3.14871	3.08587

Source: Authors

In ideal case, the individual statistics of the neural networks are horizontally the same in all datasets (minimum, maximum, residuals etc.). In this case, the differences are minimal not only between the datasets used for one set but also between the individual networks. Only based on the residual's values, the network 4. MLP 2-8-1 appears to be the most successful, which did not make the result more precise. An interesting comparison of the individual networks´ performance is represented by the scatter plot in Figure 5, showing Brent in USD/barrel on the axis X and CNY/USD on the axis Y. The actual values are shown in the graph in Figure 5.

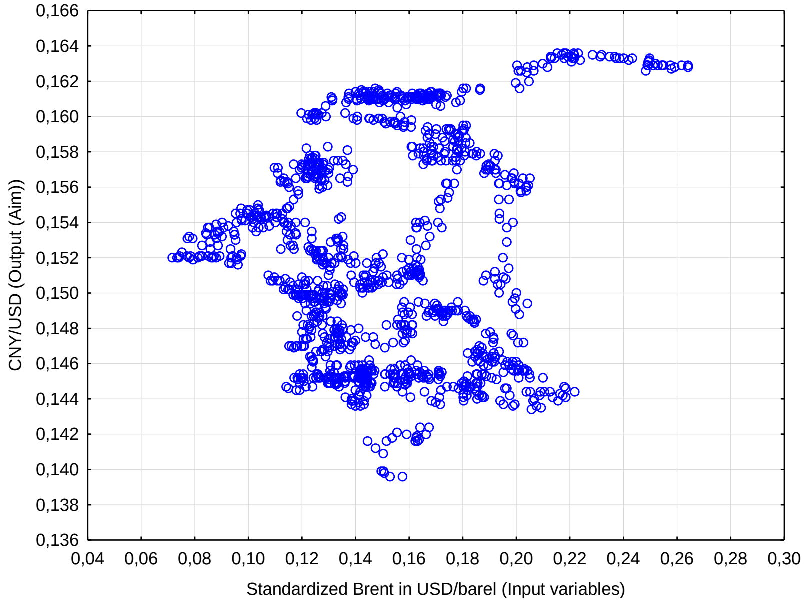

Figure 5. Scatter plot – actual values of Brent in USD/barrel and CNY/USD
Source: Authors

For the purposes of comparing, Figure 6 shows various predictions.

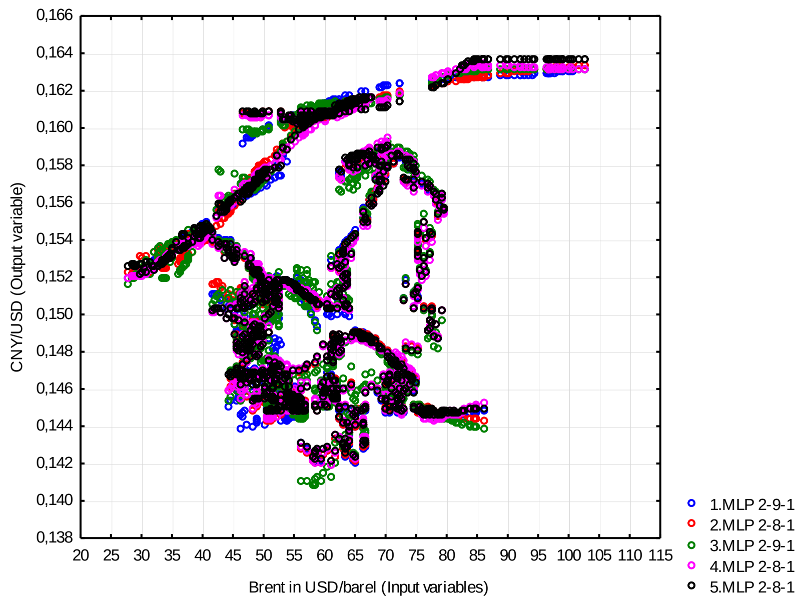

Figure 6. Scatter plot – prediction of Brent in USD/barrel and CNY/USD
Source: Authors

Figures 5 and 6 clearly indicate that the networks show high accuracy of prediction. However, it is not possible to specify which of the retained networks generates the best result.

Figure 7 shows the graphical comparison of the development of the CNY/USD dependence on Brent in USD/barrel and time.

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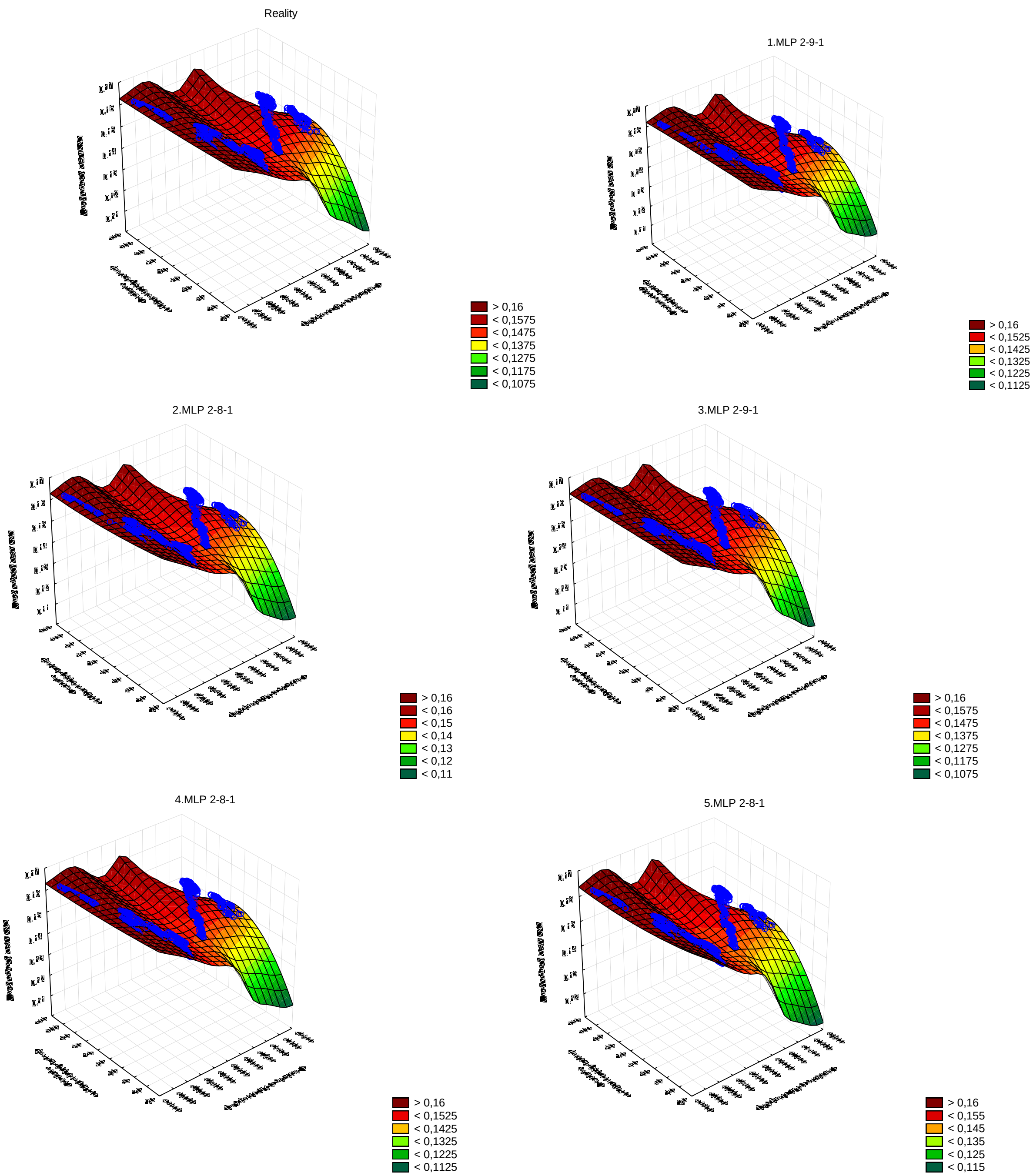

Figure 7. Graphical comparison of CNY/USD development on Brent in USD/barrel and time

Source: Authors

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It results from the figure above that the results provided by the individual networks and the reality are almost equal. It is not clear which of the retained networks shows the best characteristics, thus best explaining the relationship of CNY/USD and Brent in USD/barrel and time. However, all retained networks with the dataset represented by a 10-day lag are applicable.

Discussion – Evaluation, research questions

Based on the results obtained there is dependence of CNY/USD on Brent in USD/barrel. We can identify the dependence as well as the time lag at which this occurs. The best results were achieved in the case of a 10-day lag of the time series CNY/USD. This lag was identified in the calculation of both time series with the third variable (time) included. It was possible to examine the time series by including time as an independent variable, that was only partly corrected by the development of Brent price in USD/barrel. In order to specify the influence of Brent in USD/barrel on the price of CNY, it is necessary to carry out sensitivity analysis of the predicted values on time and Brent in USD/barrel. This is a subject of Table 16.

Table 16. Sensitivity analysis of CNY/USD over time and Brent in USD/barrel

Network	Day Brent	Brent in USD/barrel	Share of Brent in USD/barrel on prediction values
1.MLP 2-9-1	147.9889	3.62533	2.39%
2.MLP 2-8-1	132.1881	7.04795	5.06%
3.MLP 2-9-1	123.5318	13.07354	9.57%
4.MLP 2-8-1	167.4539	3.36712	1.97%
5.MLP 2-8-1	116.6771	3.33945	2.78%
Average	137.5680	6.09068	4.24%

Source: Authors.

It follows from the table that the share of oil prices on the price of CNY is created on the basis of the model prediction of (a particular retained artificial neural network) 1.97 (4. MLP 2-8-1) up to 9.57% (3. MLP 2-8-1) Brent in USD/barrel.

Question 1

Yes, CNY/USD is to a certain extent dependent on Brent in USD/barrel. However, it is not dependence that would be characterized by high correlation. When measuring only the dependence of the two variables, the measured value of the correlation coefficient was about 0.4. Nevertheless, it was not possible to specify the time lag at which CNY/USD react to a change in the price of Brent in USD/barrel. According to the analysis of the CNY/USD dependence on Brent in USD/barrel and time, it can probably be stated that the price of CNY/USD changes approximately ten days after the change in the price of Brent in USD/barrel.

Question 2

Yes, the effect of Brent in USD/barrel on CNY/USD can be measured. Depending on the model used, where all models have approximately the same factors, the influence of Brent in USD/barrel on CNY/USD ranges between 1.97% and 9.57%. Given the aggregate variable CNY/USD, the influence is thus relatively substantial.
Oil price thus immediately influences the performance of the Chinese economy.

Conclusions

The aim of the contribution was to specify whether and to which extent the development of oil price in the world market affects the value of Chinese currency.

Each model created shows a significant simplification. This is also the case of including variables such as CNY/USD and Brent in USD/barrel. In fact, the resulting price of CNY/USD is given by the supply and demand of and for Chinese currency. However, there are several factors that create both supply and demand for Chinese Yuan, for example the performance of the Chinese economy, China´s position in international trade, position of other countries in the world economy, etc. A significant role is also played by the energy demands of the production of goods and logically, also by the possibilities and abilities of the Chinese economy to satisfy such a demand. It could thus be estimated that the fluctuations of oil price in the world market will affect the price of CNY/USD; however, it was not clear to which extent. This contribution enabled to prove the existence of such influence. It can be identified at the interval of 1.97% to 9.57%. It could thus be concluded that regarding the importance of the raw material, the influence is significant. The objective of the contribution was thus achieved.

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