FRI-1.414-MIP-01

AN APPLICATION OF TIME SERIES FOR FORECASTING THE PRICES OF FINANCIAL INSTRUMENTS

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Abstract: *In this paper, technical analysis of 10 financial instruments is performed. Based on historical data, the standard deviations of the rates of return and the correlation matrix between them are estimated. Time series and in particular ARIMA models are considered to forecast the prices of the considered instruments.*

Keywords: *Time Series, ARIMA, Price Forecasting.*

INTRODUCTION

In this paper, time series are considered to forecast the prices of 10 financial instruments. Technical analysis of securities is performed with real data using Excel. It includes estimation of standard deviations of the rates of return and the correlation matrix between them. In order to forecast stock prices, SPSS built-in methods (see [3]) based on time series and in particular ARIMA models were used.

EXPOSITION

Time series modelling for stock price forecasting

Due to the specificity of the data, different time series modelling methods are suitable for the study and forecasting of stock prices. These methods include classical time series models, Autoregressive Patterns (AP), Moving Average (MA), Autoregressive - Moving Average (ARMA), Autoregressive Integrated Moving Averages (ARIMA) [5]. Standard data analysis is conducted in the following three steps: identification, estimation and diagnosis (see [5]).

Identification

The first step is time series identification, which involves examining the data by computing and plotting the graph, the autocorrelation function plots (ACFs) and the partial autocorrelation functions (PACFs). Autocorrelations are independent correlations of a series of results with themselves, skipping one or more periods back in time (lag). Partial autocorrelations are independent correlations with intermediate partial autocorrelations. Different autoregressive, moving-average patterns (subsets of the data with similar behaviour) often have influence for specific changes in autocorrelation and partial autocorrelation functions. When the time series is long, there may be trends showing periodic changes, referred to as seasonality, periodicity, or cyclicity, as previously described. Thus, seasonality is another form of autocorrelation that is commonly observed in datasets. Periodic change can also occur over shorter periods of time. These patterns can be identified using ACFs and PACFs prior to model construction and help to predetermine (p, d, q). Time series analysis is a more appropriate modelling technique for autocorrelated data than, for example, linear regression. The most common reason why linear regression and classical methods do not produce models is the violation of the assumption of independence of errors. The errors are also autocorrelated. And this has to be accounted for by the model.

Model construction and estimation

The second step in modelling time series data is to construct a model and estimate its parameters, tested against the null hypothesis that they are equal to zero.

Model diagnosis

The third step is the diagnostics, in which the residuals are examined. The residuals are the differences between the values predicted by the model and the observed data. The theoretical assumption is that the residuals are random and have a normal distribution. If this is not the case, there are probably more patterns in the data that are not accounted for. If all the patterns in the data are accounted for in the model, the residuals are random. In many time series applications, identifying and modelling patterns in the data are sufficient to find an equation that is then used to predict the future of the process.

Three parameters, p, d and q, have been used to construct ARIMA models [5]. The autoregressive element p is the impact of the data from p previous moments in the model. The integrated element d is the trend in the data, while the element q indicates how many terms are used to smooth small fluctuations using a moving average.

In general, the ARIMA model with parameters p, d and q can be represented by ([4], [5]):

$$Y_t = C + \varphi_1 \Delta^d Y_{t-1} + \cdots + \varphi_p \Delta^d Y_{t-p} - \theta_1 \varepsilon_{t-1} - \cdots \theta_q \varepsilon_{t-q} + \varepsilon_t \,,$$

where $C,\ \varphi_i\,, i = \overline{1,p},$ and $\theta_j, j = \overline{1,q}$, are the parameters that are wanted, ε_j is a randomly distributed variable with mathematical expectation equal to zero and variance σ^2. If there is no information about the distribution, then it is assumed to be normal by default [4]. Δ is an operator for the change or difference in parameter values, which is defined as follows:

$$\begin{aligned}
&\Delta^0 Y_t = Y_t,\\
&\Delta^1 Y_t = Y_t - Y_{t-1}\\
&\Delta^k Y_t = \Delta^{k-1} Y_t - \Delta^{k-1} Y_{t-1}.
\end{aligned}$$

For each combination of parameters (p, d, q), the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are considered. These functions depend on a fixed number of lags, and are computed for each time t, except for some finite where they cannot be computed. If Y_t ACF and PACF have more than one small jump outside the confidence intervals, then we choose new parameters. Large jumps and repeating patterns in the autocorrelation and partial autocorrelation functions indicate the estimated values of p and q in the ARIMA models, which was used to identify these parameters in the current paper.

The formula for the autocorrelation function ACF at the present time t for the k-th lag has the following form

$$r_k = \frac{\frac{1}{n-k}\sum_{t=1}^{n-k}(Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\frac{1}{n-1}\sum_{t=1}^{n}(Y_t - \bar{Y})^2},$$

where n is the number of observations in the whole series, k is the lag (number of lags), $\bar{Y}$ is the mean of the whole time series and the denominator is actually the variance of the whole time series. The standard error of the autocorrelation is based on the square of the autocorrelation of all previous autocorrelations.

The formulas for computing partial autocorrelations are much more complicated and involve a recursive technique (see [7]).

Data Description

In this paper, weekly data on price movements of 10 different types of financial instruments during the period April 26, 2021 to August 29, 2022 (71 observations) is tracked. The data is taken from Yahoo Finance (see [8]).

EUR/CHF represents the value of the euro against the Swiss franc. This currency pair shows traders how many Swiss francs are needed to buy one euro. According to Bank for International Settlements data from 2016, the euro is the second most traded currency in the world and the Swiss franc is in the top ten.

AUD/USD is an abbreviation of the currency pair Australian dollar and US dollar. AUD/USD is the fourth most traded currency, but is not one of the six currencies that make up the US Dollar Index (USDX).

The USD/HKD pair is a cross currency pair made up of the US dollar and the Hong Kong dollar. The US dollar is the most traded currency in the world, due to the position of the US as a world power in international trade and the status of the US dollar as the main reserve currency of the planet. The exchange rate of the US dollar to the HKD is determined by a pegged exchange rate system that has been in place since 1983 and allows the HKD to fluctuate between 7.75 and 7.85 to one US dollar. This range is set by the Hong Kong Monetary Authority, which can change either the pegged currency or the value range of the HKD against that foreign currency.

GBP/JPY (British Pound - Japanese Yen) tells traders how many Japanese Yen are needed to buy one British Pound. The British pound is the fourth most traded currency in the world, while the Japanese yen is in third place, according to Bank for International Settlements data from 2016. The Japanese yen is often used as a trade finance currency as it has historically been a low-yielding currency. As the UK is one of the larger economies in Europe, the GBP/JPY pair can be seen as an indirect indicator of economic health globally.

The ETH/USD pair compares one of the world's most popular and widely accepted cryptocurrencies, ether, with the world's strongest fiat currency, the US dollar. This popular cryptocurrency-fiat pair represents how many dollars - the quote currency - are needed to buy one ether - the base currency. Ether is a cryptocurrency that serves as "fuel" for the decentralized Ethereum software platform. Ether was launched in 2014 and is a relatively young cryptocurrency. In terms of market capitalization ($26 billion), Ether is second only to Bitcoin.

Gold, valued as a currency, commodity, or investment for thousands of years, is popular among today's investors because it can be used as a hedge against currency devaluation, inflation, or deflation, and because of its ability to provide "safety" during times of economic uncertainty. The gold market is highly liquid and there are a number of ways in which investors can acquire this precious metal, including holding physical gold (i.e., gold coins and bars) and Exchange Traded Funds (ETFs).

After gold, silver is the precious metal most invested in. For centuries, silver has been used as currency, for jewellery and as a long-term investment. Today, various silver-based instruments are available for trading and investment. These include silver futures, silver options, silver ETFs or OTC products such as silver-based mutual funds.

Platinum is considered a very important precious metal by investors, although it is mentioned less frequently than gold and silver. Many investors use platinum as a hedge against inflation or as savings for difficult economic times. Platinum is also used in the manufacture of products such as cars, jewellery and electronics. To gain exposure to the metal, investors can purchase platinum bars or coins, platinum future contracts or shares of platinum mining companies. Another option is a platinum exchange-traded fund (ETF). This instrument is usually more liquid than owning a physical commodity and does not require payment of associated storage or insurance costs.

Nasdaq is a global electronic marketplace for buying and selling securities. Its name was originally an acronym for "National Association of Securities Dealers Automated Quotations". Nasdaq started as a subsidiary of the National Association of Securities Dealers National Association of Securities Dealers (NASD), now known as the Financial Industry Regulatory Authority (FINRA). Nasdaq was launched after the Securities and Exchange Commission (SEC) pushed NASD to automate the market for unlisted securities. This resulted in the first electronic trading system. Nasdaq became operational on 8 February 1971.

The term "Russell 2000 Index" refers to a stock market index that measures the performance of 2000 smaller companies included in the Russell 3000 Index. The Russell 2000 Index is managed by London's FTSE (Financial Times Stock Exchange) Russell Group and is considered a bellwether of the U.S. economy because of its focus on smaller companies that focus on the U.S. market. Many investors compare small-cap mutual funds to the movement of the index because it is seen as a reflection of opportunities in that entire subsection of the market, rather than narrower indices that may contain biases or more stock-specific risks that can skew results.

Price forecasting

Using the data described above, ARIMA and Simple models are built that provide price forecasts for financial instruments 1 period ahead (in this case, one week or for 05.09.2022). For this purpose, the SPSS software was used and the selection of the models was made using the Expert Modeler option of the software. The Expert Modeler had proposed ARIMA models for some of the financial instruments and Simple for other of them. Simple model is appropriate for series in which there is no trend or seasonality. Its only smoothing parameter is level. Simple exponential smoothing is most similar to an ARIMA model with zero orders of autoregression, one order of differencing, one order of moving average, and no constant.

Table 1 shows the model selection for each of the financial instruments as well as the statistics for Normalized Bayesian information criterion (BIC). BIC (see [6]) has penalty $k \log n$, where k is the number of parameters in the model, and n is the number of observations. It was derived from Bayesian theory, based on the Bayes factor approach. It is an approximation to the Bayes factor, which selects the model with the greatest posterior probability. This criterion is used when trying to understand which of the variables explain the data, and find the model most likely to be true (see [1], [2]).

Table 1. Selected time series models for financial instruments

Financial instrument	Type of model	Normalized BIC
EUR_CHF	ARIMA(0,1,0)	-9.259
AUD_USD	ARIMA(1,1,0)	-8.839
USD_HKD	ARIMA(0,1,0)	-10.452
EUR_JPY	ARIMA(0,1,3)	1.013
ETH_USD	ARIMA(0,1,0)	11.824
Gold	ARIMA(1,0,0)	7.174
Silver	ARIMA(0,1,0)	-0.196
Platinum	Simple	7.434
NASDAQ_Composite	Simple	12.108
Russell_2000	Simple	8.354

For each financial instrument, the plots of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) are examined. It is checked that currency pairs EUR/CHF and USD/HKD are having one spike outside the 95% confidence intervals for the PACF, and the EUR/JPY and gold each having one small spike outside the confidence intervals for the ACF and PACF. In the models for the other financial instruments, there are no jumps outside the confidence intervals. For the purposes of the study, these forecasts are good enough.

For the EUR/CHF, ETH/USD and silver pairs, the models forecast a fall in prices, while for the other financial instruments the models forecast a rise in prices.

Table 2 shows the prices of the financial instruments predicted by the ARIMA models for 05.09.2022, the known prices for the last period considered (29.08.2022) and the expected Rate of Return (RoR) calculated as the relative difference between these prices.

Table 2. Forecast values, last known values and expected rate of return

Financial instrument	Forecasted value	Latest known value	Expected RoR
EUR_CHF	0.974366	0.976100	-0.1776%
AUD_USD	0.688159	0.679530	1.2698%
USD_HKD	7.84896	7.847800	0.0148%
EUR_JPY	161.558583	161.477478	0.0502%
ETH_USD	1558.007108	1577.641602	-1.2445%
Gold	1723.233839	1709.800000	0.7857%
Silver	17.660614	17.776000	-0.6491%
Platinum	822.628087	817.100000	0.6765%
NASDAQ_Composite	11630.926988	11630.860350	0.0006%
Russell_2000	1811.468745	1809.750000	0.0950%

It could be seen that some of the expected rates of return have positive signs, while the others have negative. This means that assets such as EUR/CHF, ETH/USD and Silver should be played in short position by the investors, while the rest instruments should be played in long position. The currency pair AUD/USD has the biggest expected weekly rate of return of 1.27%.

Based on historical data, the standard deviations of the rates of return (Table 3) and the correlation matrix between them (Table 4) are estimated. In Table 3, we can notice that the USD/HKD pair has the lowest standard deviation (approximately 0.07%), while the ETH/USD has the highest (approximately 12.73%) one.

Table 3. Estimates of standard deviations of rates of return on financial instruments

Financial instrument	Standard deviation
EUR_CHF	0.9165%
AUD_USD	1.6781%
USD_HKD	0.0668%
EUR_JPY	1.0922%
ETH_USD	12.7282%
Gold	1.8803%
Silver	3.7634%
Platinum	3.9527%
NASDAQ_Composite	3.1550%
Russell_2000	3.1025%

So far, we have obtained the expected rates of return of the examined financial instruments and have estimated the standard deviations of the rates of return and the correlation matrix between them, based on historical data. An object of future study of the authors will be how to combine these instruments in an optimal risk portfolio.

Table 4. Correlation matrix

Assets	EUR CHF	AUD USD	USD HKD	EUR JPY	ETH USD	Gold	Silver	Platinum	NASDAQ Comp.	Russell 2000
EUR CHF	1.00	0.15	0.06	0.29	-0.02	0.25	0.25	0.15	0.09	0.08
AUD USD	0.15	1.00	0.06	0.09	0.01	0.16	0.21	-0.03	-0.04	0.08
USD HKD	0.06	0.06	1.00	-0.07	0.03	-0.10	-0.02	-0.10	-0.12	-0.11

EUR JPY	0.29	0.09	-0.07	1.00	-0.14	0.20	0.12	0.20	0.20	0.13
ETH USD	-0.02	0.01	0.03	-0.14	1.00	0.10	0.00	0.04	0.04	0.07
Gold	0.25	0.16	-0.10	0.20	0.10	1.00	0.59	0.51	-0.07	-0.02
Silver	0.25	0.21	-0.02	0.12	0.00	0.59	1.00	0.35	0.05	0.08
Platinu m	0.15	-0.03	-0.10	0.20	0.04	0.51	0.35	1.00	-0.01	0.12
NASD AQ Comp.	0.09	-0.04	-0.12	0.20	0.04	-0.07	0.05	-0.01	1.00	0.73
Russell 2000	0.08	0.08	-0.11	0.13	0.07	-0.02	0.08	0.12	0.73	1.00

CONCLUSION

In the present work, for a concrete selection of financial instruments, a technical analysis is performed on real security data using Excel (based on historical data, the standard deviations of the rates of return and the correlation matrix between them are estimated). Forecasting of price movements of these instruments is done using time series and ARIMA models in particular. The resulting models estimate the expected rates of return on the financial instruments.

REFERENCES

[1] Burnham, K. P., Anderson, D. R. (2004). Multimodel inference: Understanding AIC and BIC in model selection. *Sociol. Methods Res.*, 33, 261-304.

[2] Claeskens, G., Hjort, N. L. (2008). *Model Selection and Model Averaging. Technical Report*. Cambridge University Press, Cambridge, UK.

[3] IBM SPSS Software, URL: https://www.ibm.com/analytics/spss-statistics-software (Accessed 19 September 2022).

[4] MathWorks Website. ARIMA method, URL: https://www.mathworks.com/help/econ/arimaclass.html?searchHighlight=arima&s_tid=doc_srchtitle (Accessed 15 September 2022).

[5] Ngo, T. H. D., Bros, W. (2013). The Box-Jenkins methodology for time series models. *Proceedings of the SAS Global Forum 2013 Conference*, vol. 6, pp. 1-11.

[6] Schwarz, G. (1978). Estimating the Dimension of a Model. *Ann. Stat.*, 6, 461-464.

[7] Tabachnick B., Fidell, L., Ullman, J. (2007). *Using multivariate statistics*. Boston.

[8] Yahoo Finance, URL: https://finance.yahoo.com/ (Accessed 02 September 2022).