Analysis of the performance of predictive models during Covid–19 and the Russian-Ukrainian war

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Summary

In our paper, we investigate how effectively artificial intelligence can be used to predict stock market trends in the world's leading equity markets over the period 01/01/2010 to 09/16/2022. Covid-19 and the Russian-Ukrainian war have had a strong impact on the capital markets and therefore the study was conducted in a highly volatile environment. The analysis was performed on three time intervals, using two machine learning algorithms of different complexity (decision tree, LSTM) and a parametric statistical model (linear regression). The evaluation of the results obtained was based on mean absolute percentage error (MAPE). In our study, we show that predictive models can perform better than linear regression in the period of high volatility. Another important finding is that the predictive models performed better in the post-Russian-Ukrainian war period than after the outbreak of Covid-19. Stock market price forecasting can play an important role in fundamental and technical analysis, can be incorporated into the decision criteria of algorithmic trading, or can be used on its own to automate trading.

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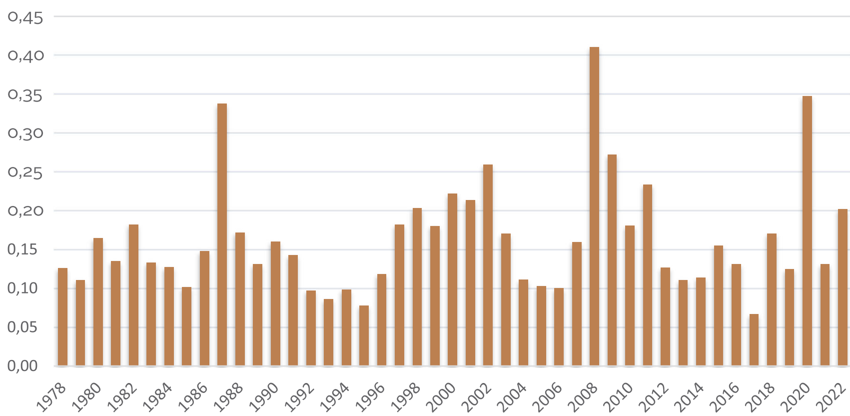
1. Introduction

Inflationary pressures are already visible in the consumer price index, not just in asset prices. This is particularly true for the Covid-19 period and the outbreak of the Russian-Ukrainian war, which shook the global financial and capital markets. In addition to the United States, other governments and central banks have also announced asset purchase programmes to try to ease the crisis (Báger & Parragh, 2020; Novák & Tatay, 2021). A study by *Török* (2020), who modelled the public debt in EU countries in light of the Covid-19 crisis, also supports this. The debt-to-GDP ratio is expected to grow in all of the countries. *Figure 1* clearly indicates the crisis periods, such as the stock market crash of 1987, the dot-com bubble of 2000, the subprime mortgage crisis of 2008, and the coronavirus crisis reaching a global scale in 2020.

Figure 1: Standard deviation of S&P500 index returns between 1978-2022



Source: own editing based on Wall Street Journal data

But not even crises can stop technological development. The rise of artificial intelligence is well indicated by the fact that it has already appeared in Hungarian public administration as well, although legal obstacles to full implementation remain (Fejes & Futó, 2021). The various learning algorithms are slowly creeping into different areas of our lives, making daily life easier, and the processes more efficient. The pros and cons of this will naturally generate a lot of debate in future, but in our view, technological progress is inevitable, particularly in the capital intensive sectors.

Forecasting the prices of different investment products has always been a challenge for statistical and financial experts (Nabipour et al., 2020). In developing predictive models, the main objective is to estimate market-generated uncertainties as accurately as possible so as to minimise the risk factor. There are varying views on how to categorise stock market price forecasts. Some researchers divide them into two (Nassirtoussi, 2014), others into three categories (Dunne, 2015; Nti et al., 2020).

The first and longest used method is fundamental analysis, and the second is the technical analysis toolbox. The third and most recent approach is technological, which combines machine learning and computational intelligence techniques in order to predict price trends (Nti et al., 2020).

The rise and increasing use of machine learning methodologies has contributed to improving the performance of predictive models as well as the accuracy of forecasts (Maqsood et al., 2019). In the course of model development, the experts in stock market forecasting are faced with numerous challenges. The difficulties relating to complexity, noisy information, development characteristics and non-linear relationships are due, among others, to stock market instability as well as the relationship between investor psychology and market behaviour (Duarte et al., 2017).

Therefore, in the course of developing predictive models, machine learning tools helping investors and traders make optimal decisions are becoming increasingly important. The primary goal of these methods is to learn, and then automatically recognise various patterns in vast data sets. The most sophisticated deep learning algorithms are constantly evolving with increasing effectiveness in predicting price fluctuations to improve trading strategies.

Risk management is particularly important in times of high volatility, such as the 2008 crisis, Covid-19, and the stock market crash caused by the Russian-Ukrainian war. The current global and presumably permanent high inflation environment also highlights the need to use risk management tools as effectively as possible. Today the most advanced risk management techniques go well beyond traditional diversification, with an increasing focus on AI-based solutions that are becoming a part of daily life. As for trading strategies, predictive models are able to identify key price levels that can be used for fundamental and technical analysis, as well as risk management and portfolio management. The primary objective of our research is to examine which of the AI-based stock price forecasting or statistical methodologies is the most accurate. As a basic hypothesis, we defined that the most complex and sophisticated method (LSTM) is able to provide the most accurate forecast even in periods of high volatility, and therefore it is considered the most "crisis-proof" model. Another novelty of the study is that the forecasts are compared over three different time horizons.

2. Literature review

Based on the literature available on the subject we can see that there are several models for predicting returns and volatility, and researchers divide them into three main groups. The first includes traditional statistical methods (ARCH and ARIMA), the second contains some kind of AI-based methods, and the third covers the so-called hybrid methods (Kim & Won, 2018; Zolfaghari & Gholami, 2021). The traditional statistical models are outside the scope of this study.

The AI-based methods include machine learning algorithms (Rather, 2021), such as ANN (Artificial Neural Networks), DNN (Deep Neural Networks), GA (Genetic Algorithms), SVM (Support Vector Machine), and FNN (Fuzzy Neural Networks).

Compared to traditional statistical models, the AI-based models have many advantages due to their complexity and the resulting much higher forecast accuracy. Because of their ability to learn, the AI-based models can recognise patterns in the data, such as non-linear movements. Stock data exhibit non-stationary and non-linear movements that the traditional statistical models are unable to detect, causing the AI-based methodologies gain dominance in this area over time. In their research, *Ormoneit and Neuneier* (1996) applied multilayer perceptron and density estimating neural networks to predict DAX index volatility between January 1983 and May 1991. Comparing the two models, they concluded that the density estimating neural network without a specific target distribution performed better than the perceptron method. *Gonzalez Miranda and Burgess* (1997) modelled the implied volatility of the IBEX35 index options using a multilayer perceptron neural network in the period November 1992 to June 1994. Our experience has shown that forecasting with non-linear NN generally produces results that dominate over forecasts involving traditional linear methods. This is due to the fact that the NN takes into account potentially complex non-linear relationships that the traditional linear models are unable to manage successfully. *Hamid and Iqbal* (2004) used the Artificial Neural Networks methodology to predict the volatility of S&P 500 index futures prices. Based on their empirical analyses, they concluded that ANN-based forecasting performed better than the implied volatility estimation models. In their research, *Kieu Tran et al.* (2020) demonstrated that the temporal effect of past information is not taken into account by ANNs for predicting time series, and therefore deep learning methods (DNN) have recently become increasingly important. Among them, RNNs (Recurrent Neural Networks) represent a prominent group, with the advantage of providing feedback in their architecture. Recent studies (Lugt & Feelders, 2019; Hajiabotorabi et al., 2019) comparing the predictive abilities of ANNs and RNNs concluded that Recurrent Neural Networks can outperform traditional neural networks. Here the long short-term memory (LSTM) model, which is widely used for sequential data sets, is particularly prominent. This model version has the advantage of demonstrating a high level of adaptability in time series analyses (Petersen et al., 2019). *Nabipour et al.* (2020) compared the predictive capabilities of nine different machine learning and two deep learning algorithms (Recurrent Neural Network, long short-term memory) for the stock data of financial, oil, non-metallic mineral and metal commodity companies on the Tehran Stock Exchange. They concluded that RNN and LSTM outperformed all other predictive models. *Long et al.* (2020) applied machine learning (Random Forest, Adaptive Boosting), bidirectional deep learning (BiLSTM) and other neural network models to analyse the predictability of Chinese stock price trends. The highest performance was demonstrated by BiLSTM, surpassing other forecasting methods by far. *Hiransha et al.* (2018) prepared forecasts for NSE and NYSE stock price developments. They used the multilayer perceptron model, RNN, LSTM, and CNN (Convolutional Neural Network). Based on empirical analysis, CNN performed the best. *Fischer and Krauss* (2018) analysed S&P500 index data for the period 1992-2015. The applied methods included Random Forest, logistic regression, and LSTM. According to their final conclusion, the long short-term memory algorithm produced the best results. *Nelson et al.* (2017) applied multilayer perceptron models for Brazil's stock market data, and they concluded that LSTM was the most accurate. *Nikou et al.* (2019) analysed basic daily iShares MSCI UK price data for the period January 2015 - June 2018. The predicted values were generated using ANN, Support Vector Machine (SVM), Random Forest and LSTM models. The best performing model was LSTM, with SVM being the second most accurate. *Kaushik and Giri* (2020) compared LSTM with vector autoregression (VAR) and SVM to predict price movements. They highlighted that in terms of forecasting, LSTM outperformed both SVM and VAR. *Huang et al.* (2005) examined the predictability of the weekly trends of the NIKKEI 225 index using the SVM, linear discriminant analysis (LDA), Elman neural network, and quadratic discriminant analysis (QDA) methods. Their results indicated the superiority of the SVM model. *Ou et al.* (2009) used ten data mining methods. They conducted research on predicting trends for the Hang Sheng index applying tree-based classification, k-nearest neighbours (KNN), SVM, Bayesian classification, and neural network models. As a result of their analysis, SVM was found to outperform the other predictive methods used. *Ballings et al.* (2015) compared the AdaBoost, Random Forest, Kernel Factory, SVM, KNN, logistic regression and ANN methods using the share price data of European companies. They tried to predict price paths for the year ahead. The final result showed that Random Forest performed the best. *Basak et al.* (2019) applied XGBoost, logistic regression, SVM, ANN and Random Forest to predict stock market trends. Based on their results, Random Forest achieved the highest performance. *Namini et al.* (2018) studied S&P500 and Nikkei225 index data, and in their final conclusion established the superiority of LSTM over the ARIMA model. *Liu's* study (2019) focused on predictions of the S&P500 index and Apple share prices, concluding that over a longer forecast horizon, LSTM and SVM performed better than the GARCH model. Based on the above, the predictive performance of LSTM can be considered fairly good.

The third category including the so-called hybrid predictive models was created due to the weaknesses of the different methodologies. These models combine the tools used for traditional statistical, artificial intelligence based and technical analyses in order to achieve more effective prediction results (Reston et al., 2014). They found that the hybrid models demonstrated outstanding sequential pattern learning ability along with better volatility forecasting. Cao et al. (2019) developed a new hybrid model called CEEMDAN (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise)-LSTM. They compared it with other combined and traditional methods, tested on S&P500 and HSI index data. The results confirmed that the CEEMDAN-LSTM model outperformed the CEEMD-SVM, CEEMD-MLP, and even the individually applied LSTM and SVM models. *Lin et al.* (2020) used the CEEMDAN-LSTM method to predict USD–AUD exchange rate fluctuations, and compared it with other models, confirming a higher level of accuracy against the SVM, RNN, MRNN (Multilayer RNN), ARIMA and Bayesian models. *Jing et al.* studied the Shanghai Stock Exchange and concluded that when some technical analytical indicator data is used as input to the LSTM model, this hybrid method provides a much more accurate estimate than using the data separately for forecasting. *Banik* *et al.* (2022) reached a similar conclusion. They also combined the LSTM model with technical indicators, using Indian stock market data for their analysis.

3. Material and method

For our analysis, we used daily price data from the CAC40, DAX, Dow Jones Industrial Average, FTSE100, Hang Seng, NASDAQ composite, Nikkei225 and S&P500 indices, which were collected from the Yahoo Finance portal. Our data covers a period of almost 12 years from 1 January 2010 to 16 September 2022. When choosing this period, we took into account the need to have at least 10 years' worth of available data prior to examining the effects of both Covid-19 and the Russian-Ukrainian war on stock markets so that we could try and define an optimal learning database for our models. All of the selected indices are considered to be well diversified portfolios, so individual risks have little or no effect on return volatility. Descriptive statistics for the applied data are shown in *Table 1*. Our study presents the estimates of the individual models for weekly (5-day), monthly (21-day) and six-monthly (125-day) forecast periods.

Our research was based on the linear regression, decision tree and LSTM models. For model development, we uniformly chose database partitioning according to a ratio of 80% to 20% (80% learning and 20% testing subsamples). To build the predictive models required for analysis, we used the Python programming language (version 3.8) relying on the Scikit-learn and TensorFlow libraries. For the neural network model, the Keras interface was used.

Table 1: Descriptive statistics

Description	N	Average	Median	Standard deviation	Min	Max
CAC40	3251	4742.78	4630.99	991.16	2781.68	7376.37
DAX	3223	10457.24	10689.26	2853.54	5072.33	16271.75
DJIA	3199	20505.34	18050.17	7414.96	9686.48	36799.65
FTSE100	3209	6583.12	6686.60	707.65	4805.80	7877.50
Hang Seng	3131	24014.04	23484.30	3164.33	16250.27	33154.12
NASDAQ composite	3199	6381.37	5082.93	3695.87	2091.79	16057.44
Nikkei225	3109	17992.54	18723.52	6268.91	8160.01	30670.10
S&P500	3199	2368.78	2108.58	975.69	1022.58	4796.56

Source: own editing

4. Results

The presentation of the results is closely connected with the definition of the evaluation criteria that are essential to establish the estimation accuracy of each model. The calculated variance indicators allow for sectoral, temporal and methodological comparisons as well. Practically, this makes it possible to look at the relationships between real and estimated data from three different aspects. First, the models are compared for sectors and forecast periods. The paper concludes with a scoring system to evaluate the relative performance of the methods used.

4.1. Evaluation of the models

For evaluating forecasting models and establishing their accuracy, the most commonly used metrics in literature include root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) (Nti et al. 2020).

a) Root mean square error (RMSE): this performance indicator shows the differences between actual and predicted values (residuals).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

where is the estimated value produced by the model, is the actual value, and n is the number of observations.

b) Mean absolute error (MAE): it measures the average magnitude of forecast errors.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

c) Mean absolute percentage error (MAPE): it measures the average magnitude of forecast errors and indicates deviations as a percentage.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

The lower the above indicator values, the more reliable and accurate the forecasts will be. It is important to note that the RMSE penalises larger deviations more, because of squaring, and therefore this evaluation indicator can yield more extreme values than the MAE. The first two are expressed as a value, while the MAPE is expressed as a percentage (with deviations expressed as a percentage of the original value). For this reason, the MAPE can also be used to compare different instruments, as it does not depend on the nominal size of price. Since we analysed indices from around the world as well as the effects of two different negative economic events, we used the MAPE indicator for comparability in the overall assessment of the models.

4.2. Decision tree

This is one of the simplest but most successful learning algorithms. It is a graphical model used in decision making that visually resembles a tree with branches, forks (nodes) and leaves (subresults). The decision tree is given an object or situation described by attributes as an input, in order to return a "decision". In practice, it represents the decision options, taking into account the possible consequences, chances, usefulness and resources, depending on the purpose. It is essentially a graph structured as a tree in which each internal node represents a prediction for its value. The edges from the vertex can be matched to corresponding outcomes. This allows the functions to be represented as a tree. It is an inductive learning method, which always returns only one result with an explanation. It is highly sensitive to errors in the learning set, and a new decision model needs to be outlined for further learning. There is a very simple algorithm, which is easy to understand (Nabipour et al., 2020). Its advantage is also a disadvantage, as it is far too primitive and therefore cannot be used for exploring complex relationships. Generally, it is used in combination with other, more complex models (Russell & Norvig, 2003).

As for parameters, our decision tree has a maximum depth of 10 units, as this is the number typically used in literature (Nabipour et al., 2020; Sadorsky, 2022). The prediction results of the decision tree are indicated in *Table 2*.

Table 2: MAPE indicator of differences between real and estimated prices for the decision tree in relation to Covid-19 and the Russian-Ukrainian war

Decision tree	5 days		21 days		125 days	
	Covid–19	War22	Covid–19	War22	Covid–19	War22
CAC40	0,0129	0,0011	0,0290	0,0118	0,0129	0,0126
DAX	0,0050	0,0371	0,0359	0,0173	0,0277	0,0221
DJIA	0,0034	0,0159	0,0771	0,0099	0,0191	0,0084
FTSE100	0,0544	0,0037	0,1028	0,0220	0,0469	0,0124
Hang Seng	0,0489	0,0051	0,0205	0,0413	0,0290	0,0458
NASDAQ composite	0,0360	0,0278	0,0108	0,0146	0,0068	0,0140
Nikkei225	0,0240	0,0082	0,0143	0,0107	0,0141	0,0107
S&P500	0,0145	0,0137	0,0373	0,0107	0,0168	0,0087
Average MAPE	0,0249	0,0141	0,0410	0,0173	0,0217	0,0168

Source: own editing

The results in Table 2 show that irrespective of the time horizon, the decision tree's prediction was more accurate during the Russian-Ukrainian war than during the stock market crash caused by Covid-19. The predictive model's performance was particularly poor for the FTSE100 5-day and 21-day periods. The most accurate forecast could be observed for the French stock market index (CAC40), with a difference of only 0.11% compared to the real price. Looking at the 5-day time horizon, only two of the eight indices (DAX and DJIA) were more accurate for Covid-19. As for the 21-day period, again there were two indices with more accurate estimates for Covid-19, in this case Hang Seng and NASDAQ. The results of the 125-day forecast are identical to the 21-day forecast. Based on the results, the decision tree provided far more accurate forecast data for the 5-day and 21-day periods than the other two models.

Linear regression

The linear regression model assumes that the output data will be a linear combination of the input information. In the estimation, we try to fit a straight line to the point cloud of sample data. The model also includes a random error that allows each observation to deviate from the expected linear relationship. The simplest and most common estimation method is the least squares method. The prediction results of the linear regression model are indicated in *Table 3*.

Table 3: MAPE indicator of differences between real and estimated prices for linear regression in relation to Covid-19 and the Russian-Ukrainian war

Linear regression	5 days		21 days		125 days	
	Covid–19	War22	Covid–19	War22	Covid–19	War22
CAC40	0,0215	0,0274	0,1974	0,0296	0,1852	0,0647
DAX	0,0477	0,0483	0,1982	0,0813	0,1217	0,0958
DJIA	0,0276	0,0692	0,1777	0,0559	0,1338	0,0940
FTSE100	0,0369	0,0532	0,2044	0,0384	0,1906	0,0378
Hang Seng	0,0494	0,0743	0,0806	0,1729	0,0697	0,1798
NASDAQ composite	0,0419	0,1414	0,1169	0,1538	0,0615	0,2364
Nikkei225	0,0512	0,0270	0,1200	0,0847	0,0881	0,0599
S&P500	0,0322	0,0699	0,1389	0,0643	0,0802	0,1341
Átlagos MAPE	0,0386	0,0638	0,1543	0,0851	0,1164	0,1128

Source: own editing

Linear regression performed worse for all time horizons than the decision tree method, with five or six times higher MAPE values in some cases. Interestingly, in addition to inaccurate estimation, the "direction of error" also changed for the 5-day forecasts, with only one prediction (Nikkei225) being more accurate for the Russian-Ukrainian war. In respect of the longer periods, we can see similar results as for the decision tree, i.e. dominantly smaller margin of error for the Russian-Ukrainian war.

4.3. LSTM

The system of neural networks includes the graph-based model, in which artificial neurons arranged in layers communicate with each other through non-linear activation functions. The LSTM architecture enables the solution of highly complex tasks. In neural networks, information flows from the input through hidden layers to the output. The network is thereby limited to a single state management. In recurrent neural networks (RNN), a subtype of which is LSTM, information flows through a cycle, which allows the network to remember previous outputs. This makes it ideal for analysing sequences and time series. The LSTM uses gates between the elements of the input sequence, so it can hide (forget) or reveal (remember) previous information, and in both cases can handle it with different weights. The cells revealed by the gates can be linked, exposing the relationships among the data. This is particularly important in detecting extreme values, among others. A typical LSTM unit combines four parameterized layers that interact to allow information flow (Roondiwala et al., 2017).

Table 4 shows the hyperparameters of the LSTM model used for the analysis.

Table 4: Hyperparameters of the LSTM model

Hyperparameters	Applied layers
Number of hidden layers	2
Number of neurons in first and second layer	150, 150
Dropout rate	0,3
Learning rate	0,001
Batch size	60
Epoch size	100
Activation function	linear
Optimizer	Adam

Source: own editing, based on Nabipour et al. (2020)

Table 5: MAPE indicator of differences between real and estimated prices for LSTM in relation to Covid-19 and the Russian-Ukrainian war

LSTM	5 days		21 days		125 days	
	Covid–19	War22	Covid–19	War22	Covid–19	War22
CAC40	0,0373	0,0330	0,0740	0,0431	0,0327	0,0447
DAX	0,0838	0,0364	0,1013	0,0356	0,0353	0,0182
DJIA	0,0787	0,0198	0,0876	0,0193	0,0324	0,0188
FTSE100	0,0379	0,0122	0,0551	0,0171	0,0229	0,0109
Hang Seng	0,0085	0,0309	0,0238	0,0401	0,0176	0,0228
NASDAQ composite	0,0773	0,1034	0,0877	0,0852	0,0329	0,0784
Nikkei225	0,0508	0,0130	0,0692	0,0283	0,0245	0,0277
S&P500	0,0515	0,0219	0,0683	0,0207	0,0399	0,0202
Average MAPE	0,0532	0,0338	0,0709	0,0362	0,0298	0,0302

Source: own editing

Based on the international literature, the LSTM models provide the most accurate estimation; however, our results show that the average MAPE values for the decision tree are lower than for the LSTM in respect of all time horizons. In the case of the LSTM method, the dominance of the Russian-Ukrainian war is apparent for the 5-day and 21-day predictions, i.e. forecasting is more accurate for this period. For the 125-day predictions, estimation accuracy is divided evenly between Covid-19 and the Russian-Ukrainian war; in fact, the average MAPE values are almost identical for this time period. Based on the results, we can also establish that the LSTM method has a lower error rate for longer-term predictions.

Conclusions

In our study, we tested the decision tree, the linear regression and the LSTM models on major stock market indices around the world for stock price predictions over horizons of 5, 21 and 125 days from the outbreak of Covid-19 and the Russian-Ukrainian war. To check the accuracy of estimations, the mean absolute percentage error (MAPE) was used. Based on the literature, the LSTM model proved to be the most accurate estimation methodology in most cases (Nelson et al., 2017; Fischer & Krauss, 2018; Nikou, 2019; Liu, 2019; Nabipour et al., 2020). Our research showed that linear regression was the least suitable method for predicting the stock market indices included in the study. The LSTM model ranked second, with the decision tree providing the most accurate predictions for all time horizons. We also found that stock price movements during the Russian-Ukrainian war could be estimated with a higher degree of accuracy than those caused by Covid-19.

The short-term stock market crash in 2020 significantly increased the global stock market risk (see *Figure 1*). The coronavirus-induced crash in 2020 was the first major shock, as the stock market boom of the past decade left the investors unprepared for risk management. Then the war between Russia and Ukraine brought about a situation the world had not faced for a long time. Our study has proved that predictive models can perform well even in periods of high volatility. Diversification alone is not enough; if there is a sudden 20-30% drop in the capital market, we need to react immediately, and we can be prepared by using the right method to predict stock prices. Price forecasting can also play an important role in fundamental and technical analysis, it can be incorporated into the decision criteria of algorithmic trading, or can even be used on its own to automate trading. ■

Appendix

Appendix 1: Correlation matrix calculated from the log returns of the indices used for analysis

	CAC40	DAX	DJIA	FTSE100	Hang Seng	NASDAQ Comp.	Nikkei225	S&P500
CAC40	1							
DAX	0,9337	1						
DJIA	0,6300	0,6173	1					
FTSE100	0,8696	0,8375	0,6137	1				
Hang Seng	0,3922	0,3791	0,2190	0,4139	1			
NASDAQ Comp.	0,5536	0,5531	0,8748	0,5175	0,2260	1		
Nikkei225	0,3066	0,2930	0,1897	0,3109	0,4887	0,1691	1	
S&P500	0,6196	0,6071	0,9689	0,5950	0,2234	0,9498	0,1832	1

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