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PhD Thesis

Rouhollah Ebrahimabadi

London South Bank University

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Contribution to Financial Modeling and Financial Forecasting

Contents

Abstract:

This is the PhD thesis for Rouhollah Ebrahimabadi student at London South bank university. This thesis consists of three chapters. Each chapter is independent research that is conducted during my study. This research is concentrated on financial time series modeling and forecasting.

On first chapter, the research aims to prove that any abnormal behavior in debt level is a signal of future unexpected return for firms that is listed in indexes in this study, hence it is a signal to buy. In order to prove this theory multiple indexes from around the world were taken into consideration. This behavior is consistent in most of indexes around the word.

The second chapter investigate the effect of United State president speech on value of United State Currency in Foreign Exchange Rate market. In this analysis it is shown that during the time the president is delivering a speech there is distinctive changes in USD value and volatility in global markets. This chapter implies that this effect cannot be captured by linear models, and the impact of the presidential speech is short term.

Finally, the third chapter which is the major research of this thesis, suggest two new methods that potentially enhance the financial time series forecasting. Firstly, the new ARMA-RNN model is presented. The suggested model is inheriting the process of Autoregressive Moving Average model which is extensively studied, and train a recurrent neural network based on it to benefit from unique ability of ARMA model as well as strength and nonlinearity of artificial neural network. Secondly the research investigates the use of different frequency of data for input layer to predict the same data on output layer. In other words, artificial neural networks are trained on higher frequency data to predict lower frequency. Finally, both stated method is combined to achieve more superior predictive model.

Introduction

This PhD thesis was conducted over four years from January of 2017 to March 2021. During this long journey I have encountered various interesting topic to peruse and many interesting academic professionals that one way or other have made this journey interesting and insightful for me. At the time of writing this thesis I am holding several certificates including Bachelor of Business Administration from University of Wollongong in Dubai, Pre-master's in finance and Economy from Queen Mary University of London, and MSc Banking and Finance from Queen Mary University of London. Within all the topics that I have covered during my education, financial market and econometrics fascinated me the most and I decided to explore more on this area. Years of research has shown to me that financial marks such as forex, commodities, and stock market has two-way relationship with economy, politics, poverty, and can even leads to military conflicts. Either of these topics can affect and be affected by financial markets. Therefore, it can be said that financial market is playing major role not only in life of investors and any individual whose career is related, but also other everyone else's wellbeing may change by market movement one way or other. Forecasting and foreseeing future is one of oldest human interest. As science and technology developed over centuries, the idea of learning from past and applying it to future become more methodical. By implementing mathematic, behavior of historical data could be explained by algorithms and mathematical models. Assuming the past can explain future, mathematician and academic professionals devoted their time to forecast the future. That is how econometrics as a subject was invented. Econometrics is a combination of statistics, economics, finance, and computer science. By gathering these divisions of science, econometricians are able to develop algorithm that can explain the future with some level of uncertainty. However, to learn from the past and applying it to future is heavily depended on quantity and quality of historical data. One of the early theories presented a pessimistic view on financial forecasting. The efficient market theory implies that all information is available to public therefore, it cannot be utilized for predicting the future. Even though this theory has been proven wrong in many studies due to unrealistic assumption such as no cost of information, it initiated many other studies. Not long after efficient market theory, the impact of information on future prices and categorizing the market based on information accessibility was investigated extensively. Storing and analyzing data is nearly impossible without computers no matter how strong and efficient the theories and algorithms are. The first personal computer became available to public in 1980s which were heavy, limited and comes with few kilobits of hard drive. Compared to today's standard they were expensive and impractical. However, that was the revolutionary act of improving the quantity and quality of data being stored and analyzed. In 21st century one of the most if not the most expensive commodities that money can buy is data, and that created new industries such as data vendors and data scientists.

Additionally, the world as we know is full of unanticipated events that will change course our life temporarily or even permanently. Coronavirus (2019), 9/11 attack (2001), great depression in (1929 – 1933), and Black Friday (1929), financial crisis (2007-2008) are few examples that affected financial market and influenced millions of people. These events could not be predicted therefore, it is impossible to forecast what exactly will happen in the future. As the forecast horizon gets longer the possibility of unexpected events or systematic risk goes higher, hence the forecasted output will be less reliable. However, it can be said, if important factors such as general macro-economic factors remain relatively constant, the future is predictable with some degree of error.

This thesis consists of three chapters. Each chapter is heavily depended on financial modeling and forecasting to proves the research question.

The main components of time series analysis are variable, frequency of data, and the underlying algorithm. Each chapter of this research take closer look at these components. Majority of models that are well known to both academia and industry, take past values or better known as historical data to estimate the future value. In other words, it is a common practice to draw a conclusion on what will happen in the future based on past movements of variable under study. However, in some cases the prediction can be enhanced if other relevant factors apart from historical value are added to forecasting algorithm. To be able to add external variable to the algorithm, it is important to test if it has any effect on target variable. Therefor chapter one and chapter two focus on this matter.

Chapter one tests whether information that can be extracted from companies' financial statement is a relevant factor for estimating future profitability of that firm. Previous studies, which are explained more extensively, aim to find a valid relationship between capital structure of firms and its future performance. If that association can be proven, then it can be used for improving the forecasting of company's financials.

In similar line of work, chapter two studies the influence of political figures such as United States president on value of that country's currency in global markets. Other studies have different yet similar approach to measure the impact of political events and media influence on financial markets including FOREX. However, less attention was paid to presidential speech which almost always is broadcasted live by media. This chapter mainly concentrate on whether there is an unusual behavior on USD value against other currency during the speech of US president regardless of its content. Each speech last from several minutes up to two hours, therefore ultra-high frequency is required to watch closely for an abnormality. In other words, these events are very short therefore more observation is needed to analyze its impact, hence increasing the frequency of the data will provide higher number of observations which leads to more unbiased conclusion.

Finally, chapter three centers around the forecasting algorithm and data frequency. Common linear predictive models including Autoregressive Moving Average models are tested, studied, and put in practice extensively. Despite of their popularity, they come with several limitations such as being linear in nature. Alternatively modern methods namely Machine learning and Deep learning approaches are extremely accurate. In chapter three the author explains the linear models and Artificial Neural Networks that will later be combined in unique manner to create new model that can outperform any other algorithm explained in this chapter. The author introduces new model which is a combination of conventional linear (ARMA) models' theory and cutting-edge deep learning model (RNN). In further analysis the performance of new approach will be compared with simple Recurrent Neural Network algorithm. Lastly the concept of single frequency models will be tested against using multiple frequency model in order to predict one step ahead.

I would like to thank my family special my parents and my wife for all the supports during this exhausting yet interesting journey. Without their unconditional love and support it would be impossible for me to continue. Many thanks to my supervisors Dr. Gurjeet Dhesi and Dr. Valerio Ficadenti for trusting me at the first place and giving me this opportunity and for his advice, my good friend and mentor Dr. Ali Habibnia who is one of the experts and brilliant minds in field of financial time series and deep learning, and finally, Dr. Ali Saedvandi who helped me during my master and co-author of the first chapter.

Forecasting stock price using changes in debt level

ABSTRACT

For many years, researchers investigate a relation between debt structure of a firm and its expected stock return however, this mechanism is still vague. Following the capital structure literature, this research finds no significant evidence of any relation between debt-to-equity ratio and stock return in an emerging market. Instead, we demonstrate that a major change in debt level, either negative or positive, is an indicator of future positive abnormal return. The evidence suggests the existence of a non-linear U-shape relationship between changes in the debt level and unexpected positive returns.

Introduction:

This paper aims at exploiting information inside debt structure to estimate expected rates of return for stocks. A body of research attempted to predict stock returns using different financial indicators. In this regard, Lakonishok, Shleifer and Vishny (1994) open a new window in modern investment theory. They introduce filtering as an instrument to evaluate the impact of underlying financial variables on stock returns.

Some studies including Bhandari (1988) find a significant relation between leverage ratios and stocks' rates of return. In this line, our contribution, here, is to incorporate capital structure theories into filtering method. Having done that, we will be able not only to produce better forecasts for rates of return, but also to make some progress on the theory of capital structure, which remains a puzzle, since Modigliani and Miller (1958, 1963).

Several papers such as Myers (1977), Ross (1977), Campbell (1979), Campbell, and Krasaw (1980) which will be discussed later in this chapter, consider the information side of changes in capital structure. As representatives for evaluating leverage changes over time, we consider two different variables, debt to equity ratio and debt growth.

Bhandari (1988) argues that the expected return of highly leveraged companies must be large enough to make up the risk of expected financial distress. To test such an idea, prior studies investigated the relationship between rate of return and debt to equity ratio. Bhandari (1988) investigates an increase in the debt level.

In the present paper, we agree with Bhandari (1988), and focus on the changes in debt level rather than debt to equity ratio. We also believe that any extreme changes in debt level, rising or falling, could result in an unexpected rate of return. Based on our theory, any significant change in debt represents a kind of internal financial restructuring and conveys information. Suppose for long time, one firm bears a specific level of debt, and suddenly repays all the outstanding debt. The reason behind this decline in debt level should be clarified. We believe that such a firm must have encountered an unexpected internal source of revenues. This internal money can come from an unexpected rise in product prices, fall in an input price, and/or access to a more efficient technology. For instance, an increase in crude oil price may make huge extra income for an oil producer.

Conversely, consider another firm with a major increase in its debt level. This may be interpreted as a negative sign of financial situation. However, this interpretation is not quite reasonable. In fact, that the firm could convince lenders to offer the loan indicates a viable financial prospect rather than distress. In other words, if a company does not obtain enough internal resources to finance some very positive NPV projects, it has no other choice but looking for external resources. On the other hand, the bright future of the projects in question motivates lenders, either banks or bondholders, to participate.

Therefore, significant changes in debt level, either increase or decrease, could be an indicator of a boost in expected return. To investigate this theory, we must test whether companies with large fall or rise in their debt levels can outperform companies with moderate changes in capital structure. This leads us to an examination of some non-linearity between debt growth and expected rate of return. In this paper, this relationship is investigated through classification of data, graphs, finally panel data regressions.

Literature review:

What is the optimal capital structure for a company? Should a corporation issue equity or bond for financing a new project? Which one is in favor of stockholders? What do managers do in this regard and what they must do? After more than 7 decades of the seminal papers of Modigliani and Miller (1958, 1963), there are still no convincing answers to the preceding questions. Modern finance theory should come up with some explanation of why there exists a variety of debt structures with respect to amount and maturity.

Theoretical Background

According to Modigliani and Miller (MM), when companies face an investment opportunity, in a perfect market financing decision do not add any value to stockholders because the external money is at the same price as internal money.

Myers (1984) categorizes ways of thinking about variety of financial structure into two main streams: static tradeoff framework and pecking order framework.

Based on the static tradeoff, firms would set a target for their debt ratio and move toward it, quite similar to determining dividend policy. On one side of the tradeoff, increasing debt to equity ratio might benefit firms because of imperfections in the market. On the other side, bankruptcy risk increases as debt-equity ratio increases, this indicates additional costs. Thus, there must be an optimal level of debt-to-value. Although this reasoning looks seamless, it empirically loses the ground.

In the old-fashioned pecking order framework firms assume no specific target for their capital structure. They prefer internal to external resources in order to finance their projects. If external funds are needed, firms issue the safest one first. Therefore, they start with debt, then possibly hybrid securities such as convertible bonds, and finally equity as the last resort. In this theory, there are two kinds of equity, internal and external, one at the top of pecking order and the other at the bottom.

In this line, Myers (1977) presented the theory that describe the effects of debt level on company’s future. Firstly, excessive amount of debt is identical to taxation since firms the part of the capital that is generated form new debt for an investment must be paid to existing debt holders. As a result, highly leveraged companies will be facing the possibility of debt overhang or underinvestment. In addition, managers of highly leveraged firms forgo positive NPV projects. In the case of adverse liquidity shock, when a highly indebted firm faces market imperfections, it is more likely to be forced to ignore positive NPV opportunities. Not investing in potentially profitable investment will increase the agency cost of the company. Myers believe that higher leverage will lead to higher possibility of bankruptcy, therefore he suggests that debt with short term maturity will be more beneficial to companies since the market value of the firm is less vulnerable to short-term debt compared to long-term alternatives.

In similar line of work, Barbiero et al. (2020) investigates the force of debt of companies’ investment level. For their analysis, 8.5 million pan-European companies’ data were gathered from 2004 to 2013. They concluded that firm’s debt level is inversely related to its investment amount in potential opportunities due to points that explained by Myers (1977). However, the industry which firms operate in is a significant factor. Moreover, their funding provide evidence that debt with shorter maturities will be a more viable option for firms to generate capital for new investment as Myers (1977) suggested.

Ross (1977) investigates different aspects of the managers’ attitudes toward changes in capital structure. Managers consider high leverage as a threat to the stability of their own job. On the other hand, they may look at capital structure as a signaling instrument of the firms’ riskiness and profitability. According to signaling theory by Ross (1977), managers increase the debt level of the firm in order to signal the market about the firm confidence and wellbeing, even though raise in leverage hinter the market that particular firm is facing capital crisis. In his paper the intensive-signaling model was presented. Although we agree with the first argument of Ross (1977), we save our reservation about the message that managers want to send, in case of a significant decrease in debt level. We suggest, and empirically present that a significant fall in the leverage level could be a result of firm's internal strength. If a company suddenly enjoys a high level of free cash flow, it might consider early settlement of its loans.

As Myers (1984), in his presidential address to the American Finance Association, asserts there is still no clear solution that could explain how firms determine their debt-to-equity mix.

In related research, Dimitrov and Jain (2008) used CRSP database to obtain 67,457 firm-year observations from year 1973 to 2004 to investigate relation between the annual change in leverage and return on stock price in subsequent years. Their findings suggest the increasing in the leverage will leads to lower price returns in the future. In addition, this study states that when firm is likely to underperform, the management may issue more debts.

Similar study is conducted by Cai and Zhang (2011) denote a negative correlation between stock return and leverage ratio exists. The magnitude of this negative correlation will raise as the leverage ratio goes higher. This analysis is performed over all companies that their data is available in both CRSP and CompStat databases between year 1975 and 2002.

In line with previous research, Bradshaw, Richardson, and Sloan, (2006) examine the impact of external financing on stock price in the future. The results provide evidence that choosing external funds to financial the firms will lower the future return. for the purposes of this analysis, Bradshaw, Richardson, and Sloan utilized 99,329 firm-year data.

Empirical Background

There are few empirical papers concentrating on the relationship between changes in capital structure and firm value. Masulis (1980, 1983) is a pioneer. He empirically shows that offering to exchange debt for equity by a firm, on average, raises the stock price. Masulis argues that such an offering can signal positive attitude of the managers about high capacity of debt. This signal could be translated into an increase in firm value or a reduction in firm risk.

Masulis (1983) inspires this chapter since his work was one of the first research that concentrate on impact of changes in leverage on company's return instead the value of the leverage. He points out that no strong evidence of a link between firm's value and its debt level is observed. So, for the first time, Masulis looks at the changes of debt instead of debt level itself. Masulis considers issuing exchange offers and recapitalizations as two forms of capital restructuring. Using panel data regression technique on NYSE firms, the proposed model explained 55% of variation in stock price. In his work Masulis (1983) concludes that there is a positive relationship between changes in leverage and stock price variation. Additionally, Masulis (1983) claim every one dollar change in debt level will influence stock prices by 0.23 to 0.45. His conclusion is in line with this chapter hypothesis.

Some researchers look at the variety of leverage ratios across countries. Raghuram and Zingales (1995) found high similarities in firms' debt structure across G-7 countries. They also conclude that discrepancy in debt level cannot be explained by institutional difference. Booth et al (2001), achieve the same result among firms in ten developing countries. They suggest that financing decision is affected by the same variables as in developing countries. Bhandari's (1988) is another inspiring paper as he uses capital structure as a determinant of expected stock returns. He suggests that since riskiness of a firm is positively associated with its leverage, the expected return of a highly leveraged firm should be relatively higher to compensate the risk. He uses an econometric model of expected return of stocks as dependent variable and debt to equity ratio along with beta and a proxy for firm size as independent variables. He finds that with risk-averse investors, a positive relationship between rate of return and capitalization ratio is expected to be observed.

This research emphasis on the idea that leveraging will increase the risk; however, on the other hand, a significant reduction in the debt level might signal some expansion in internal resources of money. By looking at significant changes in leverage, positive or negative, as a sign of opportunities and generalizing Bhandari's model, it can be assumed that a second order relation between expected rate of return as dependent variable and debt fluctuations as independent variable.

Empirical Section

In this section firstly the description of data is presented. Secondly, the filtering process is explained step by step. Furthermore, the filter will be implemented and presented by graphs. Finally, with help of panel data regression the hypothesis of this chapter will be tested.

Data Description

The data used in the empirical section is taken from Bloomberg terminal. In order to prove the proposed hypostyles, the accounting data for all companies which are listed in 8 major Indices from different countries are acquired. These indices are:

1. GLOBAL S&P1200 - global equities
2. AUSTRALIAN S&P 300 - Australia
3. BLOOMBERG EUROPE 500 - Europe
4. BLOOMBERG US – United States
5. JPX NIKKEI 400 – Japan
6. TOPIX 1000 – Japan

7. CSI 800 – China
8. DOW JONES US – United States

For purpose of this research five variable including market cap, book return, current liability, noncurrent liability, and stock price obtained for period of 13 years from 2004 to 2017. The dataset required for this chapter is acquired from Bloomberg Terminal. Since all the above-mentioned variables can only be found in financial reports the frequency of these datasets are annually. From current and noncurrent liability other variable such as total liability, current debt changes, noncurrent debt changes, and total debt changes are calculated. Debt changes variables is the difference between two consecutive year of liabilities variables. Therefore, the data for year 2004 will be excluded from further analysis. Market return obtained by differencing two consecutive average prices of all companies in the index.

Filtering Identification

The idea of filtering is taken from investing strategy that presented by Lakonishock et al (1994). They use filtering as an instrument to investigate behavior of value stocks vs. growth stocks. The proposed strategy was proven to outperform the market. The analysis conducted from 1963 to 1990 by using the data which is extracted from firm's financial reports. The firms listed on New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) were taken into consideration. Two most well-known data vendor, Center for Research in Security Prices (CRSP) and COMPUSTAT provided datasets for this research. In this study, Lakonishock et al (1994) ranked the companies based on past one to five years growth rate (stock return) and firms were allocated in 10 equally weighted portfolios. After portfolios formation next five years financial and accounting data is monitored precisely. Each year that analysis move forward the portfolios are readjusted based on given information on that year. In this strategy, one dollar investment made in all companies in each portfolio. The proposed strategy outperforms other investment method such as book-to-market-strategy considerably.

A similar method is used here. The basic idea is to allocate the firms in 10 to 12 portfolios and then tracking the return pattern of each portfolio in the following years.

The procedure of filtering can be expressed in six steps:

1. each dataset sorted based on the values of a specific variable of interest for each year. For example, all firms that are listed in TOPIX100 in year 2005 are sorted by debt growth. The companies that have missing data is omitted.
2. firms are placed in 10 to 12 portfolios based on their debt growth in ascending manner. In other words, the first portfolio contains companies with lowest debt growth (possibly negative debt growth), and last portfolio is consisted of firms with highest debt growth.
3. Keeping the list of the companies in each portfolio fixed, the average rate return in each category for one year (year2006), two years (2007), and three years ahead (2008) is computed.
4. Moving forward one year, all the steps 1, 2, and 3 repeated. (In our example steps 1 and 2 for 2005 and step 3 for years 2006, 2007, 2008.)
5. These steps are repeated until the final year (start at 2011, ends 2014).
6. Finally, 10 datasets are created.
7. The difference between the average return of each portfolio and the average return of the sample is computed. This shows the relative strength of each category in beating the market.

Debt to Equity Filter:

P debt growth total	
Mean	0.14110628
Median	0.04610693
Standard Deviation	0.77816349
Minimum	-0.9771907
Maximum	41.8502648

Table 1.1 descriptive statistics percentage changes in Debt level of S&P 1200 global components

The table 1.1 contains S&P global 1200 index descriptive statistics of percentage changes in debt growth. This variable was calculated by following formula:

$$total\ Liabilit = \frac{totalLiability_{i+1}}{totalLiability_i}$$

Equation 1.1 total Liability

Itausa SA decreased its total liability from 279.71 billion dollars in 2011 to 6.38 billion dollars in 2012 (98% decrease) which is highest negative changes in total liability in S&P 1200 global index during 2004 to 2017. On the other hand, FORTESCUE METALS GROUP LTD increased their total liability from 62,310,000$ to 2,670,000,000$ during 2006-2007 (3462% increase) which is highest increase in debt growth.

After omitting companies that contains missing data, there are 840 companies left to pass-through suggested filter. graph 1 represent the performance of each portfolio return in one, two, and three years.

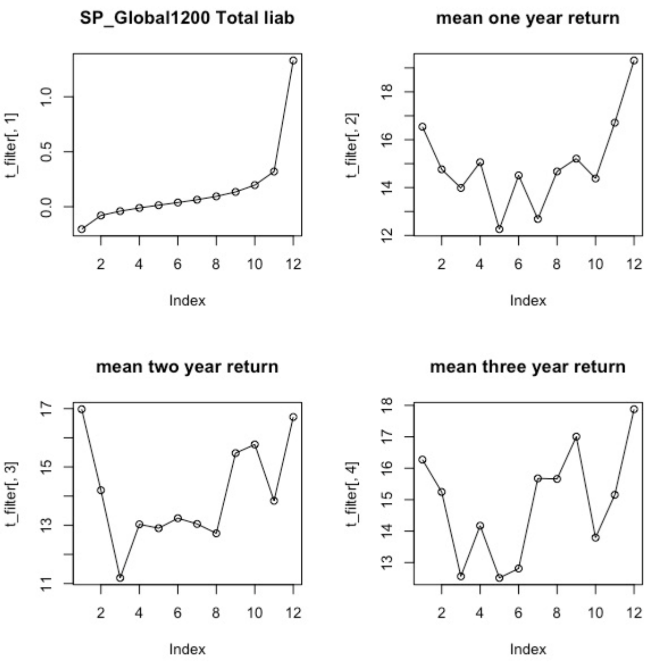


Figure 1.1 portfolios based on changes in debt growth and portfolios return for 3 consultive years

Figure 1.1 represents percentage changes of total liability for 12 portfolios. In all four plots, each point represents one portfolio with is sorted by percentage changes in debt growth in increasing manner. The top left plot, y axis shows the level of changes in debt, whereas other three plots indicate each portfolio's future book return for one, two, and three years ahead. It is clearly visible that the first (lowest or negative changes in debt growth) and last portfolio (heights changes in debt growth) are most profitable compared to other groups. In addition, this chapter's hypothesis which is a second order, U shape relationship between changes in debt growth and book return, can be observed in all plots that represent future returns. Similar behaviour can be seen in other 7 indexes (see Appendix A).

Additional Checks for Robustness

The final part of the empirical section is the regression analysis. Now the question is whether the regression analysis can confirm the preceding results or not. Several variables such as return, changes in total debt in percentage, market capitalization, and market return (index return) is included in panel data regression in order to build statistical model. By combining variable above and other variable which are constructed based on them, nine different regressions were tested on all firms. The table below points to the correlation between chosen variables for this test. Beside return which is dependent variable and percentage changes in leverage, market return shows some strong magnitude to return. This is in line with Capital Assets Pricing Model or CAPM theory. In addition, author believe that the size of the equity or market capitalization is relevant factor in book return. As table 1.2 implies market capitalization have negative impact on return. In addition to return changes in return is taken to consideration as well.

Variable	Return	Market Cap	Total Debt growth %	Market return
Return	1			
Price	0.033688581			
Market Cap	-0.035401373	1		
Total Debt growth	-0.002678808	0.010932287	1	
Market return	0.396269752	-0.056020393	-0.06985008	1

Table 1.2 variables correlation coefficients

$$return_i = C + \beta_1 return_{i-1} + \beta_2 return_{i-2} + \beta_3 \%debtgrowth_{i-1} + \beta_4 \%debtgrowth_{i-1}^2$$

Equation1.2 Regression 1

$$return_i = C + \beta_1 return_{i-1} + \beta_2 return_{i-2} + \beta_3 \%debtgrowth_{i-1} + \beta_4 \%debtgrowth_{i-1}^2 + \beta_5 marketcap_{i-1}$$

Equation 1.3 Regression 2

$$return_i = C + \beta_1 return_{i-1} + \beta_2 return_{i-2} + \beta_3 \%debtgrowth_{i-1} + \beta_4 \%debtgrowth_{i-1}^2 + \beta_5 \log{(marketcap)}_{i-1}$$

Equation 1.4 Regression 3

$$\Delta return_i = C + \beta_1 \Delta return_{i-1} + \beta_2 \Delta return_{i-2} + \beta_3 \%debtgrowth_{i-1} + \beta_4 \%debtgrowth_{i-1}^2 + \beta_5 \log{(marketcap)}_{i-1}$$

Equation 1.5 Regression 4

$$\Delta return_i = C + \beta_1 \Delta return_{i-1} + \beta_2 \Delta return_{i-2} + \beta_3 \%debtgrowth_{i-1} + \beta_4 \%debtgrowth_{i-1}^2 + \beta_5 marketcap_{i-1}$$

Equation 1.6 Regression 5

$$\Delta return_i = C + \beta_1 \Delta return_{i-1} + \beta_2 \Delta return_{i-2} + \beta_3 \%debtgrowth_{i-1} + \beta_4 \%debtgrowth_{i-1}^2$$

Equation 1.7 Regression 6

$$\Delta return_i = C + \beta_1 \Delta return_{i-1} + \beta_2 \%debtgrowth_{i-1}^2 + \beta_3 \log{(marketcap)}_{i-1}$$

Equation 1.8 Regression 7

$$\Delta return_i = C + \beta_1 \Delta return_{i-1} + \beta_2 \%debtgrowth_{i-1}^2 + \beta_3 \log{(marketcap)}_{i-1} + \beta_4 marketreturn_{i-1}$$

Equation 1.9 Regression 8

$$\Delta return_i = C + \beta_1 \Delta return_{i-1} + \beta_2 \Delta return_{i-2} + \beta_2 \%debtgrowth_{i-1} \\ + \beta_3 \%debtgrowth_{i-1}^2 + \beta_4 \log{(marketcap)}_{i-1} + \beta_5 marketreturn_{i-1}$$

Equation 1.10 Regression 9

Four different types of variables are used to predict returns: the last years’ return, the debt growth in percentage, market return, and the market capitalization. To incorporate this effect, the rate of return (or changes in rate of return) of the last year is included in the model. market capitalization or Logarithm of market capitalization of the last year is another indicator company’s riskiness. The bigger the company, the more diversified it is, and thus the less risky it is expected to be. Market capitalization is calculated by multiplying the number of shares by the closing price of the period. Since larger companies have a better chance of diversification, investors expect lower rates of return comparing to the smaller companies. In other word, an investor is willing to receive lesser amount as is bearing lower risk by keeping a large company in the portfolio. This means a negative relationship between the logarithm of market capitalization and the rate of return.

A second order debt growth term is included in the model in order to test the findings of the previous parts. The hypothesis developed earlier in this research shows a "U-shape" relationship between the logarithm of the debt growth and the lag rate of return. This can be verified by the sign of the squared term of the debt growth. A positive significant coefficient can be supportive of the hypothesis. Lastly the index return used as market return representation.

The EViews analytical software is used to estimate panel data regression on each indexes' company. The result provides is promising when second order of debt growth is added to the model. for the purpose of this research author tests whether percentage changes in leverage in first order or second is statistically relevant. Assuming the 10% confidence level, if value of Prob is below 0.1 the variable is statically significant, hence it is contributing to explain the variation in stock return. Since the companies' financials is a time dependent variable and many companies appear more than once in dataset the Least Squares algorithm with fixed effect is used.

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 13:05
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	23.67008	0.834794	28.35438	0.0000
RETURN(-1)	-0.179998	0.017323	-10.39052	0.0000
RETURN(-2)	-0.275512	0.017026	-16.18203	0.0000
P_DEBTGROWTH_TOTAL(-1)	-5.593965	1.803945	-3.100962	0.0019
P_DEBTGROWTH_TOTAL(-1)	0.136424	0.043268	3.153021	0.0016

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	36.75742	R-squared	0.165326
Mean dependent var	15.04922	Adjusted R-squared	0.080879
S.D. dependent var	40.23970	S.E. of regression	38.57812
Akaike info criterion	10.23088	Sum squared resid	4310035.
Schwarz criterion	10.79011	Log likelihood	-16024.26
Hannan-Quinn criter.	10.43141	F-statistic	1.957745
Durbin-Watson stat	2.139736	Prob(F-statistic)	0.000000

Figure 1.2 Regression1 Bloomberg Europe 500

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 15:26
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 1030
Total panel (balanced) observations: 10300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	997.1831	22.31256	44.69157	0.0000
D(RETURN(-1))	-0.709830	0.008387	-84.63671	0.0000
D(RETURN(-2))	-0.440190	0.008477	-51.93026	0.0000
P_DEBTGROWTH_TOTAL(-1)	-3.959950	0.903216	-4.384278	0.0000
P_DEBTGROWTH_TOTAL(-1)	0.066189	0.021272	3.111532	0.0019
LOG(MARKET_CAP(-1))	-44.89035	1.005581	-44.64120	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	51.64248	R-squared	0.509974
Mean dependent var	1.097511	Adjusted R-squared	0.455285
S.D. dependent var	73.77657	S.E. of regression	54.45065
Akaike info criterion	10.92754	Sum squared resid	27469546
Schwarz criterion	11.65504	Log likelihood	-55241.82
Hannan-Quinn criter.	11.17343	F-statistic	9.325089
Durbin-Watson stat	2.238901	Prob(F-statistic)	0.000000

Figure 1.3 Regression 4 Bloomberg U.S Equity Index

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 20:59
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1888.201	47.50710	39.74565	0.0000
RETURN(-1)	-0.110186	0.015262	-7.219692	0.0000
RETURN(-2)	-0.038198	0.014984	-2.549312	0.0108
P_DEBTGROWTH_TOTAL(-1)	2.929350	0.897998	3.262091	0.0011
P_DEBTGROWTH_TOTAL(-1)	-0.015682	0.004755	-3.297688	0.0010
LOG(MARKET_CAP(-1))	-79.63642	2.053660	-38.77780	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	70.97128	R-squared	0.405527
Mean dependent var	36.17453	Adjusted R-squared	0.345072
S.D. dependent var	92.06420	S.E. of regression	74.50536
Akaike info criterion	11.54766	Sum squared resid	14738034
Schwarz criterion	12.10165	Log likelihood	-16623.23
Hannan-Quinn criter.	11.74718	F-statistic	6.707927
Durbin-Watson stat	1.540579	Prob(F-statistic)	0.000000

Figure 1.4 Regression 3 CSI 800

Tables 1.2, 1.3, and 1.4 are few examples extracted from analytics software that find second order of debt changes highly significant. The result of nine panel data regressions for each index is documented in appendix A.

As it mentioned earlier the purpose of this chapter is to investigate whether the suggested variables, specifically the squared percentage changes in debt, are statistically significant. The tables 1.3 to 1.11 are the summery of P-values (T-test) of independent variable for each regression on individual index. If the P-value of certain regressor is less than 0.1, that variable is statistically significant. The result suggests that Bloomberg Europe 500 and TOPIX 100 are in line with this chapter hypothesis. All variables in nine algorithms are statistically significant. Furthermore, the regression number 7 and 8 are the best among others, since 7 out on 8 indexes have relevant independent variable. Additionally, the R-squared for regression 7 goes from 0.24 to 0.54 and adjusted-R-squared is from 0.16 to 0.49 which indicates how much of the variation in return is explained by variables. In case of regression number 8 the R-squared and range from 0.27 to 0.65 and adjusted-R-squared is between 0.20 to 0.62 which is much higher than previous regression. In all other regression there are at least 2 indexes that all independent variables are statically significant including Percentage Changes in Debt Growth and Squared PCDG.

Regression 1	lag 1 return	lag 2 return	PCDG	PCDG^2
Bloomberg Europe 500	0	0	0	0
Bloomberg U.S. Equity	0	0	0	0
CSI800	0	0	0	0
Dow jones US	0	0	0.6	0.9
JPX Nikkei	0	0	0	0
SP global 1200	0	0	0.2	0.6
S&P Australia	0	0	0.1	0.3
TOPIX 100	0.1	0	0	0

Table 1.3 Regression 1 P-values

Regression 2	lag 1 return	lag 2 return	PCDG	PCDG^2	lag 1 market cap
Bloomberg Europe 500	0	0	0	0	0
Bloomberg U.S. Equity	0	0	0	0	0.1
CSI800	0	0	0	0	0
Dow jones US	0	0	0.7	0.8	0
JPX Nikkei	0	0.7	0.1	0.04	0
SP global 1200	0	0	0.2	0.6	0
S&P Australia	0	0	0.1	0.3	0
TOPIX 100	0.08	0	0	0	0

Table 1.4 Regression 2 P-values

Regression 3	lag 1 return	lag 2 return	PCDG	PCDG^2	log of lag 1 market cap
Bloomberg Europe 500	0	0	0	0	0
Bloomberg U.S. Equity	0	0	0.1	0.4	0
CSI800	0	0	0	0	0
Dow jones US	0	0	0.3	0.1	0
JPX Nikkei	0	0.7	0.3	0.08	0
SP global 1200	0	0	0.9	0.3	0
S&P Australia	0	0	0.4	0.8	0
TOPIX 100	0	0	0	0	0

Table 1.5 Regression 3 P-values

Regression 4	Delta lag 1 return	Delta lag 2 return	PCDG	PCDG^2	log of lag 1 market cap
Bloomberg Europe 500	0	0	0	0	0
Bloomberg U.S. Equity	0	0	0	0	0
CSI800	0	0	0.4	0.4	0
Dow jones US	0	0	0.7	0.1	0
JPX Nikkei	0	0	0	0	0
SP global 1200	0	0	0.9	0	0
S&P Australia	0	0	0.6	0.4	0
TOPIX 100	0	0	0	0	0

Table 1.6 Regression 4 P-values

Regression 5	Delta lag 1 return	Delta lag 2 return	PCDG	PCDG^2	lag 1 market cap
Bloomberg Europe 500	0	0	0	0	0
Bloomberg U.S. Equity	0	0	0	0	0
CSI800	0	0	0.1	0.1	0
Dow jones US	0	0	0	0.3	0
JPX Nikkei	0	0	0	0	0
SP global 1200	0	0	0	0.5	0
S&P Australia	0	0	0	0.5	0
TOPIX 100	0	0	0	0	0

Table 1.7 Regression 5 P-values

Regression 6	Delta lag 1 return	Delta lag 2 return	PCDG	PCDG^2
Bloomberg Europe 500	0	0	0	0
Bloomberg U.S. Equity	0	0	0	0
CSI800	0	0	0.1	0.1
Dow jones US	0	0	0	0.3
JPX Nikkei	0	0	0	0
SP global 1200	0	0	0	0.5
S&P Australia	0	0	0	0.4
TOPIX 100	0	0	0	0

Table 1.8 Regression 6 P-values

Regression 7	Delta lag 1 return	PCDG^2	log of lag 1 market cap
Bloomberg Europe 500	0	0	0
Bloomberg U.S. Equity	0	0.3	0
CSI800	0	0	0
Dow jones US	0	0	0
JPX Nikkei	0	0	0
SP global 1200	0	0	0
S&P Australia	0	0.1	0
TOPIX 100	0	0.1	0

Table 1.9 Regression 7 P-values

Regression 8	Delta lag 1 return	PCDG^2	log of lag 1 market cap	lag 1 market return
Bloomberg Europe 500	0	0	0	0
Bloomberg U.S. Equity	0	0.2	0	0
CSI800	0	0	0	0
Dow jones US	0	0	0	0
JPX Nikkei	0	0	0	0
SP global 1200	0	0	0	0
S&P Australia	0	0.1	0	0
TOPIX 100	0	0.1	0	0

Table 1.10 Regression 8 P-values

Regression 9	Delta lag 1 return	Delta lag 2 return	PCDG	PCDG^2	log of lag 1 market cap	lag 1 market return
Bloomberg Europe 500	0	0	0	0	0	0
Bloomberg U.S. Equity	0	0	0	0	0	0
CSI800	0	0	0.1	0.2	0	0
Dow jones US	0	0	0.4	0.1	0	0
JPX Nikkei	0	0	0	0	0	0.2
SP global 1200	0	0	0.6	0	0	0
S&P Australia	0	0	0.4	0.4	0	0
TOPIX 100	0	0	0	0	0	0

Table 1.11 Regression 9 P-values

Table 1.12 summarises the R-squared, and adjusted R-squared of every regression separated by indexes. To confirm that the changes in debt level is a promising variable to be added, both R-squared, and adjusted R-squared of every regression is compared to identical regression without this particular independent variable. If the model benefits from adding changes in debt level and its squared version, the R-squared will increase. However, this measurement will increase when additional variable is added to the model. Therefore, the more conservative parameter is needed for this comparison, and that is adjusted R-Squared. Looking at the value of R-squared it can be concluded that when return is replaced with first difference of return and logarithmic market cap is added to model the value of R-squared and the adjusted R-squared increases dramatically. On each row the higher value fitness parameter is highlighted in green. As it is expected in all instances R-squared of model with debt variable is always above the alternative regression' R-squared. Similarly, the adjusted R-squared increases in majority of cases when variable under study is included. That provide enough evidence to claim the first and second order of changes in debt level is viable parameter in the panel data regression. In term of regressions the model 1, 2, and 3 under perform in every indexes. On the contrary, the regression 7 and 8 not only have higher value of R-squared / adjusted R-squared, but also in most of regression on individual indexes all independent variables are statistically significant. The last column of table 1.12 present the coefficient value of second order changes in debt. If the variable's p-value is less than 0.1 (is statistically significant) it is highlighted in green. It is quite noticeable that JPX Nikkei 400 index is more sensitive this this variable compared to other indexes since the value of coefficient is greater with respect to others. On the other hand, S&P Australian Stock Exchange 300 is the least sensitivity to variable under study. In most cases the variable is not statistically significant, and the coefficient value is close to zero.

Bloomberg European 500					
	with changes in debt		without changes in debt		coefficient squared changes in debt
Regression Number	Adjusted R-squared	R-squared	Adjusted R-squared	R-squared	
1	0.080878969	0.165326276	0.078288579	0.16239583	-0.00699862
2	0.088997335	0.172984411	0.086638599	0.170270311	-0.006011516
3	0.14742763	0.226027905	0.145800578	0.224015137	0.002046784
4	0.489678092	0.541432021	0.488464946	0.539989001	0.106757506
5	0.347374657	0.413560186	0.343193674	0.409350089	0.100264622
6	0.329614594	0.39737	0.324965756	0.392725316	0.099402638
7	0.312738054	0.375667025	0.311008145	0.373879462	-0.060104934
8	0.382787052	0.439495548	0.379341938	0.436172341	-0.082105335
9	0.383901294	0.44070061	0.379341938	0.436172341	0.040453557
Bloomberg U.S. Equity					
	with changes in debt		without changes in debt		coefficient squared changes in debt
Regression Number	Adjusted R-squared	R-squared	Adjusted R-squared	R-squared	
1	0.024512011	0.024803484	0.02451476	0.024660496	0.014787771
2	0.024871001	0.025235209	0.024872022	0.025090546	0.014827159
3	0.041151378	0.041509505	0.04098941	0.041204322	0.016761868

4	0.398484865	0.398709545	0.395286795	0.39542232	0.1187463
5	0.388786541	0.389014844	0.385955234	0.38609285	0.117077902
6	0.388691383	0.388874054	0.385864594	0.385956352	0.117035318
7	0.248011508	0.248180027	0.247949694	0.248062049	-0.015091127
8	0.293363312	0.293574453	0.29328447	0.293442843	-0.015939262
9	0.296981358	0.297243933	0.29328447	0.293442843	0.127789325
CSI800					
	with changes in debt		without changes in debt		coefficient squared changes in debt
Regression Number	Adjusted R-squared	R-squared	Adjusted R-squared	R-squared	
1	-0.02547458	0.068834023	-0.026741619	0.066981462	-0.01086704
2	0.068925073	0.154870451	0.068314004	0.153678738	-0.009749343
3	0.345072074	0.40552696	0.342857558	0.403067533	-0.015681726
4	0.68348954	0.715628624	0.683650067	0.715534904	0.00347727
5	0.653631154	0.688802116	0.653600472	0.688514001	0.00796265
6	0.63770596	0.674357745	0.637575916	0.673968256	0.008986994
7	0.496566165	0.542692752	0.495289946	0.541360915	-0.00495264
8	0.623405838	0.658039626	0.622497434	0.657085703	-0.004192054
9	0.623290871	0.658064022	0.622497434	0.657085703	-0.006549397
Dow Jones U.S.					
	with changes in debt		without changes in debt		coefficient squared changes in debt
Regression Number	Adjusted R-squared	R-squared	Adjusted R-squared	R-squared	
1	0.020810204	0.02127389	0.020838209	0.020810204	-0.050209833
2	0.022801911	0.02338034	0.022824282	0.023171331	-0.050220183
3	0.041905973	0.042473094	0.041860927	0.042201216	-0.051477809
4	0.411242208	0.41159075	0.409226242	0.409436083	0.07422907
5	0.398132715	0.398489018	0.396364426	0.396578836	0.07672787
6	0.397210171	0.39749565	0.395476004	0.395619155	0.076761317
7	0.264460483	0.264721714	0.263074344	0.263248826	-0.117274849
8	0.313341055	0.313666216	0.300149369	0.300315073	-0.121832905
9	0.314897214	0.315302744	0.311832278	0.312076684	0.058668033
JPX Nikkei 400					
	with changes in debt		without changes in debt		coefficient squared changes in debt
Regression Number	Adjusted R-squared	R-squared	Adjusted R-squared	R-squared	
1	-0.021808041	0.072040955	-0.022970288	0.070365286	3.495192904
2	-0.008454878	0.084473368	-0.009202311	0.083182987	3.085286751
3	0.01405695	0.10491075	0.013666129	0.103957984	2.569039856
4	0.34777978	0.413893467	0.345377856	0.411298458	5.94743283
5	0.238120837	0.315350335	0.230433424	0.307928958	9.340590884
6	0.201439026	0.282120578	0.190864922	0.272075212	10.61204792
7	0.173711246	0.249352108	0.173143349	0.248585559	2.116038371
8	0.208865626	0.281528165	0.20834955	0.280819521	2.034581833
9	0.211962606	0.284579572	0.20834955	0.280819521	6.988410315
S&P Global 1200					
	with changes in debt		without changes in debt		coefficient squared changes in debt
Regression Number	Adjusted R-squared	R-squared	Adjusted R-squared	R-squared	
1	0.027776437	0.116485655	0.027807333	0.116303278	0.015042319
2	0.028293442	0.117060661	0.028324545	0.116878581	0.014801474
3	0.104493724	0.186299904	0.104400438	0.186021266	-0.034241774
4	0.466937925	0.520504348	0.465166083	0.518783199	-0.120626152
5	0.332212564	0.39931729	0.330368097	0.397498716	-0.025924724
6	0.330856156	0.398017516	0.329010375	0.396197215	-0.025870412
7	0.300457923	0.364210973	0.297039045	0.36102759	-0.165138336
8	0.350155733	0.40944989	0.345637232	0.405272848	-0.189306235
9	0.350081859	0.409453101	0.345637232	0.405272848	-0.181973706
S&P Australian Stock Exchange 300					
	with changes in debt		without changes in debt		coefficient squared changes in debt
Regression Number	Adjusted R-squared	R-squared	Adjusted R-squared	R-squared	
1	-0.000192567	0.002560888	0.001058052	0.002433058	0.005341997
2	0.002409901	0.005842764	0.00363633	0.005693516	0.005643374
3	0.037488866	0.040801017	0.038496682	0.040481892	0.005043704
4	0.345545425	0.347799056	0.340533821	0.341896354	0.046914927
5	0.333125612	0.335422011	0.328665261	0.330052316	0.046838722
6	0.332775562	0.334613646	0.328399286	0.329324356	0.046561519
7	0.230997715	0.232585469	0.230990091	0.232048605	-0.008457057
8	0.274437392	0.276434811	0.274410204	0.275908324	-0.008374923
9	0.282319921	0.284789571	0.274410204	0.275908324	0.059795951
TOPIX 1000					
	with changes in debt		without changes in debt		coefficient squared changes in debt
Regression Number	Adjusted R-squared	R-squared	Adjusted R-squared	R-squared	
1	0.015670287	0.016091075	0.015654578	0.015864975	0.276883766

2	0.016109585	0.016635336	0.016116093	0.016431542	0.213219177
3	0.020703934	0.02122723	0.020777853	0.021091807	-0.030751267
4	0.2806459	0.281030334	0.276113881	0.276345995	6.613699439
5	0.277079322	0.277465663	0.272115945	0.272349341	6.908135884
6	0.276683159	0.276992401	0.271590769	0.271746478	6.990219712
7	0.186468687	0.186729518	0.186528728	0.186702602	-0.50663614
8	0.225108545	0.225439802	0.22519136	0.225108545	0.015741274
9	0.228855403	0.229267471	0.22519136	0.225439776	6.348884803

Table 1.12 Regressions' R-squared, adjusted R-squared and coefficient of squared changes in debt.

Policy implication, target readers, and research limitation:

This chapter findings suggests that a portfolio of heavily leveraged firms is more likely to be more profitable in one or two years with respect to overall return of the corresponding index. In addition, the result implies a long-term investing strategy with diversification that can be implemented by investors. As number of studies suggested investing firms that have low level of debt will be profitable and safe. On the other hand, highly, leveraged firm seems to be a risky asset, however this study proves that companies with high level of debt can be as profitable as low or non-leveraged firms. Correspondingly, creating a portfolio that contains companies with extreme changes in debt level will be more profitable and diversified. Annual data for length of 13 years is used in this research. In order to have more comprehensive analysis, larger dataset is required. Additionally, the period under investigation contain data from year 2007 and 2008 which is the period of global financial crisis. Accounting data unlike financial data is harder to find and are quite costly. Furthermore, other alternative to analysis that is conducted in this study, is to create portfolios with the filtering method that is mentioned earlier and performed panel data regression on data of portfolios instead of individual companies. However, that requires much leather data that was available in this study. Lastly the author believe that artificial neural networks or machine learning algorithms may perform better since the patterns between explanatory variable and dependent variable is extremely complex and might be nonlinear.

Conclusions

The contribution of this paper is to introduce a new channel for connecting capital structure to future rate of return. Using the filtering identification technique introduced by Lakonishock et al (1994), this chapter shows that the traditional debt to equity ratio (or debt to value ratio) is not a good predictor of returns. This means markets do not recognize the debt-to-equity ratio as a signal of future performance of the companies.

Our analysis proves that the real capital structure signal is the debt growth rate. Filtering identification method and visual inspection of the graphs provide enough evidence to take this hypothesis to next step. Then through panel regression analysis, the nature of the relationship between the debt growth rate and the future rate of return is discovered. Our findings show a "U-shape" relationship between rate of return and changes in debt by comparing analyzing this variable P-value. The second order relationships implies that large changes of debt level whether positive or negative will lead to positive stock price return in the future. This implies that two groups of companies are expected to beat the market in the following year: first, those which were able to return a significant portion of their debts this year. This is viewed by the market as cash flow strength.

Unlike preceding studies that suggest high leveraged firms will face lower return on its stock price (e.g., add previous study one is fine), this research shows that second group which consist of highly leveraged firms must have enough number of profitable projects in hand to convince the banking system to lend them large amounts of money with respect to their current level of debt (a large debt growth). The robustness of the results then verified.

The effect of US president’s speech on USD Value

Abstract:

FOREX market or foreign currency exchange market is of the largest market in financial industry. Due to longer opening hours and easy accessibility, this market is very liquid and highly volatile. In addition to research that use quantitative modeling of historical data to explain and forecast FX market future behavior, there are other research that aimed to capture the influence of qualitative data such as news or tweets on this market. There is an extensive literature on how new information that is broadcasted by news channels cause abnormal co-movement in most financial markets including FOREX. Topics such as political shocks, election, central bank announcements, and changes in macroeconomic fundamentals are extensively studied in relation to FX market. The aim of this research is to determine whether US president speech which is one of the major events covered by news, has any effect on US dollar exchange rate. In this research value of USD against multiple currencies are analyzed on the day of president public event. Even though graphical representation of exchange rates clearly shows unanticipated behavior during the event, this study finds no significant evidence that United State president’s speech have any impact on market movement when linear algorithms are used to. However more contemporary and powerful models such as Random Forest indicates that the events have significant impact on value of the USD which last for short period of time.

Introduction:

Among all financial markets, foreign exchange market or FOREX (or FX market) is the most popular one with highest trading volume (Y. W. Cheung and M. D. Chinn, 2001). In stock market certain portion of a registered company ownership is exchanged for a price. Similar to stock market, FOREX is a market where x amount of one currency is traded for 1 unit of base currency. Currency exchange rate can also sway other financial assets. for instance, commodities such as oil is only traded by USD, if for any given reason the value of USD against other currencies appreciate (depreciate) even if oil value remain unchanged, it makes it more expensive (cheaper) to buy oil by using other currencies rather than USD. That example can be expanded to any other financial assets. Individual traders, commercial banks, hedging firms, investment firms, and central banks are major parties who benefits from trading in FOREX, even though they are perusing different goals. Market players can be divided in two categories based on their needs. Large traders who are seeking to secure their investments against changes in currency exchange rate. Whereas small trader's aim is to make profit by trading one currency for other one. Regardless of traders' size and needs it is vital to have accurate short-term forecast in order to make profit (M. P. Taylor and H. Allen, 1992). It is worth mentioning that currency appreciation refers to situation where the value of home currency raises against other currency in the market which means more unit of foreign currency is required to be exchanged for one unit of home currency. On the other hand, when currency depreciate, the value of home currency decreases against foreign currency. There are number of factors that can influence currencies prices.

Important Factors for FX Market:

Central banks:

Central bank of each country generally is responsible for printing physical currency note. This mechanism will allow them to control amount of money that is circulating within the country as well as globally. The quantity of money that is available is also referred as money supply. Increasing money supply would cause higher inflation which cause the devaluation of that country's currency against others in FOREX. US Federal Reserve, Bank of England, European Central Bank, Bank of Japan, and Swiss National Bank are example of organizations that have privilege of printing notes and controlling money supply.

Interest rate:

Interest rate is other tool that is at central bank disposal to control economy as well as value of their currency. The interest rate determines cost of borrowing and lending the money. If interest rate sets remarkably high, it will discourage business to borrow money from banks; however, it will encourage investors to invest. This includes investors from aboard. In order to invest in other country, it is required to convert assets into their currency which will result in higher demand and currency appreciation. On the other hand, if interest is low, it will inspire business to apply for loans and expand their operations. Conversely, investors will be seeking to redirect their wealth to countries with higher interest rate and that will cause money depreciation. In addition, traders will have opportunity to borrow from low interest rate regime and deposit in countries which offers higher interest rate.

Economic growth:

It can be argued that economic growth is more important to traders than interest rate. Economic growth measurements such as Gross Domestic Product (GDP), and Consumer Price Index (CPI) normally published by governments every quarter. However, trader would consider independent investment banks reports as well as official reports.

Unemployment:

Another macroeconomic factors that influence investors decision is unemployment rate. High unemployment suggest that particular economy is struggling. In addition to official governmental report, there are several other indicators that address this matter. Non-farm payroll figure and US Labour Department’s report are two important publications that investor pay more attention to.

Inflation:

Increasing the amount of money that is circulating in the economy will result in higher inflation. When inflation raise it will devalue the currency against others. Inflation is one of the most leading factors for treaders to rely on. Similar to stock prices if value of a currency drops the investors or traders will short that certain currency in order to limit their losses. In extreme situations that will lead to further exchange rate reduction. Consumer Price Index (CPI) and Retail Price Index (RPI) are two main indicators of inflation.

Foreign trade:

Volume of import and export of a country will directly impact its currency value. If a country is importing goods or services more than exporting, it will indicate that the economy needs a foreign currency. Therefore, it will increase the supply and drop the demand for that currency. As result the value of the money will decline. On the contrary if export exceed the import, demand for home currency will raise since it is needed by overseas consumer to pay for goods and services which eventually will increase the exchange rate.

National sovereign debt:

Countries borrow from global bond market by issuing government bonds. Treasury in US, bunds in Germany, and gilts in UK are example of bonds name in different countries. In case countries borrow more than their income (tax), countries will be appeared to be in debt, and it will have negative impact on traders’ eyes since it may lead to governments deflating on their loans. In this case investors and traders consider that country’s currency as a risky and will take short position which means they are willing to sell rather than buy. this may lead to depreciation of that particular currency’s value.

Commodities prices:

Majority of commodity contracts are exchanged in Chicago and New York; therefor they are dominated by value of USD. fluctuation of commodity will volatile the US currency and vice versa. Moreover, currency of countries such as Canada and Australia which are major exporter of certain commodity, are highly corelated with commodity prices.

(Fieldhouse, 2012, pp.91–105)

FOREX market movement can be affected by external elements such as macroeconomic factors. Changes or even the rumor of changes in all above-mentioned parameter are broadcasted instantly by news agency. As many researchers stated, scheduled and unscheduled news can have negative or positive impact on FX market. The importance of news announcement, IMF, and political events have been addressed; however, there is lack of literature on presidential effect of FX market. arguably US president is one of most influential political individuals which can cause changes in policies as well as political shock. Moreover, all president deed and words are broadcasted instantly by most of news agencies. In addition, the president can affect the above explained parameters directly or indirectly. For example, the head of federal reserve is appointed by president. If in the presidents make a negative comment about the head of Federal Reserve in one of his speeches it will create speculation about the future of FED which will affect market participant decision. Moreover, president's announcement might improve or weakens the political or economic relationship with other countries which leads to changes in foregone trades, national sovereign debt, inflation or even unemployment. On the other hand, presidential statement can be seen as part of schedule news. Financial markets including FOREX responds to information as well as the speculation of the future information it may receive. The author believes market participant will speculate of what president might say and anticipate its impact before the speech. Later on, after the speech they will adjust their market position according to received information, consequently the content of the speech is not considered. The aim of this research is to prove if US president's speech as an event, regardless of its content have any impact on foreign exchange market. As a naïve example, president trump stated that he will terminate the Ari Force One (US president's airplane) contract with Boeing on 6th of December 2016. That caused 1 percent drop in Boeing share price in the following day (Clements, 2016). Despite the fact that contract was not canceled the information was received by market participant which resulted in decreases in Boeing share price. When a simple sentence of Us president can affect equity market, there is a possibility that his words can influence other financial market such as FOREX. Furthermore, according to NASDAQ official website March 2020 Dow Jones future contracts was facing downward trend however by 12th March 2020 before President Donald Trump started his speech the contract prices gone up by 300 points. However, as the speech started it went into bear market and by the time, he ended his speech the future contracts of Dow Jones dropped by 1000 points. This is a clear indication that president speeches can affect financial markets even though in this particular instance the Dow Jones was not addressed in the speech. Literature by Maligkris (2018) concluded that the speech given by presidential candidates before election is significantly important for market participants. The return of firms that are more dependent on government are more sensitive to candidates' speech since general information of future plans are presented in those speeches.

Looking at previous studies, several similar factors that can influence financial markets including FOREX is extensively investigated. Parameters such as schedule / non-schedule news, Twitter feeds, elections are proven to have significant impact on market participants. However live statement from president was not taken into the consideration. This event can be part of all the variables that studied before. President's speech is broadcasted live which is scheduled news. If a sentence or multiple sentences are very important, it will be reported by news agencies and it will be twitted shortly. And lastly it considered to be a quite important political event. Therefor the author is inspired to take a closer look at this event separately.

Literature review:

There is extensive literature on how news and news announcement can have impact financial market in particular forging exchange marker. Andersen et al. indicted financial market instrument such as currency market are responsive to broadcasted macroeconomic news that is addressing real economic development (2007). Cavusoglu (2010) conducted multiple surveys in similar literature that produced evidence of high correlation between macroeconomic fundamentals and exchange rate behaviour. Various research suggested that negative news, impact financial market in larger magnitude compared to positive news (Andersen et al., 2003; Galati and Ho, 2003; Laakkonen, 2007). In research that organized by Laakkonen (2007) provides evidence that macroeconomic news has impact on volume of trade. Fratzscher (2006) and Laakkonen (2007) concluded that 15% of exchange rate variation is explained by macroeconomics news. In addition to news, statement from organizations such as International Monetary Fund (IMF) and European Central Bank (ECB) is important to market participants. Short-term and long-term effect on EUR/USD exchange rate is captured when ECB publish an official statement on this matter, even if there are no interventions (Fratzscher, 2008). In similar literature Dominguez and Panthaki (2007) argued that FOREX market reacts to rumours of interventions. On the contrary, Jansen and De Haan (2005) suggested that statement of central banks such as ECB have small and short-term effect on EUR/USD exchange rate even if it is merged with news on macroeconomic fundamentals. Correspondingly, Siklos and Bohl (2008) showed that actual changes in interest rate have stronger impact on exchange rate movement compared to verbal communications of European Central Bank. Number of literatures stated that central banks communication in both developed and emerging countries would moderate exchange rate volatility (Fratzscher, 2004; Fišer and Horváth, 2010; Lahaye et al., 2010; Goyal and Arora, 2012). Égert and Kočenda (2014) provided proof that both central bank announcement and macroeconomic news directly affect Central and Eastern European's currency value. However, the magnitude of this factors varies notably before and during crisis periods. It is noted that market responses to central bank communication is significantly stronger during high uncertainty period compared to less volatile time. In similar literature Omrane and Savaşer (2017) argue that nature and time of news is important factor. different type of news in different state of economy such as expansion and recession would influence FX market differently. Statistically significant evidence shows that foreign currency reacts consistently with news positivity or negativity. While positive news regarding a currency would appreciate its value against others, negative news will lower the exchange rate of that currency. However regardless of news delivers positive of negative message to market, it will increase FX market volume (Rognone, Hyde and Zhang, 2020). Even though news can impact both return as well as volatility of FX market, it cannot be accounted for major factors due to low frequency of news. In addition, the information that is provided by news is already captured by market through non-scheduled news (Andersen, Bollerslev, Diebold, and Vega, 2003). Similarly, Evans and Lyons (2008) indicate that macroeconomic news accounts for 30 percent of FOREX daily price variation. News can be divided in to two categories scheduled and non-scheduled. Number of literatures debate that volatility of financial market is much persistent after non-scheduled compared to scheduled news (Dominguez and Panthaki 2006; Ederington and Lee 2001). In addition to announcements, seasonal factors such as market opening time, lunch breaks and US macroeconomics announcements (on Thursday and Friday) increases the volatility (Andersen and Bollerslev 1998). In similar work by Bauwens, Ben Omrane and Giot (2005) stated that volatility of Euro/Dollar increases before scheduled news announcement. This can be due to speculation of traders' perception of what scheduled news announcement would be and how it may affect the market. On the other hand, pre unexpected news announcement period does not carry any excess volatility except rummers of central bank intervention. However scheduled news such as Lehman shock may cause market unpredictable and even crash it which result in global financial crisis (Ochiai and Nacher, 2011). Study that is conducted by Chatrath et al. (2014) analysed the jumps of 5-minutes interval data of four currencies pair and news release. 22% to 56% variation of data were explained by information provided by news. Moreover 9% to 15% of currency jumps are caused by US announcement.

Series of literature stated that foreign exchange market is more responsive to news that is generated form large economies such as U.S. and Europe (Andersen et al., 2003; Cakan, Doytch and Upadhyaya, 2015; Chaboud et al., 2004; Ehrmann and Fratzscher, 2005; Faust et al., 2003; Gilbert et al., 2016; LUCCA and MOENCH, 2015; Savor and Wilson, 2013). Egert and Ko. enda (2014) analysed the effect of macroeconomic news on new member of European Union in two different timeline pre-crisis (2004-2007) and during crisis (2008-2009). The result indicates that in pre-crisis period, market is responsive to many types of macroeconomic news; however, during financial crisis, only key macroeconomic fundamentals such as GDP are critical for market participants.

Kočenda and Moravcová (2018) studied new EU members currency movement in respect to new information of macroeconomics indicators. Exchange rate of Czech koruna, Hungarian Forint, and Polish Zloty against both EURO and USD were analysed (intraday data from 2011-2015) when new information about euro zone/German and U.S. macroeconomic, ECB, and Federal Reserve is broadcasted. Return on exchanges rates against EURO shows unusual behaviour when there is new information is available on Purchasing Managers' Index (PMI), Business Climate Index (by IFO institution), and Gross domestic product (GDP). On the other hand, return of currencies exchange rate pair with USD response to announcement of non-farm payroll (NFP) and Gross domestic product (GDP). In general changes in return is more irregular when currencies are paired with USD compared to EURO. Bad, good, and neutral news were classified by its expected impact on market. The analysis finds that large irregular return which is the result of news announcement are more statistically significant, appear more often, and last longer when currencies are USD denominated compared to EURO.

Hayo and Kutan (2005) analysed financial market's response (such as FOREX, Stock, and bond market) of emerging markets to IMF decision in specific during Brazilian, Russian, and Asian crisis in 1997-1999. The most significant event is IMF delaying loans approval. The result shows that only negative news will impact foreign exchange market return but no implication on volatility. feather more any abnormal losses or gains as a result of IMF event will defused in following day.

News about IMF announcement and decision can send two different massages to market participants. Firstly, the news can shed light on economic situation of a country that was unknown to market before. Secondly it will signal investors about how IMF might react to financial crisis of that country. Unexpected positive IMF related news will rise next day return and conversely negative announcement will decreases return on following day (Evrensel, 2002).

An unfavourable announcement concerning state of a country's economy or delay of loan declaration by International Monetary Fund (IMF) would weaken investors' confidence and damage financial market. In the extreme cases that will lead to promptly and enormously shorting process by investors which will lead to higher volatility and greater damage to financial market.

As Brogaard and Detzel (2015) stated, changes in policy and political shocks can be captured by financial markets. US presidential election is a major event that is watched closely by most of individual around the world that includes traders. This event may stimulate market panic since investors and traders have perception of its outcome and its consequences on financial market (Goodell and Vähämaa, 2013). Correspondingly market experience lower return and higher volatility during election year compared to non-election year. This is due to policy and political intervention of newly elected president may have (Lobo, 1999). In addition, election itself bring uncertainty to financial market. Commonly returns tend to be negative before election and turn to be positive after election (Riley and Luksetich, 1980; Herbst and Slinkman, 1984; Huang, 1985).

Above literatures shed light on the importance of news, politic, and organization such as Fed and ECB to financial market, specially FROEX market. However, there is lack of literature of how (if any) political speech such as US president has on financial market return or volatility.

Data selection:

For the peruses of this research tick data which is highest frequency of data is collected from TrueFx.com. This dataset gives the author opportunity to resample the data to any lower frequency that will suit this chapter's hypothesis. Using single exchange rate for this analysis would be insufficient due to unrelated event that may affect other currency. If one currency pairs such as GBP/USD is used to investigate the correlation of USD value during the presidential speech. There is a possibility that during the days that is included in this study, there might be an abnormal change in the exchange rate due to other external information beside the speech. That will lead to biased analysis. For example, during the day of US president speech, an announcement of bank of England will lead to devaluation of GBP against all other currency. To limit the exposure of these parallel events, additional three exchange rates were taken into consideration. Currency pairs that are used in this analysis are GBP/USD, EUR/USD, USD/CHF, and USD/JPY since they are fairly stable and considered to be the major currencies in FOREX market.

Each president speech last from few minutes to few hours. In order to have enough observation during the event, the only possible solution is to reduce the time frequency of collected data. In other words, decreasing the time distance between each observation within a given period (duration of speech) will provide higher number of observations which leads to improvement of statistical model since they are all data driven. Collecting ultra-high frequency data for FOREX market is quite accessible for two main reasons. Firstly, unlike stock market, FOREX market is open 24 hours a day and five days a week. Secondly, according to IG, 6.6 trillion dollars is traded every single day in FOREX market. Due to high liquidity and longer opening hours, ultra-high frequency data is generated and available from various sources.

In addition to high frequency historical data, information of president speech is required. MillerCenter is neutral associate of University of Virginia that provide large number of political information such as United State presidents’ speech (video, audio, transcript, title, date). The date and title of 55 presidential speeches from 2009 to 2018 were obtained from MillerCenter database. The duration and starting time of each event is the missing piece of the dataset. There are no datasets that provide these two variables therefore they should be gathered manually. The process of obtaining length of each speech and when it started was quite challenging and innovative. Since president speech is a major political event, it is broadcasted live by many news channels such as BBC, CNN, Fox News. Therefore, the video of these events is available at their archive. Moreover, almost ever news agency provide local time at corner of the screen for live broadcast. By watching each video, author could obtain starting time, ending time, and time zone of each speech. Then calculating the duration was a simple task. Finally, to align each speech and market data during the speech time it is necessary to convert all databases to one time zone. The market data is based on GTM time zone. However, each events' starting and ending time are available in time zone where it took place. For instance, on June 4, 2009, President Barack Obama spoke at Cairo University, the video by American cable and satellite television network C-SPAN shows the time in Pacific Time which is 8 hours behind GTM. Therefore, the starting and ending time should be adjusted accordingly.

The author finds Python programming language the most suitable tolls for this analysis for several reason. Firstly, this language provides the best tools (library) to analyse and visuals including Pandas, NumPy, Matplotlib, Statmodels, and scikit-learn. Secondly, Python is simple to use and fast to execute compared to other available software such as EViews or SPSS. Lasty, since the procedures are the same for each currency, once required procedures are coded once, it does not need to be repeated for every dataset.

Methodology:

Visual analysis:

According to MillerCenter there are 55 US presidential speech from 2009 to 2018. To be able to use tick data in statistical modeling, it is necessary to normalize it. Therefore, all data has been resampled to 1 minute interval to have more in depth analysis. For measuring the persistence of the event's effect, two subsamples with different length are generated from available data. First subsample began from one hour before the speech to one hour after speech, and second one consists of data for the entire day of the event. Therefore, for each event, there are two subsamples on every currency pairs. Missing information is part of any data sets that needs to be dealt with carefully. The event that sufficient data is not available, would be eliminated from feature analysis. After elimination process there are 32 speeches available to this research. Plotting each dataset provide important visual insight of exchange rate movement during the event compared to pre-speech and post-speech period. In several instances price movement and volatility demonstrate unusual movement during the speech time.

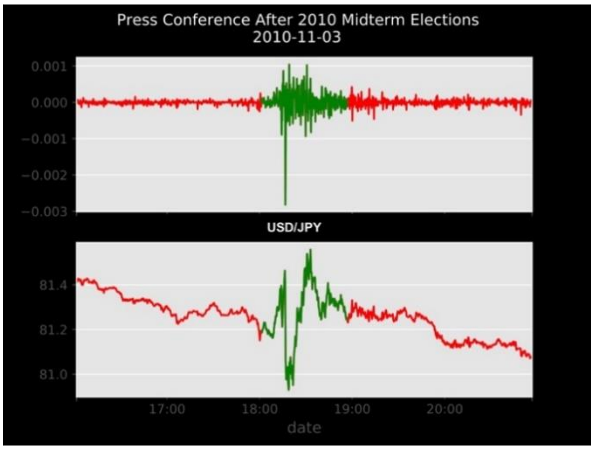


Figure 2.1 USD/JPY 2010/11/03 volatility and price

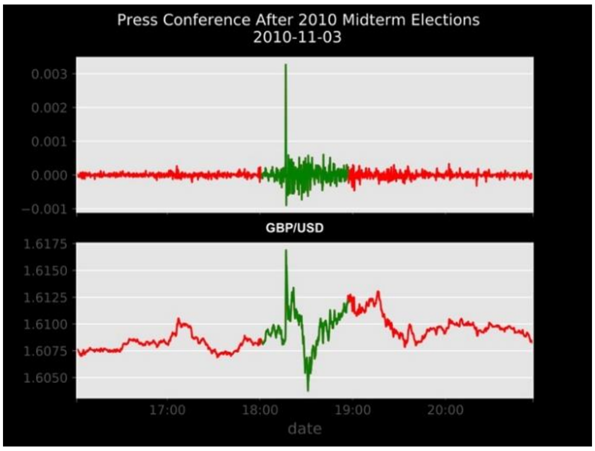


Figure 2.3 GBP/USD 2010/11/03 volatility and price

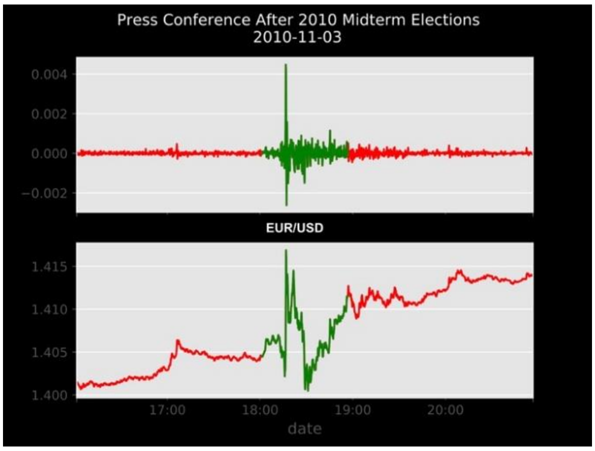


Figure 2.2 EURO/USD 2010/11/03 volatility and price

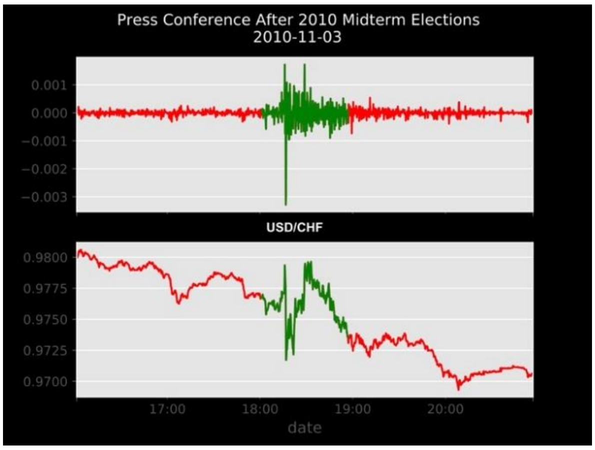


Figure 2.4 USD/CHF 2010/11/03 volatility and price

The above figers reveals important information of how market may responses to president speech. Each figure contians two subplots where the upper one presents the volatility and lower plots show the exchange rate movements. Speech time is highlighted by green area and red part of plot is befor or after the speech. All four currencies exchange rate exabit unusal upward and downward movement in price as well as large volatility during press conference after 2010 midterm election (03/11/2010). In addition it can be noticed that how market is quiet before and after the speech. Visualy it can be noticed that market participants have shown reaction to this event. Comparing volatility and trend in price before and ofter the speech market was stable in both sence before the event. As the speech initiated, market starts to became highly voltaile and price trend shows large random movement and gose back to normal as events ended. The behaviure cannot be a coinsidence as it can be seen in other example.

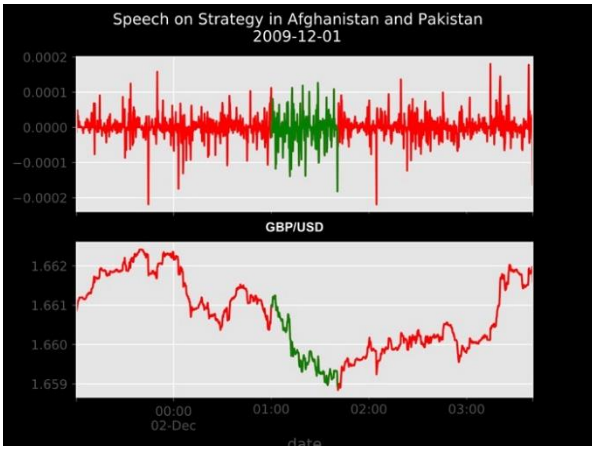


Figure 2.5 GPB/USD 2009/12/01 volatility and price

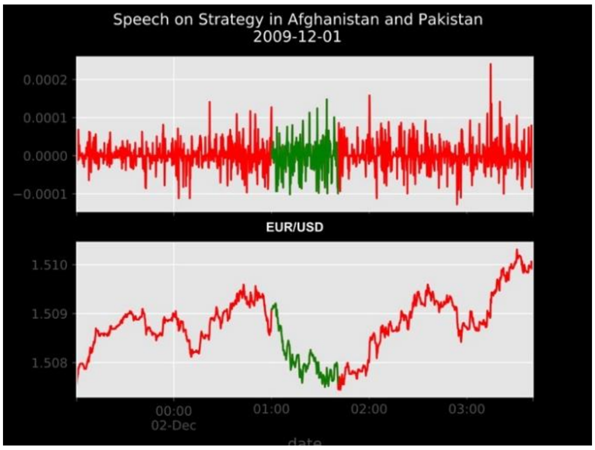


Figure 2.7 EUR/USD 2009/12/01 volatility and price

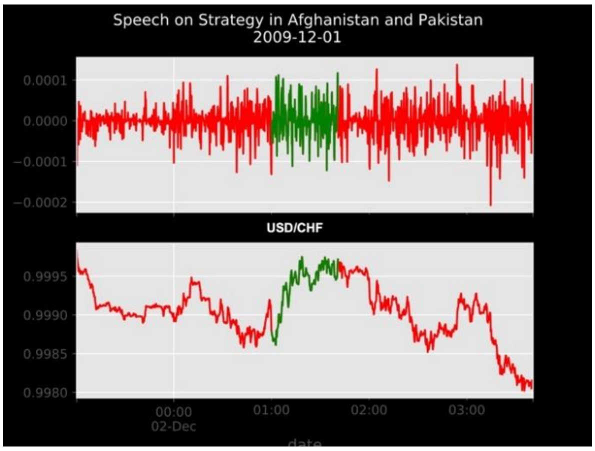


Figure 2.6 USD/CHF 2009/12/01 volatility and price

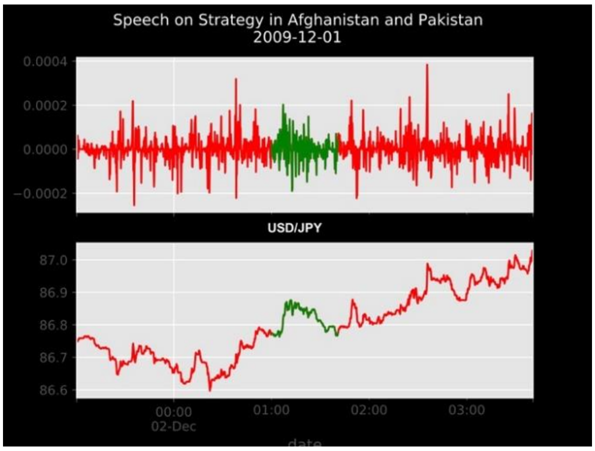


Figure 2.8 USD/JPY 2009/12/01 volatility and price

The other noticeble behaviure present during speech on strategy in Afghanistan and Pakistan on 01/12/2009. For pairs that is USD denominated, price exhabit downward trend and on USD/CHF the trend is upward. That indicated value of USD is appriciated compare to other three currencies. In addition, the trend direction switch to opposite direction briefly after the event. There is no obvious pattern in volatility amoung four datasets. USD/JPY exchange rate is rasing before and after the speech, however during the speech price show downward movement. This inconsistency might be due to changes in some factors that couse Japanees yen to depressiate against USD.

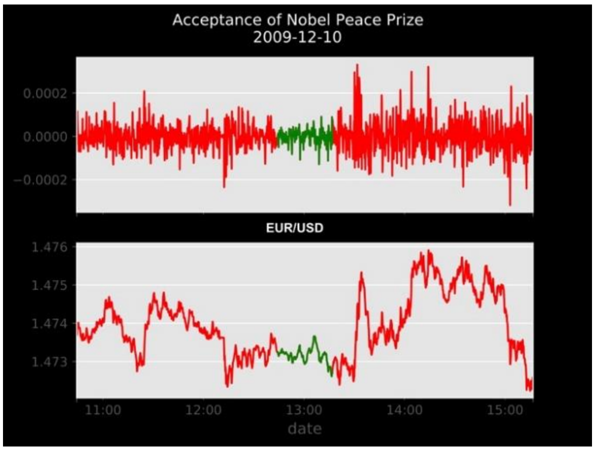


Figure 2.9 EUR/USD 2009/12/10 volatility and price

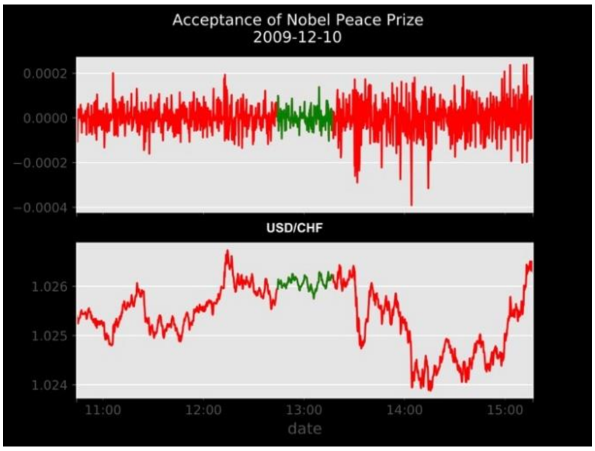


Figure 2.11 USD/CHF 2009/12/10 volatility and price

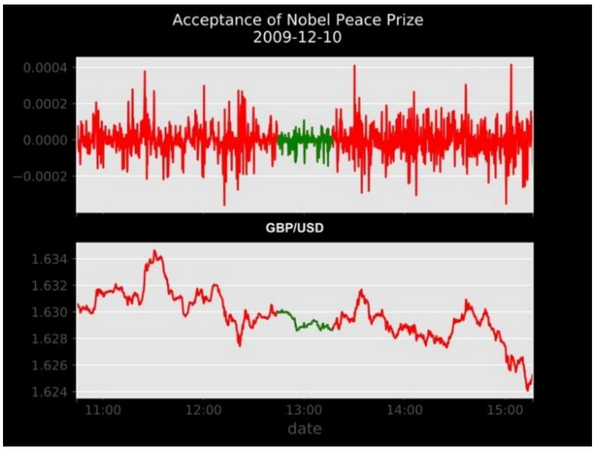


Figure 2.10 GBP/USD 2009/12/10 volatility and price

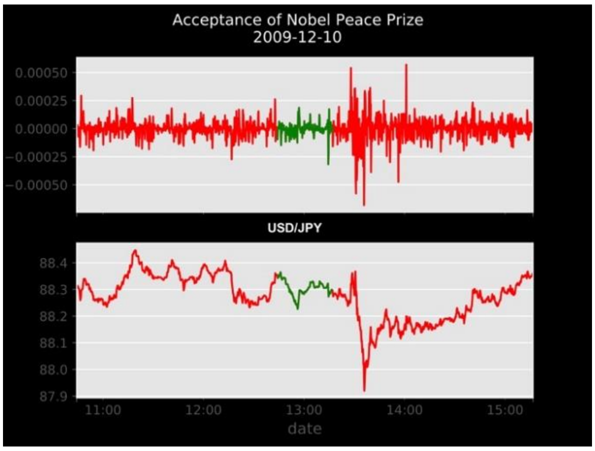


Figure 2.12 USD/JPY 2009/12/10 volatility and price

On 10th of December 2009 President Barack Obama awarded the Nobel Peace Prize and delivered a speech. Even the title of speech is not related to financial industry as well as macroeconomic fundamentals, it had influenced FOREX market noticeably. During the speech price show steady flat movement for all exchange rates. In term of volatility, it can be seen that there is massive drop as President start his speech and as soon as the event finishes market volatile increases tremendously even more than period before the event.

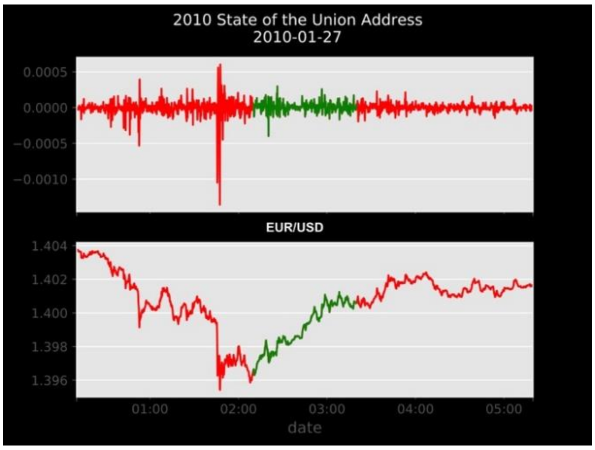


Figure 2.13 EUR/USD 2010/01/27 volatility and price

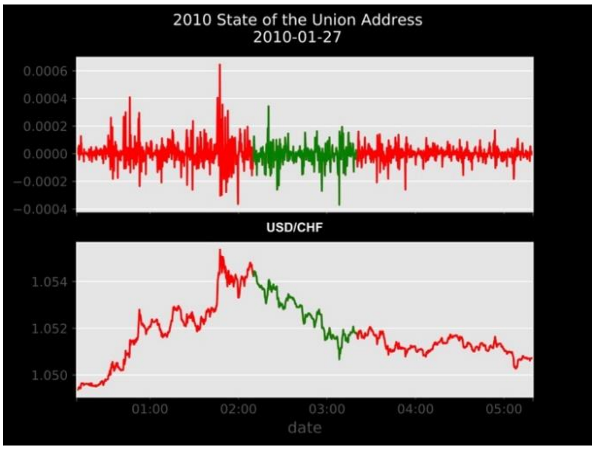


Figure 2.15 USD/CHF 2010/01/27 volatility and price

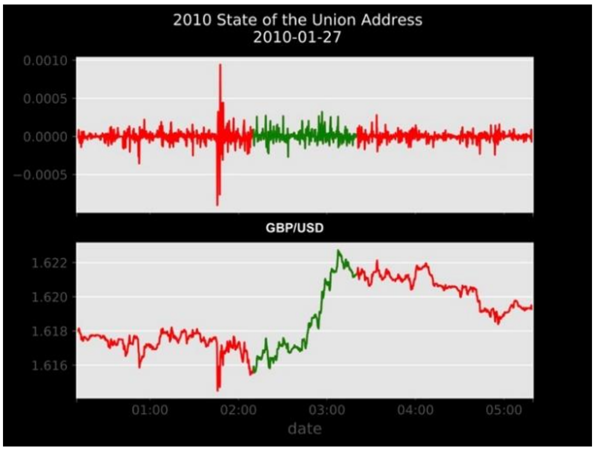


Figure 2.14 GBP/USD 2010/01/27 volatility and price

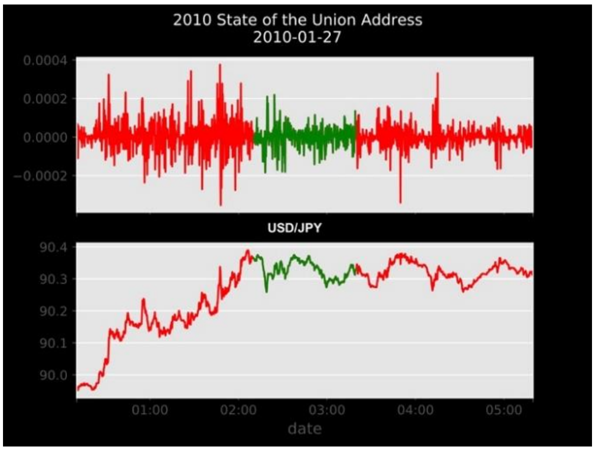


Figure 2.16 USD/JPY 2010/01/27 volatility and price

State of the Union speech by President Barak Obama have significant impact on United State dollar value. USD depreciated against all four currency that is used in this analysis while President was speaking. That can be noticed by upward movement in GPB/USD, EUR/USD and opposite direction in USD/CHF, USD/JPY. In all four cases the direction of price has changed as the speech started. Other obvious fact that can be observed is large uncertainty right before the speech. All currencies have experience neuromas increase in volatility just before President start his speech. The further analysis can uncover what is been said during this event that made market participant to devalue USD, but that is beyond the scope of this research. Appendix B provides individual graphs for each currency at the time for individual events.

Statistical Models:

Autoregressive model:

As these examples suggest, President words can manipulate US dollar value. It can change the trend of exchange rate as well as level of market uncertainty. However visual analysis is not sufficient to prove this hypothesis. Therefore, this assumption should be tested and analyzed by statistical model. In order to test this assumption author used Autoregressive and Autoregressive model (AR) with exogenous variables or known as ARX. Even though AR model is one of the capable methods that is widely used, the author implemented other models such as ARMA and ARMA-GARCH model. However, the result of AR (1) model is more promising, therefore the outputs of Autoregressive (1) model is presented in this study.

AR model:

Autoregressive is process of regressing independent at time T variable by past values. Number of past values use in AR process is call order of the model and denoted by letter p (Gujarati, 2011, pp.257–259).

$$Y_t = \sum_{i=1}^{p} \beta_0 + \beta_i Y_{t-i} + \epsilon_{t-1}$$

Equation 2.1 Autoregressive model

AR model with exogenous variables:

$$Y_t = \sum_{i=1}^{p} \beta_0 + \beta_i Y_{t-i} + \emptyset X_t + \epsilon_{t-i}$$

Equation 2.2 Autoregressive model with extra variable

exogenous variable is extra external variable that is added to model. For the prepose of this research exogenous variable is dummy variable which takes of 1 for observation at the time of speech and 0 otherwise.

One of the requirements of AR model is that underling data should be stationary process which described best by Gujarati (2011, pp.257–259) “Broadly speaking, a time series is stationary if its mean and variance are constant over time and the value of covariance between two time periods depends only on the distance or gap between the two periods and not the actual time at which the covariance is computed"

There are number of tests that can determine if the time series data is stationary or not. Dickey-Fuller test is used to define stationarity of the underlying data before applying it to AR model. In general time series of prices is not showing stationary behavior, however log-return is stationary.

Precent changes of return:

$$r_{ptc} = \frac{P_t - P_{t-1}}{P_{t-1}} * 100$$

Equation 2.3 percentage changes in price

Log return:

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right) = \log(P_t) - \log(P_{t-1})$$

Equation 2.4 logarithmic return

Even though AR model is one of most studied and promising method to evaluate time series data especially financial data, it come with few limitations. The main important cons of algorithms such as AR is being linear. The linear models attempt to solve the problem in simplest form possible which is not the optimal way always. The more modern models such as machine learning and deep learning models overcome the limitations of linear models. They are more computationally expensive, and more complex in nature; however, they produce higher accuracy since they are not bounded to linearity.

Random Forest:

Similar to other machine learning algorithm such as support vector machine, and k nearest neighbor, Random Forest exhibit powerful ability to accomplish task with great accuracy. Regression models attempt to estimate the value of Y is based on one more input variable X.

Similarly, in the machine learning Target variable is estimated and features are inputs that algorithm uses. In order to understand Random Forest model, Ensemble Learning and Decision Tree algorithm should be explained.

Decision Tree:

The decision tree algorithm is a supervised learning model that used for both classification and regression purposes. Through sets of questions that then only can be true of false the model chooses it next question to the point where an output can be generated. The process of decision tree model is quite similar to the game of twenty questions. The major issue of this model is overfitting (explained in chapter 3).

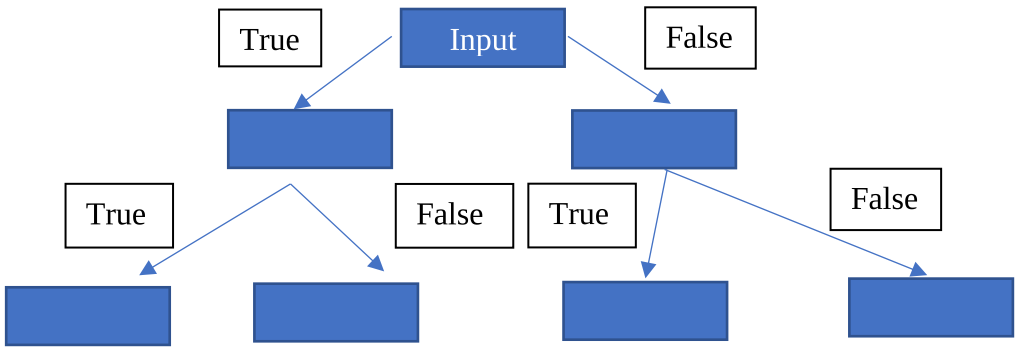


Figure 2.17 decision tree

Ensemble Learning:

In most cases one single model is not sufficient enough to accomplish a task accurately. Therefore, combining multiple algorithms and to solve one problem would be a better solution. The concept of using more than one model parallel to each other for one task is called Ensemble learning.

The Random Forest model is an ensemble learning method which is consists of multiple decision trees model running in parallel. As it mentioned earlier a single tree model might overfitted which leads to unrealistic output. However, if collection of decision trees evaluates the given task (in this case modeling logarithmic return of exchange rates based on its previous values) by taking the average of all trees output, more reliable result can be produced. In other words, a single tree might be overfitted, but it is less probable that number of trees suffer from this problem. Therefore, the average result of multiple trees will rectify the overfitting issue.

Augmented Dickey–Fuller test is more comprehensive version of Dickey-Fuller test. This test examines the presents of unit root or stationarity of given time series by following formula.

$$y_t = c + \beta t + \alpha y_{t-1} + \phi_1 \Delta Y_{t-1} + \phi_2 \Delta Y_{t-2} \ldots + \phi_p \Delta Y_{t-p} + + e_t$$

Equation 2.5 Augmented Dickey–Fuller test

In the above regression the α is determinative factor. If α is less than confidence interval (1%, 5%, or 10%), the null hypothesis can be rejected, and the given time series is stationary. To able to use linear models such as Autoregressive, the underlying data should be stationary. The logarithmic return of exchange rates is tested by ADF for presents of unit root. Tables below presents the P-value of α for all datasets under study.

topic	adfuller_EURUSD	adfuller_GBPUSD	adfuller_USDJPY	adfuller_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	1.03884E-12	4.31354E-15	0.000472228	1.49071E-13
Speech on Strategy in Afghanistan and Pakistan	4.11E-21	3.04358E-20	1.67914E-15	1.53667E-13
Acceptance of Nobel Peace Prize	9.19605E-07	4.47149E-14	2.03604E-14	1.77487E-07
2010 State of the Union Address	2.88483E-14	6.91275E-25	2.1564E-20	8.63169E-14
Remarks on Space Exploration in the 21st Century	1.41902E-14	9.57705E-13	2.14384E-07	5.06619E-14
Remarks on Wall Street Reform	1.18375E-14	1.14987E-06	0.004018213	1.83137E-15
Speech on the BP Oil Spill	1.45788E-10	2.30656E-11	6.36551E-06	2.87037E-11
Address on the End of the Combat Mission in Iraq	1.25985E-10	5.90227E-11	1.59116E-06	0.039715936
Address to the United Nations	1.15913E-14	1.53406E-05	1.27526E-23	4.37025E-17
Press Conference After 2010 Midterm Elections	2.67182E-14	5.06771E-19	6.89633E-07	6.73536E-14
Remarks at Memorial for Victims of the Tucson, AZ Shooting	9.05504E-14	9.97985E-05	1.40508E-16	7.18086E-19
2011 State of the Union Address	3.52592E-05	2.85729E-21		
Remarks on the Death of Osama Bin Laden	1.13496E-08	3.32231E-13	1.3205E-12	1.85166E-08
Speech on American Diplomacy in the Middle East and North Africa	1.05358E-21	2.6907E-15	5.25577E-19	2.43417E-16
Address to the British Parliament	3.97112E-19	2.63583E-18	5.65829E-20	6.06769E-20
2012 State of the Union Address	2.55046E-06	1.81835E-19	2.28132E-18	1.17246E-05
2012 Election Night Victory Speech	1.99285E-12	1.72364E-12	1.9432E-15	9.71858E-16
Remarks on Immigration Reform	1.42695E-10	5.77018E-24	6.85231E-21	1.65436E-10
2013 State of the Union Address	7.83224E-17	5.06023E-17	2.12179E-15	8.40745E-24
Address to the People of Israel	7.32103E-18	4.68898E-13	6.22169E-22	4.62571E-12
Remarks on Education and the Economy	6.30898E-21	4.5069E-05	7.88529E-22	1.10252E-10
Address to the Nation on Syria	9.67631E-09	2.69452E-09	8.4306E-16	6.75327E-15
Speech on Economic Mobility	7.73244E-13	4.06689E-17	2.38654E-15	4.3433E-15
2014 State of the Union Address	0.002606495	1.3261E-20	1.03839E-25	5.26461E-16
2015 State of the Union Address	2.37431E-05	1.43982E-20	4.33111E-13	2.97647E-07
2016 State of the Union Address	4.35823E-20	2.36967E-17	1.23515E-20	2.57685E-11
Remarks to the People of Cuba	9.78173E-17	0.010130453	2.28187E-15	5.50343E-13
Address to Joint Session of Congress	5.29367E-19	5.33352E-20	5.74713E-22	2.05248E-13
Speech at the Unleashing American Energy Event	1.45611E-14	1.4264E-22	7.99949E-09	6.6151E-17
Address to the United Nations General Assembly	1.32166E-05	3.67027E-18	1.05802E-21	8.86598E-06
State of the Union Address	5.02948E-19	3.09975E-05	8.45442E-23	1.30043E-22
Remarks at the House and Senate Republican Member Conference	6.66692E-15	0.030212326	2.65545E-13	3.4562E-19
Â Statement on the School Shooting in Parkland, Florida	2.24484E-12	6.47801E-06	3.89206E-10	5.80382E-11

Table 2.1 P-value of Augmented Dickey–Fuller test 60 min ± speech duration

topic	adfuller_EURUSD	adfuller_GBPUSD	adfuller_USDJPY	adfuller_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	3.43504E-12	0	0	2.19324E-25
Speech on Strategy in Afghanistan and Pakistan	0	0	0	1.13112E-12
Acceptance of Nobel Peace Prize	0	1.08593E-27	3.91191E-29	0
2010 State of the Union Address	1.05133E-18	1.1351E-18	0	0
Remarks on Space Exploration in the 21st Century	0	0	0	0
Remarks on Wall Street Reform	6.63512E-30	3.61944E-30	0	7.85055E-26
Speech on the BP Oil Spill	0	0	1.18257E-22	0
Address on the End of the Combat Mission in Iraq	0	0	5.15864E-18	7.02666E-25
Address to the United Nations	0	2.55588E-13	0	0
Press Conference After 2010 Midterm Elections	1.43069E-16	1.44849E-21	1.14941E-10	5.06777E-16
Remarks at Memorial for Victims of the Tucson, AZ Shooting	0	0	3.95736E-14	0
2011 State of the Union Address	1.65573E-26	0		
Remarks on the Death of Osama Bin Laden	7.85565E-11	0	8.72571E-19	9.25632E-11
Speech on American Diplomacy in the Middle East and North Africa	5.28316E-22	0	1.06549E-13	0
Address to the British Parliament	1.14378E-18	0	5.7321E-19	1.76001E-11
2012 State of the Union Address	0	0	1.55077E-08	6.68126E-30
2012 Election Night Victory Speech	0	0	0	0
Remarks on Immigration Reform	0	0	0	4.95766E-30
2013 State of the Union Address	1.07395E-29	1.79427E-17	1.58024E-28	0
Address to the People of Israel	0	2.87154E-24	1.01526E-17	0
Remarks on Education and the Economy	2.57432E-30	4.6443E-22	6.54715E-30	1.08759E-25
Address to the Nation on Syria	0	2.31447E-21	1.70928E-29	2.11787E-30
Speech on Economic Mobility	2.97208E-13	1.14806E-27	2.4225E-18	6.37613E-14
2014 State of the Union Address	3.06962E-09	1.7124E-27	1.21698E-10	4.50969E-17
2015 State of the Union Address	4.13483E-14	4.17205E-14	5.15567E-19	0
2016 State of the Union Address	0	0	0	7.93782E-23
Remarks to the People of Cuba	0	2.03737E-30	0	1.15101E-09
Address to Joint Session of Congress	0	1.86935E-22	6.3485E-24	0
Speech at the Unleashing American Energy Event	0	0	1.31056E-22	5.79429E-29
Address to the United Nations General Assembly	2.03086E-29	5.02082E-23	3.72749E-20	0
State of the Union Address	0	0	0	0
Remarks at the House and Senate Republican Member Conference	0	0	0	3.52536E-15
Â Statement on the School Shooting in Parkland, Florida	0	0	0	0

Table 2.2 P-value of Augmented Dickey–Fuller test the day of speech

Table 2.1 and 2.2 presents the P-value of ADF test for each dataset. As it can be noticed that the logarithmic return of all subsets is lower than 0.05 and in some cases in equal to zero. Therefore, the null hypostasis of ADF can be rejected and the available data (logarithmic return) is stationary hence it is suitable for linear regression analysis.

Two autoregressive model is applied on each subset. First model is AR (1), and second model is AR (1) with dummy variable (speech variable). By comparing the R-squared, Mean Squared Error of these two models it can be seen if dummy variable had any input in to explaining the variation of log-return. In this study 32 events have been studied. The data is collected on 4 currency pairs with two different lengths. On each dataset two AR model are applied. Therefore, in total 512 regression report is available for further evaluation.

Regression analysis on the datasets with length of 2 hours plus speech duration implies dummy variable improves the model. the higher R-squared and lower MSE is proving that speech variable is affecting the log-return.

Model / Data	r2_with_EURUSD	r2_with_GBPUSD	r2_with_USDJPY	r2_with_USDCHF
Maximum	9.98530464	11.04351432	12.96752073	9.556709035
Minimum	0.074684242	-20.2535073	0.040511345	-10.44499144
Mean	2.431172102	2.378140525	2.926462981	1.374550106
Model / Data	r2_without_EURUSD	r2_without_GBPUSD	r2_without_USDJPY	r2_without_USDCHF
Maximum	6.846698288	10.95575908	9.073479036	8.64487006
Minimum	-0.322423465	-14.76750658	0.001229448	-11.46443361
Mean	1.383136032	1.532245382	1.758116732	0.731372701

Table 2.3 Maximum, minimum, and average of R-squared grouped by currency and model, 60 min ± speech duration

Table 2.3 is summary models' R-squared of datasets with shorter period. In addition to model improvement, the output suggests that at AR (1) with or without exogenous variable is not strong model. The maximum R-squared achieved is 13%. On average 1 to 3 percent of the variation in logarithmic return can be explained by Autoregressive model. please see appendix C for each individual results. Out of 256 regressions only in 7 instances the fitness of the model is not improved by adding the speech variable.

Model / Data	mse_with_EURUSD	mse_with_GBPUSD	mse_with_USDJPY	mse_with_USDCHF
Maximum	3.91624E-06	1.25335E-06	1.08486E-06	2.06855E-06
Minimum	8.08912E-09	5.35865E-09	1.28636E-08	5.00616E-09
Mean	1.8069E-07	9.57537E-08	1.22097E-07	1.24084E-07
Model / Data	mse_without_EURUSD	mse_without_GBPUSD	mse_without_USDJPY	mse_without_USDCHF
Maximum	3.92255E-06	1.2572E-06	1.08661E-06	2.06869E-06
Minimum	8.16658E-09	5.11419E-09	1.31387E-08	5.05237E-09
Mean	1.81535E-07	9.65675E-08	1.22949E-07	1.24493E-07

Table 2.3 Maximum, minimum, and average of MSE grouped by currency and model, 60 min ± speech duration

The comparison of the MSE is addition evidence that dummy variable improves the accuracy of the model. The output indicates that including the speech variable will lead to lower Mean Squared Error.

Similarly, regression analysis on the entire day of the presidents' speech shows that dummy variable improves the AR (1) model. The R-squared increases and Mean squared Error decreases with extra independent variable.

Model / Data	r2_with_EURUSD	r2_with_GBPUSD	r2_with_USDJPY	r2_with_USDCHF
Maximum	3.231037689	3.283586642	3.177269992	1.539516879
Minimum	0.015239634	0.001024331	0.005145196	0.006292786
Mean	0.384824752	0.392900341	0.350256938	0.333270666
Model / Data	r2_without_EURUSD	r2_without_GBPUSD	r2_without_USDJPY	r2_without_USDCHF
Maximum	2.951318007	3.161023283	3.168197491	1.394316088
Minimum	0.002445037	0.0002504	5.60594E-05	3.75915E-08
Mean	0.313506175	0.326463848	0.288161089	0.278185916

Table 2.4 Maximum, minimum, and average of R-squared grouped by currency and model, the day of speech

Model / Data	mse_with_EURUSD	mse_with_GBPUSD	mse_with_USDJPY	mse_with_USDCHF
Maximum	3.91624E-06	1.25335E-06	1.08486E-06	2.06855E-06
Minimum	8.08912E-09	5.35865E-09	1.28636E-08	5.00616E-09
Mean	1.8069E-07	9.57537E-08	1.22097E-07	1.24084E-07
Model / Data	mse_without_EURUSD	mse_without_GBPUSD	mse_without_USDJPY	mse_without_USDCHF
Maximum	3.92255E-06	1.2572E-06	1.08661E-06	2.06869E-06
Minimum	8.16658E-09	5.11419E-09	1.31387E-08	5.05237E-09
Mean	1.81535E-07	9.65675E-08	1.22949E-07	1.24493E-07

Table 2.5 Maximum, minimum, and average of MSE grouped by currency and model, the day of speech

In the larger datasets only one regression report implies that dummy variable will lead to lower model fitness. However, model presents even less strength compared to smaller subsamples. On average the AR (1) model can reach 0.3 to 0.4 percent in R-Squared with maximum of 3.3%. This means that linear model including or excluding dummy variable is not a powerful tolls for explaining variation of log-return give the available datasets.

For further analysis the P-value of speech variable should be taken into consideration.

The P-value of the dummy variable or any other independent variable is a measurement that determine whether the variable is statistically significant or not. If P-value is less than confidence interval the variable is significant which means it has input in explaining the variation in response variable. The obtain result provide evidence that p-value of the exogenous variable for majority of the regressions whether on 1 day data or 2 hours data, is not statistically significant. It can be concluded that linear regressions such as AR (1) cannot capture the effect of the president speech on USD value in FOREX market.

topic	pvalues_EURUSD	pvalues_GBPUSD	pvalues_USDJPY	pvalues_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	0.87838736	0.328808214	0.290750862	0.837586748
Speech on Strategy in Afghanistan and Pakistan	0.101656792	0.044546645	0.311534046	0.129216589
Acceptance of Nobel Peace Prize	0.578644693	0.591124483	0.938179146	0.593922364
2010 State of the Union Address	0.219567014	0.170038932	0.32033925	0.273555082
Remarks on Space Exploration in the 21st Century	0.993705908	0.568412648	0.552779403	0.924489122
Remarks on Wall Street Reform	0.889920796	0.240576439	0.745367147	0.695336312
Speech on the BP Oil Spill	0.007716349	0.246464807	0.640254986	0.362048904
Address on the End of the Combat Mission in Iraq	0.236352308	0.686081066	0.335006313	0.407835755
Address to the United Nations	0.456496444	0.967254588	0.029006447	0.693624329
Press Conference After 2010 Midterm Elections	0.862909242	0.748598818	0.839327978	0.958388807
Remarks at Memorial for Victims of the Tucson, AZ Shooting	0.266267846	0.472990271	0.660676955	0.423859931
Remarks on the Death of Osama Bin Laden	0.751866785	0.44879826	0.648006729	0.805341019
Speech on American Diplomacy in the Middle East and North Africa	0.627693564	0.750852393	0.476097584	0.638798758
Address to the British Parliament	0.079024182	0.1458121	0.040236827	0.435468716
2012 State of the Union Address	0.075511796	0.415665475	0.101216745	0.101062307
2012 Election Night Victory Speech	0.913335736	0.569944535	0.221547578	0.888866727
Remarks on Immigration Reform	0.346497475	0.791402657	0.359781322	0.312192976
2013 State of the Union Address	0.658285672	0.885121922	0.4024621	0.649174597
Address to the People of Israel	0.398808018	0.793383024	0.060487445	0.696524302
Remarks on Education and the Economy	0.543222059	0.600485547	0.391932474	0.2803367
Address to the Nation on Syria	0.53075586	0.762374195	0.084623576	0.412456025
Speech on Economic Mobility	0.616074548	0.878924252	0.366706746	0.973190478
2014 State of the Union Address	0.843083893	0.72394908	0.22179976	0.664542985
2015 State of the Union Address	0.939641848	0.624990534	0.905292729	0.871748203
2016 State of the Union Address	0.180231912	0.112820848	0.953086765	0.274912974
Remarks to the People of Cuba	0.198919665	0.111459438	0.051789233	0.283648545
Address to Joint Session of Congress	0.203662625	0.076535264	0.874695059	0.101537602
Speech at the Unleashing American Energy Event	0.751267281	0.885740907	0.945944189	0.883889494
Address to the United Nations General Assembly	0.303974125	0.003968409	0.719410076	0.094977869
State of the Union Address	0.469505221	0.827380962	0.623378367	0.65623514
Remarks at the House and Senate Republican Member Conference	0.731673134	0.650474731	0.288937234	0.919424247
Â Statement on the School Shooting in Parkland, Florida	0.664176027	0.910482564	0.861035636	0.841351027

Table 2.6 P-value of speech variable, 60 min ± speech duration

topic	pvalues_EURUSD	pvalues_GBPUSD	pvalues_USDJPY	pvalues_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	0.730668894	0.502343824	0.142311286	0.82039484
Speech on Strategy in Afghanistan and Pakistan	0.25186048	0.305626559	0.818187389	0.355515971
Acceptance of Nobel Peace Prize	0.789759015	0.729091142	0.642881266	0.872370515
2010 State of the Union Address	0.009909779	0.003344387	0.892548367	0.024021426
Remarks on Space Exploration in the 21st Century	0.881646488	0.91440474	0.985753091	0.93348662
Remarks on Wall Street Reform	0.808451642	0.73458141	0.905808833	0.848842481
Speech on the BP Oil Spill	0.378337147	0.486391166	0.775900353	0.87406049
Address on the End of the Combat Mission in Iraq	0.392431568	0.719798422	0.664767694	0.820897524
Address to the United Nations	0.07311802	0.556919943	0.271604472	0.666096731
Press Conference After 2010 Midterm Elections	5.11268E-05	0.001896622	0.418920091	0.000334208
Remarks at Memorial for Victims of the Tucson, AZ Shooting	0.465075725	0.902934816	0.980369286	0.983554742
Remarks on the Death of Osama Bin Laden	0.749752188	0.665647295	0.352388671	0.796466895
Speech on American Diplomacy in the Middle East and North Africa	0.8189778	0.718564848	0.642909264	0.831624621
Address to the British Parliament	0.548550821	0.291642671	0.272714561	0.559857432
2012 State of the Union Address	0.742911141	0.9237057	0.257882081	0.708104935
2012 Election Night Victory Speech	0.674353519	0.900380454	0.805084886	0.782217718
Remarks on Immigration Reform	0.723103353	0.96295151	0.502773484	0.455649557
2013 State of the Union Address	0.946116296	0.847176161	0.950918578	0.935847289
Address to the People of Israel	0.312742563	0.972443445	0.121934315	0.668256313
Remarks on Education and the Economy	0.541893621	0.483261226	0.367203692	0.588951439
Address to the Nation on Syria	0.865668845	0.969282346	0.180147717	0.745443963
Speech on Economic Mobility	0.069254852	0.131630014	0.000294704	0.04255799
2014 State of the Union Address	0.875444259	0.99824107	0.985499885	0.810501667
2015 State of the Union Address	0.988510914	0.987610432	0.683912177	0.976706196
2016 State of the Union Address	0.57557967	0.57012025	0.805583238	0.711039219
Remarks to the People of Cuba	0.969060821	0.286931385	0.566315228	0.645759313
Address to Joint Session of Congress	0.000749529	0.000138139	0.260875075	0.001809956
Speech at the Unleashing American Energy Event	0.952992256	0.970243598	0.938818183	0.981876344
Address to the United Nations General Assembly	0.431753191	0.358484979	0.418569838	0.204443082
State of the Union Address	0.09647881	0.429292357	0.104210337	0.026937092
Remarks at the House and Senate Republican Member Conference	0.80347716	0.74320379	0.624163727	0.830302283
Â Statement on the School Shooting in Parkland, Florida	0.731627829	0.934141453	0.921794936	0.727422036

Table 2.7 P-value of speech variable, the day of speech

There are 12 cases where live president's words effected the market value of USD in 2 hours timeline. Similarly, when sample size is expanded to entire one day this number increases to 15. Therefore, out of 512 regressions only 27 regressions show statistically significant dummy variable.

The above results need further investigation. The visual inspection of the data indicates that there are significant changes in the value of USD during every president speech, and it cannot be coincidental. On the other hand, the presented P-value of speech variable is not significant in majority of cases. Therefore, another model should be applied test this chapter's hypothesis.

Random Forest is one of many supervised machine learning techniques that achieves exceptional accuracy in both classification as well as regression tasks. Several studies suggest that Random Forest perform as well as or even outperform the other algorithms such as Support Vector Machine and artificial neural network. (Vijh et al., 2020) performed a comparison between Artificial Neural Network and Random Forest model. in their research five major companies' stock price was forecasted of 10 years. They concluded that model efficiently performed. Even though the Artificial Neural Network is more accurate the difference is negligible. In similar line of work (Polamuri et al., 2019) evaluated the accuracy of Support Vector Machine, Decision Tree, Random Forest, and Linear Regression. Their work indicates that the Random Forest achieved highest accuracy among other models. Therefore, the author decided to implement Random Forest technique to investigate further this chapter's hypothesis. Both R-squared and Mean Squared Error can be calculated for this model; However, since this is not a regression method there is no P-value available to evaluate the relevance of the speech variable. On the other hand, the random forest calculates the importance of each input variable. The importance of the input variable is always sums to one or 100%. In other words, having one variable to estimate the value of Y, the feature importance would be 1, however if there are more than one the importance of each independent variable will be calculated in percentage and the sum of this value will be equal to 1. If there are more than one feature and one of them is not relevant the feature importance will be simple equal or close to zero. Similar to AR (1) model, two Random Forest is applied to each data sets. The first model is a Random Forest based on lag 1 value of Logarithmic return, and the second model receives both lag 1 log-return and dummy variable. If the R-squared increases and MSE decreases by adding the dummy variable it can be concluded that the model has been improved, therefore the speech had significant impact on USD value. To assess the hypothesis more the feature importance is calculated to measure the magnitude of this impact. Lastly the comparison of the output for 2 hours datasets and 1-day datasets provide the evidence of how long this effect lasted.

Model/ Data	Maximum	Minimum	Mean
r_squared_with_EURUSD	81.17353	59.10452	71.6968
r_squared_without_EURUSD	82.04769	55.11665	67.43399
r_squared_with_GBPUSD	81.47592	54.12973	69.92151
r_squared_without_GBPUSD	76.51212	44.50886	64.68104
r_squared_with_USDJPY	80.23773	53.15404	70.93594
r_squared_without_USDJPY	78.70936	46.01131	67.26755
r_squared_with_USDCHF	82.84947	52.35103	71.69707
r_squared_without_USDCHF	79.01223	47.48386	67.84596

Table 2.8 R-squared, 60 min ± speech duration

The table above is the summery of the Random Forest fitness which is significantly higher than linear regression with or without the dummy variable in 2 hours window. In addition, the RF model can explain 4 to 5 % more variation of log-return when the dummy variable is added. This is evidence that president speech has some influence on value of USD. One average the model that has two input variables can reach around 70 percent R-squared with maximum of 83%, whereas the simpler model on average can explain 65 to 70 percent variation in log-return.

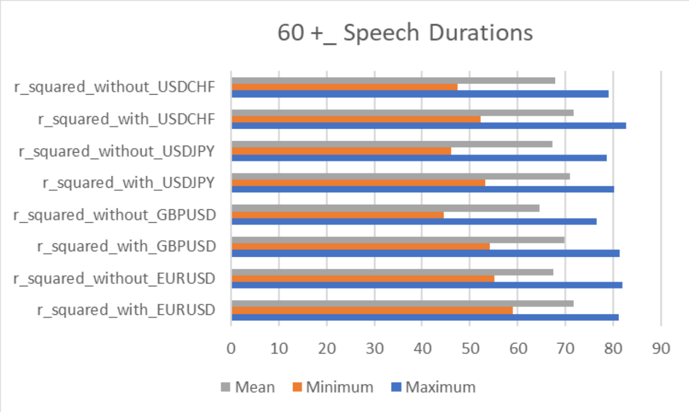


Figure 2.18 R-squared, 60 min ± speech duration

In addition to R-squared, MSE gives further confirmation that dummy variable increases the fitness of the model. the models with exogenous variable generally have lower MSE which suggest lower difference between estimated value of log-return and actual value.

Model/ Data	Maximum	Minimum	Mean
mse_with_EURUSD	5.22E-07	2.75E-09	3.25E-08
mse_without_EURUSD	4.98E-07	3.54E-09	3.39E-08
mse_with_GBPUSD	1.99E-07	2.51E-09	2.35E-08
mse_without_GBPUSD	2.29E-07	3.2E-09	2.69E-08
mse_with_USDJPY	2.35E-07	6.16E-09	3.49E-08
mse_without_USDJPY	2.71E-07	7.08E-09	3.86E-08
mse_with_USDCHF	3.26E-07	2.52E-09	2.61E-08
mse_without_USDCHF	3.18E-07	2.86E-09	2.79E-08

Table 2.9 MSE, 60 min ± speech duration

Moving to data samples with higher number of observations, similar result can be obtained. Model on 1 day data reaches higher R-squared if variable speech is incorporated into algorithm on average. However, gap between the R-squared of the two models is not as much as shorter data samples. Generally, the mean of R-squared for model with speech variable is 10% higher than the other model when number of observations is limited to one hour before to one hour after the speech. Conversely the mean of the R-Squared for 1 day data improves by 1 to 2 percent when speech effect is taken into consideration. This is an indication that speech impact is not a long-lasting factor, and as the window of time increases from few hours to 1 day the impact of the speech fade away.

Data / Model	Maximum	Minum	Mean
r_squared_with_EURUSD	76.2915944	25.10462296	37.82600451
r_squared_without_EURUSD	74.39054823	24.88379017	36.43026155
r_squared_with_GBPUSD	60.9049202	22.43651319	36.10618736
r_squared_without_GBPUSD	61.44071934	21.71448897	34.80198126
r_squared_with_USDJPY	59.08287253	19.46830189	35.74646637
r_squared_without_USDJPY	55.66426448	18.47611498	34.33489876
r_squared_with_USDCHF	65.19695916	25.85371027	37.95769442
r_squared_without_USDCHF	59.91573321	25.51486008	36.53556778

Table 2.10 R-Squared, the day of speech

Inspecting the MSE metric, suggests the above points. It can be seen clearly that that the average of the model on each currency decreases or remains unchanged when speech effect is taken into consideration.

Model / Data	Maximum	Minimum	Mean
mse_with_EURUSD	9.29E-08	1.65E-08	4.38E-08
mse_without_EURUSD	1E-07	1.65E-08	4.5E-08
mse_with_GBPUSD	8.19E-08	1.23E-08	4.34E-08
mse_without_GBPUSD	8.62E-08	1.24E-08	4.46E-08
mse_with_USDJPY	1.07E-07	1.55E-08	5.29E-08
mse_without_USDJPY	1.1E-07	1.57E-08	5.42E-08
mse_with_USDCHF	2.25E-07	1.92E-08	5.19E-08
mse_without_USDCHF	2.27E-07	1.93E-08	5.33E-08

Table 2.11 MSE, the day of speech

Final parameter that can provide concrete evidence to prove this chapter hypothesis is feature importance. The below table evidently reveals the extent of speech influence on USD value. The results suggest that on average 6 to 7 percent of R-squared is explained by variable speech in shorter timeframe. However, as the timeframe extended to one day it drops to nearly less than half. This implies that the speech parameter is less effective in long run. Refer to appendix C for case-by-case outcome.in addition in extreme cases the feature importance is as high as 14 percent, which suggests a major impact on USD value.

		Maximum	Minimum	Mean
EURUSD	60+-	9.8791586	2.745032	6.447209
	1_day	5.3426921	0.262596	2.193106
GBPUSD	60+-	14.059129	1.004865	7.222921
	1_day	5.8928631	0.190179	2.337632
USDCHF	60+-	12.633381	0.60848	6.547902
	1_day	5.9252561	0.32269	2.248704
USDJPY	60+-	10.504142	1.178708	5.940139
	1_day	6.0737158	0.210473	2.474951

Table 2.12 Feature Importance of speech variable

Policy implication, target readers, and research limitation:

The result of this chapter proposes that the US president's speech is an influencing event for USD value in FOREX market. However, this impact fades away shortly after the speech. This might suggest that market participants should trade carefully or if possible, avoid trading during the speech. In addition, this study opens up new doors for futures research. Since presidential speech is a significant event for FOREX market, the future research can investigate the similar patterns in other countries such as the impact of United Kingdom prime minister' speech on GBP value. Furthermore, this study can be expanded from president speech to all president activity such as his/her twitter account contents. Lastly, the context of the speech might be an interesting topic to investigate.

One of the limitations that this study faces is limited datasets that is available for presidential speech. It is quite lengthy process to identify each events starting and ending time. Additionally, this research can only be conducted for speeches that took place in past two decade. Beyond that time period the datasets for both market data and presidential data would be extremely difficult to access.

Conclusion:

The aim of this research is to investigate the impact of United State Presidents' Speech on value of US dollar. Previous literature stated that news in general influence financial market including florigen exchange rate market. Moreover, factors such as type of news, weather the news was schedule or non- schedule, and state of the economy when news was broadcasted, determine the how strong or week the impact would be. Announcement of organizations such as Federal Reserve, International Monitory Funds, European Central Bank is important for FX market participants. Political events and policy changes is another important element that can influence value of a currency against others. United State President is one of most politically influential person. This study explores correlation between exchange rate of US dollar and US President's speech. Data on speeches and exchange rates were collected from 2009 to 2018. Visual analysis of US dollar value against four major currencies in the world during live speech suggest that President's words might influence market prices. In several cases both volatility as well as trend of price showed dramatic changes during the speech time. To test if speech has any impact on currency value, a dummy variable created for time of speech. The dummy variable is equal to 1 during the president speech and 0 otherwise. In order to capture the persistence two sub sample is collected for each speech on 4 different currency pairs. The first datasets start from one hour before the event to one hour after the speech and second sample is 1 minute dataset for entire day of the event. Two Autoregressive order 1 model are applied on each dataset. The first model is AR (1) with exogenous variable and second model is simple AR (1). The result shows that by using the linear regression the speech variable impact on USD value cannot be captured. The P-value of dummy variable is not statistically significant. Moreover, the model performs inadequately as the obtained R-Squared is relatively low. In second analysis Autoregressive model is substituted with Random Forest algorithm. Several point can be concluded by analyzing the Random Forest outcome. Firstly, the Random Forest outperform the linear models such as AR (1) including and excluding the speech variable. Random Forest model can reach much higher R-squared and lower MSE compared to AR (1). Secondly, United States president influences the value of USD in Forex market when he delivers the speech. Since the P-value of dummy variable is statistically insignificant, the Autoregressive model fails to capture the effect of president speech. However, the Random Forest algorithm can clearly show this influence. Lastly, the impact of the speech weakens shortly after the speech. As the dataset expands from 2 hours window to whole day, the feature importance of dummy variable decreases by nearly 50 percent.

ARMA-RNN and Multi-Frequency Modeling

Abstract:

Forecasting financial time series is one of the most challenging tasks due to nature of data. By default, financial time series are nonlinear, nonstationary, and noisy. Conventional linear models such as Autoregressive Moving Average model have shown reasonable performance in modeling and forecasting financial data; however, they have their own downfalls, such as many prerequisite assumptions for underling data that is needed to be satisfied before feeding data to the model. On the other hand, both academic and industry have paid more attention to nonlinear and more computationally intense models recently. The algorithms such as artificial neural networks, and support vector machine demonstrated exceptional performance for modelling and forecasting any task including image and video recognition, natural language processing, and most importantly time series. Introducing machine learning and deep learning methods especially artificial neural networks changed the course of research from simple linear models to state-of-the-art modeling that is inherited from human brain functionality. While large number of literatures studied the advantages and disadvantages of ANN over conventional models, other researchers suggested that linear models such as ARMA are not completely obsolete. They argued that the traditional models have unique ability for modeling linear time series whereas artificial neural network perform better on nonstationary, nonlinear data. They showed that financial time series have both linear and nonlinear components, and one methodology is not sufficient to identify patterns and feature of data. Therefore, hybrid models which are combination of different models would be more plausible solution. In this research author propose that by combining the theory behind ARMA model and new state of the art technique such as artificial neural network, one step ahead forecast can be more accurate. In addition, the time frequency of input data is a

significant factor in time series analysis. The time interval of observation directly effects the level of information, and noise in time series. Moreover, the purpose of forecast determine what frequency needs to be implemented. However, this study suggests that by using training data on high frequency sample to predict low frequency, more information can be extracted consequently the forecast accuracy will improve. Finally, both proposed ideas are combined to achieve even more accuracy. The analysis implies that ARMA-RNN which is trained on mixed frequency will outperform all other models that are available in this study. To have clear understanding of these two ideas and their combination can improve the financial forecasting process the simple Recurrent Neural network will be considered as benchmark performance.

Introduction:

Time series data is referred to any sequential observation that collected over period of time with a fixed interval. Quantity of daily rainfall in a year, water reserve in a dam for specific period, heart and brain signal, macroeconomic fundamentals, air quality measurements, and financial market prices are few examples of time series. Within all different types of time series, financial data became center of attention for both market participant as well as academics, due to its complexity and financial intensive. Additionally, the state of financial market such as equity, FOREX, and commodities market is an important factor to investors as well and entire country wellbeing. Financial market has bidirectional relationship with other external event such as economy stability, environment, and politics. Therefore, having clearer picture of future is crucial to market participant as well as authorities and policy makers. Up until last two decades there were several theories and proposed techniques for forecasting financial data that could not be used due to inadequate computing power. However, as computers enhanced, it allowed us to utilize those long-forgotten method to reach better result. It is proven that artificial neural network is one of the most superior techniques in patter recognition and finding hidden feature of any type of data that could not be grasped otherwise. The idea of Artificial neural networks was developed in 1940s; however, just recently its importance and power are understood. ANN have been implemented in many fields including image/voice recognition, natural language processing, medical data, and financial data. Before ANN became the center of attention, conventional statistical models such as Autoregressive Moving average (ARMA), autoregressive conditional heteroscedasticity (ARCH) and many other models that were based on these two ideas were well studied and implemented. Despite of their acceptable performance, there were many limitations with these linear parametric models. The most important obstacle is that underlining data must be linear and stationary. Yet, majority of real-life data such as financial time series present both nonlinear and nonstationary behavior. Therefore, to able to implement models such ARMA it was required to transform and manipulate the original data. Beside linearity there are other issues that should be taken into consideration such as multicollinearity, serial correlation, heteroskedasticity which may affect the robustness of regression models. Even though the data under study, machine learning and deep learning techniques may perform better since they will not face other issues that mentioned above. In addition, if a process is presenting a nonlinear movement, it is meaningless to try to explain it by linear model. Many literatures that mainly published in 1990s suggesting that statistical models perform more accurate or as good as ANNs. However, computers were not as powerful as today's computer and artificial neural network was at early stage of development which can explain the poor performance of ANN in that time. More recent research substantiates that ANNs are more superior techniques. Despite of ANNs excellent performance, ANNs comes with several difficulties including under/overfitting, need of large datasets to train the model, and complex underling process. Looking at history of financial time series forecasting it can be noticed that this is an ongoing process and researchers always try to find new method to obtain higher accuracy which led to hybrid modeling and meta-modelling. Financial time series are both linear and nonlinear which makes either method (linear or nonlinear) less adequate for prediction. Researchers shown that by utilizing and combining more than one model, higher accuracy can be obtained. Most of hybrid models involve of using output of linear model as input for nonlinear model to achieve better forecast. The aim of this research is firstly, to combine the theory behind ARMA model and power of ANN, in order to produce more accurate model. Secondly, data with higher frequency tend to contain more information as well as carrying more noise. Conversely data with longer interval tend to be much smoother and providing less information. This paper suggests that using data with shorter time interval to model and forecast lower frequency data can balance the noise and information level, hence it might obtain better outcome.

Theorical Background:

Stationarity:

Generally, time series data can be categorized in to strictly stationary, weak stationary, and nonstationary. If time series $\{r_t\}$ is strictly stationary, the joint distribution of $(r_{t1}, \ldots, r_{tk})$ is identical to $(r_{t1+t}, \ldots, r_{tk+1})$. In other words, a time series said to be strictly stationary if the joint distribution of $(r_{t1}, \ldots, r_{tk})$ is not function of time and remain unchanged throughout the time which is nearly impossible in real world. on the other hand, weak stationary is more relaxed and more realistic condition to obtain. When mean and covariance between $r_t \; and \; r_{t-e}$ are constant over the time, dataset present weak stationary behaviour. It can be confirmed that, weak stationary time series have two conditions, firstly expect value of observation r at time t $(E(r_t))$ is equal to mean (μ) which remain unchanged. Secondly, covariance between $r_t \; and \; r_{t-e}$ is equivalent to Υ_e , and e is the only dependency. Practically, plotting weak stationary time series data with length of T $(\{r_t | t = 1, \ldots T\})$, will show constant fluctuation around the mean within fixed boundaries. Weak stationary and strictly stationary will be same only if underling data is normally distributed.

Correlation and Autocorrelation Function:

The linear dependency of two variable is measured by correlation coefficient which takes value between -1 to 1. If variable X and Y are uncorrelated, then correlation coefficient between X and Y is equal to zero or $\rho_{x,y} = 0$. Otherwise, the strength of this correlation can be measured by following equation.

$$\boldsymbol{\rho_{x,y}} = \frac{\mathbf{Cov}(\boldsymbol{X},\boldsymbol{Y})}{\sqrt{\mathbf{Var}(\boldsymbol{X})\mathbf{Var}(\boldsymbol{Y})}} = \frac{\boldsymbol{E}[(\boldsymbol{X}-\boldsymbol{\mu_x})(\boldsymbol{Y}-\boldsymbol{\mu_y})]}{\sqrt{\boldsymbol{E}(\boldsymbol{X}-\boldsymbol{\mu_x})^2\boldsymbol{E}(\boldsymbol{Y}-\boldsymbol{\mu_y})^2}}$$

Equation 3.1 correlation

Given $\{(X_t, Y_t)_{t=1}^{T}\}$ consistent correlation is

$$\boldsymbol{\rho_{x,y}} = \frac{\sum_{t=1}^{T}(\boldsymbol{x_t}-\overline{\boldsymbol{x}})(\boldsymbol{y_t}-\overline{\boldsymbol{y}})}{\sqrt{\sum_{t=1}^{T}(\boldsymbol{x_t}-\overline{\boldsymbol{x}})^2\sum_{t=1}^{T}(\boldsymbol{y_t}-\overline{\boldsymbol{y}})^2}}$$

Equation 3.2 consistent correlation

If $\{r_t\}$ is weakly stationary time series the linear correlation between r_t and past values can be estimated. Assuming dependency of r_t and i'th lag of the same series is linear, the autocorrelation of lag-i for $\{r_t\}$ can be estimated.

$$\boldsymbol{\rho_i} = \frac{\boldsymbol{Cov}(\boldsymbol{r_t},\boldsymbol{r_{t-i}})}{\sqrt{\boldsymbol{Var}(\boldsymbol{r_t})\boldsymbol{Var}(\boldsymbol{r_{t-i}})}}$$

Equation 3.3 autocorrelation

Given the properties of weakly stationary, $Var(r_t) = Var(r_{t-i})$ the Autocorrelation Function $\{r_t\}$ of time series is:

$$\boldsymbol{\widehat{\rho}_i} = \frac{\sum_{t=i+1}^{T}(\boldsymbol{x_t}-\overline{\boldsymbol{x}})(\boldsymbol{x_{t-1}}-\overline{\boldsymbol{x}})}{\sqrt{\sum_{t=1}^{T}(\boldsymbol{x_t}-\overline{\boldsymbol{x}})^2}} \quad \boldsymbol{0 < i < T-1}$$

Equation 3.4 Autocorrelation Function

White noise:

White noise process is referred to time series that is sequence of independent identically distributed random values that variance and mean are not infinite. White noise series with mean of zero and variance of σ^2 is considered Gaussian white noise. In other words, autocorrelating function of white noise process is 0 which indicates that past values do not have any impact on current observation.

Linear time series:

Linear time series can be described by following formula:

$$\boldsymbol{r_t = \mu + \sum_{i+0}^{\infty} \psi_i a_{t-i}}$$

Equation 3.5 Linear time series

Where μ represents the average or expected value of r_t and $a_{t-1}$is white noise series. In practices linear time series at time t can be defined as mean if time series plus an error term which often referred as innovation or shock. The structure of linear series is primarily depended on the weight or coefficient (ψ) of innovation. if the time series is weakly stationary, the mean and variance can be easily obtained as follow:

$$\boldsymbol{E(r_t) = \mu}$$

Equation 3.6 mean

$$\boldsymbol{Var(r_t) = \sigma^2 \sum_{i+0}^{\infty} \psi_i^2}$$

Equation 3.7 variance

The variance of is a_t represented by σ^2.

Simple Autoregressive model:

Assuming autocorrelation of first lag is significant for time series r_t. This suggests that r_{t-1} is effective explanatory variable to forecast next value. A simple regression model can be built to use this capability.

$$r_t = \phi_0 + \phi_1 r_{t-1} + a_t$$

Equation 3.8 Autoregressive model order 1

Where $\phi_0$is constant term, and a_t is series of white noise with mean of zero and standard deviation of σ^2. By using linear regression model and implementing first lag of time series as a regressor, Autoregressive model of order one (AR (1)) can be constructed. Despite of many similarities between AR and linear model's properties, there are noticeable differences that will be discussed in this section.

AR (1) model emphasis on dependency of last value.

$$E(r_t|r_{t-1}) = \phi_0 + \phi_1 r_{t-1}$$

Equation 3.9 AR (1) expected value

$$Var(r_t|r_{t-1}) = Var(a_t) = \sigma^2$$

Equation 3.10 AR (1) variance

Properties of AR (1) model:

Give the assumption that time series data r_t is weakly stationary, it can be said that $E(r_t) = \mu$, $Var(r_t) = \Upsilon_0$, and $Cov(r_t, r_{t-j}) = \Upsilon_j$ where mean and variance are constant terms and function of j, not t.

$$E(r_t) = \phi_0 + \phi_1 E(r_{t-1})$$

Equation 3.11 AR (1) expected value future value

Assuming the time series is weakly stationary

$$E(r_t) = E(r_{t-1}) = \mu$$

Equation 3.12 weakly stationary assumption

$$\mu = \phi_0 + \phi_1 r_{t-1}\mu$$

Equation 3.13 weakly stationary assumption

Therefore

$$E(r_t) = \mu = \frac{\phi_0}{1 - \phi_1}$$

Equation 3.14 AR (1) mean

Form above mathematical equations, two important point can be concluded. Firstly, the mean of time series can be calculated if $\phi_1 \neq 1$. Secondly, if $\phi_0 = 0$ the time series have mean of zero. Therefore, the AR (1) model can be rewritten in term of its mean.

$$\boldsymbol{r_t - \mu = \phi_0 + \phi_1(r_{t-1} - \mu) + a_t}$$

Equation 3.15 AR (1) model

Or

$$\boldsymbol{r_t - \mu = a_t + \phi_1 a_{t-1} + \phi_1^2 a_{t-2} + .. = \sum_{i=0}^{\infty} \phi_1^i a_{t-i}}$$

Equation 3.16 AR (1) model

As a result, $r_t - \mu$ is a linear function of a_{t-1} for $i \geq 0$. As it mentioned previously a is white noise series with mean of zero and variance of σ^2, therefore $E[(r_{t-1} - \mu)a_t] = 0$. Given the fact that r_t is a weakly stationary time series, $Cov(r_{t-1}, a_t) = E[(r_{t-1} - \mu)a_t] = 0$ due to fact that r_{t-1} take place before a_t and there is no correlation or dependency. By raising the following equation, variance of r_t $can\ be\ rerwitten$:

$$\boldsymbol{r_t - \mu = \phi_0 + \phi_1(r_{t-1} - \mu) + a_t}$$

Equation 3.17 variance of AR model

$$\boldsymbol{Var(r_t) = \phi_1^2 Var(r_{t-1}) + \sigma_a^2}$$

Equation 3.18 variance of AR model

Where σ_a^2 represent the variance of a_t. As it mentioned before, covariance between a_t and r_{t-1} is zero. Consequently, $Var(r_t) = Var(r_{t-1})$ so:

$$\boldsymbol{Var(r_t) = \frac{\sigma_a^2}{1 - \phi_1^2}}$$

Equation 3.19 variance of AR model

Above equation holds only if $\phi_1^2 < 1$ which means that the variance of random variable must be limited within a boundary and positive. Additionally, weakly stationary assumption for AR (1) model will result in $-1 < \phi_1 < 1$ or $|\phi_1| < 1$. Finally, if $|\phi_1| < 1$ and a_t being independent and white noise process it can be proven that mean and variance of r_t is not infinite and does not depend on time (time invariant).

AR(p) model:

By generalizing the idea of AR (1) model, higher order of Autoregressive model can be obtained. P is the number lags will be used as explanatory variable. Considering the mean of weakly stationery series:

$$\boldsymbol{E(r_t) = \frac{\phi_0}{1 - \phi_1 \ldots - \phi_p}}$$

Equation 3.20 mean of weakly stationery series

And denominator is greater than one, the AR(p) characteristic is:

$$\boldsymbol{1 - \phi_1 x - \phi_2 x^2 - \cdots - \phi_p x^p = 0}$$

Equation 3.21 AR(p) characteristic

Order determination of AR (p) model is an empirical process.in order to find the optimal value of P, partial autocorrelation function or information criteria method can be implemented.

Partial Autocorrelation function method:

Assuming r_t is weakly stationary time series, AR (1) to AR (4) would be:

$$\boldsymbol{r_t = \phi_{0,1} + \phi_{1,1} r_{t-1} + e_{1t}}$$

Equation 3.22 AR (1) model

$$\boldsymbol{r_t = \phi_{0,2} + \phi_{1,2} r_{t-1} + \phi_{2,2} r_{t-2} + e_{2t}}$$

Equation 3.23 AR (2) model

$$\boldsymbol{r_t = \phi_{0,3} + \phi_{1,3} r_{t-1} + \phi_{2,3} r_{t-2} + \phi_{3,3} r_{t-3} + e_{3t}}$$

Equation 3.24 AR (3) model

$$\boldsymbol{r_t = \phi_{0,4} + \phi_{1,4} r_{t-1} + \phi_{2,4} r_{t-2} + \phi_{3,4} r_{t-3} + \phi_{4,4} r_{t-4} + e_{4t}}$$

Equation 3.25 AR (4) model

Where:

- $\phi_{0,j}$ is the constant term
- $\phi_{i,j}$ is coefficient of r_{t-i}
- $e_{i,j}$ is error term or innovation

Since these models are linear regression, coefficients and constant term can be estimated using ordinary least square method. Furthermore, partial F test can be applied to find whether added lag had any contribution to estimate r_t.

Information criteria:

There are variety of Information criteria that can be helpful to find the optimal P order of Autoregressive model. Akaike Information criteria (AIC) and Schwarz–Bayesian information criterion (BIC) are the most commonly used methods for this purpose.

$$\boldsymbol{AIC(k) = In\left(\sigma_k^2\right) + \frac{2k}{T}}$$

Equation 3.26 Akaike Information criteria

$$\boldsymbol{BIC(k) = In\left(\sigma_k^2\right) + \frac{kIn(T)}{T}}$$

Equation 3.27 Schwarz–Bayesian information criterion

Where K is number of the parameter (in this case number of lags used in AR model), T is the sample size, and $In(\sigma_k^2)$ is maximum likelihood of error term's variance. To find the best order for Autoregressive model, multiple AR with different order should be estimated (for example p=1,…,10). The regression with minimum AIC or BIC determined number of lags that is significant to estimate r_t more accurately.

Forecasting using Autoregressive model**:**

Looking at AR model:

$$\boldsymbol{r_{h+e} = \phi_0 + \phi_1 r_{h+e-1} + \cdots + \phi_p r_{h+e-p} + a_{h+e}}$$

Equation 3.28 Forecasting Autoregressive model

Therefore, *e* step ahead prediction can be written as following

$$\widehat{r_h}(e) = \phi_0 \sum_{i=1}^{p} \phi_i \hat{r}_h(e-i)$$

Equation 3.29 Forecasting Autoregressive model

Simple Moving Average model:

Moving Average model can be described as extension of AR model. Given AR (1) formula:

$$r_t = \phi_0 + \phi_1 r_{t-1} + a_t$$

Equation 3.30 AR (1) model

Then model can be rearranged with respect to a_t

$$r_t - \phi_1 r_{t-1} = \phi_0 + a_t$$

Equation 3.31 AR (1) model

Then AR (1) model for r_{t-1}would be:

$$r_{t-1} - \phi_1 r_{t-2} = \phi_0 + a_{t-1}$$

Equation 3.32 AR (1) model for r_{t-1}

By multiplying $\phi_1$to r_{t-1} formula and subtracting the solution from r_t equation, following result can be obtained.

$$r_t = \phi_0(1-\phi_1) + a_t - \phi_1 a_{t-1}$$

Equation 3.33 AR (1) model for r_t

This above formula is Moving Average order of one that describe r_t as linear function of past error terms. For simplicity MA (1) model is:

$$r_t = C_0 + a_t - \phi_1 a_{t-1}$$

Equation 3.34 MA (1) model

Similar to Autoregressive model, more than one explanatory variable can be added. In other words, more lag value of error term can be used as regressor to explain r_t. the order of Moving Average model is denoted by letter q.

$$r_t = C_0 + a_t - \phi_1 a_{t-1} - \phi_2 a_{t-2}$$

Equation 3.35 MA (2) model

MA (q):

$$\boldsymbol{r_t = C_0 + a_t - \phi_1 a_{t-1} - \ \dots \ - \phi_q a_{t-q}}$$

Equation 3.36 MA (q) model

Properties of Moving Average model:

Stationarity:

In order to use Moving Average model to explain time series of r_t as finite linear combinations of past error terms that are white noise proses, r_t must be weakly stationary.

For instance, considering the expected value of MA (1):

$$\boldsymbol{E(r_t) = C_0}$$

Equation 3.37 expected value of MA (1)

that is not dependent on time variable. Therefore, the variance is:

$$\boldsymbol{Var(r_t) = \sigma_a^2 + \phi_1^2\sigma_a^2 = (1 + \phi_1^2)\sigma_a^2}$$

Equation 3.38 variable of MA (1)

The formula of the variance indicates that, the variance like expected value is time invariant. In addition, considering that error terms are white noise, a_t and $a_{t-1}$are uncorrelated.

Autocorrelation Function:

Taking Moving average order 1 model that has constant term of zero and multiplying it by r_{t-e}:

$$\boldsymbol{r_{t-e}r_t = r_{t-e}a_t - \phi_1 r_{t-e}a_{t-1}}$$

Equation 3.39 autocorrelation function MA (1)

Therefore, the expectation is:

$$\boldsymbol{\gamma_1 = -\phi_1\sigma_a^2}$$

$$\boldsymbol{\gamma_e = 0 \qquad for\ e > 1}$$

Equation 3.40 expectation of Autocorrelation Function MA (1)

Taking to consideration above results and the fact that $Var(r_t) = (1 + \phi_1^2)\sigma_a^2$, lags autocorrelation function can be obtained:

$$\boldsymbol{\rho_0 \ = \ 1}$$

$$\boldsymbol{\rho_1 = \frac{\phi_1}{1 - \phi_1^2}}$$

$$\boldsymbol{\rho_e = 0 \quad for\ e > 1}$$

Equation 3.41 autocorrelation function MA (1)

In other words, all Autocorrelation Functions for all lags is zero except lag_1 for MA (1) model. Respectively, for MA (2) model Autocorrelation functions will converge to zero after lag_2.

$$\boldsymbol{\rho_0 \ = \ 1}$$

$$\boldsymbol{\rho_1 = \frac{-\phi_1 + \phi_1\phi_2}{1 + \phi_1^2 + \phi_2^2}}$$

$$\boldsymbol{\rho_2 = \frac{-\phi_2}{1 + \phi_1^2 + \phi_2^2}}$$

$$\boldsymbol{\rho_e = 0 \quad for\ e > 2}$$

Equation 3.42 autocorrelation function MA (2)

Generalizing this property of MA (1) and MA (2) model, it can be stated that ACFs of MA (q) model will cut off after lag_q or the model memory is not infinite.

To determine the relevant order of Moving Average model or value of q, plotting Autocorrelation functions can show up to what lags is relevant.

Forecasting by Moving Average model**:**

Assuming forecast start at point h and F_h is information that is available at this point, one step ahead forecast is:

$$\boldsymbol{r_{h+1} = c_0 + a_{h+1} - \phi_1 a_h}$$

Equation 3.43 moving average model forecasting

And conditional expectation value is:

$$\hat{r}_h(1) = E(r_{h+1}|F_n) = c_0 - \phi_1 a_h$$

Equation 3.44 moving average model forecasting, conditional expectation value

$$e_h(1) = r_{h+1} - \hat{r}_h(1) = a_{h+1}$$

Equation 3.45 moving average model forecasting, conditional expectation value

Respectively 2 steps ahead forecast of MA (1) model and expected values would be:

$$r_{h+2} = c_0 + a_{h+2} - \phi_1 a_{h+1}$$

Equation 3.46 two steps ahead forecast of MA (1)

$$\hat{r}_h(2) = E(r_{h+2}|F_n) = c_0$$

Equation 3.47 two steps ahead forecast of MA (1)

$$e_h(1) = r_{h+1} - \hat{r}_h(1) = a_{h+2} - \phi_1 a_{h+1}$$

Equation 3.48 two steps ahead forecast of MA (1)

In other words, 2 steps ahead forecast will be equal to unconditional average of the model. Therefore, for any q order of Moving average model, n step ahead forecast will converge to unconditional mean of model for n greater than q.

Autoregressive Moving Average model:

Previously Autoregressive and Moving Average model were discussed in depth. However, each of these models comes with downside and difficulties. To overcome the issues of these models Box, Jenkins, and Reinsel (1994) proposed Autoregressive Moving Average or ARMA model, which is the combination of previously reviewed models. By merging AR and MA model, a smaller number of parameters need to be estimated. Even though ARMA model may not be suitable for financial time series, volatility models that are based on ARMA model such as Generalized Autoregressive Conditional Heteroscedastic (GARCH) performer well. Similar to AR an MA model, the orders of ARMA model defined by letter p and q, where p represent order of AR and q defines order of MA process.

ARMA (1,1):

$$\boldsymbol{r_t = \phi_0 + \phi_1 r_{t-1} - \theta_1 a_{t-1} + a_t}$$

Equation 3.49 Autoregressive Moving Average (1,1) model

Where ϕ_1 is the coefficient of AR model, $\theta_1$is the coefficient of MA, and a_t is white noise process. ARMA model can be significant if $\phi_1 \neq \theta_1$. Therefore, general from of ARMA (p, q) is:

$$\boldsymbol{r_t = \phi_0 + \sum_{i=1}^{p} \phi_i \, r_{t-i} - \sum_{i=1}^{q} \theta_q \, a_{t-i} + a_t}$$

Equation 3.50 Autoregressive Moving Average (p, q) model

Unit-root Nonstationary:

Financial data such as exchange rates, interest rates or stock prices are not stationary in general unlike return value. The fluctuations beyond a fixed level cause these series present nonstationary behaviour or be unit-root nonstationary. There are different type of unit-root non-stationarity including Random Walk, Random Walk with Drift, and Trend Stationary

Random Walk:

Time series $\{p_t\}$ is said to be random walk if:

$$\boldsymbol{p_t = p_{t-1} + a_t}$$

Equation 3.51 Random Walk

Assuming $\{p_t\}$ is log prices of Apple stock, where p_0 is log price of first time Apple shares were sold publicly of IPO (initial public offering). Therefore p_t is a linear function of log price at time t-1 plus a_t. If a_t is normally distributed white noise process, then log price at time t is equal to last price plus 50/50 chance of going up or down by value of error term which cannot be estimated. In other words, random walk is special form of AR (1) model where coefficient of first-lag order is equal to 1 therefore it is not weakly stationary.

Random Walk with Drift:

If random walk series such as previous example comes with small positive mean, then modelling log price is:

$$\boldsymbol{p_t} = \mu + \boldsymbol{p_{t-1}} + \boldsymbol{a_t}$$

Equation 3.52 Random Walk with Drift

Where like random walk $\{a_t\}$ is white noise series with no mean. In addition, $\mu = E(p_t - p_{t-1})$. In financial literature constant mean or μ is called trend or drift of the model.

Trend Stationary:

Trend stationary time series is quite similar to random walk with drift, however in trend stationary mean or drift of the model in time dependent whereas in random walk with drift mean is constant. Variance of trend stationary time series is constant and time invariant.

$$\boldsymbol{p_t} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 t} + \boldsymbol{r_t}$$

Equation 3.53 Trend Stationary

(Tsay, 2010, pp.26–108)

Description of neural network:

What Is Machine Learning:

Machine learning is sets of algorithms and computer programs that can learn and gain experience from given dataset. Almost every individual is surrounded by machine learning programs in today’s time. Face recognition system in smart phone, spam classifier for incoming emails, targeted advertisement based on search history, and virtual assistant platforms are few examples of daily used services that were not exist without machine learning techniques.

Machine learning techniques are much more powerful compared to simple computer programmes. For example, if a computer program is created for purpose of recognizing spam email, number of key words that is commonly used in spam emails should be pre-determined. Then program use this keywords library to classify emails. If over time, there is slight change in those pre-determined words for example instead of “For U” spams use “4U” the program fails to classify correctly. On the other hand, for machine learning techniques to accomplish the same goal a training sets of spam and non-spam emails is required in order to teach the model. Then model is capable of identifying much more patterns than few keywords, and model can adapt as patterns changes.

Type of Machine Learning:

The machine learning techniques are classified by method of their learning process. Categories of machine learning are:

1. Supervised Learning
2. Unsupervised learning
3. Semi-supervised learning
4. Reinforcement Learning
5. Batch learning
6. Online learning

Supervised Learning:

In supervised learning machine the model is fed by training data as well as solution. Then model learns by analysing the dependent and independent variable. Therefore, model is supervised by human by identifying the training set and its solution. After learning process model is able to predict any observation beyond training set. Supervised learning is capable of both classification and regression tasks. Email classification and financial modelling/forecasting are examples of supervised learning.

Supervised learning algorithms:

- k-Nearest Neighbours
- Linear Regression
- Logistic Regression
- Support Vector Machines
- Decision Trees and Random Forests
- Neural networks

Unsupervised learning**:**

Unlike supervised learning, unsupervised method is not provided by any solution or label. Machine is forced to identify hidden features or patterns within training sets and decide accordingly without any human supervision. Similarly, unsupervised techniques can be utilized for classification and regressions situations.

- K-Means
- DBSCAN
- Hierarchical Cluster Analysis (HCA)
- One-class SVM
- Isolation Forest
- Principal Component Analysis (PCA)
- Kernel PCA
- Locally Linear Embedding (LLE)
- t-Distributed Stochastic Neighbour Embedding (t-SNE)

Semi-supervised learning:

In cases where labelling the data by human is costly or complex, combination of unsupervised and supervised learning can be implemented. Semi-supervised machine learning is trained on partially labelled and partially not labelled data set.

Reinforcement Learning:

Reinforcement learning generally known as Artificial Intelligence is quite different method. The learning process start by creating an agent. Then Agent will analyse all possible solution and will be rewarded for each trial that achieved desirable outcome and will be given penalties otherwise. The reward and penalties are numerical numbers that agent will be using when encounters real situations and asked to make optimal decision. Self-drive cars and algorithmic financial trading robots are the most comment instances of Reinforcement learning.

Batch learning vs Online learning:

Batch learning or offline learning system are trained model in isolation by using all available data at the time of creating the model for intended purpose that is trained for. newly generated incoming data will not be considered in training set after learning process is over. On the contrary, online learning system is trained by using available data and it is designed in the way that it can learn incrementally by new data. Therefore, learning is an ongoing process.

Main Challenges of Machine Learning:

Even though machine learning algorithms producing extraordinary result, there are few challenges that might compromise their performances.

Insufficient Quantity of Training Data:

For human to distinguish between two objects such as cat and dog, it will take a fraction of second since our brain have been trained and is training since birth. Conversely, the same plain calcification task would require thousands even millions of images of both objects to train machine learning model. ML process is generally known as data driven methods. Therefore, the larger the training set is, the superior output will be produced. The quality of forecast is directly affected by number of observations that is used in training set. Generally, as training set grows the prediction accuracy increases.

Nonrepresentative Training Data:

For machine learning system to be accurate, the training sets which model use to learn from and the test subject should be from same class. In other words, if machine is trained to distinguish the type of flowers, it is limited to those categorize that is available within training data. If an unknown type of flowers is given to model to be classified, system will try to fit it to classes that is known to machine which result in inaccurate prediction. Similar issue exists with regression task.

Poor-Quality Data:

Any real-life data sets contain several anomalies. Missing data, noises, and outliers are the most well-known issues that might be available in datasets. Therefore, training machine learning model without dealing with these irregularities will compromise the performance of model. Pre-processing, elimination, and interpolation/extrapolation are methods to increase the quality of the data.

Overfitting the Training Data:

Overgeneralization seems to be common misbehaviour between human man machines. In term of machine overgeneralisation or overfitting refers to condition where the model works extremely accurate in fitting training data and underperform when it is assessed against out of sample data.

Underfitting the Training Data:

Underfitting is the opposite of overfitting. Machine learning model is said to be underfitted if model is too simple to capture features or patterns during learning process. If model is underfitting it can be tuned/hyper-parameterized or be replaced by more complex powerful algorithms.

Gradient Descent:

Gradient Descent is an algorithm to find optimal value for parameter in order to minimise the cost function. Gradient Descent is an iterative process that calculate the value of local Gradient for given parameter θ, then move toward decreasing gradient direction. In other words, the value of parameter θ start with random initial value, and cost function is calculated, by subtracting estimated value, from actual value. Then value of θ replaced to lower the error function. This process continues until minimum cost function is achieved. Step size or learning rate defined by how much the parameters need to be tweaked. Since the it is unknow at which level cost function is minimized (global minimum), the learning rate plays an important role. If step sized is too large the algorithm may diverge and never capture the global minimum. in opposition, small learning rate will lead to extremely time-consuming process to identify the global minimum.

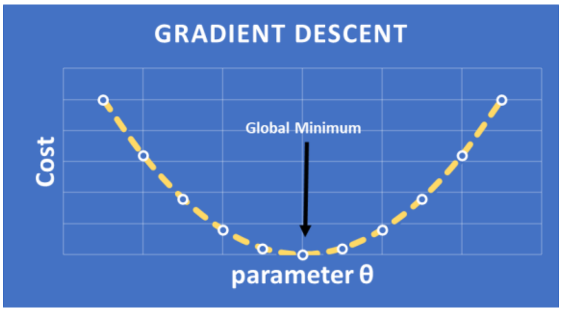


Figure 3.1 Gradient Descent

generally, plot of cost function against different value of parameter θ is convex shape. However, some cost function plots have several peak and troughs. However only one of the troughs is global minimum and rest is called local minimum. stopping to early may lead to getting trapped in local minimum instead identifying of global minimum.

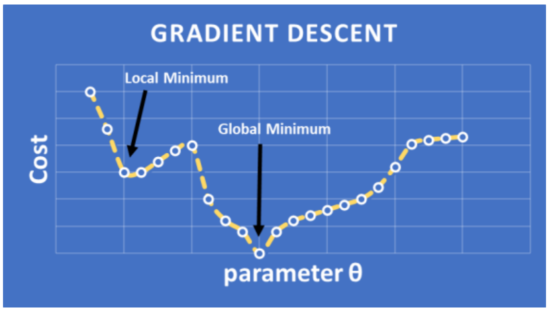


Figure 3.2 Gradient Descent Local Minimum vs Global Minimum

The model's dimension is determined by number of parameters that is used in model. Therefore, finding global minimum in space with n dimensions is quite complex process compared to one- or two-dimension environment. the gradient value is calculated by taking partial derivative of the cost function and this process must continue for every small change in each individual parameter in order to find the optimal solution.

$$\frac{\partial}{\partial \theta_j} MSE(\theta) = \frac{2}{m}\sum_{i=1}^{m}\left(\theta^t x^{(i)} - y^{(i)}\right)x_j^{(i)}$$

Equation 3.54 Gradient Descent

Batch Gradient Descent:

Computing gradient for each parameter individually in each step can be quite cumbersome and lengthy process. On the other hand, calculating partial derivative of cost function for batches of parameter at the time is much faster process to achieve the same goal.

$$\nabla_\theta MSE(\theta) = \begin{pmatrix} \frac{\partial}{\partial \theta_1} MSE(\theta) \\ \frac{\partial}{\partial \theta_2} MSE(\theta) \\ \vdots \\ \frac{\partial}{\partial \theta_n} MSE(\theta) \end{pmatrix} = \frac{2}{m} X^t (X\theta - y)$$

Equation 3.55 Batch Gradient Descent

the result of gradient vector and learning rate will approximate the direction and value of next step toward optimising the model.

$$\boldsymbol{\theta}^{(next\ step)} = \boldsymbol{\theta} - \boldsymbol{\eta}\nabla_{\boldsymbol{\theta}}\boldsymbol{MSE}(\boldsymbol{\theta})$$

Equation 3.56 Batch Gradient Descent next step optimising

Stochastic Gradient Descent:

Even though batch gradient descent is more feasible solution compared to gradient descent, it is still computationally complex and slow process since it will use entire dataset to find global minimum point. On the contrary, Stochastic gradient descent focus on single instance of data randomly to calculate the gradient value at each iteration. This randomness and taking single part of data at the time instead of whole set will allow gradient descent algorithm to identify the global minimum much faster. In addition, there is less chance that algorithm be trapped in local minimum; however, it is possible that the stochastic gradient descent never converges due to its randomness. In order to minimise the possibility of divergent, learning rate or step size should be reduced progressively from one step to next.

Artificial Neural Networks:

Throughout the history human paid attention to surrounding natural events and duplicate it to his advantage. For example, birds inspired human to pursue flying that lead to creation of airplane. Similarly, Deep learning or Artificial Neural Networks is technique that program computers to simulate human brain functionality to solve the problems. Deep Learning is one of well-studied topic of 21st century that is used to solve complex problems in many areas including financial market, medical purposes, and car industry, even though the idea was published nearly 80 years ago by McCulloch and Pitts (1943). Soon after the introduction of Artificial Neural Network, it became centre of attention for a while and due to inadequate computing power and lack of database it could not be enhanced and used which led researchers to pursue different methods. This cycle repeated several times until today that computing power and databases have improved drastically. In order to understand how artificial neural network operates it is essential to have some basic knowledge of our brain functionality or biological neural networks.

Biological Neurons:

Each Neurons have several main components. The first component that is located at the centre of neuron is called cell body. The functionality of cell body's subcomponents such as Nucleus are complex and beyond the scope of this research. Each cell body has many branches called dendrites which are responsible for receiving data from other neurons. Beside dendrites there is a quite distinctive large branch that Is called Axon. The length of axon goes from couple of times to couple thousand time longer that its body cell's length. One end of axon is attached to body cell and other end contains many branches. These branches or synapse are connecting port to other dendrites of other neurons. Neurons generate electrical impulses that transmitted from on neuron through axon to synapses. When synapses receive enough signal, they generate their own signal to other connected neurons. Human brain is made of billions of neurons that communicate with each other is the same manner.

Threshold Logic Unit:

In 1957 Frank Rosenblatt proposed Threshold Logic Unit (TLU) model that became the foundation of today's artificial neural networks methods. The TLU model is terribly similar to linear regression models. Assuming the independent variable or input is represented by red circles, and coefficients are indicated by straight line. Then the output value is equal to sums of input values multiplied by coefficient.

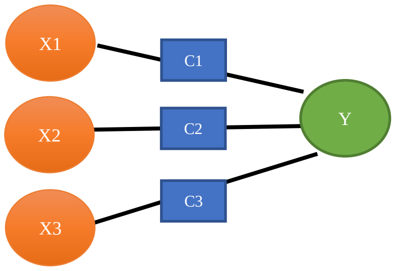


Figure 3.3 simple linear model

Threshold Logic Unit have similar designs except the step function is applied to final result.

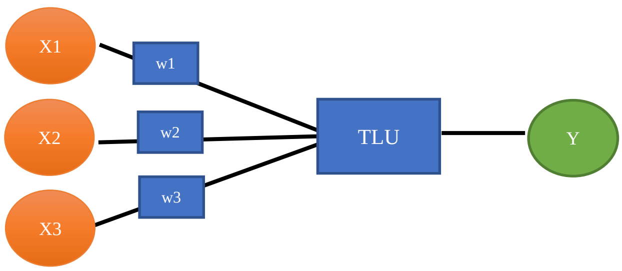


Figure 3.4 Threshold Logic Unit

One of most commonly used step function is called Heaviside.

$$\boldsymbol{Heaviside(z) = \begin{cases} 0 \; if \; Z < 0 \\ 1 \; if \; z \geq 0 \end{cases}}$$

Equation 3.57 Heaviside

However, TLU is only limited binary classification task, and does not have many applications. A Perceptron model is constructed of multiple TLUs that is connected to every input variable. Fully connected layer or dense layer is referred to network where each neuron is connected to all neuron in next layer.

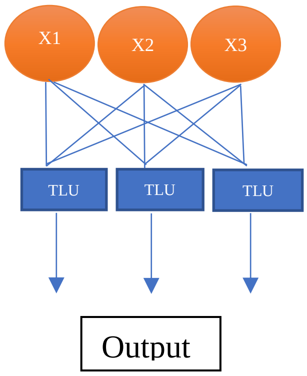


Figure 3.5 multiple Threshold Logic Unit or Perceptron model

The following equation is the mathematical representation of above diagram.

$$\boldsymbol{h_{w,b}(X) = \phi(XW + b)}$$

Equation 3.58 multiple Threshold Logic Unit

Where X defies the input matrix which each column represents a feature, and each row is dedicated to one instance of that feature. Wight matrix is symbolized by W, and most importantly ϕ which is defines what activation function is been used. In this case activation function is TLUs step function. Training a perceptron network start by feeding one instance of training set to the network and obtain the prediction. The difference between the actual output and estimated value is the error term. After obtaining the error value network tweak the connection weight in order to minimize or eliminated the error. This iteration will continue until every instance of training set is fed to model and optimal weight is calculated.

$$\boldsymbol{w_{i,j}^{(nextstep)}} = \boldsymbol{w_{i,j}} + \boldsymbol{\eta}(\boldsymbol{y_j} - \boldsymbol{\hat{y}_j})\boldsymbol{x_i}$$

Equation 3.59 multiple Threshold Logic Unit next step

It can be noticed that perceptron learning algorithm is quite similar to stochastic gradient descent that was explained earlier.

The Multilayer Perceptron and Backpropagation

The perceptron algorithm's performance is as good as any other linear models and even underperform in simple classification task. However, the accuracy of this algorithm will drastically improve if several layers of perceptron staked on top of each other. This new architecture is called Multilayer Perceptron (MLP) Artificial Neural Network. The MLP is consists of one input layer, multiple hidden layers of TLUs, and one final layer which is called output. Any artificial neural networks that are consist of multiple hidden (normally more than 10) layers stack on each other is called Deep Neural Network.

The MPL performance is not significantly better than perceptron model unless the backpropagation algorithm is applied. The backpropagation algorithm proposed by Rumelhart, Hinton, and Williams (1985) is an extraordinary method that allow flow of information to be forward and backwards for computing gradient descent and updating neural networks weight. The process of backpropagation can be explained in six steps:

1. Training set is divided into multi mini batches, and each mini batch fed to neural network at the time. Epoch refers to every time that all mini batches passed through the network once.

2. Each mini batch passed into first layer of neural network or input layer for computing inputs of first hidden layer. The result of first hidden layer will move to next layer and this process continue until last layer or output layer. This is forward feeding component of backpropagation. The result of output layer as well as all hidden layers are saved for backward feeding.
3. Cost functions such as RMSE, or MSE compute the error term. Cost functions determines how close or how far estimated value is from actual value. Neural network measures the error term by using cost function.
4. The contribution of each layer's output for error term can be obtained by chain rule.
5. Next, algorithm works backwards to measure how much of the errors is caused by each connection. This is backward flow of information.
6. Lastly, neural networks compute the gradient descent for next step using the information that is obtained from forward and backward process.

For gradient descent to be applicable the activation function should not be linear, however step function in TLU is a flat and linear. Number of activation function has been developed and evaluated that will increase the efficiency of multilayer perceptron. Sigmoid, the hyperbolic tangent function (tanh), and Rectified Linear Unit function (ReLU) are most commonly applied activation function that have exceptional performance.

$Sigmoid\ Function$:

$$\boldsymbol{f}(\boldsymbol{x}) = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{e}^{-\boldsymbol{x}}}$$

Equation 3.60 Sigmoid Function

Hyperbolic Tangent Function:

$$\boldsymbol{f}(\mathbf{x}) = \boldsymbol{tahn}(\boldsymbol{x}) = \frac{\mathbf{2}}{\mathbf{1} + \boldsymbol{e}^{-\mathbf{2}\boldsymbol{x}}} - \mathbf{1}$$

Equation 3.61 Hyperbolic Tangent Function

Rectified Linear Unit function:

$$\boldsymbol{f}(\boldsymbol{x}) = \begin{cases} \mathbf{0}\ \boldsymbol{if}\ \boldsymbol{x} < \mathbf{0} \\ \boldsymbol{x}\ \boldsymbol{if}\ \boldsymbol{x} \geq \mathbf{0} \end{cases}$$

Equation 3.62 Rectified Linear Unit function

The Vanishing/Exploding Gradients Problems:

One of the most important obstacles for using artificial neural networks is Vanishing/Exploding Gradients. Either of these problems can seriously affect the performance of ANNs. Vanishing gradient problems referred to situation when the value of gradient gets lower and lower after each epoch. Because of this decrease in gradient leaves furthers layers' weights unchanged, thereby network is not learning anything. On the contrary, on several cases the value of gradient keeps growing and that will lead to model divergent (Exploding Gradient). the reason behind Vanishing/Exploding Gradients dilemma was unknown to researchers therefore, ANN was ignored until Glorot and Bengio (2010) investigated the source of this problem. In their work they find that if the variance of each layer's output is greater than input layer it will cause Vanishing/Exploding Gradients Problems and it is related to initial weighting and activation function.

Flowing techniques can prevent Vanishing/Exploding Gradients Problems:

1. Glorot and He Initialization
2. Using Non-saturating Activation Functions
3. Batch Normalization
4. Gradient Clipping

Dropout:

Overfitting is one of the challenges of any artificial neural networks which was discussed earlier. The most common method to avoid overfitting is Dropout. Hinton et al. (2012) suggested that if some nodes randomly be eliminated in one training step and return to training process on next step, it will increase the accuracy of neural network as well as avoiding overfitting trap. What percentage of eliminated connection is defined by dropout rate.

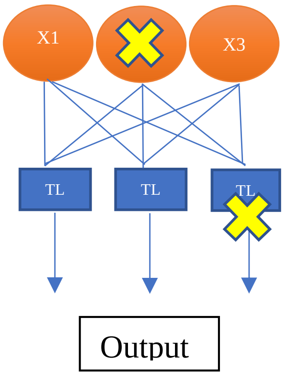


Figure 3.6 dropout technique

Recurrent Neural Networks (RNNs):

Recurrent Neural Network is the state-of-the-art artificial neural networks the mainly applied to time series data due to its backward connection or memory gates. So far, all ANNs that is described in this work have forward connection. In other words, each layer is connected to next layer sequentially all the way to output layer. However, RNN network connect each layer to next as well as to previous layers. The least complex from of Recurrent Neural Network generates output by redirecting the output of each layer to itself addition to next layer. As the result each neuron in Recurrent Network accepts inputs of y_{t-1} in addition to x_t.

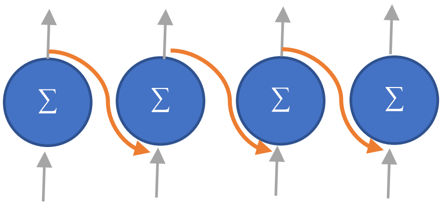


Figure 3.7 Recurrent Neural Network

Since each neuron receives two sets of input, then two sets of weight should be calculated one for y_{t-1} and other one for x_t . Therefore, the weight updating equation is as follow:

$$y_t = \emptyset(w_x^t x_t + w_y^t y_{t-1} + b)$$

Equation 3.63 RNN weight updating equation

In this basic example every neuron receiving input from one step before; however, this number can be increased. Feeding each neuron from past output can be seen as passing memory or creating memory blocks for the network, and this memory block is an important element for sequential data that are depended on past values such as Natural Language Processing and financial data. Similar to any other models RNN have some downfalls. Recurrent neural networks suffer from memory lost. In other words, as learning process continues the effect of earlier inputs will fade away, therefore there is not long-term memory dependency. To overcome this problem multiple techniques such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) is suggested.

Long Short-Term Memory:

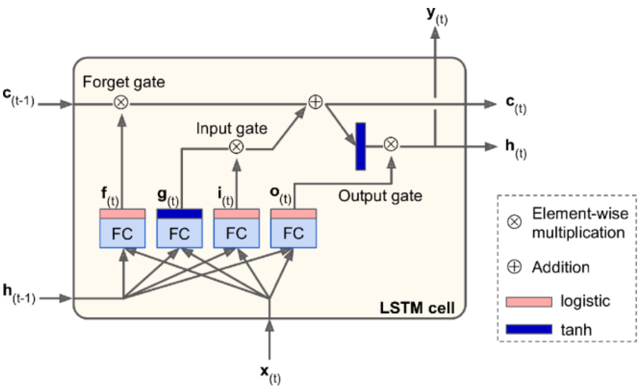


Figure 3.8 LSTM cell (Géron, 2019, Figure 15-9, p. 516)

LSTM model is quite complex compared to other type of artificial neural networks since it takes to account the short term and long-term memory dependency. In addition, LSTM are less prone to face vanishing/exploding gradients problems. The LSTM cell constructed from three inputs, several gates to decide how much if any information should travel, and three output for next cell. The first input data entering the LSTM cell is long-term memory shown as $c_{(t-1)}$, which pass through the forget gate. The forget gate is responsible to decide how much of long-term memory should be passed on into LSTM block as well as adding to it from other operations in the LSTM cell if it is relevant. Newly generated log-term dependency by one cell ($c_{(t)}$) will be passed on to next cell as input. The output $h_{(t)}$ is the short-term state. The short-term memory is developed from partially long-term memory and new information from internal operation of LSTM cell, which is passed through tanh activation function. The short-term memory and prediction of the cell $y_{(t)}$, are identical. In the inner operation of LSTM cell, outputs (represented by $g_{(t)}$) role is to assess the input data $x_{(t)}$ and short-term memory $h_{(t-1)}$ collectively. The result of this analysis will determine the value of $y_{(t)}$ and $h_{(t)}$. In addition, LSTM cell will extract the important information from $g_{(t)}$ and includes it to long-term state. The remaining gates including $f_{(t)}, i_{(t)}, and\ o_{(t)}$ operate by sigmoid activation function. This activation function produces number between 0 and 1 that can be interpreted as how close or open these gates should be. Forget gate denoted by $f_{(t)}$, controls the quantity of long-term memory travels to next cell. Similarly, input gate repressed by $i_{(t)}$ determines the important information that is obtained from $g_{(t)}$ that must be added to long-term state. Finally, output gate ($o_{(t)}$) controls the influence of long-term state on short-term memory $h_{(t)}$ as well as output $y_{(t)}$.

The below equations illustrate how mathematically each component of LSTM operates.

$$\boldsymbol{i_t = \sigma(w_{xi}^T x_{(t)} + w_{hi}^T h_{t-1} + b_i)}$$

$$\boldsymbol{f_t = \sigma\left(w_{xf}^T x_{(t)} + w_{hf}^T h_{t-1} + b_f\right)}$$

$$\boldsymbol{o_t = \sigma(w_{xo}^T x_{(t)} + w_{ho}^T h_{t-1} + b_o)}$$

$$\boldsymbol{g_t = tanh(w_{xg}^T x_{(t)} + w_{hg}^T h_{t-1} + b_g)}$$

$$\boldsymbol{c_t = f_t \otimes c_{t-1}\ i_t\ g_t}$$

$$\boldsymbol{y_t = h_t = o_t \otimes \mathbf{tanh}(c_t)}$$

Equation 3.64 Long Short-Term Memory

In these equations, similar to any artificial neural networks, $w_{xi}, w_{xf}, w_{xo}, and\ w_{xg}$ are representing the matrices of weight for input x. additionally $w_{hi}, w_{hf}, w_{ho}, and\ w_{hg}$ are weight matrices for connection layers of short-term memory (h_{t-1}).

Gated Recurrent Unit (GRU):

Cho et al. (2014) proposed a simplified version of LSTM neural network that produce output just as accurate. To simplify the LSTM model, in their work long-term and short-term memories are combined (h_t). Additionally, in GRU network, input gate and forget gate operate in conjunction which is represented by z_t. Finally, the output gate is replaced by a new gate r_t that administer the flow of information from previous layer to g_t.

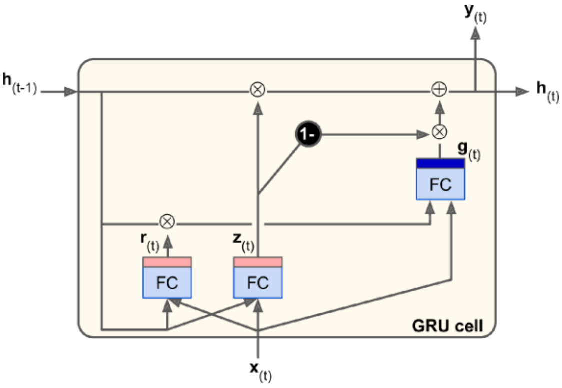


Figure 3.9 GRU cell (Géron, 2019 Figure 15-10, p. 519)

$$\boldsymbol{z_t = \sigma(w_{xz}^T x_{(t)} + w_{hz}^T h_{t-1} + b_z)}$$

$$\boldsymbol{r_t = \sigma\left(w_{xr}^T x_{(t)} + w_{hr}^T h_{t-1} + b_r\right)}$$

$$\boldsymbol{g_t = tanh\left(w_{xg}^T x_{(t)} + w_{hg}^T (r_t \otimes h_{t-1}) + b_z\right)}$$

$$\boldsymbol{h_t = z_t \otimes h_{t-1} + (1 - z_t) \otimes g_t}$$

Equation 3.65 Gated Recurrent Unit

(Géron, 2019, pp.279–520)

Related literature:

History of Financial Markets Prediction:

In this section the early theory and empirical result of financial market prediction is presented. Samuelson (1965) explains that the unpredictability in financial market is due to the fact that large number of market participant are seeking profitable trade. That was one of the earliest of random walk theory in financial industry. Therefore, unexpected market information can impact price movement. Inspired by this Idea, Fama et al. (1969) introduced “efficient market hypothesis “which states that the reaction of market to new information fades away quickly as majority of market participant would try to take advantage of new information and trade accordingly. Even though these two literatures seem to explain the dynamic of financial market, there are several research that shade light on their inadequacy. Grossman (1976) and Grossman and Stiglitz (1980) argued that, in order to have meaningful trading activity there should be a cost attached to information gathering process. If information is freely available to entire market, that indicates the current price is already adjusted to all the information that is exist. Therefore, there would be no justification for trade in financial market due to the fact that there would be no profitable trade execution, thus financial market will disintegrate in future. Therefore, there should be a cost for gathering financial market information in order to have perfectly efficient market. Black (1986) suggests there are two types of traders in the market. Noninformation based traders or people who speculate and information-based traders. Speculative traders lose their money on average and information-based traders have profitable operation. As the result the cost of information gathering, and trade execution is covered by the loss of noninformation based investors. However, from Black perspective, it can be concluded that efficient market is economically inefficient. It can be noticed that efficient market theory is fairly unrealistic, due to many unanswered questions and unapproachable assumptions. However, that is a motivation for developing new revised theory based on efficient market hypothesis. White (1988) distinguished between information that is available to market and information exist from all other sources which is not accessible easily and freely. As a result, efficient market theory is satisfactory with respect to information that is presented, not all possible information. That creates opportunity for exploiting more information which leads to profitable trads that can cover the cost of information gathering. Generating excess profit may not be possible without having competitive edge such as better technology, advance information or superior knowledge, over other players in market. Since financial market is quite competitive, the power of competitive advantages or innovations will not last forever, because these innovations cannot be patented or exclusively owned and will be duplicated in short periods of time. However, it creates limited time opportunity to utilize them and have profitable trades until other traders catch up and copy the strategy. In other words, market is relatively efficient with respect to information that is available; however, market players with comitative advantages such as advance statistical models or complex technology have potential to produce excess profit (Lo and MacKinlay, 1999). If the theory of relative efficient market is correct, that might suggest that forecasting of financial market can be possible by using advance technology and methodology. Predicting future prices creates competitive advantage over other market participants, especially irrational traders, which may lead to potential profit.

Previously discussed theories initiated large literature on financial market forecasting and testing whether it is predictable or not. As literature developed on efficient market theory, markets were categorized in three classes based on information availability which are weak, semi-strong and strong efficient market. A market is said to be weak efficient if historical data is the only source of information that is available to participants. Whare as, in semi-strong efficient market all public information is accessible in addition to historical prices. In contrast, strong efficient market not only provides public and historical information but also privet data is attainable. Majority of empirical research centred around historical data which means that financial market is at least weakly efficient. The assumption of past behaviour can explain the future, encouraged researchers to develop statistical and mathematical models to find patterns in historical data that can be generalise and used in prediction process. The term of seasonality has been studied extensively. Seasonality tests whether specific time of day, day of week, or month of year present a constant, yet unusual behaviour compared to others.

For instance, the study that is conducted by Gibbons and Hess (1981) suggests that among all weekdays, Monday have substantial low return in NYSE. This literature stated that on average stock market return were 33% lower on Mondays from 1962 to 1978. However, study by Harris (1986) implies that, the gap between open prices of Mondays and Fridays' close leads to this seasonality effect. Moreover, investors in New York Stock Exchange enjoyed higher returns for nearly 50 years (1941,1991) during month of January compared to other months of the year (Fama 1991). Reinganum (1983) conducted a similar work that suggests financial asset that was secured in month of December produced return of nearly 8% by end of January. If efficient market theory is correct, all market participants should be aware of January effect. If large number of investors purchase financial asset in December to take advantage of seasonal January effect, then the price raise will take place much earlier than what anticipated and probably seasonality effect will vanish completely.

While the literature on seasonality were developing, other researchers took different approaches to test market predictability. First order autocorrelation is one of the most extensively studied subjects. In other words, large number of studies investigate whether historical data at time t-1 is significant variable to predict price at time t. Early works such as Fama (1965), Cootner (1974) and Korsvold, (1975) stated that first order autocorrelation is not proper parameter to forecast future since outliers can result in biased outcome. Therefore, it should not be used to assess efficient market hypothesis. On the contrary, Lo and MacKinlay, (1988, 1989) used variance estimators to reject the hypnosis that financial market is a random walk process. Additionally, these studies shows that variance ratio test have superiority over more conventional tests such as Dickey-Fuller and Box-Pierce tests. Other studies focused on alternative methods such as Capital Asset Pricing Theory. CAPM and other method which is based on CAPM suggest that stock return is function of entire market return. However, empirical evidence showed no significant evidence (e.g., Fama and

MacBeth, 1973). Nonlinear relationship of return and historical data is another approach that was investigated. Fama and Blume (1966) developed trading strategy based on nonlinear formula that defines lower and upper barrier. If price cross the low barrier, assets will be sold and purchase stock when price is over the upper boundary. Even though this approach is economically profitable, trading costs outweigh the profit. While literature on financial market forecasting developed around building statical and mathematical models, the concept of technical analysis was topic of interest for other studies. Technical analysis is rules of generating signal of buy and sell purely based on graphical representation of financial assets. Rules such as head and shoulders (Levy, 1967) is widely used by some traders; however, there is little evidence supporting their profitability.

To summarize all previously discussed literatures, the history of financial forecasting started with idea that it is not possible to forecast the future prices. However, as research grows, new models and terminology such as seasonality, linear and nonlinear, technical analysis have been introduced to this filed. Exponentially increasing literature led to creation of noble statistical models such as Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARAM), Autoregressive Conditional Heteroscedasticity (ARCH), Generalized Autoregressive Conditional Heteroscedasticity (GARCH), which became standard practice of market participants. Additionally, large number of algorithms were suggested based on previously mentioned models (e.g., ARIMA, SARIMA, IGARCH, TGARCH, GJR). These econometrics models were extensively implemented and studied due to its simplicity, and acceptable performance. However, financial market data is anything but simple. Computer and computing power have enhanced substantially which allows researchers to develop and test more computationally complex algorithms. Moreover, the application of machine learning, and deep learning have expanded to other fields and financial industry is no exception.

Early studies comparing deep leaning and machine learning with statistical models:

Whether artificial neural networks can outperform conventional models is a well-studied subject. Even though majority of literature implies that artificial neural networks are superior compared to traditional models, some researchers suggest otherwise. Foster, F. Collopy and L.H. Ungar (1992) concluded that linear regressions are more robust compared to ANNs. In similar literature M. Casey Brace, J. Schmidt, and M. Hadlin (1991) find statistical models more accurate for forecasting process. Denton (1995) reports that if all assumption of linear models for underling dataset are satisfied, the performance of linear statistical models is as good as artificial neural network. However, if dataset contains outliers or there is presents of multicollinearity, ANNs are more precise. Similarly, Hann and Steurer (1996) implies no improvement by using artificial neural networks instead of linear model to forecast monthly data. Casey and Taskaya (2005) show that Autoregressive model is more suitable method versus ANNs in certain circumstances. Bhatt, Hinds, and Shiffer (2004) stated that the artificial neural networks are not as robust as many literatures implies for several reasons. Firstly, different architectures and different type of artificial neural networks produce different result. Secondly neural networks are extremely sensitive to changes in its components such as training size, activation function, batch size and optimization function. Lastly, the performance of neural network can deteriorate if training set contains high level of noise. However, Guoqiang Zhang, B. Eddy Patuwo and Hu (1998) reported that if the time series is linear and stationary then nonlinear models such as artificial neural network will perform poorly therefore, using linear method is more beneficial. On the contrary, Adebiyi, Adewumi and Ayo (2014) reviewed the predicting capability of stock prices by ARIMA and ANN method. Both models are universally used for modelling time series data including financial market data. The result from analysis implies that even though prediction accuracy is fairly close, Artificial Neural Network have superior power over conventional Box-Jenkins

ARIMA model. Similarly, study by Jain and Kumar (2007) concluded that traditional linear model such Autoregressive simply underperformed compared to ANN. The Artificial Neural Networks is superior model to uncover hidden patterns and features of complex time series such as financial data. The most important reason is that conventional model requires several conditions such as stationarity unlike ANN. However, modelling financial time series can be improved if pre-processed data were used instead of raw observation like daily closing price. The proposed model suggests that by filtering out long-term and seasonality variation of timeseries before training the model, ANN can forecast more accurately.

Why ANN is superior:

Neural networks became one of the primary techniques of financial forecasting and utilized as multivariate forecasting model due to substantial prediction capability (Sharda and Patil, 1993; Van and Robert, 1997). Market fundamentals, and technical indicators can be added to input features to enhance the neural networks. Several studies highlight the advantages of neural networks which makes it centre of attention for both academic and industry purpose.

1. Zhang, Patuwo, and Hu (1998) pointed out that ANNs are data driven, nonparametric methods. Which means that in cases that data patterns are complex and enough is available to train a neural network, this technique is the ultimate solution. The generalization capability of neural network helps to uncover hidden pattern of training data which can be used for prediction.
2. Nonstationary datasets are prone to high uncertainty and unanticipated changes. The adaptive nature of neural networks and its strong generalization characteristic, able these algorithms to be accurate under any circumstances (Cao and Tay, 2001).
3. The number of parameters in ANNs increases linearly whereas in other models it raises exponentially for identical task (Chakradhara Panda and V. Narasimhan, 2007).

4. ANNs is a nonlinear model with no pre-assumption of input data unlike conventional linear/nonlinear statistical models (Cybenko, 1989; Funahashi, 1989; Hornik, 1991; Hornik, Stinchcombe, and White, 1989).

Pros and cons**:**

Number of studies highlighted the importance of multivariate forecasting in various industries such as, financial market prediction (Moews, Herrmann, and Ibikunle, 2018), heart and brain signal analysis (Fernandez-Fraga, Aceves-Fernandez, Pedraza-Ortega, and Ramos-Arreguin, 2018), energy consumption forecasting (LuisM. Candanedo, Veronique Feldheim, and Deramaix, 2017), and environment forecasting (Zamoramartínez, Romeu, Botellarocamora, and Pardo, 2014). Multivariate statistical models such as ARIMA significantly identify log-term time dependency by concentrating on seasonality/regularity presents in data, assuming time series is stationary. However, spatial correlations of input variable are not accounted for (Amini et al., 2016; Geetha and Nasira, 2016). Moreover, econometrics' models (e.g., ARIMA) present poor performance when time series is nonstationary. On the contrary, machine learning algorithm such as Support Vector Regression, which is commonly used for time series analysis, transform regressor variable to higher dimensions. This space transformation facilitates to extract spatial correlations. Unlike linear models, SVR is not capable of detecting long-term time dependency (Gestel et al., 2001; Jie and Zio, 2016). Similar to ARIMA model, state-of- the-art Recurrent Neural Network architectures, in particular LSTM (Hochreiter and Schmidhuber, 1997) and GRU (Chung, Gulcehre, Cho, and Bengio, 2014), are not proficient of extracting spatial correlations due to serially connection of networks (Han and Xu, 2018; Sivakumar and Sivakumar, 2017). Number of literatures suggested attention-based neural network, (Riemer, Vempaty, Calmon, Hull, and Khabiri, 2016) or hybrid artificial neural network (Yolcu, Bas, Egrioglu, and Yolcu, 2018) to build long-terms time dependency as well as identifying spatial correlations between variables.

New Architectures:

Recently number of new neural networks architectures are proposed by researcher that are more powerful. There are several downfalls using recurrent neural networks (RNNs) that can weaken the performance of the model. These challenges are complicated dependency, parallelization, and vanishing/exploding gradients. In order to overcome this challenges Dilated-RNN is presented. While RNN is serially conceded to previous cells, Dilated-RNN skip some connections that allow RNN be more flexible. In addition to more flexibility, skipping connection would lower the number of parameters to be estimated. That cause less complexity/ dependency, lower exposer to vanishing and exploding gradients. The idea of skipping connection or dilated can be applied to other ANN architectures such as CNN. Dilated-RNN present strong long memory which is essential for other fields data science including natural language process. Dilated-RNN and Dilated-CNN shows strong performance for forecasting volatility. (Zhang et al., 2018). To overcome the gradient vanishing Li et al. (2018) introduced independent recurrent neural networks (Ind-RNN) which combine output, hidden and input layers and use them as input layer for another neural network. To improve parallelism quasi-recurrent neural network (QRNN) is proposed. This model is combination of CNN and RNN that the model swich from one to another (Bradbury et al., 2016). The skip recurrent neural networks (SkipRNN), as it is obvious from its name, omits some part of learning process randomly regardless of being informative or not. The number of new architectures is growing rapidly. Highway network (RHN) (Zilly et al., 2017; Srivastava et al., 2015), hierarchical multi-scale recurrent neural network (HM-RNN) (Chung et al., 2016), and the fast-slow recurrent neural network (FS-RNN) (Mujika et al., 2017) are few examples of newly proposed ANN frameworks. One of the parameters of Artificial

Neural Networks specifically LSTM that needs to be taken into consideration is whether to train data unidirectionally or bidirectionally. In other words, the flow of information should be limited from left to right (input to output) or let information to travel forward and backward. The study shows that the forecast accuracy of bidirectional LSTM is 37 to78 percent higher than unidirectional LSTM. In addition, BiLSTM is capable of capturing more features; however, training time is longer (Siami Namini, Tavakoli and Siami Namin, 2019). Wen et al. (2019) shows that convolutional neural networks or CNN which primarily used for image recognition can be applied to financial time series. In this research CNN is applied to data as signal and pattern extraction toll. Comparing this method to ordinary recurrent neural networks which mainly used for financial time series forecast, it is noticeable that proposed convolutional neural networks produce much better forecast. The result shows that CNN is more advance in term of capturing hidden patterns as well as identifying trend of stock prices. Even though multilayer perceptron neural network is another commonly used by researchers to model irregular nonlinear data due to its accuracy, MLP is highly exposed to issues such as local minimum, over fitting, computational cost, and slow convergence. Pao (1989) proposed Functional Link Artificial Neural Networks or FLANN which is constructed by single input layer and no hidden layer to overcome previously mentioned difficulties. Multiple studies stated that FLANN is less computational costly due to elimination of hidden layers and converge faster than MLP (Majhi et al., 2005; Chakravarty and Dash, 2009).

Hybrid Models:

The attempt of developing an algorithm that can forecast financial time series (e.g., stock prices, currency exchange rates, commodity prices) started from theories that claim this process is impossible; however, multiple following publication suggested the opposite. Simple linear models such as AR, MA, ARMA, ARIMA, SARIMA, ARCH, GARCH, CAPM were early algorithms that was proposed for this goal. These models produced reasonable accuracy; the methods have multiple drawbacks. Firstly, financial time series are not linear therefore linear algorithm is inadequate for this purpose. Secondly, multiple pre-determined condition had to be satisfied before implementing mentioned models. Therefore, new pre-processed should be used instated of raw input. Lastly some assumptions regarding underling data are unrealistic. Additionally, complexity of financial markets, computational power, and research on this area has grown concurrently. Therefore, the need for more compelling methods initiated new area of research. Applying and testing the Artificial neural networks which was inspired by human brain biological neurons' functionality, on financial time series produced promising outcomes that outperform traditional models. Recently large number of studies suggested that financial time series have both linear and nonlinear aspect. Therefore, a suitable method for this objective should be combination of linear and nonlinear algorithms. On the contrary, other literature stated that by filtering or pre-processing raw data before training, artificial neural networks can achieve lower modelling error.

There is distinctive difference between time series prediction and trend prediction. Time series prediction is process of training models based on historical data from same dataset. In contrast trend prediction is referred to using technical variable as well as historical data collectively. Number of literatures suggest applying machine learning algorithm such as support vector machines (Lee, 2009), Naive Bayes (Zuo and Kita, 2012), Decision Trees (Tsai et al., 2011) Neural Networks (Tsai et al., 2011), and Logistic Regressions (Tsai et al., 2011) for trend prediction purpose. Alternatively, large number of studies focused on artificial intelligence based on machine and deep learning techniques such as Fuzzy Logic, Artificial Neural Networks, and Genetic Algorithms (Hadavandi et al., 2010; Zarandi et al., 2012). Tsai and Hsiao (2010) stated that stepwise regression analysis, principal component analysis, and Decision Tree are most import techniques for dimensionally reduction and feature selection. Hsieh et al. (2011) suggested that by use Wavelet Transformation before applying to backpropagation neural network more accurate forecast is obtained. Wang et al. (2009) shows that by combining Empirical Mode Decomposition (EMD) and Support Vector Regression (SVR), the forecasting power is improved compared to simple SVR.

Newbold and Granger (1974) imply that combination of several methods such as Box-Jenkins, Holt-Winters and stepwise autoregression can lead to better predictive model versus using each model in isolation.

Winkler (1989) stated that forecasted values can be interpreted as information therefore, the combination of forecast is aggregated information. However, there are number of difficulties considering the how the models merging process should be done, since there are conflicts on models' assumptions regarding underling data used for applying to different model. He acknowledged that further research would reveal more insight on this matter. In 1989 when this research was published, Artificial Neural network was not explored as much as today.

Zhang (2003) suggested that merging Autoregressive Integrated Moving Average and ANN will yield to greater accuracy. ARIMA model has unique ability for modelling linear part of time series and robust ANN discover nonlinear features within the dataset. Observed result indicates that the hybrid model generates more accurate prediction contrasted to each model separately.

Yu, Wang, and Lai (2005) studied the forecasting power of generalized linear auto-regression (GLAR), artificial neural networks (ANN) and linear and nonlinear blend of these models. All four algorithms were evaluated by applying them to four currency exchange rate datasets. The experimental result suggests that nonlinear hybrid model is better predictor method using identical measurement for comparison.

Predicting prices in financial market can be seen as difficult act. When a problem is large enough it can be divided into multiple smaller problem. The new model is polynomial pipelined neural network that used to forecast three major currencies exchanged including

EURO, YEN, and GBP against USD. These FX time series are highly noisy and nonstationary. The polynomial pipelined neural network is constructed from multiple connected Recurrent Neural Networks. Therefore, the output of each network is a solution to one small problem which putting them together leads to better prediction model comparing to FLN or MPL method (Hussain et al., 2006).

Time series data share common characteristics regardless of origin of data. Therefore, models that is used to forecast financial time series can be applied to any other time series such as air quality data set. Díaz-Robles et al. (2008) suggested hybrid ARIMA-ANN model to forecast air quality datasets. This works stated that using hybrid ARIMA-ANN model can be effective since both linear and nonlinear aspect of dataset can be managed hence higher accuracy forecast can be obtained. The empirical result shows that prediction is fairly accurate as long as the future data is volatile within certain boundary. If air quality is at alert or pre-emergency level the model underperformed. In addition, prediction of air quality over longer time horizon (one year ahead) is as accurate as shorter horizon such as one month ahead.

Yu, Wang, and Lai (2009) argued that meta-modelling can be the solution for forecasting financial time series. financial data contain extreme volatility and noise that compromise the prediction result. The idea of meta-model in this work described in multiple stages. At first, the data set is divided to smaller subset by verity sampling method. Then each subset is treated as training set for range of Artificial Neural Networks with different parameters and architectures. Principal Component Analysis (PCA) which is Dimensional dimensionality reduction technique were applied on output of ANNs. Finally, the result of PCA is feed to last Artificial Neural network for final prediction. The meta-model described above is more accurate than simple ANN algorithm.

Kozarzewski (2010) used Wavelet's analysis as pre-possessing toll for neural network to cluster investment decisions. The observed outputs implies that the model accuracy is improved.

The research that organized by Dhamija and Bhalla (2010) assessed the accuracy of several Artificial Neural Networks and multiple ARCH/GARCH family models with respect to exchange rate prediction. For purposes of comparison Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), ARCH, GARCH, GARCH-M, TGARCH, EGARCH and IGARCH is assessed by using five currency exchange rate time series. Within conventional models under study, IGARCH and TGARCH performance are more accurate than others. Result proves that RBF model outperform compared to MLP.

There are two main limitations with proposed hybrid ANN models. Firstly, there might be conflicts between the assumptions or requirements of the models which are being used to create the hybrid models. Secondly, these models require large number of observations to uncover patterns and hidden features of data. Combination Autoregressive Integrated Moving Average, Artificial Neural Network, and Fuzzy model can overcome these limitations. Empirical result suggests that using this model can outperform other hybrid models in forecasting exchange rate market (Khashei, Mehdi; Bijari, Mehdi, 2014). Similar literature by Khashei and Bijari (2010) denotes that ARIMA-ANN model can supersede linear Autoregressive Integrated Moving Average, and nonlinear model such as Artificial Neural Networks. In this work it was proposed that to achieve more accurate prediction, estimated values that is generated by ARIMA model should be used as input layer for ANN. Therefore, raw data should be transferred from non-stationery to stationary. This work claims that suggested model is more accurate than simple ANN for purpose of predicting exchange rate. Guresen, et al. (2011) compared MLP and two other models that is based on artificial neural network with classical ANN model. The first model was suggested by Ghiassi and Saidane

(2005) is implementing Deep Artificial Neural network with dynamic number of hidden layers. Second model combines GARCH and EGARCH model with ANN that was studied by Roh (2007). The empirical result indicates that simple multilayer perceptron artificial natural network or ANN MLP produce more accurate forecasting output compared to other models. To have an unbiased comparison all models were tested against same datasets.

Enhancing the financial time series forecast is ongoing process which resulted in introduction of several methods with acceptable performance. The number of literatures that attempt to forecast time series more accurately is growing rapidly. Majority of these literatures indicates that using combination of multiple models specifically combination of two systematically different model would lead to better result compared to single model used in isolation. Even though algorithms such as ANN proven to be accurate and have multiple application including pattern recognition, classification, clustering, depending solely on ANN may produce inconclusive result. Therefore, hybrid models with linear and nonlinear component would perform better especially when financial time series being analysed. Hybrid model of ARIMA and MLP model can yield better performance compared to other combined models as well as conventional model. Using unique ability of ARIMA model linear underling structure of data and further applying multilayer perceptron neural networks to extract hidden, nonlinear features of data can be promising solution for financial forecasting (Mehdi Khashei and Mehdi Bijari, 2011).

Modelling financial time series that present linear behaviour is efficiently done by traditional model such as ARIMA. On the other hand, SVM and ANN have proven their strength in forecasting nonlinear dataset specifically time series. But facing real dataset it is fairly difficult task to determine definitely if the time series is linear or not. Therefore, the dynamic model such as Autoregressive Integrated Moving Average/ Gaussian Process or ARMA-GP can overcome this obstacle. Have a model partially linear and partially nonlinear algorithms can deal with both behaviour of a real time series data (Lee and Tong, 2011).

Traditionally Random Walk model believed to be optimal model for linear time series forecasting. On the other hand, the capability of ANN for modelling nonlinear series is proven. Dhikari and Agrawal (2013) suggested that the strength of these two models can be combined to achieve superior result compared to each model. Dhikari and Agrawal proposed that part of financial time series that present linear behaviour should be modelled by RW method and residual will be used as input for feedforward ANN. The empirical result shows that proposed model outperform the RW and FANN.

Other research confirms that hybrid models or merging models would improve the forecasting power over using single method individually. In this literature RW, FNN, EANN merged and result of the newly developed model on four financial market data were compared against each model separately. Result implies that proposed model outperforms each singled model (Adhikari and Agrawal, 2013).

An altered ANN model is introduced by Wang and Wang (2015) to improve model accuracy. stochastic time effective neural network with principal component analysis (PCA) used to fit and predict several indexes such as SSE, HS300, DJIA, and S&P 500. In order to have complete understanding of proposed model, the results were compared against other algorithms including BPNN, STNN and PCA-BPNN using several loos functions. The result shows that the proposed model have superiority, modelling these financial time series.

Rout et al. (2017) presented new Functional Link Artificial Neural Network with single layer ANN. The hidden layers in this model transfer features of input to higher dimensions using polynomial or trigonometric functions. This operation lowers the complexity of network as well as increasing forecasting accuracy.

Bao, Yue, and Rao (2017) recommended three steps forecasting framework the benefits from wavelet transforms (WT), stacked autoencoders (SAEs), and long-short term memory (LSTM). Firstly, the noises of financial time series are eliminated by wavelet transforms method. This step will help model to focus on actual features and patterns of data and not be misled by noises. Then denoised data is filtered through stacked autoencoders (SAEs) which is unsupervised machine learning algorithm to generate long-term memory dependency. Lastly the output of SAEs is used to train long-short term memory (LSTM). The forecasting result indicate higher accuracy compared to other Deep learning techniques.

The financial time series is influenced by external factors such as politics, economy, and investor psychology. Moreover, financial time series carry large number of noise and present nonstationary behaviour. It is proven that Artificial Neural Networks is capable to model nonstationary datasets unlike traditional linear models. However, the learning process of Neural Networks will be affected negatively buy noises of data. Wavelet analysis is capable method to reduces noises and highlighting real signals or information. Therefore, filtering data by Wavelet analysis before training model would improve the learning and prediction process. Pre-processing data by Wavelet analysis before feeding data to LSTM model, will increase the model's prediction ability. This proposed model is more accurate than other machine learning algorithms such as MLP, SVM, and K-nearest neighbours (Yan and Ouyang, 2018).

Yang (2018) conducted research on forecasting gold price. In his work he used ESMD method to decompose the raw data into multiple eigenmode components. The eigenmode components were combined to high, medium, and low frequency parts. Each frequency was modelled and forecasted by appropriate method. Least square support vector machine was used to predict low frequency. High and medium frequency were applied to nonlinear autoregressive neural network and multi-task model, respectively. Future gold price can be obtained by aggregating outcome of three frequency prediction models.

Chang, Sun, Wu, and Lin (2018) expanded the idea of model combinations. In that research proposed model is using convolutional neural network to extract correlations. Next implement recurrent neural networks to learn nonlinear patterns of data and finally Autoregressive linear model to enhance the prediction further.

Cao, Li, and Li (2019) suggested CEEMDAN-LSTM model. This model is described in three steps. Firstly, dataset that consist of closing prices of popular indices such as S&P500, HSI, DAX, and SSE is decomposed to number of Intrinsic Mode Function (IMF) and one residual using by CEEMDAN signal decomposition algorithm. Secondly, LSTM model used to predict each IMF and its residuals. Finally, the forecasted value can be obtained by reconstruction of predicted vale for each IMF and its residuals. The proposed model outperforms other algorithms such as LSTM, SVM, CEEMDAN-SVM, CEEMDAN-MLP, EMD-LSTM.

Araújo et al. (2019) argued that generally Artificial Neural Networks, Machine Learning and deep linear algorithms are suffering from 1-step delay forecast. In order to overcome this problem, the DIDLP model is suggested. DIDLP stands for Decreasing Increasing Deep Linear Perceptron. This specific neural network is hybrid model which consists of both linear and nonlinear elements. In addition, each element has increasing and decreasing operators. Moreover, model is benefiting from back-propagation algorithm to enhance the network further. The result from analysis confirms that the introduced model is more stable. Additionally, the 1-step delay which is the common main issue of other forecasting method is resolved in DIDLP.

(Alhnaity and Abbod, 2020) conducted extensive research on several hybrid model. Their research is performed in three steps. Firstly, number of Intrinsic Mode Functions generated by using EEMD decomposition process. Secondly, several algorithms including Recurrent Neural Network, Support Vector Machine, and Back Propagation Neural Networks were trained on generated IMFs. Lastly, the final prediction result is reconstructed on forecasted IMFs by above mentioned models. Every model was compared separately. In addition, Generic Algorithm Weighted Average method was utilized to combine EEMD-SVR, EEMDBPNN and EEMD-RNN output. The result suggests that EEMD-GA-WA model contains lowest forecasting error.

Methodology initiated by Wedding and Cios (1996) illustrate a hybrid model which is constructed by linear Box–Jenkins ARIMA models and nonlinear radial basis function networks (RBF). Luxhoj, Riis, and Stensballe (1996) suggested combination of ANN and econometric model to forecast sales volume. An artificial intelligence framework developed by combining rule-based systems technique and neural networks to predict S&P500 price Tsaih, Hsu, and Lai (1998). KARIMA is hybrid model that is developed by Voort, Dougherty, and Watson (1996). The model is the result of merging autoregressive integrated moving average and Kohonen self-organizing map. Medeiros and Veiga (2000) suggested that using neural networks and autoregressive model jointly can be on ideal hybrid model to control time shifting parameters that is the result of autoregressive model. Over past two decades there is extensive literature on hybrid models. Mainly due to increasing popularity of machine learning and deep learning topics, majority of suggested models are based on these novel algorithms. Pai and Lin (2005) suggested hybrid method that benefits from ARIMA models and support vector machine collectively to forecast stock prices. In similar work Chen and Wang (2007) pioneered combined model formed by support vector machine and seasonal autoregressive integrated moving average model. The study of Armano, Marchesi, and Murru (2005) suggested utilizing ANN model and generic algorithm (GA) to model stock market data. Yu, Wang, and Lai (2005) showed that to achieve higher accuracy for forecasting exchange rate combination of artificial neural network and generalized linear auto regression can be applied. The study by Kim and Shin (2007) proposed that temporal patterns of stock market can be predicted by hybrid model that is integrated adaptive time delay neural networks and genetic algorithm. SARIMABP is a hybrid model that is proposed by merging seasonal autoregressive integrated moving average model and back-propagation ANN Tseng, Yu, and Tzeng (2002). Khashei, Hejazi, and Bijari (2008) introduced new hybrid method based on artificial neural network that can conquer the limitations of neural networks specifically the situation where missing data is presented.

Majority of prior studies that explained extensively above provide evidence that hybrid models are outperforming the machine / deep learning model and linear models are less accurate compared to modern techniques.

In this study the proposed model that is inspired by to previous literature such as Zhang (2003), Díaz-Robles et al. (2008), and Khashei and Bijari (2010). These studies have proven that the combination of ARMA or ARIMA model with artificial neural network will improve the modelling and forecasting the time series. the above-mentioned hybrid models are forecasting the data with linear model and obtain the residuals. Then use artificial neural networks to model the residuals to lower the forecasting error. This prosses is similar to GARCH model. However, the model that is presented in this chapter is quite different. In simple words, the ARMA-RNN model that is described and analysed in this chapter is constructed by two parallel Recurrent Neural Network that on network is trained on AR values and second one will be trained by MA value. As Hussain et al. (2006) stated the forecasting financial time series can be divided to multiple smaller and simpler task. This division might increase the accuracy of forecast. The proposed model divided the dataset to two AR and MA subcomponent. Each subcomponent will be estimated by separated RNN and in final stage the model will use the output of these two parallel networks to generate the forecasted value. In addition to new model the idea of multi frequency data is explored.

Data selection:

The financial time series data is a quite expensive commodity. This corresponds to relatively efficient market theory. Multiple sources such as Yahoo finance and Google finance provides free limited data for number of securities and indexes. However, the lowest frequency available is daily. For purposes of this study, large dataset with ultra-heigh frequency is required. As it mentioned before artificial neural networks are data driven hence, if the training set is not large enough it will lead to inconclusive result. Acquiring stock, commodity, or derivatives prices is incredibly costly and complex process; however, many data vendors provide ultra-high frequency such as tick data for currency exchange rate free of cost. Additionally, FOREX market is most liquid type of financial assets with largest trading volume. FOREX market is more global market and less complex, whereas stock market is more limited to contain geography and market participant are more specialized. It is worth mentioning the value of a currency can be influenced easier that stock prices therefore, FOREX market are generally more volatile. If the proposed model outperforms on exchange rate compared to benchmark Recurrent Neural Network, it is safe to argue that it will produce more accurate result when applied to stock and commodity time series. TrueFx.com provides tick-data for number of currencies exchange rate to public. Great Britain Pound (GBP/USD), Japanese Yen (USD/JPY), Swiss Franc (USD/CHF), and Euro (EUR/USD) are currencies selected for this study. The data collected from 01/01/2013 to 31/07/2018. Since time interval of data sets are uneven, all datasets are required to be resampled. Observations were transformed to 30 second frequency by averaging all observation every half a minute. In order to lower the difficulties of data, observation on weekends is eliminated from further analysis. Every real-life dataset contains number of missing data. However, chosen data includes negligible amount of missing data that was filled by immediate previous value. Datasets are divided into two subsets, training, and test sets. First 80% of observations (training set) is used by model to learn from. The remaining 20% percent of observation or tests set is used to compare estimated to actual value to assess the network accuracy. Similar process can be observed in regression analysis. Data is divided to in-sample and out of sample to calculate the accuracy of model as well as its prediction.

Artificial Neural Networks are quite sensitive to any abnormality in data. To reduce the chance of networks being misled, all observation is pre-possessed by using Min-Max-scaler method. This method rescales all observation between 0 to 1 where maximum value is 1 and minimum value is equal to 0. This pre-processing technique will increase the neural network accuracy without compromising the patterns or features of data. in this case the assumption is model never been exposed to out of sample or test set. Therefore, minimum, and maximum value that is used for rescaling process is calculated from training set and not the entire data.

$$x_{pre-processed} = \frac{x - Max\_value}{Max\_value - Min\_value}$$

Equation 3.66 Min-Max scalers

One aspect of this research is behavior of proposed model under different frequency or mixed frequency for fixed period of time. Consequently, multiple different lower frequency datasets are generated by using organized 30-second data. Table below indicates number of observations for each generated dataset.

Frequency	EURUSD	GBPUSD	USDCHF	USDJPY
1D	1506	1506	1506	1506
12H	2933	2933	2933	2933
6H	5784	5784	5784	5784
1H	33679	33679	33679	33679
30T	67251	67251	67251	67251
1T	2006360	2006360	2006360	2006360

Table 3.1 Number of observations for each currency/frequency, T: Minutes, H: Hours, D: Days.

Frequency	total observation	Train Set Size	Test Set Size
1D	1506	1205	301
12H	2933	2346	587
6H	5784	4627	1157
1H	33679	26943	6736
30T	67251	53801	13450
1T	2006360	1605088	401272

Table 3.2 Total observation, train size, and test size, T: Minutes, H: Hours, D: Days

Methodology:

In this study new ARMA-RNN hybrid model is proposed to be tested against conventional RNN model. Multiple RNN and hybrid RNN with different parameters are analyzed for better understanding. With regard to recurrent neural network, both Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architecture are contracted for both benchmark and suggested model. In addition, two activation functions Rectified Linear Unit (ReLU) and hyperbolic tangent (tanh) are applied to all models separately. And finally, all models are trained on both unidirectional (forward) and bidirectional method. The table below contains all different model that is been tested against each other using four different exchange rate data.

lSTM Tanh Forward Single frequency 1 Day	**lSTM Tanh Forward Multi frequency input: input: 12 Hour output: 1 Day input**
lSTM Tanh Forward Single frequency 12 Hour	**lSTM Tanh Forward Multi frequency input: 6 Hour input: 12 Hour**
lSTM Tanh Forward Single frequency 6 Hour	**lSTM Tanh Forward Multi frequency input: 1 Hour input: 6 Hour**
lSTM Tanh Forward Single frequency 1 Hour	**lSTM Tanh Forward Multi frequency input: 30 Minute input: 1 Hour**
lSTM Tanh Forward Single frequency 30 Minute	**lSTM Tanh Forward Multi frequency input: 1 Minute input: 30 Minute**
lSTM Tanh Bidirectional Single frequency 1 Day	**lSTM Tanh Bidirectional Multi frequency input: input: 12 Hour output: 1 Day input**
lSTM Tanh Bidirectional Single frequency 12 Hour	**lSTM Tanh Bidirectional Multi frequency input: 6 Hour input: 12 Hour**
lSTM Tanh Bidirectional Single frequency 6 Hour	**lSTM Tanh Bidirectional Multi frequency input: 1 Hour input: 6 Hour**
lSTM Tanh Bidirectional Single frequency 1 Hour	**lSTM Tanh Bidirectional Multi frequency input: 30 Minute input: 1 Hour**
lSTM Tanh Bidirectional Single frequency 30 Minute	**lSTM Tanh Bidirectional Multi frequency input: 1 Minute input: 30 Minute**
lSTM Relu Forward Single frequency 1 Day	**lSTM Relu Forward Multi frequency input: input: 12 Hour output: 1 Day input**
lSTM Relu Forward Single frequency 12 Hour	**lSTM Relu Forward Multi frequency input: 6 Hour input: 12 Hour**
lSTM Relu Forward Single frequency 6 Hour	**lSTM Relu Forward Multi frequency input: 1 Hour input: 6 Hour**
lSTM Relu Forward Single frequency 1 Hour	**lSTM Relu Forward Multi frequency input: 30 Minute input: 1 Hour**
lSTM Relu Forward Single frequency 30 Minute	**lSTM Relu Forward Multi frequency input: 1 Minute input: 30 Minute**
lSTM Relu Bidirectional Single frequency 1 Day	**lSTM Relu Bidirectional Multi frequency input: input: 12 Hour output: 1 Day input**
lSTM Relu Bidirectional Single frequency 12 Hour	**lSTM Relu Bidirectional Multi frequency input: 6 Hour input: 12 Hour**
lSTM Relu Bidirectional Single frequency 6 Hour	**lSTM Relu Bidirectional Multi frequency input: 1 Hour input: 6 Hour**
lSTM Relu Bidirectional Single frequency 1 Hour	**lSTM Relu Bidirectional Multi frequency input: 30 Minute input: 1 Hour**
lSTM Relu Bidirectional Single frequency 30 Minute	**lSTM Relu Bidirectional Multi frequency input: 1 Minute input: 30 Minute**

GRU Tanh Forward Single frequency 1 Day	**GRU Tanh Forward Multi frequency input: input: 12 Hour output: 1 Day input**
GRU Tanh Forward Single frequency 12 Hour	**GRU Tanh Forward Multi frequency input: 6 Hour input: 12 Hour**
GRU Tanh Forward Single frequency 6 Hour	**GRU Tanh Forward Multi frequency input: 1 Hour input: 6 Hour**
GRU Tanh Forward Single frequency 1 Hour	**GRU Tanh Forward Multi frequency input: 30 Minute input: 1 Hour**
GRU Tanh Forward Single frequency 30 Minute	**GRU Tanh Forward Multi frequency input: 1 Minute input: 30 Minute**
GRU Tanh Bidirectional Single frequency 1 Day	**GRU Tanh Bidirectional Multi frequency input: input: 12 Hour output: 1 Day input**
GRU Tanh Bidirectional Single frequency 12 Hour	**GRU Tanh Bidirectional Multi frequency input: 6 Hour input: 12 Hour**
GRU Tanh Bidirectional Single frequency 6 Hour	**GRU Tanh Bidirectional Multi frequency input: 1 Hour input: 6 Hour**
GRU Tanh Bidirectional Single frequency 1 Hour	**GRU Tanh Bidirectional Multi frequency input: 30 Minute input: 1 Hour**
GRU Tanh Bidirectional Single frequency 30 Minute	**GRU Tanh Bidirectional Multi frequency input: 1 Minute input: 30 Minute**
GRU Relu Forward Single frequency 1 Day	**GRU Relu Forward Multi frequency input: input: 12 Hour output: 1 Day input**
GRU Relu Forward Single frequency 12 Hour	**GRU Relu Forward Multi frequency input: 6 Hour input: 12 Hour**
GRU Relu Forward Single frequency 6 Hour	**GRU Relu Forward Multi frequency input: 1 Hour input: 6 Hour**
GRU Relu Forward Single frequency 1 Hour	**GRU Relu Forward Multi frequency input: 30 Minute input: 1 Hour**
GRU Relu Forward Single frequency 30 Minute	**GRU Relu Forward Multi frequency input: 1 Minute input: 30 Minute**
GRU Relu Bidirectional Single frequency 1 Day	**GRU Relu Bidirectional Multi frequency input: input: 12 Hour output: 1 Day input**
GRU Relu Bidirectional Single frequency 12 Hour	**GRU Relu Bidirectional Multi frequency input: 6 Hour input: 12 Hour**
GRU Relu Bidirectional Single frequency 6 Hour	**GRU Relu Bidirectional Multi frequency input: 1 Hour input: 6 Hour**
GRU Relu Bidirectional Single frequency 1 Hour	**GRU Relu Bidirectional Multi frequency input: 30 Minute input: 1 Hour**
GRU Relu Bidirectional Single frequency 30 Minute	**GRU Relu Bidirectional Multi frequency input: 1 Minute input: 30 Minute**

Table 3.3 Combinations model's parameters and frequency

For simplicity other parameters remain unchanged. All models trained for 20 epochs, with batch size of 64 and dropout rate of 10%. Additionally, 50 previous observation is considered for each input. In other words, each input layer will contain 50 lags regardless of data's frequency. The look back is equivalate to order of AR or MA model therefore this model can be seen as equivalent of ARMA (50,50).

Proposed ARMA-RNN hybrid Model:

Extensive literature pointed out the unique ability of Autoregressive Moving Average model and other algorithms based on it for modeling time series despite its shortcomings. On the contrary, many studies indicates that machine learning, and deep learning are more superior models compare to traditional statistical models. However, in recent year the interest in hybrid models is increasing gradually. It seems the financial data is more complex than one model can handle therefore, ability of more than one algorithm is required to have more accurate prediction. The previous studies suggested to merge the linear models such as ARMA with number of neural networks to boost the performance. The combination mainly involved using the output of one model as input of the other one or applying neural networks to residual linear models. Even though the accuracy of those hybrid models exceeds the accuracy of each model in isolation, this study proposes new way to merge ARMA and recurrent neural network. The new hybrid model is constructed of two recurrent neural networks that are parallel to each other. Each RNNs starts with an input layer followed by two hidden layers with 64 hidden nodes. One of the independent RNN is fed with past values up to 50 lags on each instance which performs as Autoregressive models. Meanwhile, the second network receives the residuals which is Moving average component of the model. In the other word, in this study a new recurrent network constricted that have inputs of ARMA model; however, underling process is not linear regression. Similar to ARMA model which is Autoregressive model + Moving Average Model the new proposed model is contracted of two RNN model. the first RNN model is receiving AR inputs and second model will be trained on MA variable.

The two networks will be concatenated at third layer and produce output in forth layer. The input for Autoregressive component of this model does not require any calculation; however, the input of Moving Average network needs to be computed before training the model. the MA training data is obtained in two steps. First, the rolling moving average with window of 3 is calculated for entire training set. Secondly, the actual value at time t is subtracted from the moving average at same instance.

$$\sigma_t = x_i - (\frac{1}{n}\sum_{i=1}^{n} x_i)$$

Equation 3.67 calculating MA values for moving average neural network

To summarize, the proposed model is constructed from two independent recurrent neural networks, which one networks act as Autoregressive part and other is the Moving Average component. Each RNN models are constructed of an input layer and two hidden layers. The purpose of hidden layers as it is discussed before are to uncover the patterns or relationship between the input and output. After two hidden layers, these networks get concatenated and creates ARMA-RNN model. lastly, the concatenated layer is responsible for predicting the output.

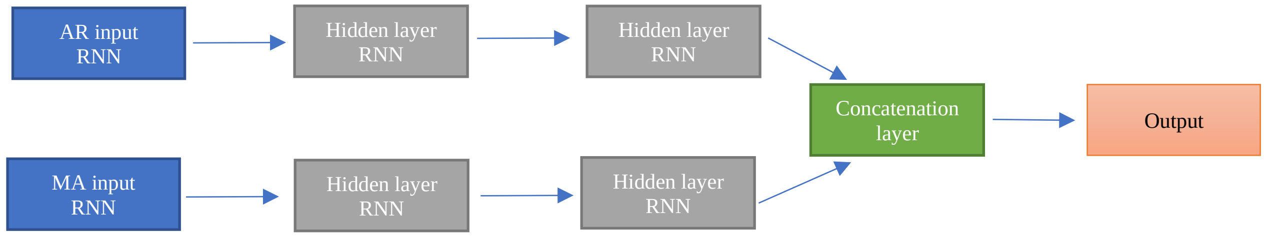


Figure 3.10 graphical representation of proposed model

Multifrequency:

Using higher frequency to train the neural network in other to produce output on lower frequency is another aspect of this study. The choice of frequency is directly corelated with forecast horizon. As forecast horizon increases the prediction accuracy decreases regardless of predictive model. for longer forecast horizon lower frequency data is required because less steps ahead prediction is needed. Increasing or decreasing time interval of time series is a tradeoff. High frequency data contains more observations hence more details or information is embedded, however more information comes at the expense of more random variation in data or noises that can misled the algorithm. On the contrary, increasing time interval of data by averaging n number of sequential observations at the time will smooth out the trend of the data or denoise it. However, during this transformation part of information will be eliminated alongside with noises. Generally, all financial models including conventional and nonparametric algorithm use same frequency data for input and output. However, in this study the use of multi frequency is proposed. Since the data on higher frequency is more informative, the new hybrid model that is described earlier will be trained on frequency 2 time higher than the output layer. If forecast frequency is 12-hour and look back period or order of the network is 50 lags, at first $x_{-1} to\ x_{-50}$ and their time stamp is extracted from dataset with 12-hour frequency for input layer. Secondly, each observation is replaced by two observations with half of time interval (in this case 6-hour). Therefore, each instance of the network will be trained on higher frequency input which potentially contains more information hence it will lead to higher frequency.

Performance analysis:

All datasets are divided in to in-sample (the first 80% observations) and out-of-sample (the last 20% observations) to evaluate each model for both the model and forecast accuracy. Comparison of different models requires unique measurement that can be obtained for all output and base on that measurement it can be decided which model outperform the other. In this research Mean Squared Error or MSE is computed on both in-sample and out-of-sample for all networks/datasets by following formula.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

Equation 3.68 Mean Squared Error

Where n is number of steps ahead forecast. Y and $\hat{Y}$ representing actual and estimated value, respectively. Each model is trained on four exchange rate dataset and each data set is transformed into five different frequencies. Therefore, each model is trained and forecasted 20 times. To be able to compare all model and fined the optimal architectures for neural network, MSE of in-sample and forecast is computed for every dataset. However, comparing 40 MSE (20 in-sample and 20 out-of-sample) is not feasible. Hence, the models are compared by using the MSEs average.

For the purpose of comparison, simple Recurrent Neural Network is considered to be the benchmark. The performance multifrequency, ARMA-RNN, and multifrequency ARMA-RNN are compared with simple RNN to see whether the proposed idea can improve the accuracy of in-sample and out of sample modeling.

In this section the author analysis compares the result of all models against each other. There are several points in this section that is being investigated.

1. In each model which parameters generate more accurate estimate (LSTM VS GRU, TANH VS RELU, and bidirectional VS unidirectional).
2. If multi-frequency produces more accurate result with respect to single frequency.
3. Dose proposed model ARMA-RNN perform better than benchmark model RNN?
4. Is ARMA-RNN with multi-frequency superior model of all?

There are 4 main models including RNN single frequency, RNN multi frequency, ARMA-RNN single frequency and ARMA-RNN multi frequency. Each network is constructed with all possible combination of parameters. Therefore, every neural network is built 8 times and trained on 20 datasets. In other words, there 640 result that requires to be compared. Since the number of outcomes is substantial and it is impractical to compare them one by one, the author decided to focus on minimum, maximum, and average of obtained MSE for every model with unique sets of parameters. At first every individual model is analysed separately to identify the best sets of parameters that reaches the lowest MSE. Lastly, the bast of all 4 models are compared against each other. Please see appendix D for model's virtualisation.

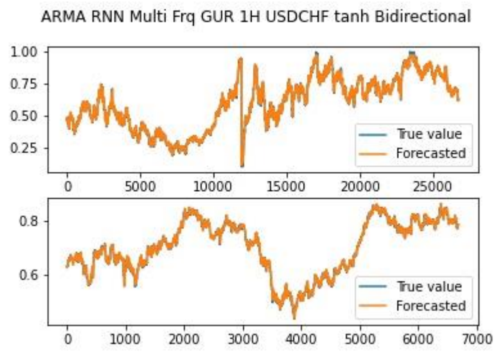


Figure 3.11 ARMA-RNN Multi frequency 1 hour interval

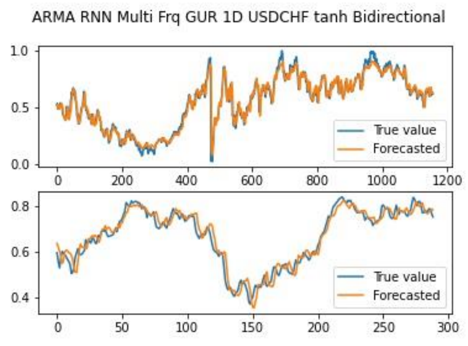


Figure 3.12 ARMA-RNN Multi frequency 1 day interval

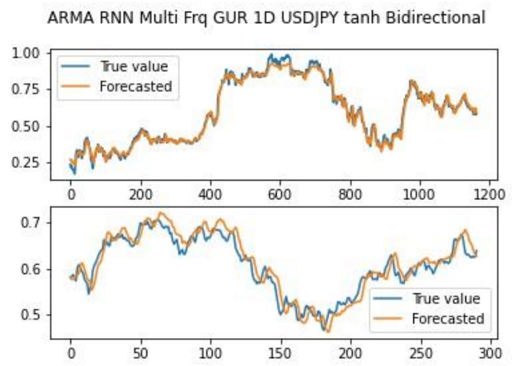


Figure 3.13 ARMA-RNN Multi frequency 1 hour interval

The figure 3.11, 3.12, and 3.13 presents the performance of ARMA-RNN multifrequency model in training sets as well as out of sample. The upper plot is in-sample datasets where blue line represents the actual value and orange line show the estimated value by the model. the lower plot indicates the forecasting performance. It is clear that the estimated value and actual value are extremely close which provide evidence how well the proposed model perform.

RNN single frequency:

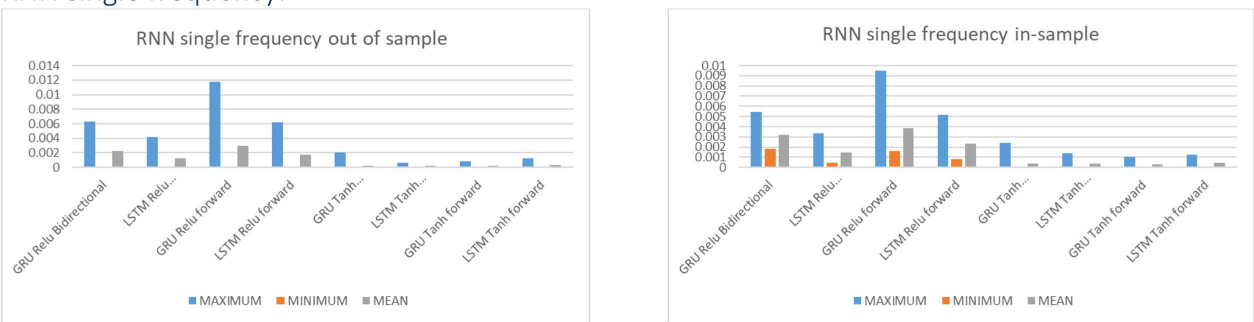


Figure 3.14 Minimum, Maximum, and Average MSE RNN single frequency

The figure above presents the maximum, minimum and average of RNN single frequency with different sets of parameters. There are few points that are quite noticeable. Firstly, the gap between minimum and maximum is enormous. For some models such as GRU, Tanh, bidirectional model the minimum is so small that cannot be seen. Secondly the difference between maximum and average is huge, and it prevents us to have better understanding of each model performance on average. Therefore, the mean of MSE is plotted separately for further assessment.

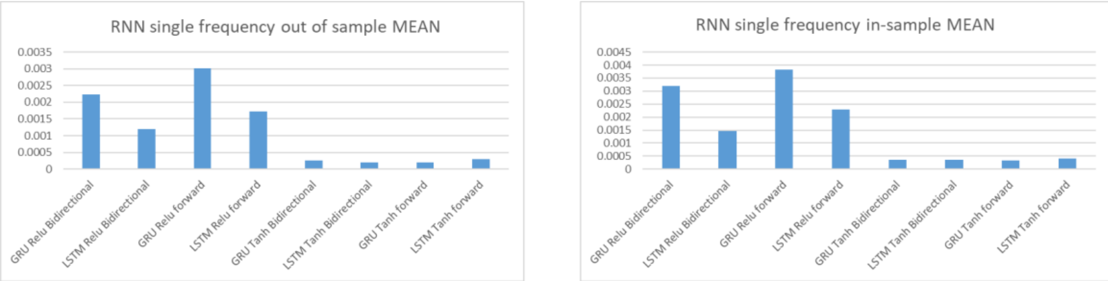


Figure 3.15 Average MSE RNN single frequency

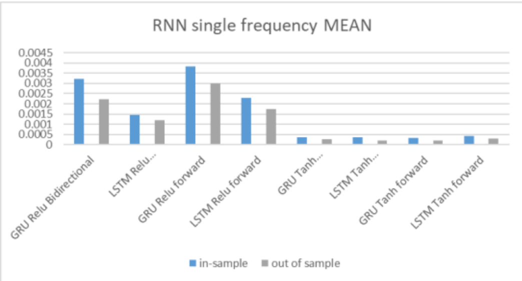


Figure 3.16 Average MSE RNN single frequency in-sample and out of sample aggregated

The above figures indicate clearly that when Relu is set as activation function, the model performance is extremely poor compared to Tanh in both in-sample and out of sample modelling. Since the Tanh activation function more superior, Relu is eliminated from further analysis.

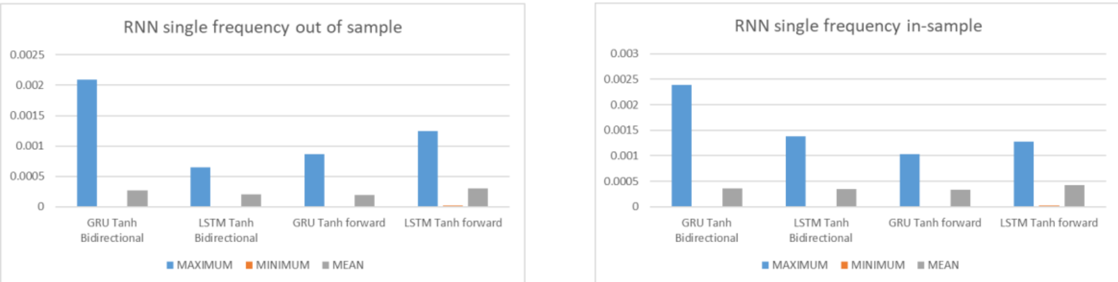


Figure 3.17 Minimum, Maximum, and Average MSE RNN single frequency Tanh activation function

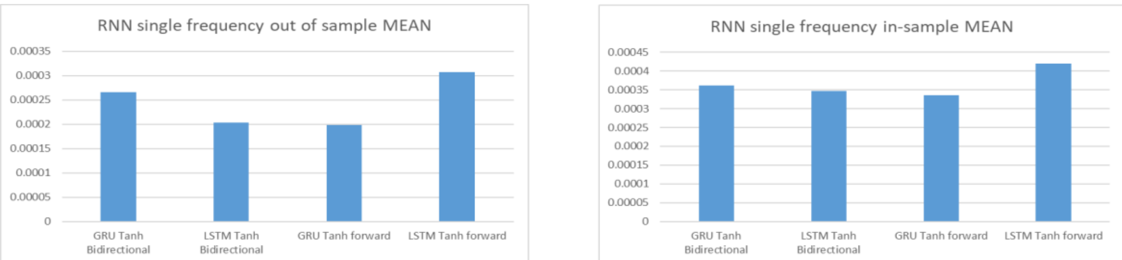


Figure 3.18 Average MSE RNN single frequency Tanh activation function

After choosing more superior activation function, it is possible to find the optimal model that reaches the lowest MSE. It can be seen that LSTM that flow of information is bidirectional, and GRU forward feeding model outperform the other models. However, the GRU is slightly more accurate.

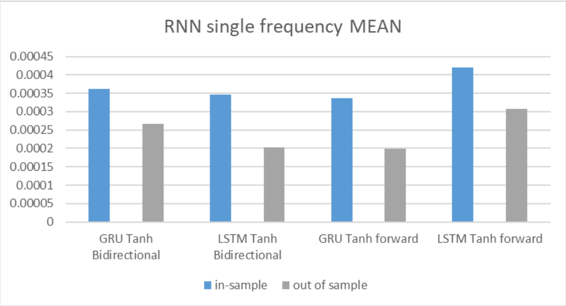
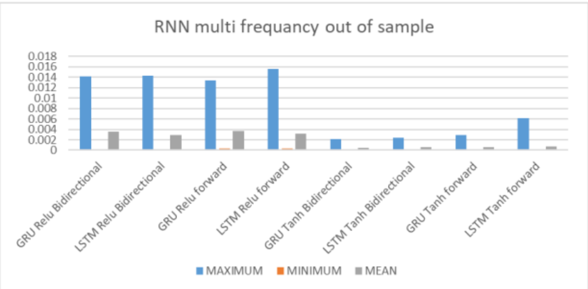


Figure 3.19 Average MSE RNN single frequency Tanh activation function in-sample out of sample aggregated

RNN multi frequency:

The tables below are presenting the performance of Recurrent Neural Network which is trained on multiple frequency data. the results are quite similar to previous model. Once again it can be seen that Relu activation function is less accurate. Consequently, we will take a closer look in to models that unutilized Tanh activation function. In addition, it seems that the average of MSE is relatively good parameter to compare the models.



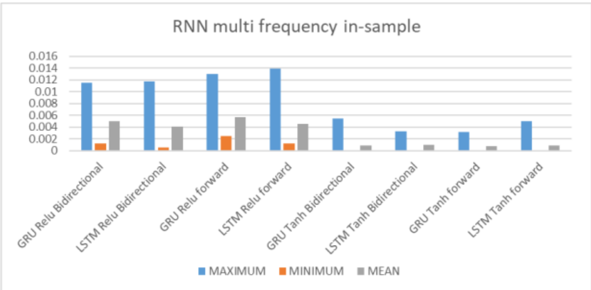


Figure 3.20 Minimum, Maximum, and Average MSE RNN multiple frequency

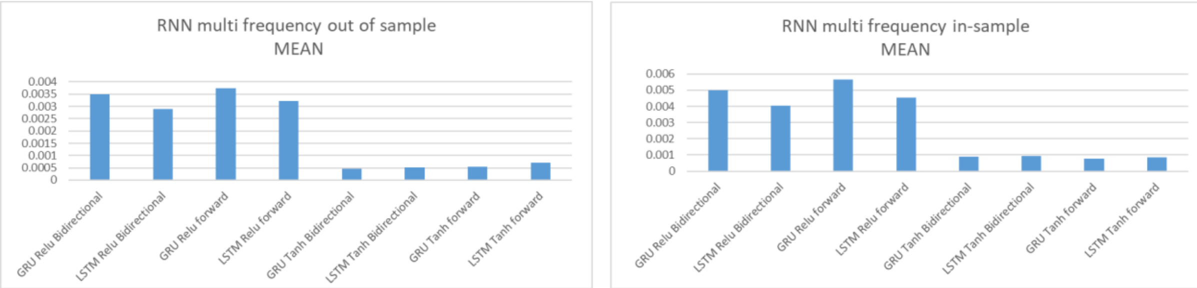


Figure 3.21 Average MSE RNN multiple frequency

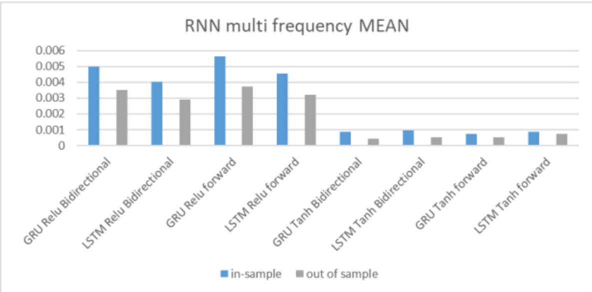


Figure 3.22 Average MSE RNN multiple frequency in-sample and out of sample aggregated

Analysing the plots of models with Tanh activation function, it can be noticed that the high maximum prevents the reader to have better understanding of minimum or the average performance of each network.

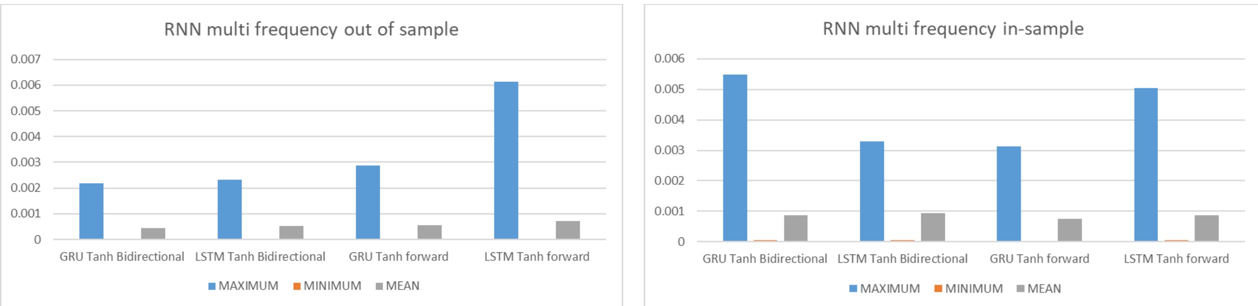


Figure 3.23 Minimum, Maximum, and Average MSE RNN multiple frequency, Tanh activation function

Separating the average MSE provide a clearer picture. GRU generally outperform the LSTM model in in-sample modelling. In addition, forward feeding method is slightly more accurate since it obtains lower average MSE. Moving on to out of sample forecasting accuracy, the result is somehow similar. Similar to in-sample outputs, GRU is performing better however, bidirectional flow of information will lead to lower average MSE. Hence there is not one optimal model. Even though the difference between forward and bidirectional model is not huge one model is more accurate in in-sample training and other one performs better on untrained part of data sets (out of sample).

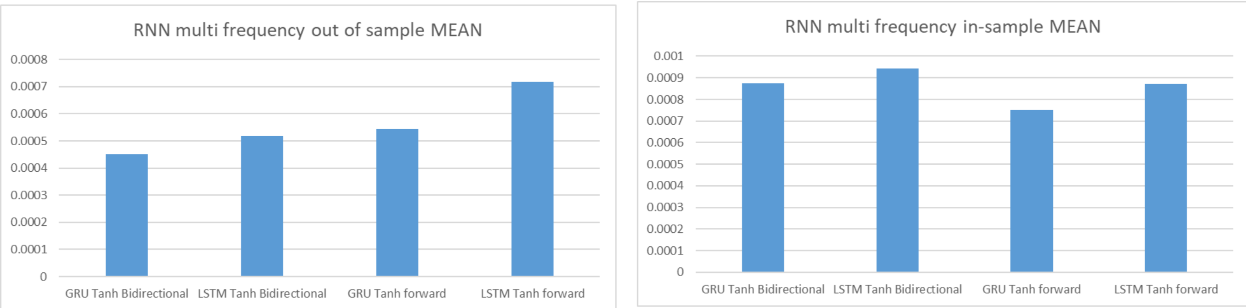


Figure 3.24 Average MSE RNN multiple frequency, Tanh activation function

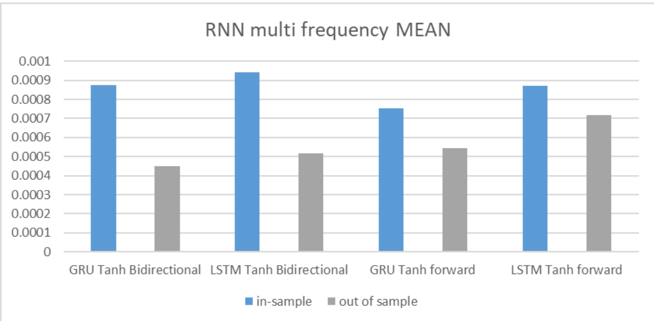


Figure 3.25 Average MSE RNN multiple frequency, Tanh activation function, in-sample and out of sample aggregated

ARMA-RNN single frequency:

The proposed ARMA-RNN model is described extensively. First glance on the obtained result proved enough evidence that Relu is not appropriate activation function for purpose of modelling financial time series. The mean and maximum of models with Tanh activation function is significantly lower than Relu. The effect of other model’s parameters such as flow of information and architectures of networks (LSTM, GRU) is not as large as activation function.

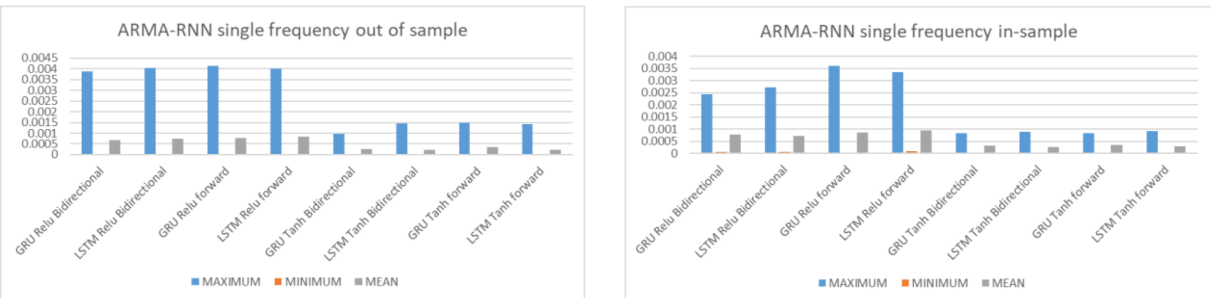


Figure 3.26 Minimum, Maximum, and Average MSE ARMA-RNN single frequency

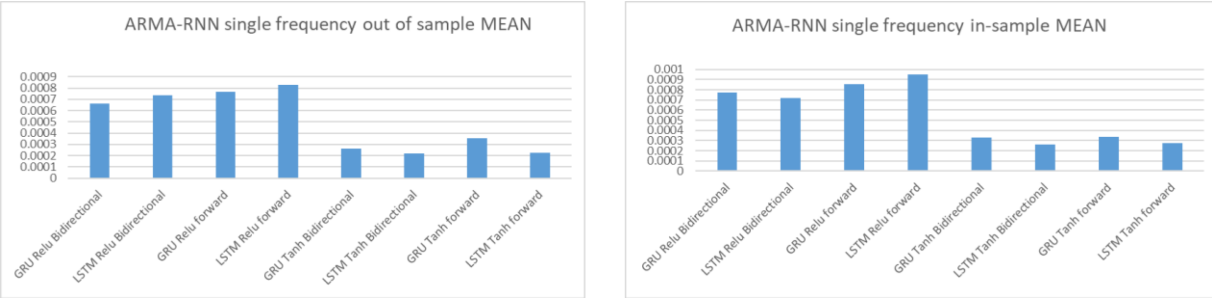


Figure 3.27 Average MSE ARMA-RNN single frequency

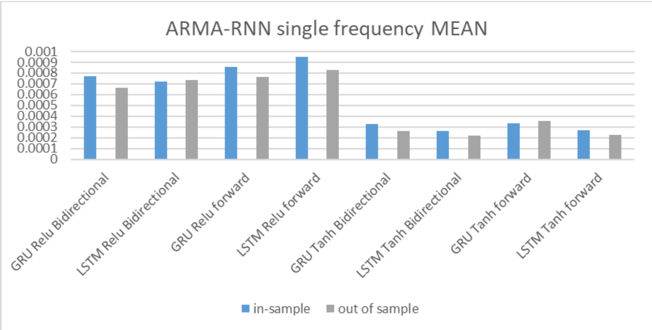


Figure 3.28 Average MSE ARMA-RNN single frequency in-sample and out of sample aggregated

After eliminating the result that is obtioned from Relu models, it is noticiable that generaly LSTM is more accurate on in-sampel data as well as out of sample subset. Even though LSTM has higher maximum, on average their performance is much more accurate than GRU models.

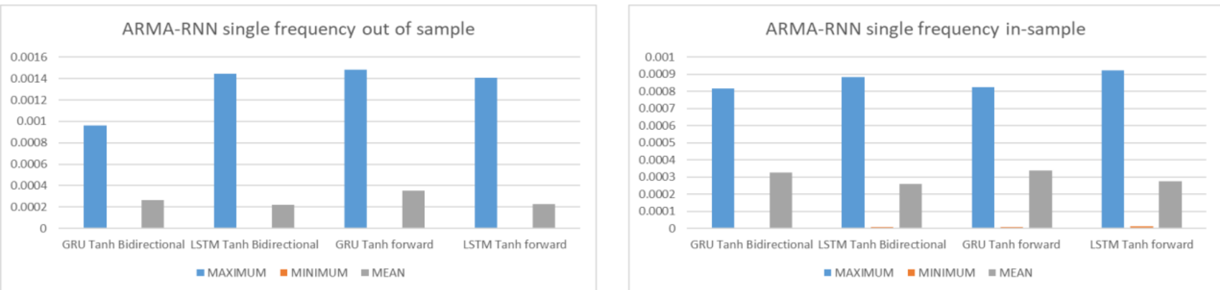


Figure 3.29 Minimum, Maximum, and Average MSE ARMA-RNN single frequency Tanh activation function

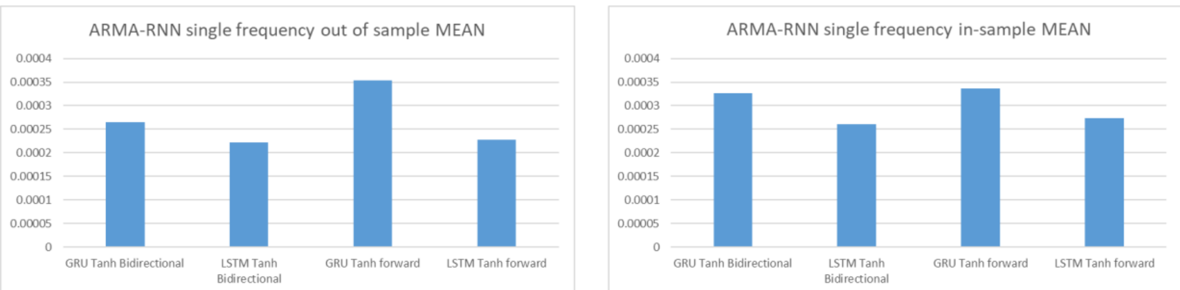


Figure 3.31 Average MSE ARMA-RNN single frequency Tanh activation function

While LSTM outperfom the GRU, regardless of whether it is forward feeding or bidirectional, the LSTM- bidirectional model is the optimal choice with a very small margin.

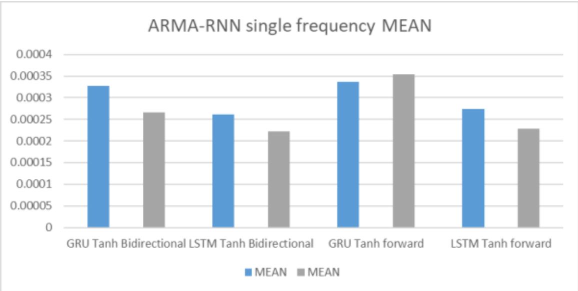


Figure 3.31 Average MSE ARMA-RNN single frequency Tanh activation function in-sample and out of sample aggregated

ARMA-RNN multi frequency:

The final model is ARMA-RNN multi frequency. The result is presented in blow indicates that Relu is under performing as it expected. Unlike previous three models the gap between minimum and maximum is not mass massive first four models which Relu is set as activation function. However, maximum, minimum, and mean of MSE for models that uses Than is significantly lower and in the next 5 plots is barely visible. Therefore, they will be presented separately.

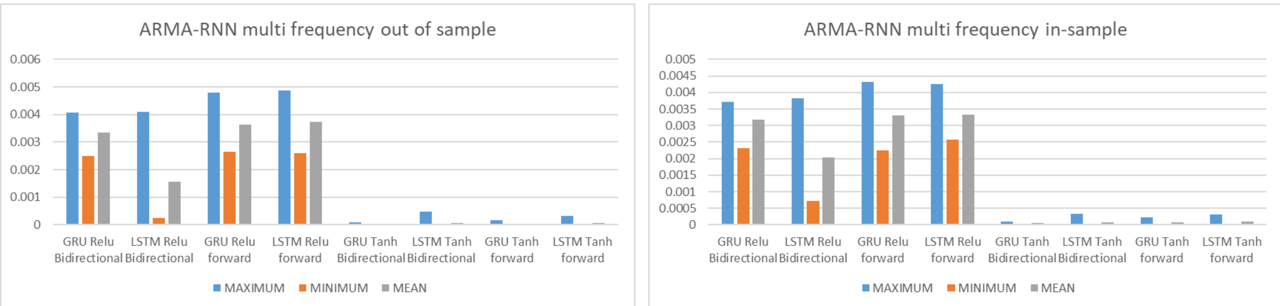


Figure 3.32 Minimum, Maximum, and Average MSE ARMA-RNN multi frequency

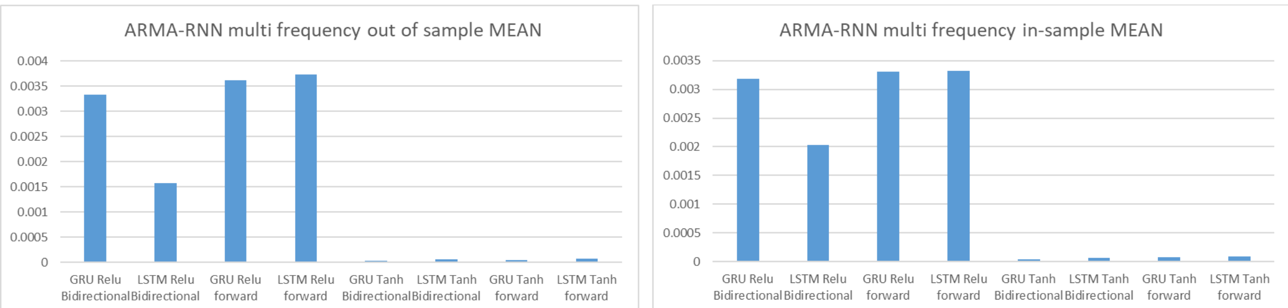


Figure 3.33 Average MSE ARMA-RNN single frequency

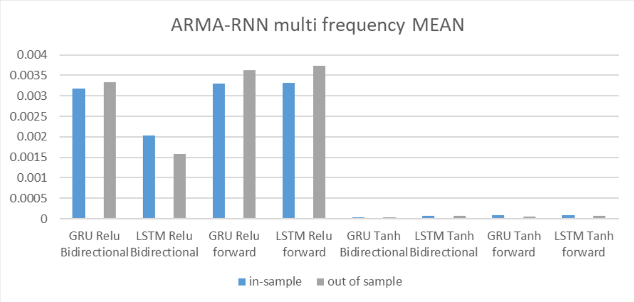
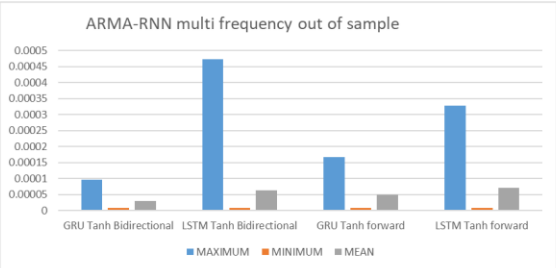


Figure 3.34 Average MSE ARMA-RNN single frequency in-sample and out of sample aggregated

The following figures describe the average MSE of models with Tanh activation function. In training set or in-sample sample the direction of information tend to be the determining factor. forward feeding model is less accurate in training set compared to its alternative. On the other hand, forecasting result indicates that the architecture of the model is more important parameter since GRU model is more accurate on average.



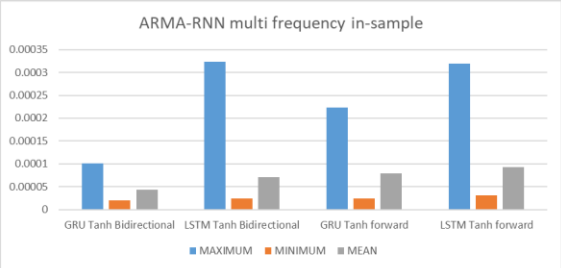
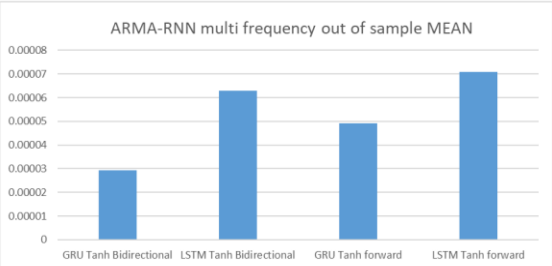


Figure 3.35 Minimum, Maximum, and Average MSE ARMA-RNN multi frequency, Tanh activation function



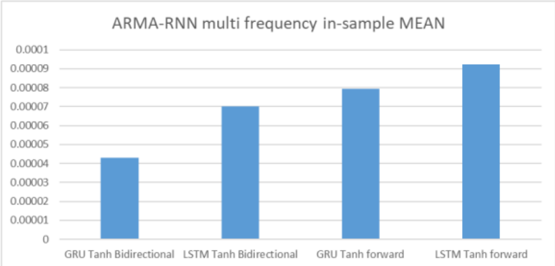


Figure 3.36 Average MSE ARMA-RNN multi frequency, Tanh activation function

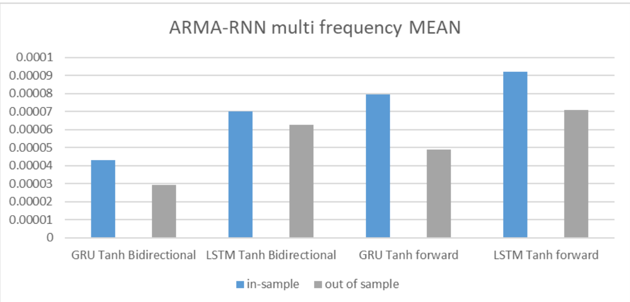


Figure 3.37 Average MSE ARMA-RNN multi frequency, Tanh activation function, in-sample and out of sample aggregated

When the ARMA-RNN multi frequency model uses GRU architecture, with Than activation function and information move forward and backwards the average MSE is extremely smaller compared to other models. On average the optimal model achieves nearly 50% less MSE compared to next best model both in training and testing subsample.

Comparing the best models:

In previous section the optimum sets of parameters for each model are defined. The best models are presented in below table:

model	Architecture	Activation function	Direction of information
RNN single frq	GRU	TANH	Forward
RNN multi frq	GRU	TANH	Forward
RNN multi frq	GRU	TANH	Bidirectional
ARMA-RNN single frq	LSTM	TANH	Bidirectional
ARMA-RNN multi frq	GRU	TANH	Bidirectional

Table 3.4 Best model / parameters

In order to test this chapter’s hypothesis, it is necessary to compare all models that are mentioned above. Firstly, multi frequency proposal is tested against benchmark model RNN single frequency. As the previous section showed there was two models that were chosen to have optimal sets of parameters for RNN multi frequency. One is more accurate in training set whereas the other one was more dependable in forecasting process. However, both models are underperforming with respect to benchmark model. RNN single frequency archives lower mean squared error on average in modelling the training dataset as well as testing set. As the graph below shows, the benchmark model is nearly twice more accurate than RNN multi frequency since the average MSE is almost 50% lower.

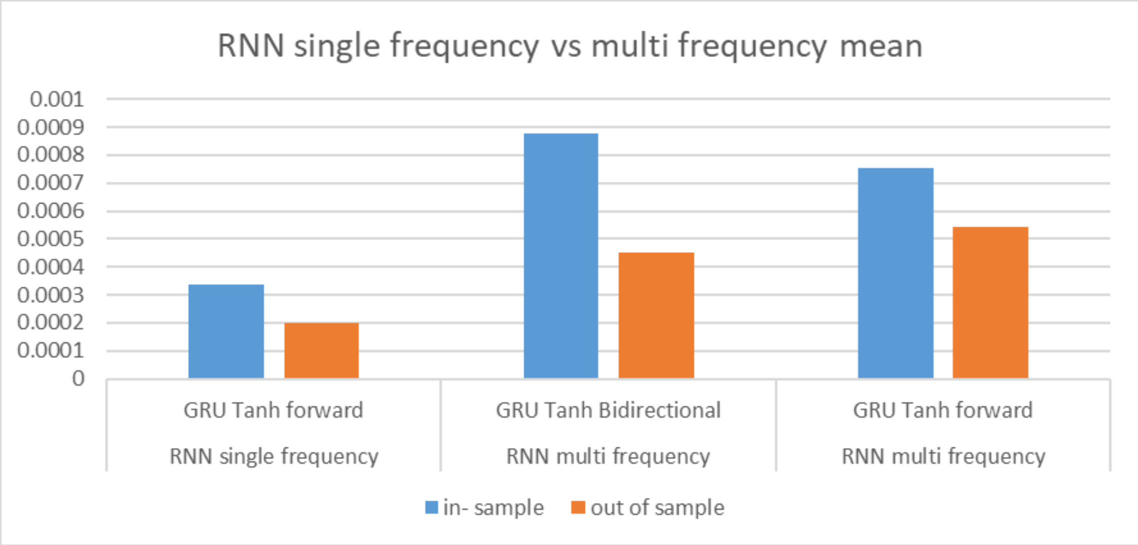


Figure 3.38 Average MSE RNN single frequency vs multi frequency

However, when the idea of using different frequency is applied to proposed model ARMA-RNN, the result changes drastically. RNN-ARMA model with lower time intervals data for input compared to output, the MSE on average decreases nearly 5 times compared to ARMA-RNN neural networks with single frequency. This pattern can be seen in both in-sample and out of sample datasets. Therefore, multi frequency is exceedingly more accurate when ARMA-RNN model is applied.

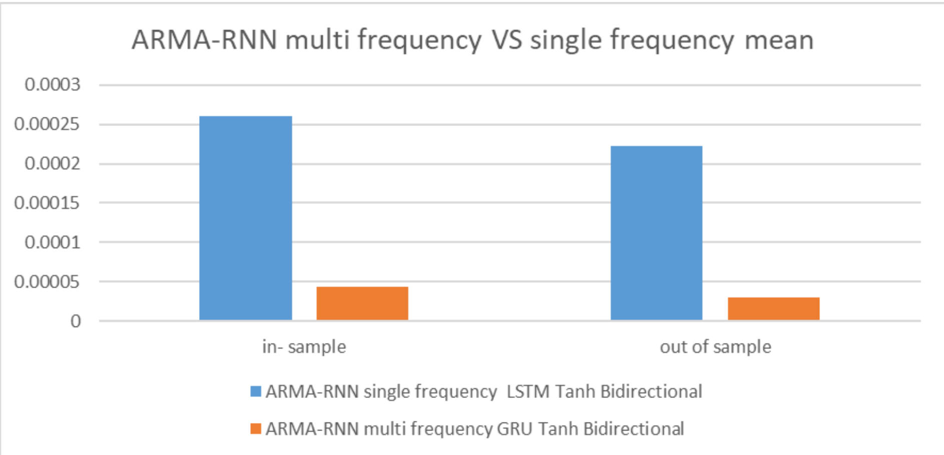


Figure 3.39 Average MSE ARMA-RNN single frequency vs multi frequency

The results of comparing benchmark model (RNN single frequency) with its alternative proposed model is somehow confusing. The figure blow presents the average MSE of RNN and ARMA-RNN. The results implies that the proposed model is more accurate on training sets. The difference of MSE is quite noticeable for in-sample datasets. On the other hand, out of sample result implies that RNN model is more optimal method to forecast the future value. This confusion might result from existence of an outlier. This means there is one or more than one value that is extremely high or low that increases or decreases the average drastically. Therefore, it is required to take closer look at individual results.

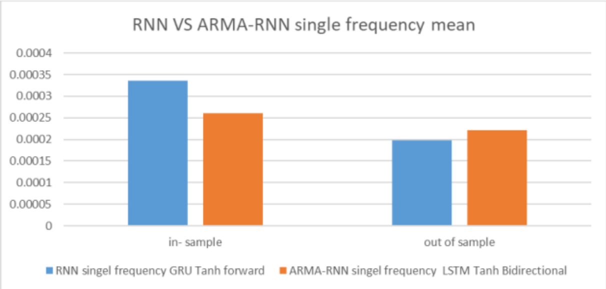


Figure 3.40 Average MSE RNN vs ARMA-RNN single frequency

The below table shows the results of in-sample and out of sample in details for every dataset and model. The lower MSE on each row is shown by green background. It is noticeable that in training set the ARMA-RNN model reaches lower MSE score in 13 out of 20 datasets. Similarly, the proposed model is more accurate. Out of 20 datasets, ARMA-RNN forecasted 12 datasets more precisely than benchmark model. Therefore, it can be concluded that ARMA-RNN is superior model compared to RNN when single frequency input data is used.

Currency_Frq	RNN single GRU Tanh Bidirectional In Sample	RNN single GRU Tanh Bidirectional Out of Sample	ARMA-RNN single LSTM Tanh Bidirectional In Sample	ARMA-RNN single LSTM Tanh Bidirectional Out of Sample
EURUSD_1D	0.000550794	0.000538757	0.000883073	0.000751868
EURUSD_12H	0.002389571	0.002087286	0.000774773	0.00041462
EURUSD_6H	0.000154944	0.000102952	0.000128633	0.000131254
EURUSD_1H	0.000262996	3.0793E-05	1.61315E-05	3.35139E-05
EURUSD_30T	8.90448E-05	9.09626E-05	6.7174E-06	5.26913E-06
GBPUSD_1D	0.00040952	0.000186909	0.000762349	0.001442196
GBPUSD_12H	0.000425576	0.000104514	0.000667682	0.00082987
GBPUSD_6H	0.000133072	5.86544E-05	0.000112767	7.66441E-05
GBPUSD_1H	2.73753E-05	1.76291E-05	1.42706E-05	1.6364E-05
GBPUSD_30T	0.000102446	1.08221E-05	7.53079E-06	5.21931E-06
USDCHF_1D	0.001419555	0.001377875	0.000263464	8.9031E-05
USDCHF_12H	0.000235081	0.000122869	0.000165185	6.45356E-05
USDCHF_6H	0.000117892	5.99677E-05	8.23448E-05	2.46476E-05
USDCHF_1H	4.53476E-05	3.73461E-05	1.81946E-05	1.24335E-05
USDCHF_30T	1.63055E-05	6.90432E-06	1.25902E-05	5.74303E-06
USDJPY_1D	0.00040242	0.000200462	0.000613552	0.000320303
USDJPY_12H	0.000251021	0.000202049	0.000523591	0.000153092
USDJPY_6H	0.000108625	6.03387E-05	0.000135167	4.84964E-05
USDJPY_1H	4.00549E-05	2.29787E-05	1.98276E-05	6.12584E-06
USDJPY_30T	4.04063E-05	8.09388E-06	1.11556E-05	1.1947E-05

Table 3.5 MSE of Best RNN vs ARMA-RNN single frequency

Moving on to testing next comparison, the following figure clearly indicates that ARMA-RNN is extremely more accurate model against RNN when multi frequency data is fed to model. the average MSE of ARMA-RNN nearly 10 times lower. This plot proves that the combination of two proposed ideas can create a model more accurate than benchmark or any other model that is tested here. In order to have more evidence for this matter, ARMA-RNN multi frequency model is compared to RNN single frequency.

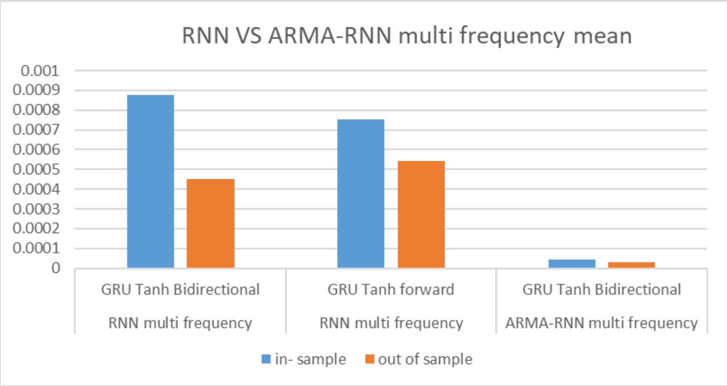


Figure 3.41 Average MSE RNN vs ARMA-RNN multi frequency

As it expected the combination of ARMA-RNN model with idea of uneven frequency will lead to significant drop on MSE in both datasets (in-sample and out of sample). The final model is more accurate than any other model that studied in this chapter including the benchmark model by huge margin which proves this chapter hypnotises.

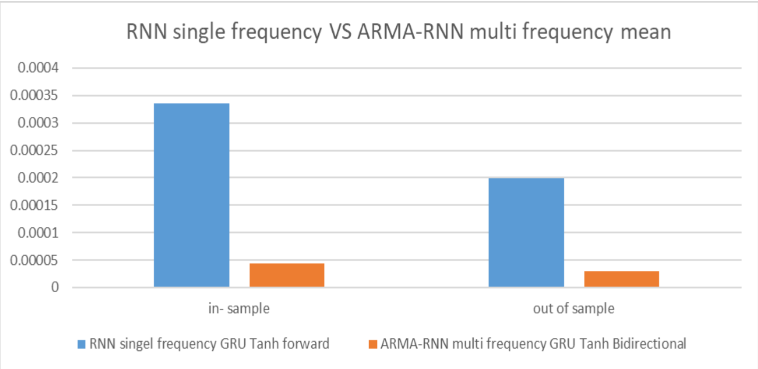


Figure 3.42 Average MSE RNN single frequency vs ARMA-RNN multi frequency

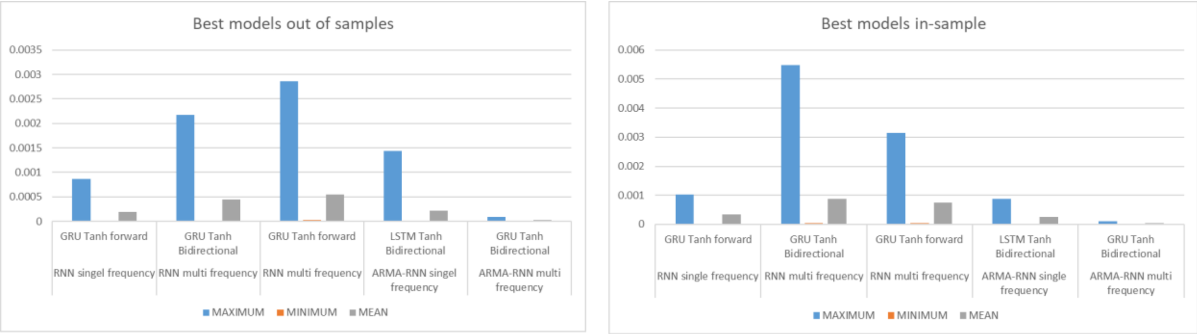


Figure 3.43 Maximum, Minimum, and Average MSE the optimum models

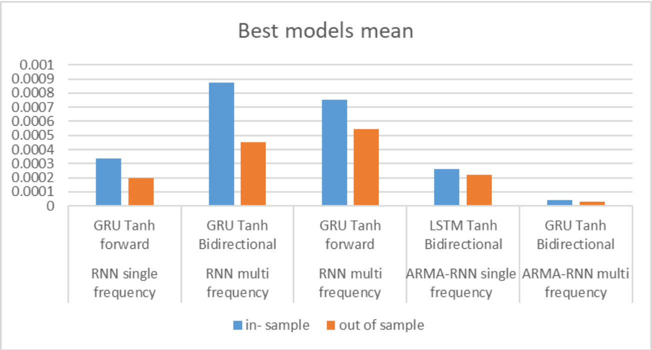


Figure 3.44 MSE Average the optimum models, in-sample and out of sample aggregated

In summary it can be said that Relu activation function is not a suitable choice for modelling time series. In addition, using the theorical background of ARMA model and create Recurrent Neural network base on it will create a model that can produces more accurate model for forecasting financial time series. Furthermore, the ARMA-RNN model with multi frequency input will dramatically lower the modelling and forecasting result, hence it is extremely more accurate model specially against the benchmark model.

Model	RNN single	ARMA-RNN single	RNN multi	RNN multi	ARMA-RNN multi
	GRU Tanh Bidirectional	LSTM Tanh Bidirectional	GRU Tanh Bidirectional	GRU Tanh forward	GRU Tanh Bidirectional
Currency_Frq	In Sample	In Sample	In Sample	In Sample	In Sample
EURUSD_1D	0.000550794	0.000883073	0.000806388	0.000779434	7.40023E-05
EURUSD_12H	0.002389571	0.000774773	0.000422621	0.000900803	2.24999E-05
EURUSD_6H	0.000154944	0.000128633	0.000377615	0.000304427	4.30507E-05
EURUSD_1H	0.000262996	1.61315E-05	0.000318452	5.80367E-05	2.35035E-05
EURUSD_30T	8.90448E-05	6.7174E-06	0.000152552	0.000544223	2.58168E-05
GBPUSD_1D	0.00040952	0.000762349	0.000619897	0.000946543	3.28545E-05
GBPUSD_12H	0.000425576	0.000667682	0.005478862	0.000387108	3.2947E-05
GBPUSD_6H	0.000133072	0.000112767	0.000222009	0.000210813	0.00010088
GBPUSD_1H	2.73753E-05	1.42706E-05	0.000241073	6.71052E-05	6.15475E-05
GBPUSD_30T	0.000102446	7.53079E-06	4.02096E-05	0.000107711	1.96347E-05
USDCHF_1D	0.001419555	0.000263464	0.003309961	0.002757218	5.56519E-05
USDCHF_12H	0.000235081	0.000165185	0.00149262	0.003139904	4.02598E-05
USDCHF_6H	0.000117892	8.23448E-05	0.000625067	0.000681481	4.03861E-05
USDCHF_1H	4.53476E-05	1.81946E-05	0.000622972	0.000233971	5.31597E-05
USDCHF_30T	1.63055E-05	1.25902E-05	4.11397E-05	4.95584E-05	3.85803E-05
USDJPY_1D	0.00040242	0.000613552	0.001356887	0.001257887	2.88762E-05
USDJPY_12H	0.000251021	0.000523591	0.000524949	0.002211989	6.68357E-05
USDJPY_6H	0.000108625	0.000135167	0.000367799	0.000255254	1.95264E-05
USDJPY_1H	4.00549E-05	1.98276E-05	0.000226138	0.000101651	3.87414E-05
USDJPY_30T	4.04063E-05	1.11556E-05	0.000250732	3.75444E-05	3.90356E-05
	Out of Sample	Out of Sample	Out of Sample	Out of Sample	Out of Sample
EURUSD_1D	0.000538757	0.000751868	0.000650794	0.000498998	2.32894E-05
EURUSD_12H	0.002087286	0.00041462	0.000299481	0.000739943	9.35139E-06
EURUSD_6H	0.000102952	0.000131254	0.000151466	0.000168922	6.52748E-05
EURUSD_1H	3.0793E-05	3.35139E-05	0.000259541	6.77597E-05	1.19071E-05
EURUSD_30T	9.09626E-05	5.26913E-06	9.68159E-05	0.00015724	1.13381E-05
GBPUSD_1D	0.000186909	0.001442196	0.000518153	0.00105262	2.86702E-05
GBPUSD_12H	0.000104514	0.00082987	0.001164701	0.000217407	1.9246E-05
GBPUSD_6H	5.86544E-05	7.66441E-05	0.000138404	0.000108503	9.6837E-05
GBPUSD_1H	1.76291E-05	1.6364E-05	0.000169746	2.30927E-05	3.69361E-05
GBPUSD_30T	1.08221E-05	5.21931E-06	1.64931E-05	7.67386E-05	1.29145E-05
USDCHF_1D	0.001377875	8.9031E-05	0.002171862	0.001303155	3.41068E-05
USDCHF_12H	0.000122869	6.45356E-05	0.00076994	0.002862081	1.15508E-05
USDCHF_6H	5.99677E-05	2.46476E-05	0.000269836	0.00025657	1.24733E-05
USDCHF_1H	3.73461E-05	1.24335E-05	0.000719392	0.000176866	5.85053E-05
USDCHF_30T	6.90432E-06	5.74303E-06	4.14724E-05	5.02027E-05	5.36023E-05
USDJPY_1D	0.000200462	0.000320303	0.000712293	0.001158159	8.95289E-06
USDJPY_12H	0.000202049	0.000153092	0.00024101	0.001772744	4.79812E-05
USDJPY_6H	6.03387E-05	4.84964E-05	0.000208181	0.000101026	8.49935E-06
USDJPY_1H	2.29787E-05	6.12584E-06	0.000175771	2.49695E-05	1.70213E-05
USDJPY_30T	8.09388E-06	1.1947E-05	0.000255995	3.6878E-05	1.97307E-05

Table 3.6 MSE of optimal Models

For further evidence, the individual result of each chosen models is gathered in table above to analyse each dataset separately. Upper half of the table are in-sample MSE, and lower half is presenting the out of sample forecasting error. The lowest value of each row indicates which models fitted the best with respect to other, and it is highlighted. Looking at in-sample output it is clear that ARMA-RNN model regardless of input frequency obtains lower MSE compared to RNN. This proves that ARMA-RNN concept that described extensively before is better model than RNN. Additionally, ARMA-RNN multi frequency outperform in 60 % of dataset (12 out if 20). Similarly, out of sample presents the same patterns. Except two instances, the combination of ARMA and RNN will generate more accurate forecast. Finally, the concept of multi frequency will improve the ARMA-RNN forecasting power and make it the optimum model compared to other three. Please see appendix E for all statistical results.

Policy implication, target readers, and research limitation:

The proposed model is more accurate compared to benchmark RNN model. The contribution of this study is beyond introducing a hybrid model. The methodology of how this model is constructed can be applied to other models such as ARIMA, ARCH, and GARCH. This model is potentially can be used for trading purposes. Even though the analytic results clearly indicate that both presented ideas increases the financial forecasting accuracy, there are several limitations that requires further research.

1. For multifrequency modelling, data at higher frequency is required which is not easily accessible for all financial assets.
2. Forecasting by multifrequency data is limited to one step ahead forecast since predicted outcome is at lower different frequency than input and cannot be refed to network for next step.
3. It takes longer time to prepare training set and train the model when mixed frequency is used.
4. With respect to proposed hybrid model, the only area to investigate is how to choose the input variable such as variance. It is possible if different activation function is applied or different method to compute MA element of the model, it will yield a better result.

Conclusion:

In this study the author introduced new Recurrent Neural Network based on Autoregressive Moving Average model. Additionally, the idea of using more timely dense data as input to forecast output at lower frequency is analyzed.

The new ARMA-RNN method is constructed to independent recurrent network that one is trained at past values or in other words it acts as Autoregressive component of ARMA model. and other network will learn from residuals and handle Moving Average element of the network. multiple combinations of LSTM and GRU with different activation function and training direction are trained both for RNN and ARMA-RNN. The result indicates that the proposed model is significantly more robust compared to benchmark RNN model. On second part of this research, it is suggested that data on higher frequency carries more information. Therefore, if neural network is trained on higher frequency data to forecast on same dataset with longer time interval, it will yield to more accurate predictive model. applying the method to traditional recurrent neural networks will produce a mix result. On the other hand, applying the multifrequency method to ARMA-RNN model that is presented in this study will increase the performance of the training set as well as forecast considerably.

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list of Acronyms:

ADF	**Augmented Dickey–Fuller**
AIC	**Akaike's Information Criteria**
AMEX	**American Stock Exchange**
ANN	**Artificial Neural Networks**
AR	**Autoregressive**
ARCH	**Autoregressive Conditional Heteroskedasticity**
ARIMA	**Autoregressive Integrated Moving Average**
ARMA	**Autoregressive Moving Average**
ARMA-GP	**Autoregressive Integrated Moving Average Gaussian Process**
ARMA-RNN	**Autoregressive Moving Average Recurrent Neural Network**
ARX	**Autoregressive with Extra Input**
BIC	**Bayesian Information Criterion**
BILSTM	**Bidirectional Long Short-Term Memory**
BPNN	**Backpropagation Neural Network**
CAMP	**Capital Asset Pricing Model**
CEEMDAN	**Complete Ensemble Empirical Mode Decomposition Adaptive Noise**
CEEMDAN-LSTM	**Complete Ensemble Empirical Mode Decomposition Adaptive Noise - Long Short-Term Memory**
CEEMDAN-MLP	**Complete Ensemble Empirical Mode Decomposition Adaptive Noise - Multi Layer Perceptron**
CEEMDAN-SVM	**Complete Ensemble Empirical Mode Decomposition Adaptive Noise -Support Vector Machines**
CNN	**Convolutional Neural Network**
CPI	**Consumer Price Index**
CRSP	**Centre for Research in Security Prices**
DAX	**Deutscher Aktien Index**
DIDLP	**Deep Increasing Decreasing Linear Perceptron**
EANN	**Emotional Artificial Neural Network**
ECB	**European Central Bank**
EEMD	**Ensemble Empirical Mode Decomposition**
EEMDBPNN	**Ensemble Empirical Mode Decomposition - Backpropagation Neural Network**
EEMD-GA-WA	**Ensemble Empirical Mode Decomposition - Genetic Algorithm - Weighted Average**
EEMD-RNN	**Ensemble Empirical Mode Decomposition - Recurrent Neural Network**
EEMD-SVR	**Ensemble Empirical Mode Decomposition - Support Vector Regression**
EMD	**Empirical Mode Decomposition**
EMD-LSTM	**Empirical Mode Decomposition - Long Short-Term Memory**
ESMD	**Extreme-point Symmetric Mode Decomposition**
FANN	**Fast Artificial Neural Network**
FED	**Federal Reserve System**
FLN	**Fuzzy Lattice Neurocomputing**
FOREX	**Foreign Exchange Market**
FS-RNN	**Fast Slow Recurrent Neural Network**
GARCH	**Generalized Autoregressive Conditional Heteroskedasticity**
GDP	**Gross Domestic Product**
GJR	**Glosten-Jagannathan-Runkle**
GLAR	**Integrating Generalized Linear Auto Regression**
GRU	**Gated Recurrent Units**
HCA	**Hierarchical Cluster Analysis**
HIS	**Hang Seng Index**

HM-RNN	**Hierarchical Multiscale Recurrent Neural Network**
IGARCH	**Integrated Generalized Autoregressive Conditional Heteroskedasticity**
IMF	**International Monetary Fund / Intrinsic Mode Function**
IND-RNN	**Independent Recurrent Neural Network**
IPO	**Initial Public Offering**
KAMRIMA	**Kohonen Autoregressive Integrated Moving Average**
LLE	**Locally Linear Embedding**
LSTM	**Long Short-Term Memory**
MA	**Moving Average**
ML	**Machine Learning**
MLP	**Multi-Layer Perceptron**
MM	**Modigliani-Miller theorem**
MSE	**Mean Squared Error**
NFP	**Non-Farm Payroll**
NPV	**Net Present Value**
NYSE	**New York Stock Exchange**
PCA	**Principal Component Analysis**
PCABPNN	**Principal Component Analysis Backpropagation Neural Network**
PCDG	**Percentage Changes in Debt Growth**
PMI	**Purchasing Managers' Index**
QRNN	**quaternion Recurrent Neural Network**
RBF	**Radial Basis Function**
RELU	**Rectified Linear Activation Unit**
RHN	**Recurrent Highway Network**
RMSE	**Root Mean Squared Error**
RNN	**Recurrent Neural Network**
RPI	**Retail Price Index**
RW	**Random Walk**
S&P	**Standard and Poor's**
SAEs	**Stacked Autoencoders**
SARIMABP	**Seasonality Autoregressive Integrated Moving Average Back Propagation**
SARMIA	**Seasonal Autoregressive Integrated Moving Average**
SKIPRNN	**Skip Recurrent Neural Network**
SSE	**Shanghai Stock Exchange**
STNN	**Spatio-Temporal Neural Networks**
SVM	**Support Vector Machines**
SVR	**Support Vector Regression**
TANH	**Hyperbolic Tangent Function**
TGARCH	**Threshold Generalized Autoregressive Conditional Heteroskedasticity**
TLU	**Threshold Logic Unit**
T-SNE	**t-Distributed Stochastic Neighbour Embedding**
WT	**Wavelet Transforms**

List of tables:

List of figures

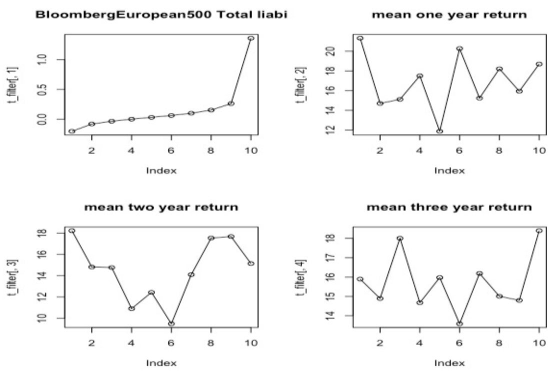
List of equations:

Appendix:

Appendix A:

Regressions with Debt changes variable

Bloomberg Europe 500



Regression 1

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 13:05
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	23.67008	0.834794	28.35438	0.0000
RETURN(-1)	-0.179998	0.017323	-10.39052	0.0000
RETURN(-2)	-0.275512	0.017026	-16.18203	0.0000
P_DEBTGROWTH_TOTAL(-1)	-5.593965	1.803945	-3.100962	0.0019
P_DEBTGROWTH_TOTAL(-1)	0.136424	0.043268	3.153021	0.0016

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	36.75742	R-squared	0.165326
Mean dependent var	15.04922	Adjusted R-squared	0.080879
S.D. dependent var	40.23970	S.E. of regression	38.57812
Akaike info criterion	10.23088	Sum squared resid	4310035.
Schwarz criterion	10.79011	Log likelihood	-16024.26
Hannan-Quinn criter.	10.43141	F-statistic	1.957745
Durbin-Watson stat	2.139736	Prob(F-statistic)	0.000000

Regression 2

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 14:10
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	27.88774	1.163741	23.96386	0.0000
RETURN(-1)	-0.171280	0.017329	-9.884244	0.0000
RETURN(-2)	-0.267888	0.017014	-15.74489	0.0000
P_DEBTGROWTH_TOTAL(-1)	-5.397882	1.796360	-3.004900	0.0027
P_DEBTGROWTH_TOTAL(-1)	0.131117	0.043089	3.042971	0.0024
MARKET_CAP(-1)	-1.70E-10	3.29E-11	-5.177605	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	36.58841	R-squared	0.172984
Mean dependent var	15.04922	Adjusted R-squared	0.088997
S.D. dependent var	40.23970	S.E. of regression	38.40737
Akaike info criterion	10.22229	Sum squared resid	4270490.
Schwarz criterion	10.78342	Log likelihood	-16009.56
Hannan-Quinn criter.	10.42350	F-statistic	2.059655
Durbin-Watson stat	2.129761	Prob(F-statistic)	0.000000

Regression 3

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 14:13
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	536.2062	34.02389	15.75970	0.0000
RETURN(-1)	-0.104065	0.017429	-5.970863	0.0000
RETURN(-2)	-0.189200	0.017370	-10.89264	0.0000
P_DEBTGROWTH_TOTAL(-1)	-4.305279	1.739515	-2.474988	0.0134
P_DEBTGROWTH_TOTAL(-1)	0.114195	0.041698	2.738606	0.0062
LOG(MARKET_CAP(-1))	-22.43808	1.489100	-15.06821	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	35.39560	R-squared	0.226028
Mean dependent var	15.04922	Adjusted R-squared	0.147428
S.D. dependent var	40.23970	S.E. of regression	37.15527
Akaike info criterion	10.15601	Sum squared resid	3996588.
Schwarz criterion	10.71713	Log likelihood	-15903.83
Hannan-Quinn criter.	10.35721	F-statistic	2.875663
Durbin-Watson stat	2.037269	Prob(F-statistic)	0.000000

Regression 4

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 14:35
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 290
Total panel (balanced) observations: 2900

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1102.920	38.56211	28.60113	0.0000
D(RETURN(-1))	-0.641184	0.014692	-43.64056	0.0000
D(RETURN(-2))	-0.433704	0.014682	-29.53934	0.0000
P_DEBTGROWTH_TOTAL(-1)	-7.710745	2.694125	-2.862059	0.0042
P_DEBTGROWTH_TOTAL(-1)	0.275059	0.109632	2.508932	0.0122
LOG(MARKET_CAP(-1))	-48.00597	1.678103	-28.60729	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	40.93847	R-squared	0.541432
Mean dependent var	1.232221	Adjusted R-squared	0.489678
S.D. dependent var	60.46508	S.E. of regression	43.19433
Akaike info criterion	10.46547	Sum squared resid	4860279.
Schwarz criterion	11.07301	Log likelihood	-14879.93
Hannan-Quinn criter.	10.68437	F-statistic	10.46166
Durbin-Watson stat	2.152106	Prob(F-statistic)	0.000000

Regression 5

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 14:39
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 290
Total panel (balanced) observations: 2900

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	10.22056	1.529830	6.680849	0.0000
D(RETURN(-1))	-0.647254	0.016619	-38.94684	0.0000
D(RETURN(-2))	-0.484163	0.016468	-29.39958	0.0000
P_DEBTGROWTH_TOTAL(-1)	-13.13857	3.038163	-4.324510	0.0000
P_DEBTGROWTH_TOTAL(-1)	0.460770	0.123734	3.723878	0.0002
MARKET_CAP(-1)	-3.84E-10	4.53E-11	-8.480434	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	46.29578	R-squared	0.413560
Mean dependent var	1.232221	Adjusted R-squared	0.347375
S.D. dependent var	60.46508	S.E. of regression	48.84685
Akaike info criterion	10.71143	Sum squared resid	6215569.
Schwarz criterion	11.31897	Log likelihood	-15236.57
Hannan-Quinn criter.	10.93034	F-statistic	6.248499
Durbin-Watson stat	2.368014	Prob(F-statistic)	0.000000

Regression 6

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 14:40
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 290
Total panel (balanced) observations: 2900

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.021657	0.958315	0.022599	0.9820
D(RETURN(-1))	-0.651969	0.016834	-38.72914	0.0000
D(RETURN(-2))	-0.491434	0.016668	-29.48319	0.0000
P_DEBTGROWTH_TOTAL(-1)	-13.79523	3.078224	-4.481555	0.0000
P_DEBTGROWTH_TOTAL(-1)	0.482462	0.125379	3.848020	0.0001

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	46.93049	R-squared	0.397370
Mean dependent var	1.232221	Adjusted R-squared	0.329615
S.D. dependent var	60.46508	S.E. of regression	49.50703
Akaike info criterion	10.73797	Sum squared resid	6387166.
Schwarz criterion	11.34346	Log likelihood	-15276.06
Hannan-Quinn criter.	10.95614	F-statistic	5.864772
Durbin-Watson stat	2.388942	Prob(F-statistic)	0.000000

Regression 9

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 15:05
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 290
Total panel (balanced) observations: 2900

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1049.525	39.30325	26.70327	0.0000
D(RETURN(-1))	-0.572455	0.018489	-30.96238	0.0000
D(RETURN(-2))	-0.395965	0.015859	-24.96752	0.0000
P_DEBTGROWTH_TOTAL(-1)	-9.205650	2.687245	-3.425683	0.0006
P_DEBTGROWTH_TOTAL(-1)	0.322700	0.109173	2.955843	0.0031
LOG(MARKET_CAP(-1))	-45.49730	1.717474	-26.49082	0.0000
MARKET_RETURN(-1)	-0.268628	0.044371	-6.054080	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	40.65336	R-squared	0.547797
Mean dependent var	1.232221	Adjusted R-squared	0.496568
S.D. dependent var	60.46508	S.E. of regression	42.90175
Akaike info criterion	10.45218	Sum squared resid	4792819.
Schwarz criterion	11.06178	Log likelihood	-14859.66
Hannan-Quinn criter.	10.67183	F-statistic	10.69313
Durbin-Watson stat	2.181240	Prob(F-statistic)	0.000000

Regression 7

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 14:44
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

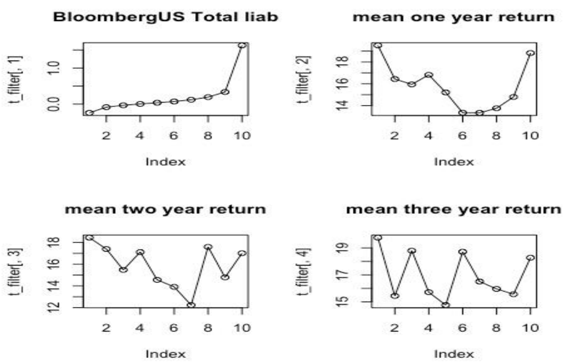
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1174.719	42.01016	27.96274	0.0000
D(RETURN(-1))	-0.453312	0.014687	-30.86378	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.060105	0.020870	-2.880029	0.0040
LOG(MARKET_CAP(-1))	-51.22836	1.828224	-28.02083	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	47.49223	R-squared	0.375667
Mean dependent var	-1.349539	Adjusted R-squared	0.312738
S.D. dependent var	60.11495	S.E. of regression	49.83606
Akaike info criterion	10.74271	Sum squared resid	7195083.
Schwarz criterion	11.30003	Log likelihood	-16841.62
Hannan-Quinn criter.	10.94255	F-statistic	5.969699
Durbin-Watson stat	2.258850	Prob(F-statistic)	0.000000

Bloomberg U.S. Equity



Regression 8

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 15:03
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1021.311	40.69806	25.09483	0.0000
D(RETURN(-1))	-0.308447	0.016043	-19.22662	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.082105	0.019814	-4.143701	0.0000
LOG(MARKET_CAP(-1))	-43.99286	1.777773	-24.74606	0.0000
MARKET_RETURN(-1)	-0.761518	0.041934	-18.16005	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	44.99911	R-squared	0.439496
Mean dependent var	-1.349539	Adjusted R-squared	0.382787
S.D. dependent var	60.11495	S.E. of regression	47.22805
Akaike info criterion	10.63549	Sum squared resid	6459496.
Schwarz criterion	11.19471	Log likelihood	-16669.60
Hannan-Quinn criter.	10.83601	F-statistic	7.750083
Durbin-Watson stat	2.403540	Prob(F-statistic)	0.000000

Regression 1

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 15:20
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 1030
Total panel (balanced) observations: 11330

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	23.42912	0.523413	44.76217	0.0000
RETURN(-1)	-0.189307	0.009765	-19.38638	0.0000
RETURN(-2)	-0.215192	0.009778	-22.00821	0.0000
P_DEBTGROWTH_TOTAL(-1)	-2.194049	0.758944	-2.890924	0.0038
P_DEBTGROWTH_TOTAL(-1)	0.035428	0.018140	1.953076	0.0508

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	45.92258	R-squared	0.118018
Mean dependent var	16.55663	Adjusted R-squared	0.029529
S.D. dependent var	48.90077	S.E. of regression	48.17337
Akaike info criterion	10.67432	Sum squared resid	23893652
Schwarz criterion	11.34374	Log likelihood	-59436.00
Hannan-Quinn criter.	10.89951	F-statistic	1.333699
Durbin-Watson stat	2.089500	Prob(F-statistic)	0.000000

Regression 2

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 15:25
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 1030
Total panel (balanced) observations: 11330

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	23.60810	0.536610	43.99491	0.0000
RETURN(-1)	-0.188938	0.009767	-19.34375	0.0000
RETURN(-2)	-0.214760	0.009781	-21.95598	0.0000
P_DEBTGROWTH_TOTAL(-1)	-2.173788	0.759015	-2.863960	0.0042
P_DEBTGROWTH_TOTAL(-1)	0.035016	0.018141	1.930278	0.0536
MARKET_CAP(-1)	-1.44E-12	9.50E-13	-1.511404	0.1307

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	45.91749	R-squared	0.118214
Mean dependent var	16.55663	Adjusted R-squared	0.029650
S.D. dependent var	48.90077	S.E. of regression	48.17036
Akaike info criterion	10.67427	Sum squared resid	23888351
Schwarz criterion	11.34434	Log likelihood	-59434.74
Hannan-Quinn criter.	10.89968	F-statistic	1.334784
Durbin-Watson stat	2.089854	Prob(F-statistic)	0.000000

Regression 3

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 15:25
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 1030
Total panel (balanced) observations: 11330

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	514.5834	18.32932	28.07433	0.0000
RETURN(-1)	-0.134285	0.009662	-13.89822	0.0000
RETURN(-2)	-0.148053	0.009780	-15.13820	0.0000
P_DEBTGROWTH_TOTAL(-1)	-1.182641	0.734773	-1.609533	0.1075
P_DEBTGROWTH_TOTAL(-1)	0.014201	0.017557	0.808882	0.4186
LOG(MARKET_CAP(-1))	-22.24379	0.829797	-26.80632	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	44.39921	R-squared	0.175563
Mean dependent var	16.55663	Adjusted R-squared	0.092759
S.D. dependent var	48.90077	S.E. of regression	46.57759
Akaike info criterion	10.60702	Sum squared resid	22334715
Schwarz criterion	11.27710	Log likelihood	-59053.78
Hannan-Quinn criter.	10.83244	F-statistic	2.120221
Durbin-Watson stat	2.041424	Prob(F-statistic)	0.000000

Regression 4

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 15:26
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 1030
Total panel (balanced) observations: 10300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	997.1831	22.31256	44.69157	0.0000
D(RETURN(-1))	-0.709830	0.008387	-84.63671	0.0000
D(RETURN(-2))	-0.440190	0.008477	-51.93026	0.0000
P_DEBTGROWTH_TOTAL(-1)	-3.959950	0.903216	-4.384278	0.0000
P_DEBTGROWTH_TOTAL(-1)	0.066189	0.021272	3.111532	0.0019
LOG(MARKET_CAP(-1))	-44.89035	1.005581	-44.64120	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	51.64248	R-squared	0.509974
Mean dependent var	1.097511	Adjusted R-squared	0.455285
S.D. dependent var	73.77657	S.E. of regression	54.45065
Akaike info criterion	10.92754	Sum squared resid	27469546
Schwarz criterion	11.65504	Log likelihood	-55241.82
Hannan-Quinn criter.	11.17343	F-statistic	9.325089
Durbin-Watson stat	2.238901	Prob(F-statistic)	0.000000

Regression 5

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 15:28
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 1030
Total panel (balanced) observations: 10300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.136161	0.638979	3.343086	0.0008
D(RETURN(-1))	-0.712678	0.009238	-77.14928	0.0000
D(RETURN(-2))	-0.464610	0.009317	-49.86562	0.0000
P_DEBTGROWTH_TOTAL(-1)	-6.902439	0.992205	-6.956666	0.0000
P_DEBTGROWTH_TOTAL(-1)	0.130309	0.023377	5.574213	0.0000
MARKET_CAP(-1)	-5.43E-12	1.45E-12	-3.734456	0.0002

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	56.88336	R-squared	0.405467
Mean dependent var	1.097511	Adjusted R-squared	0.339116
S.D. dependent var	73.77657	S.E. of regression	59.97651
Akaike info criterion	11.12085	Sum squared resid	33327887
Schwarz criterion	11.84836	Log likelihood	-56237.40
Hannan-Quinn criter.	11.36675	F-statistic	6.110894
Durbin-Watson stat	2.347323	Prob(F-statistic)	0.000000

Regression 6

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 15:29
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 1030
Total panel (balanced) observations: 10300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.431051	0.610872	2.342636	0.0192
D(RETURN(-1))	-0.712656	0.009244	-77.09306	0.0000
D(RETURN(-2))	-0.464681	0.009324	-49.83862	0.0000
P_DEBTGROWTH_TOTAL(-1)	-6.919069	0.992888	-6.968631	0.0000
P_DEBTGROWTH_TOTAL(-1)	0.130650	0.023393	5.584964	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	56.92616	R-squared	0.404572
Mean dependent var	1.097511	Adjusted R-squared	0.338192
S.D. dependent var	73.77657	S.E. of regression	60.01839
Akaike info criterion	11.12216	Sum squared resid	33378054
Schwarz criterion	11.84897	Log likelihood	-56245.14
Hannan-Quinn criter.	11.36782	F-statistic	6.094794
Durbin-Watson stat	2.347007	Prob(F-statistic)	0.000000

Regression 7

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 15:30
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 1030
Total panel (balanced) observations: 11330

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	972.1855	22.86144	42.52511	0.0000
D(RETURN(-1))	-0.498452	0.008011	-62.22182	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.011750	0.011515	-1.020370	0.3076
LOG(MARKET_CAP(-1))	-43.81853	1.030577	-42.51842	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	57.97637	R-squared	0.351041
Mean dependent var	0.115949	Adjusted R-squared	0.286000
S.D. dependent var	71.97164	S.E. of regression	60.81499
Akaike info criterion	11.14030	Sum squared resid	38083068
Schwarz criterion	11.80908	Log likelihood	-62076.78
Hannan-Quinn criter.	11.36528	F-statistic	5.397228
Durbin-Watson stat	2.398207	Prob(F-statistic)	0.000000

Regression 8

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 15:30
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 1030
Total panel (balanced) observations: 11330

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	906.2594	22.40529	40.44845	0.0000
D(RETURN(-1))	-0.409540	0.008616	-47.53412	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.012591	0.011202	-1.123983	0.2610
LOG(MARKET_CAP(-1))	-40.36602	1.012622	-39.86288	0.0000
MARKET_RETURN(-1)	-0.650470	0.026883	-24.19631	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	56.39514	R-squared	0.385957
Mean dependent var	0.115949	Adjusted R-squared	0.324350
S.D. dependent var	71.97164	S.E. of regression	59.15921
Akaike info criterion	11.08517	Sum squared resid	36034063
Schwarz criterion	11.75459	Log likelihood	-61763.47
Hannan-Quinn criter.	11.31036	F-statistic	6.264813
Durbin-Watson stat	2.454435	Prob(F-statistic)	0.000000

Regression 9

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 15:32
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 1030
Total panel (balanced) observations: 10300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	969.7872	22.39414	43.30539	0.0000
D(RETURN(-1))	-0.661995	0.009756	-67.85395	0.0000
D(RETURN(-2))	-0.414070	0.008876	-46.65244	0.0000
P_DEBTGROWTH_TOTAL(-1)	-4.317032	0.899714	-4.798226	0.0000
P_DEBTGROWTH_TOTAL(-1)	0.073356	0.021185	3.462725	0.0005
LOG(MARKET_CAP(-1))	-43.47396	1.011916	-42.96204	0.0000
MARKET_RETURN(-1)	-0.248501	0.026240	-9.470481	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	51.39430	R-squared	0.514672
Mean dependent var	1.097511	Adjusted R-squared	0.460450
S.D. dependent var	73.77657	S.E. of regression	54.19188
Akaike info criterion	10.91810	Sum squared resid	27206148
Schwarz criterion	11.64630	Log likelihood	-55192.20
Hannan-Quinn criter.	11.16423	F-statistic	9.491916
Durbin-Watson stat	2.265525	Prob(F-statistic)	0.000000

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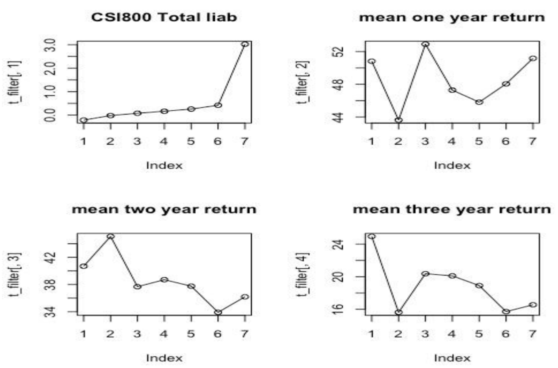

Regression 1

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 20:57
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	47.20277	2.165803	21.79458	0.0000
RETURN(-1)	-0.208648	0.018831	-11.07985	0.0000
RETURN(-2)	-0.065092	0.018729	-3.475442	0.0005
P_DEBTGROWTH_TOTAL(-1)	2.403437	1.123547	2.139151	0.0325
P_DEBTGROWTH_TOTAL(-1)	-0.010867	0.005948	-1.826877	0.0678

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	88.82395	R-squared	0.068834
Mean dependent var	36.17453	Adjusted R-squared	-0.025475
S.D. dependent var	92.06420	S.E. of regression	93.22947
Akaike info criterion	11.99574	Sum squared resid	23085245
Schwarz criterion	12.54768	Log likelihood	-17279.77
Hannan-Quinn criter.	12.19453	F-statistic	0.729881
Durbin-Watson stat	1.790901	Prob(F-statistic)	0.999532

Regression 2

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 20:58
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	80.00378	2.870457	27.87145	0.0000
RETURN(-1)	-0.164388	0.018144	-9.059959	0.0000
RETURN(-2)	-0.049670	0.017871	-2.779374	0.0055
P_DEBTGROWTH_TOTAL(-1)	2.031323	1.070824	1.896971	0.0579
P_DEBTGROWTH_TOTAL(-1)	-0.009749	0.005668	-1.719936	0.0856
MARKET_CAP(-1)	-1.59E-09	9.69E-11	-16.44038	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	84.62101	R-squared	0.154870
Mean dependent var	36.17453	Adjusted R-squared	0.068925
S.D. dependent var	92.06420	S.E. of regression	88.83479
Akaike info criterion	11.89948	Sum squared resid	20952251
Schwarz criterion	12.45346	Log likelihood	-17137.94
Hannan-Quinn criter.	12.09900	F-statistic	1.801964
Durbin-Watson stat	1.795026	Prob(F-statistic)	0.000000

Regression 3

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 20:59
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1888.201	47.50710	39.74565	0.0000
RETURN(-1)	-0.110186	0.015262	-7.219692	0.0000
RETURN(-2)	-0.038198	0.014984	-2.549312	0.0108
P_DEBTGROWTH_TOTAL(-1)	2.929350	0.897998	3.262091	0.0011
P_DEBTGROWTH_TOTAL(-1)	-0.015682	0.004755	-3.297688	0.0010
LOG(MARKET_CAP(-1))	-79.63642	2.053660	-38.77780	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	70.97128	R-squared	0.405527
Mean dependent var	36.17453	Adjusted R-squared	0.345072
S.D. dependent var	92.06420	S.E. of regression	74.50536
Akaike info criterion	11.54766	Sum squared resid	14738034
Schwarz criterion	12.10165	Log likelihood	-16623.23
Hannan-Quinn criter.	11.74718	F-statistic	6.707927
Durbin-Watson stat	1.540579	Prob(F-statistic)	0.000000

Regression 4

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:16
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 266
Total panel (balanced) observations: 2660

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1103.795	60.71848	18.17890	0.0000
D(RETURN(-1))	-0.852940	0.012948	-65.87514	0.0000
D(RETURN(-2))	-0.409559	0.012274	-33.36898	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.781632	0.971131	-0.804867	0.4210
P_DEBTGROWTH_TOTAL(-1)	0.003477	0.005131	0.677647	0.4981
LOG(MARKET_CAP(-1))	-48.51801	2.605650	-18.62031	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	72.95737	R-squared	0.715629
Mean dependent var	-19.72200	Adjusted R-squared	0.683490
S.D. dependent var	136.8384	S.E. of regression	76.98425
Akaike info criterion	11.62139	Sum squared resid	14158588
Schwarz criterion	12.22106	Log likelihood	-15185.44
Hannan-Quinn criter.	11.83841	F-statistic	22.26662
Durbin-Watson stat	1.396557	Prob(F-statistic)	0.000000

Regression 5

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:17
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 266
Total panel (balanced) observations: 2660

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.336991	2.714443	-1.229347	0.2191
D(RETURN(-1))	-0.893172	0.013258	-67.36669	0.0000
D(RETURN(-2))	-0.427814	0.012795	-33.43576	0.0000
P_DEBTGROWTH_TOTAL(-1)	-1.435856	1.015076	-1.414530	0.1573
P_DEBTGROWTH_TOTAL(-1)	0.007963	0.005360	1.485590	0.1375
MARKET_CAP(-1)	-9.86E-10	9.36E-11	-10.53026	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	76.32108	R-squared	0.688802
Mean dependent var	-19.72200	Adjusted R-squared	0.653631
S.D. dependent var	136.8384	S.E. of regression	80.53363
Akaike info criterion	11.71153	Sum squared resid	15494255
Schwarz criterion	12.31121	Log likelihood	-15305.34
Hannan-Quinn criter.	11.92856	F-statistic	19.58440
Durbin-Watson stat	1.597927	Prob(F-statistic)	0.000000

Regression 6

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:18
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 266
Total panel (balanced) observations: 2660

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-26.44431	1.634106	-16.18274	0.0000
D(RETURN(-1))	-0.920411	0.013299	-69.20836	0.0000
D(RETURN(-2))	-0.446693	0.012957	-34.47544	0.0000
P_DEBTGROWTH_TOTAL(-1)	-1.528887	1.038110	-1.472760	0.1409
P_DEBTGROWTH_TOTAL(-1)	0.008987	0.005481	1.639706	0.1012

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	78.07223	R-squared	0.674358
Mean dependent var	-19.72200	Adjusted R-squared	0.637706
S.D. dependent var	136.8384	S.E. of regression	82.36419
Akaike info criterion	11.75615	Sum squared resid	16213427
Schwarz criterion	12.35361	Log likelihood	-15365.68
Hannan-Quinn criter.	11.97238	F-statistic	18.39904
Durbin-Watson stat	1.622623	Prob(F-statistic)	0.000000

Regression 7

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:19
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2150.348	64.61445	33.27968	0.0000
D(RETURN(-1))	-0.527053	0.012753	-41.32893	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.004953	0.001780	-2.781745	0.0054
LOG(MARKET_CAP(-1))	-93.04240	2.785385	-33.40378	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	97.21811	R-squared	0.542693
Mean dependent var	-7.132741	Adjusted R-squared	0.496566
S.D. dependent var	143.7863	S.E. of regression	102.0208
Akaike info criterion	12.17566	Sum squared resid	27654683
Schwarz criterion	12.72556	Log likelihood	-17543.99
Hannan-Quinn criter.	12.37371	F-statistic	11.76529
Durbin-Watson stat	2.063964	Prob(F-statistic)	0.000000

Regression 8

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:20
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2213.666	55.92502	39.58275	0.0000
D(RETURN(-1))	-0.245925	0.014487	-16.97564	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.004192	0.001540	-2.721966	0.0065
LOG(MARKET_CAP(-1))	-94.14432	2.409359	-39.07442	0.0000
MARKET_RETURN(-1)	-0.871916	0.029130	-29.93154	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	84.06806	R-squared	0.658040
Mean dependent var	-7.132741	Adjusted R-squared	0.623406
S.D. dependent var	143.7863	S.E. of regression	88.23770
Akaike info criterion	11.88568	Sum squared resid	20679326
Schwarz criterion	12.43762	Log likelihood	-17118.75
Hannan-Quinn criter.	12.08447	F-statistic	18.99993
Durbin-Watson stat	2.100872	Prob(F-statistic)	0.000000

Regression 9

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:21
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 266
Total panel (balanced) observations: 2660

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1183.497	51.32103	23.06066	0.0000
D(RETURN(-1))	-0.524855	0.015201	-34.52666	0.0000
D(RETURN(-2))	-0.270564	0.011286	-23.97243	0.0000
P_DEBTGROWTH_TOTAL(-1)	-1.123437	0.819875	-1.370254	0.1707
P_DEBTGROWTH_TOTAL(-1)	0.004936	0.004332	1.139337	0.2547
LOG(MARKET_CAP(-1))	-50.59559	2.200633	-22.99139	0.0000
MARKET_RETURN(-1)	-0.737750	0.023757	-31.05465	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	61.57564	R-squared	0.797434
Mean dependent var	-19.72200	Adjusted R-squared	0.774447
S.D. dependent var	136.8384	S.E. of regression	64.98792
Akaike info criterion	11.28292	Sum squared resid	10085550
Schwarz criterion	11.88481	Log likelihood	-14734.29
Hannan-Quinn criter.	11.50075	F-statistic	34.68922
Durbin-Watson stat	1.980835	Prob(F-statistic)	0.000000

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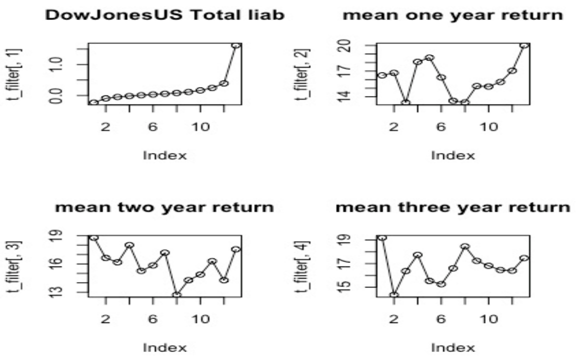

Regression 1

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 21:26
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 650
Total panel (balanced) observations: 7150

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	22.79114	0.595853	38.24959	0.0000
RETURN(-1)	-0.192091	0.012271	-15.65403	0.0000
RETURN(-2)	-0.198445	0.012238	-16.21533	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.457919	1.101209	-0.415833	0.6775
P_DEBTGROWTH_TOTAL(-1)	-0.002960	0.053158	-0.055683	0.9556

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	39.64397	R-squared	0.115108
Mean dependent var	16.36954	Adjusted R-squared	0.026156
S.D. dependent var	42.14658	S.E. of regression	41.59175
Akaike info criterion	10.38069	Sum squared resid	11237259
Schwarz criterion	11.00953	Log likelihood	-36456.97
Hannan-Quinn criter.	10.59715	F-statistic	1.294040
Durbin-Watson stat	2.077354	Prob(F-statistic)	0.000002

Regression 2

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 21:28
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 650
Total panel (balanced) observations: 7150

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	27.12298	0.828537	32.73601	0.0000
RETURN(-1)	-0.187236	0.012236	-15.30145	0.0000
RETURN(-2)	-0.192368	0.012214	-15.75045	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.367747	1.096633	-0.335342	0.7374
P_DEBTGROWTH_TOTAL(-1)	-0.007630	0.052938	-0.144133	0.8854
MARKET_CAP(-1)	-2.61E-10	3.48E-11	-7.490786	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	39.47383	R-squared	0.122687
Mean dependent var	16.36954	Adjusted R-squared	0.034348
S.D. dependent var	42.14658	S.E. of regression	41.41643
Akaike info criterion	10.37237	Sum squared resid	11141009
Schwarz criterion	11.00217	Log likelihood	-36426.22
Hannan-Quinn criter.	10.58916	F-statistic	1.388821
Durbin-Watson stat	2.072570	Prob(F-statistic)	0.000000

Regression 3

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 21:35
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 650
Total panel (balanced) observations: 7150

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	510.2020	22.31623	22.86237	0.0000
RETURN(-1)	-0.139975	0.012082	-11.58516	0.0000
RETURN(-2)	-0.134638	0.012168	-11.06465	0.0000
P_DEBTGROWTH_TOTAL(-1)	1.004169	1.065031	0.942854	0.3458
P_DEBTGROWTH_TOTAL(-1)	-0.074622	0.051415	-1.451359	0.1467
LOG(MARKET_CAP(-1))	-21.70659	0.993512	-21.84835	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	38.26284	R-squared	0.175691
Mean dependent var	16.36954	Adjusted R-squared	0.092688
S.D. dependent var	42.14658	S.E. of regression	40.14584
Akaike info criterion	10.31005	Sum squared resid	10467919
Schwarz criterion	10.93985	Log likelihood	-36203.44
Hannan-Quinn criter.	10.52684	F-statistic	2.116701
Durbin-Watson stat	2.020354	Prob(F-statistic)	0.000000

Regression 4

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:36
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 650
Total panel (balanced) observations: 6500

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	932.7092	26.62988	35.02492	0.0000
D(RETURN(-1))	-0.727424	0.010476	-69.43598	0.0000
D(RETURN(-2))	-0.456794	0.010525	-43.40071	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.432961	1.310218	-0.330449	0.7411
P_DEBTGROWTH_TOTAL(-1)	-0.101211	0.061532	-1.644850	0.1001
LOG(MARKET_CAP(-1))	-41.31976	1.180124	-35.01306	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	44.20311	R-squared	0.517867
Mean dependent var	0.734325	Adjusted R-squared	0.463921
S.D. dependent var	63.66529	S.E. of regression	46.61409
Akaike info criterion	10.61701	Sum squared resid	12700447
Schwarz criterion	11.30018	Log likelihood	-33850.27
Hannan-Quinn criter.	10.85329	F-statistic	9.599703
Durbin-Watson stat	2.237877	Prob(F-statistic)	0.000000

Regression 5

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:37
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 650
Total panel (balanced) observations: 6500

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.576437	1.039689	8.249044	0.0000
D(RETURN(-1))	-0.725584	0.011426	-63.50479	0.0000
D(RETURN(-2))	-0.469880	0.011471	-40.96293	0.0000
P_DEBTGROWTH_TOTAL(-1)	-4.221926	1.423587	-2.965695	0.0030
P_DEBTGROWTH_TOTAL(-1)	0.057463	0.066909	0.858832	0.3905
MARKET_CAP(-1)	-4.57E-10	4.58E-11	-9.983044	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	48.20888	R-squared	0.426524
Mean dependent var	0.734325	Adjusted R-squared	0.362357
S.D. dependent var	63.66529	S.E. of regression	50.83835
Akaike info criterion	10.79050	Sum squared resid	15106626
Schwarz criterion	11.47367	Log likelihood	-34414.13
Hannan-Quinn criter.	11.02679	F-statistic	6.647134
Durbin-Watson stat	2.331881	Prob(F-statistic)	0.000000

Regression 6

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:38
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 650
Total panel (balanced) observations: 6500

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.556588	0.665535	0.836301	0.4030
D(RETURN(-1))	-0.724562	0.011521	-62.88941	0.0000
D(RETURN(-2))	-0.470936	0.011567	-40.71463	0.0000
P_DEBTGROWTH_TOTAL(-1)	-4.513986	1.435247	-3.145094	0.0017
P_DEBTGROWTH_TOTAL(-1)	0.068612	0.067462	1.017058	0.3092

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	48.61814	R-squared	0.416746
Mean dependent var	0.734325	Adjusted R-squared	0.351596
S.D. dependent var	63.66529	S.E. of regression	51.26555
Akaike info criterion	10.80710	Sum squared resid	15364204
Schwarz criterion	11.48923	Log likelihood	-34469.08
Hannan-Quinn criter.	11.04303	F-statistic	6.396737
Durbin-Watson stat	2.341932	Prob(F-statistic)	0.000000

Regression 9

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:40
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 650
Total panel (balanced) observations: 6500

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	902.0319	26.87698	33.56150	0.0000
D(RETURN(-1))	-0.679143	0.012491	-54.37009	0.0000
D(RETURN(-2))	-0.429676	0.011169	-38.46999	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.935939	1.306786	-0.716214	0.4739
P_DEBTGROWTH_TOTAL(-1)	-0.089746	0.061301	-1.464035	0.1432
LOG(MARKET_CAP(-1))	-39.80043	1.194978	-33.30641	0.0000
MARKET_RETURN(-1)	-0.218714	0.031115	-7.029193	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	44.01742	R-squared	0.521909
Mean dependent var	0.734325	Adjusted R-squared	0.468324
S.D. dependent var	63.66529	S.E. of regression	46.42225
Akaike info criterion	10.60889	Sum squared resid	12593969
Schwarz criterion	11.29311	Log likelihood	-33822.91
Hannan-Quinn criter.	10.84554	F-statistic	9.739867
Durbin-Watson stat	2.259147	Prob(F-statistic)	0.000000

Regression 7

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:38
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 650
Total panel (balanced) observations: 7150

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	917.7514	28.01776	32.75606	0.0000
D(RETURN(-1))	-0.506481	0.009978	-50.75896	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.163880	0.040126	-4.084139	0.0000
LOG(MARKET_CAP(-1))	-40.68787	1.242145	-32.75615	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	49.99016	R-squared	0.356071
Mean dependent var	-0.053618	Adjusted R-squared	0.291451
S.D. dependent var	62.30115	S.E. of regression	52.44223
Akaike info criterion	10.84419	Sum squared resid	17867965
Schwarz criterion	11.47206	Log likelihood	-38114.97
Hannan-Quinn criter.	11.06031	F-statistic	5.510165
Durbin-Watson stat	2.418899	Prob(F-statistic)	0.000000

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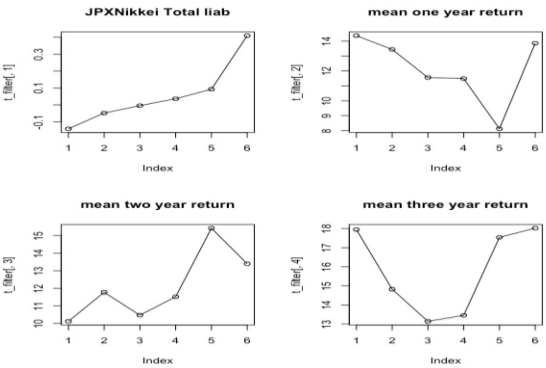

Regression 8

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:39
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 650
Total panel (balanced) observations: 7150

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	839.8126	27.43897	30.60657	0.0000
D(RETURN(-1))	-0.408314	0.010815	-37.75474	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.174447	0.038915	-4.482804	0.0000
LOG(MARKET_CAP(-1))	-36.76595	1.219905	-30.13836	0.0000
MARKET_RETURN(-1)	-0.641112	0.031548	-20.32154	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	48.47313	R-squared	0.394560
Mean dependent var	-0.053618	Adjusted R-squared	0.333700
S.D. dependent var	62.30115	S.E. of regression	50.85470
Akaike info criterion	10.78283	Sum squared resid	16799955
Schwarz criterion	11.41167	Log likelihood	-37894.63
Hannan-Quinn criter.	10.99929	F-statistic	6.482995
Durbin-Watson stat	2.473075	Prob(F-statistic)	0.000000

Regression 1

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 21:48
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 300
Total panel (balanced) observations: 3300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	16.01077	0.789466	20.28051	0.0000
RETURN(-1)	0.010316	0.018109	0.569641	0.5690
RETURN(-2)	-0.145986	0.016811	-8.684053	0.0000
P_DEBTGROWTH_TOTAL(-1)	-8.541959	4.461708	-1.914504	0.0557
P_DEBTGROWTH_TOTAL(-1)	3.495193	1.510444	2.314017	0.0207

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	38.32425	R-squared	0.072041
Mean dependent var	13.56119	Adjusted R-squared	-0.021808
S.D. dependent var	39.79010	S.E. of regression	40.22163
Akaike info criterion	10.31429	Sum squared resid	4846868.
Schwarz criterion	10.87638	Log likelihood	-16714.57
Hannan-Quinn criter.	10.51549	F-statistic	0.767626
Durbin-Watson stat	2.167055	Prob(F-statistic)	0.998506

Regression 2

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 21:49
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 300
Total panel (balanced) observations: 3300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	22.42347	1.275235	17.58379	0.0000
RETURN(-1)	0.005208	0.018009	0.289207	0.7724
RETURN(-2)	-0.122744	0.017094	-7.180684	0.0000
P_DEBTGROWTH_TOTAL(-1)	-6.842189	4.440465	-1.540872	0.1235
P_DEBTGROWTH_TOTAL(-1)	3.085287	1.501918	2.054231	0.0400
MARKET_CAP(-1)	-8.56E-12	1.34E-12	-6.377356	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	38.06666	R-squared	0.084473
Mean dependent var	13.56119	Adjusted R-squared	-0.008455
S.D. dependent var	39.79010	S.E. of regression	39.95796
Akaike info criterion	10.30140	Sum squared resid	4781932.
Schwarz criterion	10.86535	Log likelihood	-16692.31
Hannan-Quinn criter.	10.50327	F-statistic	0.909017
Durbin-Watson stat	2.152496	Prob(F-statistic)	0.860527

Regression 3

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 21:49
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 300
Total panel (balanced) observations: 3300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	504.0728	46.54484	10.82983	0.0000
RETURN(-1)	-0.003672	0.017839	-0.205828	0.8369
RETURN(-2)	-0.055110	0.018649	-2.955184	0.0031
P_DEBTGROWTH_TOTAL(-1)	-4.522564	4.399433	-1.027988	0.3040
P_DEBTGROWTH_TOTAL(-1)	2.569040	1.486325	1.728451	0.0840
LOG(MARKET_CAP(-1))	-18.40674	1.755145	-10.48730	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	37.63937	R-squared	0.104911
Mean dependent var	13.56119	Adjusted R-squared	0.014057
S.D. dependent var	39.79010	S.E. of regression	39.50945
Akaike info criterion	10.27883	Sum squared resid	4675184.
Schwarz criterion	10.84277	Log likelihood	-16655.06
Hannan-Quinn criter.	10.48069	F-statistic	1.154721
Durbin-Watson stat	2.110274	Prob(F-statistic)	0.040404

Regression 4

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:50
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 300
Total panel (balanced) observations: 3000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1347.684	54.60554	24.68035	0.0000
D(RETURN(-1))	-0.750975	0.017807	-42.17362	0.0000
D(RETURN(-2))	-0.364169	0.015596	-23.34985	0.0000
P_DEBTGROWTH_TOTAL(-1)	-16.40837	5.377128	-3.051512	0.0023
P_DEBTGROWTH_TOTAL(-1)	5.947433	1.763352	3.372800	0.0008
LOG(MARKET_CAP(-1))	-50.60786	2.055956	-24.61524	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	43.03039	R-squared	0.413893
Mean dependent var	3.738773	Adjusted R-squared	0.347780
S.D. dependent var	56.21593	S.E. of regression	45.40007
Akaike info criterion	10.56502	Sum squared resid	5554843.
Schwarz criterion	11.17567	Log likelihood	-15542.54
Hannan-Quinn criter.	10.78467	F-statistic	6.260330
Durbin-Watson stat	2.371084	Prob(F-statistic)	0.000000

Regression 5

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:51
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 300
Total panel (balanced) observations: 3000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	18.90207	1.615718	11.69886	0.0000
D(RETURN(-1))	-0.610694	0.017880	-34.15606	0.0000
D(RETURN(-2))	-0.303721	0.016575	-18.32441	0.0000
P_DEBTGROWTH_TOTAL(-1)	-29.95435	5.770963	-5.190529	0.0000
P_DEBTGROWTH_TOTAL(-1)	9.340591	1.898054	4.921140	0.0000
MARKET_CAP(-1)	-1.98E-11	1.73E-12	-11.43691	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	46.50731	R-squared	0.315350
Mean dependent var	3.738773	Adjusted R-squared	0.238121
S.D. dependent var	56.21593	S.E. of regression	49.06846
Akaike info criterion	10.72043	Sum squared resid	6488789.
Schwarz criterion	11.33108	Log likelihood	-15775.64
Hannan-Quinn criter.	10.94008	F-statistic	4.083289
Durbin-Watson stat	2.422606	Prob(F-statistic)	0.000000

Regression 6

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:51
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 300
Total panel (balanced) observations: 3000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.718950	0.942858	3.944338	0.0001
D(RETURN(-1))	-0.565147	0.017845	-31.66972	0.0000
D(RETURN(-2))	-0.282820	0.016866	-16.76910	0.0000
P_DEBTGROWTH_TOTAL(-1)	-35.15356	5.889896	-5.968451	0.0000
P_DEBTGROWTH_TOTAL(-1)	10.61205	1.939874	5.470484	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	47.62256	R-squared	0.282121
Mean dependent var	3.738773	Adjusted R-squared	0.201439
S.D. dependent var	56.21593	S.E. of regression	50.23581
Akaike info criterion	10.76716	Sum squared resid	6803725.
Schwarz criterion	11.37580	Log likelihood	-15846.74
Hannan-Quinn criter.	10.98609	F-statistic	3.496717
Durbin-Watson stat	2.435118	Prob(F-statistic)	0.000000

Regression 7

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:51
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 300
Total panel (balanced) observations: 3300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1073.738	55.78767	19.24687	0.0000
D(RETURN(-1))	-0.494883	0.016351	-30.26635	0.0000
P_DEBTGROWTH_TOTAL(-1)	2.116038	1.209562	1.749425	0.0803
LOG(MARKET_CAP(-1))	-40.38893	2.098606	-19.24560	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	47.35563	R-squared	0.249352
Mean dependent var	2.044152	Adjusted R-squared	0.173711
S.D. dependent var	54.66625	S.E. of regression	49.69186
Akaike info criterion	10.73688	Sum squared resid	7400435.
Schwarz criterion	11.29713	Log likelihood	-17412.86
Hannan-Quinn criter.	10.93743	F-statistic	3.296527
Durbin-Watson stat	2.439381	Prob(F-statistic)	0.000000

Regression 8

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:52
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 300
Total panel (balanced) observations: 3300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	983.1140	55.14583	17.82753	0.0000
D(RETURN(-1))	-0.422858	0.017165	-24.63472	0.0000
P_DEBTGROWTH_TOTAL(-1)	2.034582	1.183573	1.719016	0.0857
LOG(MARKET_CAP(-1))	-36.78046	2.076974	-17.70868	0.0000
MARKET_RETURN(-1)	-0.434467	0.037508	-11.58330	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	46.32958	R-squared	0.281528
Mean dependent var	2.044152	Adjusted R-squared	0.208866
S.D. dependent var	54.66625	S.E. of regression	48.62330
Akaike info criterion	10.69368	Sum squared resid	7083219.
Schwarz criterion	11.25577	Log likelihood	-17340.57
Hannan-Quinn criter.	10.89489	F-statistic	3.874461
Durbin-Watson stat	2.422953	Prob(F-statistic)	0.000000

Regression 9

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 21:52
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 300
Total panel (balanced) observations: 3000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1330.493	56.44580	23.57115	0.0000
D(RETURN(-1))	-0.737698	0.020957	-35.20030	0.0000
D(RETURN(-2))	-0.354894	0.017402	-20.39411	0.0000
P_DEBTGROWTH_TOTAL(-1)	-16.02165	5.386317	-2.974509	0.0030
P_DEBTGROWTH_TOTAL(-1)	5.851400	1.765019	3.315206	0.0009
LOG(MARKET_CAP(-1))	-49.93849	2.129982	-23.44550	0.0000
MARKET_RETURN(-1)	-0.047430	0.039488	-1.201127	0.2298

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	43.01887	R-squared	0.414207
Mean dependent var	3.738773	Adjusted R-squared	0.347887
S.D. dependent var	56.21593	S.E. of regression	45.39634
Akaike info criterion	10.56515	Sum squared resid	5551870.
Schwarz criterion	11.17780	Log likelihood	-15541.73
Hannan-Quinn criter.	10.78552	F-statistic	6.245559
Durbin-Watson stat	2.366262	Prob(F-statistic)	0.000000

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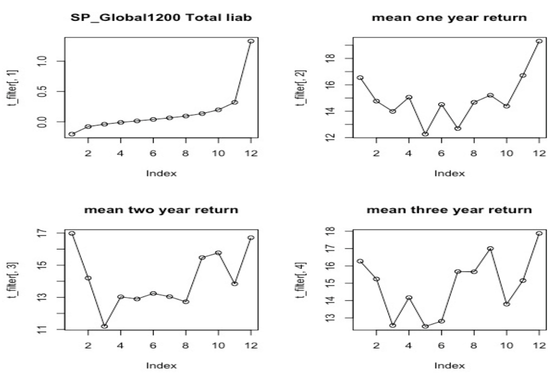

Regression 1

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 21:58
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 840
Total panel (balanced) observations: 9240

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.76614	0.488093	42.54546	0.0000
RETURN(-1)	-0.176699	0.010739	-16.45446	0.0000
RETURN(-2)	-0.193426	0.010537	-18.35639	0.0000
P_DEBTGROWTH_TOTAL(-1)	-1.052878	0.979842	-1.074539	0.2826
P_DEBTGROWTH_TOTAL(-1)	0.015042	0.035049	0.429175	0.6678

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	36.76011	R-squared	0.116486
Mean dependent var	14.80215	Adjusted R-squared	0.027776
S.D. dependent var	39.11051	S.E. of regression	38.56351
Akaike info criterion	10.22939	Sum squared resid	12486062
Schwarz criterion	10.88077	Log likelihood	-46415.77
Hannan-Quinn criter.	10.45075	F-statistic	1.313118
Durbin-Watson stat	2.106008	Prob(F-statistic)	0.000000

Regression 2

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 22:00
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 840
Total panel (balanced) observations: 9240

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	21.02194	0.500077	42.03743	0.0000
RETURN(-1)	-0.176202	0.010738	-16.40939	0.0000
RETURN(-2)	-0.192926	0.010537	-18.31006	0.0000
P_DEBTGROWTH_TOTAL(-1)	-1.048104	0.979583	-1.069949	0.2847
P_DEBTGROWTH_TOTAL(-1)	0.014801	0.035040	0.422414	0.6727
MARKET_CAP(-1)	-3.48E-13	1.49E-13	-2.338197	0.0194

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	36.74814	R-squared	0.117061
Mean dependent var	14.80215	Adjusted R-squared	0.028293
S.D. dependent var	39.11051	S.E. of regression	38.55325
Akaike info criterion	10.22895	Sum squared resid	12477936
Schwarz criterion	10.88111	Log likelihood	-46412.76
Hannan-Quinn criter.	10.45057	F-statistic	1.318738
Durbin-Watson stat	2.105690	Prob(F-statistic)	0.000000

Regression 3

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 22:01
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 840
Total panel (balanced) observations: 9240

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	603.6259	21.72275	27.78772	0.0000
RETURN(-1)	-0.120768	0.010515	-11.48544	0.0000
RETURN(-2)	-0.116445	0.010512	-11.07746	0.0000
P_DEBTGROWTH_TOTAL(-1)	0.033119	0.941258	0.035186	0.9719
P_DEBTGROWTH_TOTAL(-1)	-0.034242	0.033688	-1.016432	0.3095
LOG(MARKET_CAP(-1))	-24.18258	0.901058	-26.83800	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	35.27785	R-squared	0.186300
Mean dependent var	14.80215	Adjusted R-squared	0.104494
S.D. dependent var	39.11051	S.E. of regression	37.01074
Akaike info criterion	10.14729	Sum squared resid	11499428
Schwarz criterion	10.79945	Log likelihood	-46035.47
Hannan-Quinn criter.	10.36891	F-statistic	2.277333
Durbin-Watson stat	2.033502	Prob(F-statistic)	0.000000

Regression 4

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:01
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 840
Total panel (balanced) observations: 8400

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1125.907	25.64563	43.90248	0.0000
D(RETURN(-1))	-0.715984	0.009158	-78.18519	0.0000
D(RETURN(-2))	-0.427274	0.009159	-46.64843	0.0000
P_DEBTGROWTH_TOTAL(-1)	0.050651	1.179228	0.042953	0.9657
P_DEBTGROWTH_TOTAL(-1)	-0.120626	0.040837	-2.953842	0.0031
LOG(MARKET_CAP(-1))	-46.54215	1.059441	-43.93085	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	40.72747	R-squared	0.520504
Mean dependent var	0.805524	Adjusted R-squared	0.466938
S.D. dependent var	58.81945	S.E. of regression	42.94473
Akaike info criterion	10.45287	Sum squared resid	13933305
Schwarz criterion	11.16066	Log likelihood	-43057.07
Hannan-Quinn criter.	10.69455	F-statistic	9.716989
Durbin-Watson stat	2.158079	Prob(F-statistic)	0.000000

Regression 5

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:02
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 840
Total panel (balanced) observations: 8400

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.115668	0.568730	0.203380	0.8388
D(RETURN(-1))	-0.702119	0.010244	-68.54243	0.0000
D(RETURN(-2))	-0.443263	0.010244	-43.27217	0.0000
P_DEBTGROWTH_TOTAL(-1)	-2.891986	1.317725	-2.194681	0.0282
P_DEBTGROWTH_TOTAL(-1)	-0.025925	0.045643	-0.567984	0.5701
MARKET_CAP(-1)	-8.01E-13	1.98E-13	-4.043232	0.0001

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	45.58455	R-squared	0.399317
Mean dependent var	0.805524	Adjusted R-squared	0.332213
S.D. dependent var	58.81945	S.E. of regression	48.06623
Akaike info criterion	10.67821	Sum squared resid	17454789
Schwarz criterion	11.38599	Log likelihood	-44003.46
Hannan-Quinn criter.	10.91988	F-statistic	5.950658
Durbin-Watson stat	2.295895	Prob(F-statistic)	0.000000

Regression 6

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:02
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 840
Total panel (balanced) observations: 8400

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.523516	0.546872	-0.957291	0.3385
D(RETURN(-1))	-0.701815	0.010254	-68.44515	0.0000
D(RETURN(-2))	-0.443353	0.010254	-43.23714	0.0000
P_DEBTGROWTH_TOTAL(-1)	-2.895078	1.319062	-2.194800	0.0282
P_DEBTGROWTH_TOTAL(-1)	-0.025870	0.045690	-0.566220	0.5713

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	45.63384	R-squared	0.398018
Mean dependent var	0.805524	Adjusted R-squared	0.330856
S.D. dependent var	58.81945	S.E. of regression	48.11502
Akaike info criterion	10.68013	Sum squared resid	17492558
Schwarz criterion	11.38708	Log likelihood	-44012.54
Hannan-Quinn criter.	10.92152	F-statistic	5.926287
Durbin-Watson stat	2.297280	Prob(F-statistic)	0.000000

Regression 7

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:03
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 840
Total panel (balanced) observations: 9240

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1093.274	27.01178	40.47398	0.0000
D(RETURN(-1))	-0.502668	0.008717	-57.66285	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.165138	0.025468	-6.484105	0.0000
LOG(MARKET_CAP(-1))	-45.22090	1.116282	-40.51028	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	45.94886	R-squared	0.364211
Mean dependent var	-0.199782	Adjusted R-squared	0.300458
S.D. dependent var	57.62909	S.E. of regression	48.20018
Akaike info criterion	10.67540	Sum squared resid	19508394
Schwarz criterion	11.32602	Log likelihood	-48477.36
Hannan-Quinn criter.	10.89650	F-statistic	5.712840
Durbin-Watson stat	2.368340	Prob(F-statistic)	0.000000

Regression 8

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:04
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 840
Total panel (balanced) observations: 9240

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	990.5015	26.34811	37.59289	0.0000
D(RETURN(-1))	-0.394013	0.009431	-41.77724	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.189306	0.024565	-7.706236	0.0000
LOG(MARKET_CAP(-1))	-40.53248	1.091667	-37.12899	0.0000
MARKET_RETURN(-1)	-0.699389	0.027578	-25.36086	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	44.28398	R-squared	0.409450
Mean dependent var	-0.199782	Adjusted R-squared	0.350156
S.D. dependent var	57.62909	S.E. of regression	46.45649
Akaike info criterion	10.60181	Sum squared resid	18120294
Schwarz criterion	11.25319	Log likelihood	-48136.35
Hannan-Quinn criter.	10.82317	F-statistic	6.905400
Durbin-Watson stat	2.441735	Prob(F-statistic)	0.000000

Regression 9

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:04
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 840
Total panel (balanced) observations: 8400

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1078.258	25.95584	41.54203	0.0000
D(RETURN(-1))	-0.656359	0.010976	-59.79699	0.0000
D(RETURN(-2))	-0.396089	0.009652	-41.03548	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.502620	1.173385	-0.428351	0.6684
P_DEBTGROWTH_TOTAL(-1)	-0.116358	0.040589	-2.866727	0.0042
LOG(MARKET_CAP(-1))	-44.40856	1.075597	-41.28735	0.0000
MARKET_RETURN(-1)	-0.269520	0.027735	-9.717660	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	40.47526	R-squared	0.526425
Mean dependent var	0.805524	Adjusted R-squared	0.473450
S.D. dependent var	58.81945	S.E. of regression	42.68161
Akaike info criterion	10.44069	Sum squared resid	13761275
Schwarz criterion	11.14931	Log likelihood	-43004.89
Hannan-Quinn criter.	10.68265	F-statistic	9.937273
Durbin-Watson stat	2.177372	Prob(F-statistic)	0.000000

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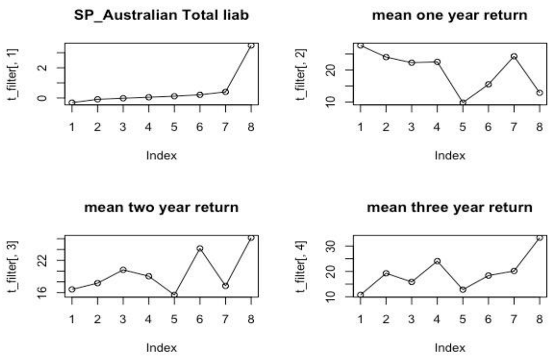

Regression 3

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 22:11
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 112
Total panel (balanced) observations: 1232

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	576.2008	62.97132	9.150209	0.0000
RETURN(-1)	-0.067024	0.028383	-2.361438	0.0184
RETURN(-2)	-0.046119	0.029916	-1.541614	0.1235
P_DEBTGROWTH_TOTAL(-1)	-1.006489	1.478206	-0.680885	0.4961
P_DEBTGROWTH_TOTAL(-1)	0.002952	0.017829	0.165592	0.8685
LOG(MARKET_CAP(-1))	-26.33706	3.004914	-8.764664	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	61.58164	R-squared	0.149083
Mean dependent var	19.96070	Adjusted R-squared	0.060557
S.D. dependent var	66.78577	S.E. of regression	64.73203
Akaike info criterion	11.26854	Sum squared resid	4672112.
Schwarz criterion	11.75443	Log likelihood	-6824.421
Hannan-Quinn criter.	11.45133	F-statistic	1.684056
Durbin-Watson stat	2.070639	Prob(F-statistic)	0.000022

Regression 1

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 22:09
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 112
Total panel (balanced) observations: 1232

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	24.57265	2.125146	11.56280	0.0000
RETURN(-1)	-0.070261	0.029329	-2.395628	0.0168
RETURN(-2)	-0.122244	0.029584	-4.132049	0.0000
P_DEBTGROWTH_TOTAL(-1)	-2.129363	1.521846	-1.399197	0.1620
P_DEBTGROWTH_TOTAL(-1)	0.017943	0.018339	0.978372	0.3281

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	63.66769	R-squared	0.090458
Mean dependent var	19.96070	Adjusted R-squared	-0.003268
S.D. dependent var	66.78577	S.E. of regression	66.89479
Akaike info criterion	11.33354	Sum squared resid	4994003.
Schwarz criterion	11.81528	Log likelihood	-6865.463
Hannan-Quinn criter.	11.51477	F-statistic	0.965135
Durbin-Watson stat	2.115750	Prob(F-statistic)	0.585986

Regression 4

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:11
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 112
Total panel (balanced) observations: 1120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1069.456	76.88846	13.90919	0.0000
D(RETURN(-1))	-0.731893	0.026896	-27.21196	0.0000
D(RETURN(-2))	-0.421515	0.026752	-15.75662	0.0000
P_DEBTGROWTH_TOTAL(-1)	-1.352887	2.862893	-0.472560	0.6366
P_DEBTGROWTH_TOTAL(-1)	-0.073848	0.089207	-0.827829	0.4080
LOG(MARKET_CAP(-1))	-50.79866	3.654738	-13.89940	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	70.52415	R-squared	0.468196
Mean dependent var	-0.243732	Adjusted R-squared	0.406691
S.D. dependent var	96.75115	S.E. of regression	74.52405
Akaike info criterion	11.55872	Sum squared resid	5570495.
Schwarz criterion	12.08324	Log likelihood	-6355.881
Hannan-Quinn criter.	11.75697	F-statistic	7.612361
Durbin-Watson stat	2.153847	Prob(F-statistic)	0.000000

Regression 2

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/07/20 Time: 22:10
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 112
Total panel (balanced) observations: 1232

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	29.73308	2.843202	10.45760	0.0000
RETURN(-1)	-0.070419	0.029245	-2.407924	0.0162
RETURN(-2)	-0.116800	0.029567	-3.950320	0.0001
P_DEBTGROWTH_TOTAL(-1)	-2.062754	1.517691	-1.359139	0.1744
P_DEBTGROWTH_TOTAL(-1)	0.017138	0.018289	0.937049	0.3489
MARKET_CAP(-1)	-8.34E-10	3.07E-10	-2.722301	0.0066

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	63.45715	R-squared	0.096463
Mean dependent var	19.96070	Adjusted R-squared	0.002463
S.D. dependent var	66.78577	S.E. of regression	66.70348
Akaike info criterion	11.32854	Sum squared resid	4961030.
Schwarz criterion	11.81443	Log likelihood	-6861.382
Hannan-Quinn criter.	11.51134	F-statistic	1.026199
Durbin-Watson stat	2.114862	Prob(F-statistic)	0.410871

Regression 5

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:12
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 112
Total panel (balanced) observations: 1120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.352075	3.530232	2.365871	0.0182
D(RETURN(-1))	-0.666075	0.028772	-23.15023	0.0000
D(RETURN(-2))	-0.400874	0.029053	-13.79778	0.0000
P_DEBTGROWTH_TOTAL(-1)	-6.829570	3.083386	-2.214958	0.0270
P_DEBTGROWTH_TOTAL(-1)	0.061538	0.096460	0.637968	0.5236
MARKET_CAP(-1)	-1.11E-09	3.87E-10	-2.861552	0.0043

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	76.70479	R-squared	0.370899
Mean dependent var	-0.243732	Adjusted R-squared	0.298141
S.D. dependent var	96.75115	S.E. of regression	81.05523
Akaike info criterion	11.72673	Sum squared resid	6589660.
Schwarz criterion	12.25126	Log likelihood	-6449.971
Hannan-Quinn criter.	11.92499	F-statistic	5.097736
Durbin-Watson stat	2.223029	Prob(F-statistic)	0.000000

Regression 6

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:13
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 112
Total panel (balanced) observations: 1120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.232461	2.513399	0.490356	0.6240
D(RETURN(-1))	-0.662656	0.028850	-22.96918	0.0000
D(RETURN(-2))	-0.401310	0.029157	-13.76379	0.0000
P_DEBTGROWTH_TOTAL(-1)	-7.324536	3.089532	-2.370759	0.0179
P_DEBTGROWTH_TOTAL(-1)	0.077345	0.096646	0.800301	0.4237

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	77.01726	R-squared	0.365763
Mean dependent var	-0.243732	Adjusted R-squared	0.293116
S.D. dependent var	96.75115	S.E. of regression	81.34488
Akaike info criterion	11.73308	Sum squared resid	6643458.
Schwarz criterion	12.25312	Log likelihood	-6454.524
Hannan-Quinn criter.	11.92964	F-statistic	5.034812
Durbin-Watson stat	2.222078	Prob(F-statistic)	0.000000

Regression 9

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:14
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 112
Total panel (balanced) observations: 1120

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1011.503	75.70488	13.36113	0.0000
D(RETURN(-1))	-0.643565	0.029361	-21.91891	0.0000
D(RETURN(-2))	-0.392275	0.026524	-14.78926	0.0000
P_DEBTGROWTH_TOTAL(-1)	-2.309826	2.804351	-0.823658	0.4103
P_DEBTGROWTH_TOTAL(-1)	-0.067430	0.087278	-0.772596	0.4399
LOG(MARKET_CAP(-1))	-47.45013	3.609417	-13.14620	0.0000
MARKET_RETURN(-1)	-0.632582	0.093302	-6.779933	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	68.96009	R-squared	0.491523
Mean dependent var	-0.243732	Adjusted R-squared	0.432150
S.D. dependent var	96.75115	S.E. of regression	72.90763
Akaike info criterion	11.51565	Sum squared resid	5326154.
Schwarz criterion	12.04465	Log likelihood	-6330.762
Hannan-Quinn criter.	11.71560	F-statistic	8.278550
Durbin-Watson stat	2.193327	Prob(F-statistic)	0.000000

Regression 7

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:13
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 112
Total panel (balanced) observations: 1232

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	923.8843	77.91537	11.85754	0.0000
D(RETURN(-1))	-0.537238	0.025030	-21.46355	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.012615	0.008948	-1.409900	0.1588
LOG(MARKET_CAP(-1))	-43.98242	3.705235	-11.87035	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	78.25807	R-squared	0.320491
Mean dependent var	-1.004984	Adjusted R-squared	0.251141
S.D. dependent var	94.97468	S.E. of regression	82.18790
Akaike info criterion	11.74459	Sum squared resid	7545169.
Schwarz criterion	12.22217	Log likelihood	-7119.667
Hannan-Quinn criter.	11.92426	F-statistic	4.621351
Durbin-Watson stat	2.425981	Prob(F-statistic)	0.000000

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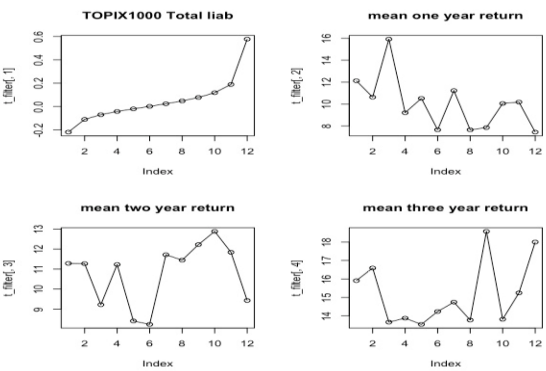


Regression 8

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/07/20 Time: 22:14
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 112
Total panel (balanced) observations: 1232

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	893.9868	75.52937	11.83628	0.0000
D(RETURN(-1))	-0.445694	0.026438	-16.85782	0.0000
P_DEBTGROWTH_TOTAL(-1)	-0.012346	0.008665	-1.424896	0.1545
LOG(MARKET_CAP(-1))	-41.72599	3.597450	-11.59877	0.0000
MARKET_RETURN(-1)	-0.839075	0.096778	-8.670090	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	75.74854	R-squared	0.363372
Mean dependent var	-1.004984	Adjusted R-squared	0.297770
S.D. dependent var	94.97468	S.E. of regression	79.58799
Akaike info criterion	11.68103	Sum squared resid	7069020.
Schwarz criterion	12.16277	Log likelihood	-7079.513
Hannan-Quinn criter.	11.86226	F-statistic	5.539017
Durbin-Watson stat	2.454538	Prob(F-statistic)	0.000000

Regression 1

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/08/20 Time: 15:04
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 720
Total panel (balanced) observations: 7920

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15.25423	0.519441	29.36663	0.0000
RETURN(-1)	-0.016593	0.011871	-1.397724	0.1622
RETURN(-2)	-0.129058	0.010088	-12.79282	0.0000
P_DEBTGROWTH_TOTAL(-1)	-14.08853	2.975486	-4.734866	0.0000
P_DEBTGROWTH_TOTAL(-1)	5.002001	1.275378	3.921976	0.0001

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	40.30571	R-squared	0.072157
Mean dependent var	12.78724	Adjusted R-squared	-0.021066
S.D. dependent var	41.84627	S.E. of regression	42.28473
Akaike info criterion	10.41369	Sum squared resid	12866436
Schwarz criterion	11.05150	Log likelihood	-40514.22
Hannan-Quinn criter.	10.63211	F-statistic	0.774028
Durbin-Watson stat	2.150692	Prob(F-statistic)	0.999996

Regression 2

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/08/20 Time: 15:06
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 720
Total panel (balanced) observations: 7920

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	19.56000	0.732200	26.71403	0.0000
RETURN(-1)	-0.020083	0.011823	-1.698631	0.0894
RETURN(-2)	-0.116516	0.010154	-11.47502	0.0000
P_DEBTGROWTH_TOTAL(-1)	-12.82064	2.965466	-4.323316	0.0000
P_DEBTGROWTH_TOTAL(-1)	4.649125	1.270108	3.660417	0.0003
MARKET_CAP(-1)	-1.10E-11	1.33E-12	-8.304592	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	40.11391	R-squared	0.080966
Mean dependent var	12.78724	Adjusted R-squared	-0.011512
S.D. dependent var	41.84627	S.E. of regression	42.08644
Akaike info criterion	10.40440	Sum squared resid	12744279
Schwarz criterion	11.04310	Log likelihood	-40476.44
Hannan-Quinn criter.	10.62313	F-statistic	0.875517
Durbin-Watson stat	2.142320	Prob(F-statistic)	0.990677

Regression 5

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/08/20 Time: 15:07
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 720
Total panel (balanced) observations: 7200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13.39801	0.931756	14.37931	0.0000
D(RETURN(-1))	-0.598612	0.011655	-51.36153	0.0000
D(RETURN(-2))	-0.247149	0.010235	-24.14815	0.0000
P_DEBTGROWTH_TOTAL(-1)	-37.40491	3.886556	-9.624178	0.0000
P_DEBTGROWTH_TOTAL(-1)	12.13478	1.628591	7.451090	0.0000
MARKET_CAP(-1)	-2.24E-11	1.75E-12	-12.80746	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	49.72772	R-squared	0.298845
Mean dependent var	4.371710	Adjusted R-squared	0.220445
S.D. dependent var	59.39114	S.E. of regression	52.43786
Akaike info criterion	10.85239	Sum squared resid	17804494
Schwarz criterion	11.54535	Log likelihood	-38343.61
Hannan-Quinn criter.	11.09084	F-statistic	3.811824
Durbin-Watson stat	2.432637	Prob(F-statistic)	0.000000

Regression 3

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 06/08/20 Time: 15:06
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 720
Total panel (balanced) observations: 7920

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	639.8309	30.45628	21.00818	0.0000
RETURN(-1)	-0.043947	0.011617	-3.783178	0.0002
RETURN(-2)	-0.032103	0.010886	-2.948978	0.0032
P_DEBTGROWTH_TOTAL(-1)	-5.836865	2.920189	-1.998797	0.0457
P_DEBTGROWTH_TOTAL(-1)	2.803965	1.244363	2.253334	0.0243
LOG(MARKET_CAP(-1))	-24.41632	1.190451	-20.51014	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	39.17671	R-squared	0.123408
Mean dependent var	12.78724	Adjusted R-squared	0.035201
S.D. dependent var	41.84627	S.E. of regression	41.10316
Akaike info criterion	10.35712	Sum squared resid	12155734
Schwarz criterion	10.99581	Log likelihood	-40289.21
Hannan-Quinn criter.	10.57585	F-statistic	1.399068
Durbin-Watson stat	2.084586	Prob(F-statistic)	0.000000

Regression 6

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/08/20 Time: 15:08
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 720
Total panel (balanced) observations: 7200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.619238	0.639035	7.228453	0.0000
D(RETURN(-1))	-0.574009	0.011639	-49.31657	0.0000
D(RETURN(-2))	-0.235903	0.010325	-22.84883	0.0000
P_DEBTGROWTH_TOTAL(-1)	-40.36020	3.928232	-10.27439	0.0000
P_DEBTGROWTH_TOTAL(-1)	12.94849	1.647708	7.858486	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	50.35366	R-squared	0.281082
Mean dependent var	4.371710	Adjusted R-squared	0.200820
S.D. dependent var	59.39114	S.E. of regression	53.09381
Akaike info criterion	10.87713	Sum squared resid	18255535
Schwarz criterion	11.56914	Log likelihood	-38433.67
Hannan-Quinn criter.	11.11525	F-statistic	3.502057
Durbin-Watson stat	2.439295	Prob(F-statistic)	0.000000

Regression 4

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/08/20 Time: 15:07
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 720
Total panel (balanced) observations: 7200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1387.702	38.14791	36.37687	0.0000
D(RETURN(-1))	-0.756576	0.011746	-64.40985	0.0000
D(RETURN(-2))	-0.320891	0.009701	-33.07775	0.0000
P_DEBTGROWTH_TOTAL(-1)	-18.10134	3.633912	-4.981227	0.0000
P_DEBTGROWTH_TOTAL(-1)	6.834163	1.511783	4.520599	0.0000
LOG(MARKET_CAP(-1))	-54.04446	1.490470	-36.26002	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	45.90797	R-squared	0.402424
Mean dependent var	4.371710	Adjusted R-squared	0.335606
S.D. dependent var	59.39114	S.E. of regression	48.40993
Akaike info criterion	10.69254	Sum squared resid	15174300
Schwarz criterion	11.38551	Log likelihood	-37768.16
Hannan-Quinn criter.	10.93099	F-statistic	6.022710
Durbin-Watson stat	2.366290	Prob(F-statistic)	0.000000

Regression 7

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/08/20 Time: 15:08
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 720
Total panel (balanced) observations: 7920

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1102.397	37.70877	29.23451	0.0000
D(RETURN(-1))	-0.468368	0.010168	-46.06251	0.0000
P_DEBTGROWTH_TOTAL(-1)	1.558790	1.146658	1.359421	0.1741
LOG(MARKET_CAP(-1))	-42.97676	1.471452	-29.20704	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	50.21363	R-squared	0.241502
Mean dependent var	3.080139	Adjusted R-squared	0.165410
S.D. dependent var	57.65962	S.E. of regression	52.67547
Akaike info criterion	10.85303	Sum squared resid	19969554
Schwarz criterion	11.48995	Log likelihood	-42254.98
Hannan-Quinn criter.	11.07115	F-statistic	3.173808
Durbin-Watson stat	2.459135	Prob(F-statistic)	0.000000

Regression 8

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/08/20 Time: 15:09
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 720
Total panel (balanced) observations: 7920

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1065.249	36.94708	28.83176	0.0000
D(RETURN(-1))	-0.410998	0.010445	-39.34887	0.0000
P_DEBTGROWTH_TOTAL(-1)	1.674509	1.121762	1.492749	0.1355
LOG(MARKET_CAP(-1))	-41.33387	1.442369	-28.65692	0.0000
MARKET_RETURN(-1)	-0.481658	0.026749	-18.00680	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	49.11919	R-squared	0.274206
Mean dependent var	3.080139	Adjusted R-squared	0.201283
S.D. dependent var	57.65962	S.E. of regression	51.53096
Akaike info criterion	10.80920	Sum squared resid	19108542
Schwarz criterion	11.44701	Log likelihood	-42080.45
Hannan-Quinn criter.	11.02763	F-statistic	3.760240
Durbin-Watson stat	2.445193	Prob(F-statistic)	0.000000

Regression 9

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 06/08/20 Time: 15:09
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 720
Total panel (balanced) observations: 7200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1353.417	38.59083	35.07095	0.0000
D(RETURN(-1))	-0.724509	0.013139	-55.14304	0.0000
D(RETURN(-2))	-0.299236	0.010477	-28.55990	0.0000
P_DEBTGROWTH_TOTAL(-1)	-16.96932	3.632085	-4.672062	0.0000
P_DEBTGROWTH_TOTAL(-1)	6.545821	1.509449	4.336563	0.0000
LOG(MARKET_CAP(-1))	-52.64136	1.509755	-34.86749	0.0000
MARKET_RETURN(-1)	-0.148653	0.027522	-5.401145	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	45.80488	R-squared	0.405105
Mean dependent var	4.371710	Adjusted R-squared	0.338484
S.D. dependent var	59.39114	S.E. of regression	48.30496
Akaike info criterion	10.68833	Sum squared resid	15106230
Schwarz criterion	11.38224	Log likelihood	-37751.97
Hannan-Quinn criter.	10.92710	F-statistic	6.080808
Durbin-Watson stat	2.356935	Prob(F-statistic)	0.000000

Regressions without changes in debt variable.

Bloomberg Europe 500 Regression 1-9

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 17:54
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 290
Total panel (balanced) observations: 2900

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.158034	0.924391	-1.252754	0.2104
D(RETURN(-1))	-0.640012	0.016654	-38.42948	0.0000
D(RETURN(-2))	-0.487011	0.016683	-29.19213	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.392725	Mean dependent var	1.232221
Adjusted R-squared	0.324966	S.D. dependent var	60.46508
S.E. of regression	49.67839	Akaike info criterion	10.74427
Sum squared resid	6436394.	Schwarz criterion	11.34563
Log likelihood	-15287.19	Hannan-Quinn criter.	10.96095
F-statistic	5.795866	Durbin-Watson stat	2.386420
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 17:34
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	27.38871	1.153870	23.73639	0.0000
RETURN(-1)	-0.164840	0.017096	-9.642262	0.0000
RETURN(-2)	-0.271936	0.016953	-16.04072	0.0000
MARKET_CAP(-1)	-1.73E-10	3.29E-11	-5.243447	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.170270	Mean dependent var	15.04922
Adjusted R-squared	0.086639	S.D. dependent var	40.23970
S.E. of regression	38.45706	Akaike info criterion	10.22432
Sum squared resid	4284505.	Schwarz criterion	10.78164
Log likelihood	-16014.78	Hannan-Quinn criter.	10.42416
F-statistic	2.035954	Durbin-Watson stat	2.131870
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 18:18
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1035.817	40.66022	25.47496	0.0000
D(RETURN(-1))	-0.315072	0.016007	-19.68292	0.0000
LOG(MARKET_CAP(-1))	-44.63662	1.775907	-25.13455	0.0000
MARKET_RETURN(-1)	-0.750894	0.041972	-17.89041	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.436172	Mean dependent var	-1.349539
Adjusted R-squared	0.379342	S.D. dependent var	60.11495
S.E. of regression	47.35968	Akaike info criterion	10.64077
Sum squared resid	6497794.	Schwarz criterion	11.19810
Log likelihood	-16679.03	Hannan-Quinn criter.	10.84062
F-statistic	7.674982	Durbin-Watson stat	2.369323
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 17:36
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	538.7857	34.00965	15.84214	0.0000
RETURN(-1)	-0.097086	0.017209	-5.641615	0.0000
RETURN(-2)	-0.191568	0.017336	-11.05060	0.0000
LOG(MARKET_CAP(-1))	-22.57136	1.488167	-15.16722	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.224015	Mean dependent var	15.04922
Adjusted R-squared	0.145801	S.D. dependent var	40.23970
S.E. of regression	37.19070	Akaike info criterion	10.15735
Sum squared resid	4006981.	Schwarz criterion	10.71467
Log likelihood	-15907.97	Hannan-Quinn criter.	10.35719
F-statistic	2.864110	Durbin-Watson stat	2.040836
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 18:21
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1035.817	40.66022	25.47496	0.0000
D(RETURN(-1))	-0.315072	0.016007	-19.68292	0.0000
LOG(MARKET_CAP(-1))	-44.63662	1.775907	-25.13455	0.0000
MARKET_RETURN(-1)	-0.750894	0.041972	-17.89041	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.436172	Mean dependent var	-1.349539
Adjusted R-squared	0.379342	S.D. dependent var	60.11495
S.E. of regression	47.35968	Akaike info criterion	10.64077
Sum squared resid	6497794.	Schwarz criterion	11.19810
Log likelihood	-16679.03	Hannan-Quinn criter.	10.84062
F-statistic	7.674982	Durbin-Watson stat	2.369323
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 17:32
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	23.09138	0.815946	28.30014	0.0000
RETURN(-1)	-0.173360	0.017096	-10.14047	0.0000
RETURN(-2)	-0.279794	0.016964	-16.49383	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.162396	Mean dependent var	15.04922
Adjusted R-squared	0.078289	S.D. dependent var	40.23970
S.E. of regression	38.63245	Akaike info criterion	10.23313
Sum squared resid	4325167.	Schwarz criterion	10.78855
Log likelihood	-16029.85	Hannan-Quinn criter.	10.43229
F-statistic	1.930818	Durbin-Watson stat	2.142602
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 17:52
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 290
Total panel (balanced) observations: 2900

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.230816	1.517325	6.083612	0.0000
D(RETURN(-1))	-0.635830	0.016435	-38.68746	0.0000
D(RETURN(-2))	-0.479872	0.016477	-29.12329	0.0000
MARKET_CAP(-1)	-3.89E-10	4.54E-11	-8.566103	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.409350	Mean dependent var	1.232221
Adjusted R-squared	0.343194	S.D. dependent var	60.46508
S.E. of regression	49.00307	Akaike info criterion	10.71720
Sum squared resid	6260191.	Schwarz criterion	11.32063
Log likelihood	-15246.94	Hannan-Quinn criter.	10.93463
F-statistic	6.187610	Durbin-Watson stat	2.364853
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 17:39
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 290
Total panel (balanced) observations: 2900

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1110.966	38.50471	28.85273	0.0000
D(RETURN(-1))	-0.634536	0.014499	-43.76436	0.0000
D(RETURN(-2))	-0.430850	0.014652	-29.40501	0.0000
LOG(MARKET_CAP(-1))	-48.38462	1.674839	-28.88912	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.539989	Mean dependent var	1.232221
Adjusted R-squared	0.488465	S.D. dependent var	60.46508
S.E. of regression	43.24564	Akaike info criterion	10.46723
Sum squared resid	4875573.	Schwarz criterion	11.07065
Log likelihood	-14884.48	Hannan-Quinn criter.	10.68465
F-statistic	10.48033	Durbin-Watson stat	2.147372
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 18:14
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 290
Total panel (balanced) observations: 3190

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1183.806	41.94420	28.22334	0.0000
D(RETURN(-1))	-0.456694	0.014659	-31.15478	0.0000
LOG(MARKET_CAP(-1))	-51.62722	1.825264	-28.28480	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.373879	Mean dependent var	-1.349539
Adjusted R-squared	0.311008	S.D. dependent var	60.11495
S.E. of regression	49.89874	Akaike info criterion	10.74494
Sum squared resid	7215684.	Schwarz criterion	11.30036
Log likelihood	-16846.18	Hannan-Quinn criter.	10.94410
F-statistic	5.946741	Durbin-Watson stat	2.236623
Prob(F-statistic)	0.000000		

Bloomberg U.S. Equity Regression 1-9

Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 18:33
Sample (adjusted): 3 13390
Included observations: 13388 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.84573	0.459411	45.37488	0.0000
RETURN(-1)	-0.103227	0.008572	-12.04215	0.0000
RETURN(-2)	-0.128157	0.008572	-14.95058	0.0000

R-squared	0.024660	Mean dependent var	16.92920
Adjusted R-squared	0.024515	S.D. dependent var	47.60172
S.E. of regression	47.01463	Akaike info criterion	10.53902
Sum squared resid	29585874	Schwarz criterion	10.54070
Log likelihood	-70545.19	Hannan-Quinn criter.	10.53958
F-statistic	169.2133	Durbin-Watson stat	1.988174
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 18:41
Sample (adjusted): 4 13390
Included observations: 13387 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	80.05596	5.550459	14.42330	0.0000
D(RETURN(-1))	-0.702584	0.007698	-91.26718	0.0000
D(RETURN(-2))	-0.439700	0.007699	-57.11390	0.0000
LOG(MARKET_CAP(-1))	-3.606434	0.249141	-14.47549	0.0000

R-squared	0.395422	Mean dependent var	0.001582
Adjusted R-squared	0.395287	S.D. dependent var	70.33464
S.E. of regression	54.69454	Akaike info criterion	10.84170
Sum squared resid	40035149	Schwarz criterion	10.84395
Log likelihood	-72564.94	Hannan-Quinn criter.	10.84245
F-statistic	2917.704	Durbin-Watson stat	2.243168
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 18:58
Sample (adjusted): 3 13390
Included observations: 13388 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	88.96819	6.001796	14.82360	0.0000
D(RETURN(-1))	-0.397739	0.007895	-50.38160	0.0000
LOG(MARKET_CAP(-1))	-3.423448	0.269553	-12.70044	0.0000
MARKET_RETURN(-1)	-0.766600	0.026147	-29.31942	0.0000

R-squared	0.293443	Mean dependent var	0.002186
Adjusted R-squared	0.293284	S.D. dependent var	70.33205
S.E. of regression	59.12560	Akaike info criterion	10.99750
Sum squared resid	46788278	Schwarz criterion	10.99975
Log likelihood	-73613.29	Hannan-Quinn criter.	10.99825
F-statistic	1852.853	Durbin-Watson stat	2.474440
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 18:40
Sample (adjusted): 3 13390
Included observations: 13388 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	92.40298	4.730732	19.53249	0.0000
RETURN(-1)	-0.101318	0.008500	-11.91924	0.0000
RETURN(-2)	-0.125021	0.008502	-14.70518	0.0000
LOG(MARKET_CAP(-1))	-3.227544	0.212385	-15.19665	0.0000

R-squared	0.041204	Mean dependent var	16.92920
Adjusted R-squared	0.040989	S.D. dependent var	47.60172
S.E. of regression	46.61593	Akaike info criterion	10.52206
Sum squared resid	29084035	Schwarz criterion	10.52430
Log likelihood	-70430.67	Hannan-Quinn criter.	10.52281
F-statistic	191.7262	Durbin-Watson stat	1.983092
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 18:36
Sample (adjusted): 3 13390
Included observations: 13388 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.94107	0.461000	45.42531	0.0000
RETURN(-1)	-0.103308	0.008571	-12.05371	0.0000
RETURN(-2)	-0.128222	0.008571	-14.96086	0.0000
MARKET_CAP(-1)	-6.73E-13	2.77E-13	-2.429799	0.0151

R-squared	0.025091	Mean dependent var	16.92920
Adjusted R-squared	0.024872	S.D. dependent var	47.60172
S.E. of regression	47.00602	Akaike info criterion	10.53873
Sum squared resid	29572829	Schwarz criterion	10.54097
Log likelihood	-70542.24	Hannan-Quinn criter.	10.53947
F-statistic	114.8181	Durbin-Watson stat	1.988354
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 18:43
Sample (adjusted): 4 13390
Included observations: 13387 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.079584	0.478455	0.166335	0.8679
D(RETURN(-1))	-0.702557	0.007757	-90.56742	0.0000
D(RETURN(-2))	-0.441036	0.007757	-56.85447	0.0000
MARKET_CAP(-1)	-5.60E-13	3.25E-13	-1.724997	0.0846

R-squared	0.386093	Mean dependent var	0.001582
Adjusted R-squared	0.385955	S.D. dependent var	70.33464
S.E. of regression	55.11493	Akaike info criterion	10.85702
Sum squared resid	40652947	Schwarz criterion	10.85926
Log likelihood	-72667.44	Hannan-Quinn criter.	10.85777
F-statistic	2805.571	Durbin-Watson stat	2.253766
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 18:47
Sample (adjusted): 4 13390
Included observations: 13387 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002276	0.476387	0.004779	0.9962
D(RETURN(-1))	-0.702545	0.007758	-90.55924	0.0000
D(RETURN(-2))	-0.441025	0.007758	-56.84886	0.0000

R-squared	0.385956	Mean dependent var	0.001582
Adjusted R-squared	0.385865	S.D. dependent var	70.33464
S.E. of regression	55.11900	Akaike info criterion	10.85709
Sum squared resid	40661985	Schwarz criterion	10.85877
Log likelihood	-72668.93	Hannan-Quinn criter.	10.85765
F-statistic	4206.248	Durbin-Watson stat	2.253761
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 19:01
Sample (adjusted): 3 13390
Included observations: 13388 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	88.96819	6.001796	14.82360	0.0000
D(RETURN(-1))	-0.397739	0.007895	-50.38160	0.0000
LOG(MARKET_CAP(-1))	-3.423448	0.269553	-12.70044	0.0000
MARKET_RETURN(-1)	-0.766600	0.026147	-29.31942	0.0000

R-squared	0.293443	Mean dependent var	0.002186
Adjusted R-squared	0.293284	S.D. dependent var	70.33205
S.E. of regression	59.12560	Akaike info criterion	10.99750
Sum squared resid	46788278	Schwarz criterion	10.99975
Log likelihood	-73613.29	Hannan-Quinn criter.	10.99825
F-statistic	1852.853	Durbin-Watson stat	2.474440
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 18:56
Sample (adjusted): 3 13390
Included observations: 13388 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	83.80710	6.188643	13.54208	0.0000
D(RETURN(-1))	-0.488248	0.007495	-65.13990	0.0000
LOG(MARKET_CAP(-1))	-3.775444	0.277789	-13.59105	0.0000

R-squared	0.248062	Mean dependent var	0.002186
Adjusted R-squared	0.247950	S.D. dependent var	70.33205
S.E. of regression	60.99254	Akaike info criterion	11.05960
Sum squared resid	49793399	Schwarz criterion	11.06129
Log likelihood	-74029.99	Hannan-Quinn criter.	11.06017
F-statistic	2207.835	Durbin-Watson stat	2.414746
Prob(F-statistic)	0.000000		

CSI 800 Regression 1-9

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 19:16
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 266
Total panel (balanced) observations: 2660

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-26.87268	1.600935	-16.78562	0.0000
D(RETURN(-1))	-0.920580	0.013274	-69.35023	0.0000
D(RETURN(-2))	-0.446257	0.012934	-34.50172	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.673968	Mean dependent var	-19.72200
Adjusted R-squared	0.637576	S.D. dependent var	136.8384
S.E. of regression	82.37898	Akaike info criterion	11.75585
Sum squared resid	16232819	Schwarz criterion	12.34888
Log likelihood	-15367.27	Hannan-Quinn criter.	11.97047
F-statistic	18.51951	Durbin-Watson stat	1.621962
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 19:18
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2144.150	64.65781	33.16149	0.0000
D(RETURN(-1))	-0.527778	0.012766	-41.34204	0.0000
LOG(MARKET_CAP(-1))	-92.78253	2.787344	-33.28707	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.541361	Mean dependent var	-7.132741
Adjusted R-squared	0.495290	S.D. dependent var	143.7863
S.E. of regression	102.1500	Akaike info criterion	12.17788
Sum squared resid	27735223	Schwarz criterion	12.72574
Log likelihood	-17548.24	Hannan-Quinn criter.	12.37520
F-statistic	11.75059	Durbin-Watson stat	2.068274
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 19:15
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 266
Total panel (balanced) observations: 2660

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.694300	2.694674	-1.370964	0.1705
D(RETURN(-1))	-0.893482	0.013229	-67.54191	0.0000
D(RETURN(-2))	-0.427613	0.012768	-33.49186	0.0000
MARKET_CAP(-1)	-9.89E-10	9.36E-11	-10.56668	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.688514	Mean dependent var	-19.72200
Adjusted R-squared	0.653600	S.D. dependent var	136.8384
S.E. of regression	80.53720	Akaike info criterion	11.71096
Sum squared resid	15508600	Schwarz criterion	12.30620
Log likelihood	-15306.57	Hannan-Quinn criter.	11.92638
F-statistic	19.72055	Durbin-Watson stat	1.597834
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 19:13
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 266
Total panel (balanced) observations: 2660

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1104.021	60.52109	18.24193	0.0000
D(RETURN(-1))	-0.853527	0.012910	-66.11188	0.0000
D(RETURN(-2))	-0.409928	0.012240	-33.49211	0.0000
LOG(MARKET_CAP(-1))	-48.53905	2.596830	-18.69166	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.715535	Mean dependent var	-19.72200
Adjusted R-squared	0.683650	S.D. dependent var	136.8384
S.E. of regression	76.96473	Akaike info criterion	11.62021
Sum squared resid	14163254	Schwarz criterion	12.21546
Log likelihood	-15185.88	Hannan-Quinn criter.	11.83564
F-statistic	22.44123	Durbin-Watson stat	1.395551
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 19:23
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2208.516	55.96038	39.46571	0.0000
D(RETURN(-1))	-0.246117	0.014504	-16.96861	0.0000
LOG(MARKET_CAP(-1))	-93.92607	2.410927	-38.95848	0.0000
MARKET_RETURN(-1)	-0.873224	0.029161	-29.94444	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.657086	Mean dependent var	-7.132741
Adjusted R-squared	0.622497	S.D. dependent var	143.7863
S.E. of regression	88.34405	Akaike info criterion	11.88778
Sum squared resid	20737012	Schwarz criterion	12.43768
Log likelihood	-17122.83	Hannan-Quinn criter.	12.08583
F-statistic	18.99736	Durbin-Watson stat	2.103368
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 19:09
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	80.64511	2.852070	28.27600	0.0000
RETURN(-1)	-0.161391	0.018064	-8.934327	0.0000
RETURN(-2)	-0.049088	0.017862	-2.748111	0.0060
MARKET_CAP(-1)	-1.60E-09	9.68E-11	-16.49798	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.153679	Mean dependent var	36.17453
Adjusted R-squared	0.068314	S.D. dependent var	92.06420
S.E. of regression	88.86394	Akaike info criterion	11.89952
Sum squared resid	20981795	Schwarz criterion	12.44942
Log likelihood	-17140.00	Hannan-Quinn criter.	12.09757
F-statistic	1.800260	Durbin-Watson stat	1.794258
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 19:07
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	47.83090	2.145818	22.29029	0.0000
RETURN(-1)	-0.204807	0.018761	-10.91669	0.0000
RETURN(-2)	-0.064169	0.018727	-3.426574	0.0006

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.066981	Mean dependent var	36.17453
Adjusted R-squared	-0.026742	S.D. dependent var	92.06420
S.E. of regression	93.28705	Akaike info criterion	11.99636
Sum squared resid	23131174	Schwarz criterion	12.54421
Log likelihood	-17282.68	Hannan-Quinn criter.	12.19367
F-statistic	0.714674	Durbin-Watson stat	1.792091
Prob(F-statistic)	0.999776		

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 19:11
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1885.484	47.54321	39.65833	0.0000
RETURN(-1)	-0.107353	0.015219	-7.053813	0.0000
RETURN(-2)	-0.038180	0.014997	-2.545890	0.0110
LOG(MARKET_CAP(-1))	-79.48440	2.055055	-38.67750	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.403068	Mean dependent var	36.17453
Adjusted R-squared	0.342858	S.D. dependent var	92.06420
S.E. of regression	74.63122	Akaike info criterion	11.55042
Sum squared resid	14799008	Schwarz criterion	12.10032
Log likelihood	-16629.27	Hannan-Quinn criter.	11.74847
F-statistic	6.694365	Durbin-Watson stat	1.536022
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 19:25
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 266
Total panel (balanced) observations: 2926

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2208.516	55.96038	39.46571	0.0000
D(RETURN(-1))	-0.246117	0.014504	-16.96861	0.0000
LOG(MARKET_CAP(-1))	-93.92607	2.410927	-38.95848	0.0000
MARKET_RETURN(-1)	-0.873224	0.029161	-29.94444	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.657086	Mean dependent var	-7.132741
Adjusted R-squared	0.622497	S.D. dependent var	143.7863
S.E. of regression	88.34405	Akaike info criterion	11.88778
Sum squared resid	20737012	Schwarz criterion	12.43768
Log likelihood	-17122.83	Hannan-Quinn criter.	12.08583
F-statistic	18.99736	Durbin-Watson stat	2.103368
Prob(F-statistic)	0.000000		

Dow Jones US Regression1-9

Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 19:29
Sample (adjusted): 3 8450
Included observations: 8448 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.26606	0.515311	39.32782	0.0000
RETURN(-1)	-0.106505	0.010816	-9.846860	0.0000
RETURN(-2)	-0.109364	0.010816	-10.11137	0.0000

R-squared	0.021070	Mean dependent var	16.66869
Adjusted R-squared	0.020838	S.D. dependent var	40.94718
S.E. of regression	40.51830	Akaike info criterion	10.24174
Sum squared resid	13864432	Schwarz criterion	10.24424
Log likelihood	-43258.11	Hannan-Quinn criter.	10.24259
F-statistic	90.88318	Durbin-Watson stat	1.986563
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 19:30
Sample (adjusted): 3 8450
Included observations: 8448 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	21.05675	0.547198	38.48103	0.0000
RETURN(-1)	-0.106360	0.010805	-9.843426	0.0000
RETURN(-2)	-0.109417	0.010805	-10.12653	0.0000
MARKET_CAP(-1)	-4.45E-11	1.04E-11	-4.261941	0.0000

R-squared	0.023171	Mean dependent var	16.66869
Adjusted R-squared	0.022824	S.D. dependent var	40.94718
S.E. of regression	40.47719	Akaike info criterion	10.23983
Sum squared resid	13834672	Schwarz criterion	10.24316
Log likelihood	-43249.03	Hannan-Quinn criter.	10.24097
F-statistic	66.76665	Durbin-Watson stat	1.985574
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 19:38
Sample (adjusted): 4 8450
Included observations: 8447 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003633	0.512901	0.007083	0.9943
D(RETURN(-1))	-0.719120	0.009760	-73.68230	0.0000
D(RETURN(-2))	-0.442386	0.009760	-45.32758	0.0000

R-squared	0.395619	Mean dependent var	0.002507
Adjusted R-squared	0.395476	S.D. dependent var	60.62869
S.E. of regression	47.13950	Akaike info criterion	10.54445
Sum squared resid	18763685	Schwarz criterion	10.54696
Log likelihood	-44531.50	Hannan-Quinn criter.	10.54531
F-statistic	2763.661	Durbin-Watson stat	2.259911
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 19:36
Sample (adjusted): 4 8450
Included observations: 8447 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.796410	0.556315	1.431580	0.1523
D(RETURN(-1))	-0.718988	0.009753	-73.72244	0.0000
D(RETURN(-2))	-0.442319	0.009753	-45.35397	0.0000
MARKET_CAP(-1)	-4.45E-11	1.22E-11	-3.664390	0.0002

R-squared	0.396579	Mean dependent var	0.002507
Adjusted R-squared	0.396364	S.D. dependent var	60.62869
S.E. of regression	47.10485	Akaike info criterion	10.54310
Sum squared resid	18733890	Schwarz criterion	10.54644
Log likelihood	-44524.79	Hannan-Quinn criter.	10.54424
F-statistic	1849.629	Durbin-Watson stat	2.258609
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 19:44
Sample (adjusted): 3 8450
Included observations: 8448 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	123.5978	9.255027	13.35467	0.0000
D(RETURN(-1))	-0.398524	0.009915	-40.19378	0.0000
LOG(MARKET_CAP(-1))	-4.927150	0.410070	-12.01538	0.0000
MARKET_RETURN(-1)	-0.744605	0.030415	-24.48149	0.0000

R-squared	0.312077	Mean dependent var	0.003465
Adjusted R-squared	0.311832	S.D. dependent var	60.62516
S.E. of regression	50.29214	Akaike info criterion	10.67405
Sum squared resid	21357400	Schwarz criterion	10.67738
Log likelihood	-45083.18	Hannan-Quinn criter.	10.67519
F-statistic	1276.875	Durbin-Watson stat	2.479582
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 19:34
Sample (adjusted): 4 8450
Included observations: 8447 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	120.3644	8.578750	14.03053	0.0000
D(RETURN(-1))	-0.718884	0.009648	-74.51020	0.0000
D(RETURN(-2))	-0.441093	0.009649	-45.71594	0.0000
LOG(MARKET_CAP(-1))	-5.333579	0.379488	-14.05467	0.0000

R-squared	0.409436	Mean dependent var	0.002507
Adjusted R-squared	0.409226	S.D. dependent var	60.62869
S.E. of regression	46.60031	Akaike info criterion	10.52156
Sum squared resid	18334723	Schwarz criterion	10.52490
Log likelihood	-44433.83	Hannan-Quinn criter.	10.52270
F-statistic	1951.168	Durbin-Watson stat	2.241947
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 19:40
Sample (adjusted): 3 8450
Included observations: 8448 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	124.0530	9.577265	12.95286	0.0000
D(RETURN(-1))	-0.498981	0.009340	-53.42186	0.0000
LOG(MARKET_CAP(-1))	-5.497100	0.423664	-12.97513	0.0000

R-squared	0.263249	Mean dependent var	0.003465
Adjusted R-squared	0.263074	S.D. dependent var	60.62516
S.E. of regression	52.04329	Akaike info criterion	10.74238
Sum squared resid	22873319	Schwarz criterion	10.74488
Log likelihood	-45372.83	Hannan-Quinn criter.	10.74324
F-statistic	1508.743	Durbin-Watson stat	2.417572
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 19:32
Sample (adjusted): 3 8450
Included observations: 8448 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	120.7003	7.376031	16.36386	0.0000
RETURN(-1)	-0.102320	0.010704	-9.559180	0.0000
RETURN(-2)	-0.104499	0.010705	-9.761497	0.0000
LOG(MARKET_CAP(-1))	-4.457327	0.326570	-13.64893	0.0000

R-squared	0.042201	Mean dependent var	16.66869
Adjusted R-squared	0.041861	S.D. dependent var	40.94718
S.E. of regression	40.08097	Akaike info criterion	10.22015
Sum squared resid	13565155	Schwarz criterion	10.22349
Log likelihood	-43165.93	Hannan-Quinn criter.	10.22129
F-statistic	124.0160	Durbin-Watson stat	1.975308
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 19:42
Sample (adjusted): 3 8450
Included observations: 8448 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	12.75625	0.751539	16.97350	0.0000
D(RETURN(-1))	-0.395350	0.009995	-39.55349	0.0000
MARKET_RETURN(-1)	-0.765353	0.030623	-24.99303	0.0000

R-squared	0.300315	Mean dependent var	0.003465
Adjusted R-squared	0.300149	S.D. dependent var	60.62516
S.E. of regression	50.71724	Akaike info criterion	10.69076
Sum squared resid	21722553	Schwarz criterion	10.69326
Log likelihood	-45154.79	Hannan-Quinn criter.	10.69162
F-statistic	1812.359	Durbin-Watson stat	2.502589
Prob(F-statistic)	0.000000		

JPX Nikkei Regression 1-9

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 19:47
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 300
Total panel (balanced) observations: 3300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15.90419	0.779175	20.41159	0.0000
RETURN(-1)	0.009207	0.018111	0.508349	0.6112
RETURN(-2)	-0.151875	0.016576	-9.162475	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.070365	Mean dependent var	13.56119
Adjusted R-squared	-0.022970	S.D. dependent var	39.79010
S.E. of regression	40.24450	Akaike info criterion	10.31488
Sum squared resid	4855620.	Schwarz criterion	10.87327
Log likelihood	-16717.55	Hannan-Quinn criter.	10.51476
F-statistic	0.753896	Durbin-Watson stat	2.169486
Prob(F-statistic)	0.999199		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 20:10
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 300
Total panel (balanced) observations: 3000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.687858	0.925280	2.904913	0.0037
D(RETURN(-1))	-0.556548	0.017907	-31.08002	0.0000
D(RETURN(-2))	-0.285664	0.016970	-16.83357	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.272075	Mean dependent var	3.738773
Adjusted R-squared	0.190865	S.D. dependent var	56.21593
S.E. of regression	50.56732	Akaike info criterion	10.77972
Sum squared resid	6898931.	Schwarz criterion	11.38436
Log likelihood	-15867.58	Hannan-Quinn criter.	10.99721
F-statistic	3.350255	Durbin-Watson stat	2.430167
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 20:13
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 300
Total panel (balanced) observations: 3300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1073.318	55.80632	19.23291	0.0000
D(RETURN(-1))	-0.494434	0.016355	-30.23226	0.0000
LOG(MARKET_CAP(-1))	-40.36753	2.099291	-19.22912	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.248586	Mean dependent var	2.044152
Adjusted R-squared	0.173143	S.D. dependent var	54.66625
S.E. of regression	49.70893	Akaike info criterion	10.73730
Sum squared resid	7407992.	Schwarz criterion	11.29570
Log likelihood	-17414.54	Hannan-Quinn criter.	10.93718
F-statistic	3.295046	Durbin-Watson stat	2.440874
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 20:16
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 300
Total panel (balanced) observations: 3300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	982.6301	55.16310	17.81318	0.0000
D(RETURN(-1))	-0.422363	0.017168	-24.60134	0.0000
LOG(MARKET_CAP(-1))	-36.75671	2.077605	-17.69187	0.0000
MARKET_RETURN(-1)	-0.434850	0.037520	-11.58994	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.280820	Mean dependent var	2.044152
Adjusted R-squared	0.208350	S.D. dependent var	54.66625
S.E. of regression	48.63916	Akaike info criterion	10.69406
Sum squared resid	7090206.	Schwarz criterion	11.25431
Log likelihood	-17342.20	Hannan-Quinn criter.	10.89460
F-statistic	3.874978	Durbin-Watson stat	2.424210
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 20:02
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 300
Total panel (balanced) observations: 3300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	507.5043	46.38413	10.94133	0.0000
RETURN(-1)	-0.004373	0.017830	-0.245287	0.8063
RETURN(-2)	-0.057826	0.018537	-3.119422	0.0018
LOG(MARKET_CAP(-1))	-18.53621	1.748716	-10.59990	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.103958	Mean dependent var	13.56119
Adjusted R-squared	0.013666	S.D. dependent var	39.79010
S.E. of regression	39.51728	Akaike info criterion	10.27868
Sum squared resid	4680161.	Schwarz criterion	10.83892
Log likelihood	-16656.82	Hannan-Quinn criter.	10.47922
F-statistic	1.151355	Durbin-Watson stat	2.111396
Prob(F-statistic)	0.044047		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 20:14
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 300
Total panel (balanced) observations: 3300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	982.6301	55.16310	17.81318	0.0000
D(RETURN(-1))	-0.422363	0.017168	-24.60134	0.0000
LOG(MARKET_CAP(-1))	-36.75671	2.077605	-17.69187	0.0000
MARKET_RETURN(-1)	-0.434850	0.037520	-11.58994	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.280820	Mean dependent var	2.044152
Adjusted R-squared	0.208350	S.D. dependent var	54.66625
S.E. of regression	48.63916	Akaike info criterion	10.69406
Sum squared resid	7090206.	Schwarz criterion	11.25431
Log likelihood	-17342.20	Hannan-Quinn criter.	10.89460
F-statistic	3.874978	Durbin-Watson stat	2.424210
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 20:05
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 300
Total panel (balanced) observations: 3000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1370.825	54.17915	25.30171	0.0000
D(RETURN(-1))	-0.750135	0.017838	-42.05347	0.0000
D(RETURN(-2))	-0.367086	0.015601	-23.53025	0.0000
LOG(MARKET_CAP(-1))	-51.49453	2.038977	-25.25508	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.411298	Mean dependent var	3.738773
Adjusted R-squared	0.345378	S.D. dependent var	56.21593
S.E. of regression	45.48359	Akaike info criterion	10.56811
Sum squared resid	5579438.	Schwarz criterion	11.17475
Log likelihood	-15549.16	Hannan-Quinn criter.	10.78632
F-statistic	6.239301	Durbin-Watson stat	2.369260
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 20:08
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 300
Total panel (balanced) observations: 3000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	18.58811	1.619787	11.47565	0.0000
D(RETURN(-1))	-0.604979	0.017938	-33.72648	0.0000
D(RETURN(-2))	-0.306930	0.016647	-18.43728	0.0000
MARKET_CAP(-1)	-2.05E-11	1.74E-12	-11.82041	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.307929	Mean dependent var	3.738773
Adjusted R-squared	0.230433	S.D. dependent var	56.21593
S.E. of regression	49.31539	Akaike info criterion	10.72988
Sum squared resid	6559125.	Schwarz criterion	11.33652
Log likelihood	-15791.82	Hannan-Quinn criter.	10.94809
F-statistic	3.973506	Durbin-Watson stat	2.418001
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 20:00
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 300
Total panel (balanced) observations: 3300

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	22.44703	1.273039	17.63263	0.0000
RETURN(-1)	0.004246	0.018005	0.235805	0.8136
RETURN(-2)	-0.127233	0.016898	-7.529406	0.0000
MARKET_CAP(-1)	-8.67E-12	1.34E-12	-6.473023	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.083183	Mean dependent var	13.56119
Adjusted R-squared	-0.009202	S.D. dependent var	39.79010
S.E. of regression	39.97276	Akaike info criterion	10.30160
Sum squared resid	4788672.	Schwarz criterion	10.86184
Log likelihood	-16694.64	Hannan-Quinn criter.	10.50214
F-statistic	0.900392	Durbin-Watson stat	2.154239
Prob(F-statistic)	0.882566		

SP global 1200 Regression 1-9

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 21:04
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 840
Total panel (balanced) observations: 8400

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.919655	0.526587	-1.746446	0.0808
D(RETURN(-1))	-0.701660	0.010203	-68.76910	0.0000
D(RETURN(-2))	-0.443380	0.010252	-43.24851	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.396197	Mean dependent var	0.805524
Adjusted R-squared	0.329010	S.D. dependent var	58.81945
S.E. of regression	48.18134	Akaike info criterion	10.68267
Sum squared resid	17545453	Schwarz criterion	11.38795
Log likelihood	-44025.22	Hannan-Quinn criter.	10.92349
F-statistic	5.896947	Durbin-Watson stat	2.284393
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 21:02
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 840
Total panel (balanced) observations: 8400

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.279676	0.549384	-0.509072	0.6107
D(RETURN(-1))	-0.701966	0.010193	-68.86686	0.0000
D(RETURN(-2))	-0.443291	0.010242	-43.28355	0.0000
MARKET_CAP(-1)	-8.02E-13	1.98E-13	-4.040340	0.0001

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.397499	Mean dependent var	0.805524
Adjusted R-squared	0.330368	S.D. dependent var	58.81945
S.E. of regression	48.13257	Akaike info criterion	10.68075
Sum squared resid	17507633	Schwarz criterion	11.38686
Log likelihood	-44016.16	Hannan-Quinn criter.	10.92185
F-statistic	5.921273	Durbin-Watson stat	2.282993
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 21:01
Sample (adjusted): 2008 2017
Periods included: 10
Cross-sections included: 840
Total panel (balanced) observations: 8400

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1124.411	25.65241	43.83255	0.0000
D(RETURN(-1))	-0.718320	0.009117	-78.78727	0.0000
D(RETURN(-2))	-0.428564	0.009159	-46.79121	0.0000
LOG(MARKET_CAP(-1))	-46.48322	1.059428	-43.87577	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.518783	Mean dependent var	0.805524
Adjusted R-squared	0.465166	S.D. dependent var	58.81945
S.E. of regression	43.01604	Akaike info criterion	10.45598
Sum squared resid	13983318	Schwarz criterion	11.16209
Log likelihood	-43072.12	Hannan-Quinn criter.	10.69708
F-statistic	9.675701	Durbin-Watson stat	2.145589
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 20:56
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 840
Total panel (balanced) observations: 9240

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.64536	0.473459	43.60535	0.0000
RETURN(-1)	-0.176803	0.010681	-16.55274	0.0000
RETURN(-2)	-0.194259	0.010518	-18.46900	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.116303	Mean dependent var	14.80215
Adjusted R-squared	0.027807	S.D. dependent var	39.11051
S.E. of regression	38.56289	Akaike info criterion	10.22916
Sum squared resid	12488639	Schwarz criterion	10.87900
Log likelihood	-46416.72	Hannan-Quinn criter.	10.45000
F-statistic	1.314222	Durbin-Watson stat	2.105936
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 21:06
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 840
Total panel (balanced) observations: 9240

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	990.1689	26.43952	37.45034	0.0000
D(RETURN(-1))	-0.397895	0.009451	-42.10306	0.0000
LOG(MARKET_CAP(-1))	-40.52859	1.095455	-36.99704	0.0000
MARKET_RETURN(-1)	-0.691145	0.027652	-24.99405	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.405273	Mean dependent var	-0.199782
Adjusted R-squared	0.345637	S.D. dependent var	57.62909
S.E. of regression	46.61772	Akaike info criterion	10.60864
Sum squared resid	18248461	Schwarz criterion	11.25925
Log likelihood	-48168.91	Hannan-Quinn criter.	10.82974
F-statistic	6.795819	Durbin-Watson stat	2.441037
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 20:59
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 840
Total panel (balanced) observations: 9240

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	602.3737	21.69639	27.76377	0.0000
RETURN(-1)	-0.122448	0.010450	-11.71730	0.0000
RETURN(-2)	-0.117183	0.010496	-11.16411	0.0000
LOG(MARKET_CAP(-1))	-24.12992	0.899762	-26.81810	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.186021	Mean dependent var	14.80215
Adjusted R-squared	0.104400	S.D. dependent var	39.11051
S.E. of regression	37.01267	Akaike info criterion	10.14720
Sum squared resid	11503366	Schwarz criterion	10.79781
Log likelihood	-46037.05	Hannan-Quinn criter.	10.36830
F-statistic	2.279091	Durbin-Watson stat	2.035038
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 21:05
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 840
Total panel (balanced) observations: 9240

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1091.925	27.07691	40.32681	0.0000
D(RETURN(-1))	-0.504940	0.008732	-57.82930	0.0000
LOG(MARKET_CAP(-1))	-45.16922	1.118978	-40.36650	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.361028	Mean dependent var	-0.199782
Adjusted R-squared	0.297039	S.D. dependent var	57.62909
S.E. of regression	48.31782	Akaike info criterion	10.68018
Sum squared resid	19606072	Schwarz criterion	11.33002
Log likelihood	-48500.44	Hannan-Quinn criter.	10.90102
F-statistic	5.642066	Durbin-Watson stat	2.368125
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Panel Least Squares
Date: 04/17/22 Time: 20:58
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 840
Total panel (balanced) observations: 9240

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.90184	0.485871	43.01933	0.0000
RETURN(-1)	-0.176314	0.010680	-16.50818	0.0000
RETURN(-2)	-0.193758	0.010517	-18.42249	0.0000
MARKET_CAP(-1)	-3.48E-13	1.49E-13	-2.338838	0.0194

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.116879	Mean dependent var	14.80215
Adjusted R-squared	0.028325	S.D. dependent var	39.11051
S.E. of regression	38.55264	Akaike info criterion	10.22873
Sum squared resid	12480509	Schwarz criterion	10.87934
Log likelihood	-46413.71	Hannan-Quinn criter.	10.44982
F-statistic	1.319856	Durbin-Watson stat	2.105626
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Panel Least Squares
Date: 04/17/22 Time: 21:09
Sample (adjusted): 2007 2017
Periods included: 11
Cross-sections included: 840
Total panel (balanced) observations: 9240

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	990.1689	26.43952	37.45034	0.0000
D(RETURN(-1))	-0.397895	0.009451	-42.10306	0.0000
LOG(MARKET_CAP(-1))	-40.52859	1.095455	-36.99704	0.0000
MARKET_RETURN(-1)	-0.691145	0.027652	-24.99405	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.405273	Mean dependent var	-0.199782
Adjusted R-squared	0.345637	S.D. dependent var	57.62909
S.E. of regression	46.61772	Akaike info criterion	10.60864
Sum squared resid	18248461	Schwarz criterion	11.25925
Log likelihood	-48168.91	Hannan-Quinn criter.	10.82974
F-statistic	6.795819	Durbin-Watson stat	2.441037
Prob(F-statistic)	0.000000		

S&P Australia Regression 1-9

Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 21:17
Sample (adjusted): 3 1456
Included observations: 1454 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	22.72947	1.907851	11.91365	0.0000
RETURN(-1)	0.010305	0.026225	0.392965	0.6944
RETURN(-2)	-0.048352	0.026227	-1.843587	0.0654

R-squared	0.002433	Mean dependent var	21.89583
Adjusted R-squared	0.001058	S.D. dependent var	65.91724
S.E. of regression	65.88235	Akaike info criterion	11.21568
Sum squared resid	6298043.	Schwarz criterion	11.22658
Log likelihood	-8150.799	Hannan-Quinn criter.	11.21975
F-statistic	1.769489	Durbin-Watson stat	1.996856
Prob(F-statistic)	0.170788		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:22
Sample (adjusted): 4 1456
Included observations: 1453 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	120.1584	22.93072	5.240063	0.0000
D(RETURN(-1))	-0.656387	0.024239	-27.07949	0.0000
D(RETURN(-2))	-0.375898	0.024170	-15.55217	0.0000
LOG(MARKET_CAP(-1))	-5.718898	1.086984	-5.261253	0.0000

R-squared	0.341896	Mean dependent var	-0.035120
Adjusted R-squared	0.340534	S.D. dependent var	92.78884
S.E. of regression	75.35152	Akaike info criterion	11.48495
Sum squared resid	8227206.	Schwarz criterion	11.49949
Log likelihood	-8339.819	Hannan-Quinn criter.	11.49038
F-statistic	250.9269	Durbin-Watson stat	2.129278
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:27
Sample (adjusted): 4 1456
Included observations: 1453 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.036772	1.994888	-0.018433	0.9853
D(RETURN(-1))	-0.645819	0.024377	-26.49282	0.0000
D(RETURN(-2))	-0.372315	0.024382	-15.27018	0.0000

R-squared	0.329324	Mean dependent var	-0.035120
Adjusted R-squared	0.328399	S.D. dependent var	92.78884
S.E. of regression	76.04161	Akaike info criterion	11.50250
Sum squared resid	8384374.	Schwarz criterion	11.51341
Log likelihood	-8353.567	Hannan-Quinn criter.	11.50657
F-statistic	355.9994	Durbin-Watson stat	2.148129
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 21:19
Sample (adjusted): 3 1456
Included observations: 1454 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	24.02006	1.995196	12.03894	0.0000
RETURN(-1)	0.008401	0.026205	0.320593	0.7486
RETURN(-2)	-0.048827	0.026194	-1.864014	0.0625
MARKET_CAP(-1)	-1.98E-10	9.10E-11	-2.180535	0.0294

R-squared	0.005694	Mean dependent var	21.89583
Adjusted R-squared	0.003636	S.D. dependent var	65.91724
S.E. of regression	65.79728	Akaike info criterion	11.21378
Sum squared resid	6277459.	Schwarz criterion	11.22831
Log likelihood	-8148.419	Hannan-Quinn criter.	11.21920
F-statistic	2.767623	Durbin-Watson stat	1.995269
Prob(F-statistic)	0.040529		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:28
Sample (adjusted): 3 1456
Included observations: 1454 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	110.1541	24.74392	4.451767	0.0000
D(RETURN(-1))	-0.478870	0.023083	-20.74534	0.0000
LOG(MARKET_CAP(-1))	-5.242616	1.172928	-4.469682	0.0000

R-squared	0.232049	Mean dependent var	-0.041376
Adjusted R-squared	0.230990	S.D. dependent var	92.75721
S.E. of regression	81.34177	Akaike info criterion	11.63726
Sum squared resid	9600519.	Schwarz criterion	11.64816
Log likelihood	-8457.286	Hannan-Quinn criter.	11.64132
F-statistic	219.2212	Durbin-Watson stat	2.334918
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:30
Sample (adjusted): 3 1456
Included observations: 1454 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	124.2754	24.08240	5.160425	0.0000
D(RETURN(-1))	-0.394649	0.024156	-16.33749	0.0000
LOG(MARKET_CAP(-1))	-4.992002	1.139648	-4.380303	0.0000
MARKET_RETURN(-1)	-0.885144	0.094448	-9.371738	0.0000

R-squared	0.275908	Mean dependent var	-0.041376
Adjusted R-squared	0.274410	S.D. dependent var	92.75721
S.E. of regression	79.01204	Akaike info criterion	11.57982
Sum squared resid	9052208.	Schwarz criterion	11.59436
Log likelihood	-8414.533	Hannan-Quinn criter.	11.58525
F-statistic	184.1696	Durbin-Watson stat	2.378963
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:31
Sample (adjusted): 3 1456
Included observations: 1454 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	124.2754	24.08240	5.160425	0.0000
D(RETURN(-1))	-0.394649	0.024156	-16.33749	0.0000
LOG(MARKET_CAP(-1))	-4.992002	1.139648	-4.380303	0.0000
MARKET_RETURN(-1)	-0.885144	0.094448	-9.371738	0.0000

R-squared	0.275908	Mean dependent var	-0.041376
Adjusted R-squared	0.274410	S.D. dependent var	92.75721
S.E. of regression	79.01204	Akaike info criterion	11.57982
Sum squared resid	9052208.	Schwarz criterion	11.59436
Log likelihood	-8414.533	Hannan-Quinn criter.	11.58525
F-statistic	184.1696	Durbin-Watson stat	2.378963
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 21:21
Sample (adjusted): 3 1456
Included observations: 1454 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	172.0170	19.77650	8.698052	0.0000
RETURN(-1)	-0.010006	0.025867	-0.386830	0.6989
RETURN(-2)	-0.046662	0.025732	-1.813385	0.0700
LOG(MARKET_CAP(-1))	-7.083649	0.934177	-7.582774	0.0000

R-squared	0.040482	Mean dependent var	21.89583
Adjusted R-squared	0.038497	S.D. dependent var	65.91724
S.E. of regression	64.63599	Akaike info criterion	11.17817
Sum squared resid	6057826.	Schwarz criterion	11.19270
Log likelihood	-8122.527	Hannan-Quinn criter.	11.18359
F-statistic	20.39174	Durbin-Watson stat	1.980929
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:25
Sample (adjusted): 4 1456
Included observations: 1453 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.786768	2.099705	0.374704	0.7079
D(RETURN(-1))	-0.646378	0.024376	-26.51657	0.0000
D(RETURN(-2))	-0.372494	0.024377	-15.28028	0.0000
MARKET_CAP(-1)	-1.32E-10	1.05E-10	-1.254780	0.2098

R-squared	0.330052	Mean dependent var	-0.035120
Adjusted R-squared	0.328665	S.D. dependent var	92.78884
S.E. of regression	76.02655	Akaike info criterion	11.50279
Sum squared resid	8375273.	Schwarz criterion	11.51733
Log likelihood	-8352.778	Hannan-Quinn criter.	11.50822
F-statistic	237.9518	Durbin-Watson stat	2.146883
Prob(F-statistic)	0.000000		

TOPIX 100 Regression 1-9

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:49
Sample (adjusted): 3 9360
Included observations: 9358 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	59.41531	11.13043	5.338095	0.0000
D(RETURN(-1))	-0.365626	0.009702	-37.68695	0.0000
LOG(MARKET_CAP(-1))	-1.991796	0.433195	-4.597915	0.0000
MARKET_RETURN(-1)	-0.524989	0.024273	-21.62893	0.0000

R-squared	0.225440	Mean dependent var	0.003443
Adjusted R-squared	0.225191	S.D. dependent var	65.72115
S.E. of regression	57.84987	Akaike info criterion	10.95401
Sum squared resid	31304169	Schwarz criterion	10.95706
Log likelihood	-51249.80	Hannan-Quinn criter.	10.95504
F-statistic	907.5101	Durbin-Watson stat	2.324148
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:44
Sample (adjusted): 4 9360
Included observations: 9357 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000783	0.579893	-0.001350	0.9989
D(RETURN(-1))	-0.569923	0.009770	-58.33608	0.0000
D(RETURN(-2))	-0.327010	0.009766	-33.48421	0.0000

R-squared	0.271746	Mean dependent var	0.004084
Adjusted R-squared	0.271591	S.D. dependent var	65.72464
S.E. of regression	56.09394	Akaike info criterion	10.89225
Sum squared resid	29432639	Schwarz criterion	10.89454
Log likelihood	-50956.41	Hannan-Quinn criter.	10.89303
F-statistic	1745.214	Durbin-Watson stat	2.243135
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:41
Sample (adjusted): 4 9360
Included observations: 9357 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	82.99866	10.78039	7.699042	0.0000
D(RETURN(-1))	-0.579899	0.009825	-59.02377	0.0000
D(RETURN(-2))	-0.331753	0.009755	-34.00803	0.0000
LOG(MARKET_CAP(-1))	-3.232854	0.419295	-7.710208	0.0000

R-squared	0.276346	Mean dependent var	0.004084
Adjusted R-squared	0.276114	S.D. dependent var	65.72464
S.E. of regression	55.91951	Akaike info criterion	10.88613
Sum squared resid	29246747	Schwarz criterion	10.88918
Log likelihood	-50926.76	Hannan-Quinn criter.	10.88717
F-statistic	1190.562	Durbin-Watson stat	2.244354
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 21:37
Sample (adjusted): 3 9360
Included observations: 9358 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.93817	0.565222	31.73650	0.0000
RETURN(-1)	0.015239	0.010261	1.485122	0.1375
RETURN(-2)	-0.124336	0.010255	-12.12473	0.0000
MARKET_CAP(-1)	-1.08E-12	4.66E-13	-2.321249	0.0203

R-squared	0.016432	Mean dependent var	15.76723
Adjusted R-squared	0.016116	S.D. dependent var	46.80688
S.E. of regression	46.42817	Akaike info criterion	10.51412
Sum squared resid	20163252	Schwarz criterion	10.51717
Log likelihood	-49191.56	Hannan-Quinn criter.	10.51515
F-statistic	52.08946	Durbin-Watson stat	2.024915
Prob(F-statistic)	0.000000		

Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 21:36
Sample (adjusted): 3 9360
Included observations: 9358 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.48822	0.531069	32.93023	0.0000
RETURN(-1)	0.016041	0.010258	1.563839	0.1179
RETURN(-2)	-0.125088	0.010252	-12.20128	0.0000

R-squared	0.015865	Mean dependent var	15.76723
Adjusted R-squared	0.015655	S.D. dependent var	46.80688
S.E. of regression	46.43906	Akaike info criterion	10.51448
Sum squared resid	20174867	Schwarz criterion	10.51677
Log likelihood	-49194.25	Hannan-Quinn criter.	10.51526
F-statistic	75.40472	Durbin-Watson stat	2.024852
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:43
Sample (adjusted): 4 9360
Included observations: 9357 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.650061	0.625058	1.040001	0.2984
D(RETURN(-1))	-0.571383	0.009780	-58.42243	0.0000
D(RETURN(-2))	-0.327783	0.009767	-33.56191	0.0000
MARKET_CAP(-1)	-1.57E-12	5.62E-13	-2.783705	0.0054

R-squared	0.272349	Mean dependent var	0.004084
Adjusted R-squared	0.272116	S.D. dependent var	65.72464
S.E. of regression	56.07371	Akaike info criterion	10.89164
Sum squared resid	29408274	Schwarz criterion	10.89469
Log likelihood	-50952.53	Hannan-Quinn criter.	10.89268
F-statistic	1166.899	Durbin-Watson stat	2.243313
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:46
Sample (adjusted): 3 9360
Included observations: 9358 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	59.92591	11.40473	5.254479	0.0000
D(RETURN(-1))	-0.434868	0.009384	-46.34159	0.0000
LOG(MARKET_CAP(-1))	-2.334262	0.443575	-5.262380	0.0000

R-squared	0.186703	Mean dependent var	0.003443
Adjusted R-squared	0.186529	S.D. dependent var	65.72115
S.E. of regression	59.27565	Akaike info criterion	11.00259
Sum squared resid	32869748	Schwarz criterion	11.00488
Log likelihood	-51478.14	Hannan-Quinn criter.	11.00337
F-statistic	1073.779	Durbin-Watson stat	2.283626
Prob(F-statistic)	0.000000		

Dependent Variable: D(RETURN)
Method: Least Squares
Date: 04/17/22 Time: 21:47
Sample (adjusted): 3 9360
Included observations: 9358 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	59.41531	11.13043	5.338095	0.0000
D(RETURN(-1))	-0.365626	0.009702	-37.68695	0.0000
LOG(MARKET_CAP(-1))	-1.991796	0.433195	-4.597915	0.0000
MARKET_RETURN(-1)	-0.524989	0.024273	-21.62893	0.0000

R-squared	0.225440	Mean dependent var	0.003443
Adjusted R-squared	0.225191	S.D. dependent var	65.72115
S.E. of regression	57.84987	Akaike info criterion	10.95401
Sum squared resid	31304169	Schwarz criterion	10.95706
Log likelihood	-51249.80	Hannan-Quinn criter.	10.95504
F-statistic	907.5101	Durbin-Watson stat	2.324148
Prob(F-statistic)	0.000000		

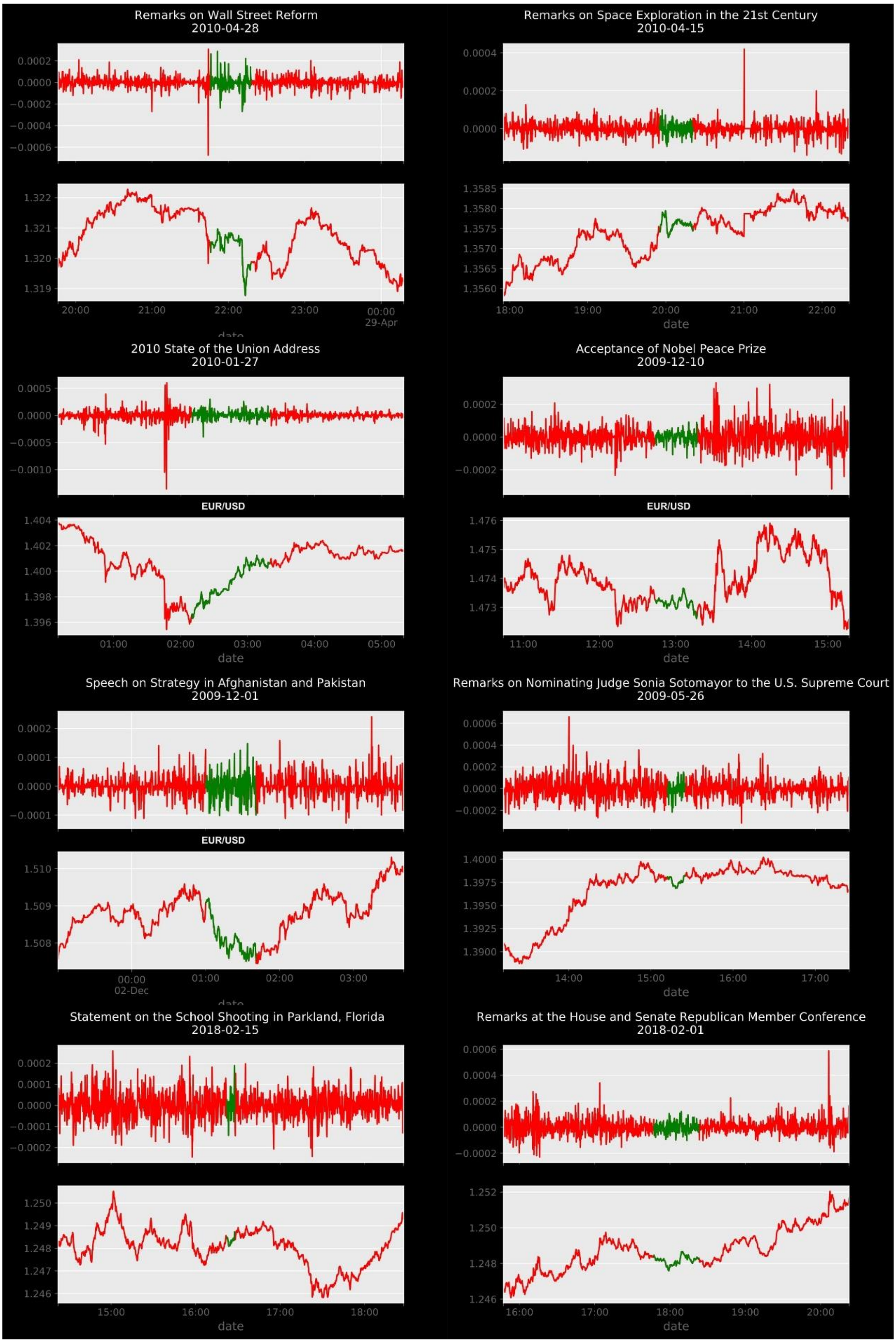
Dependent Variable: RETURN
Method: Least Squares
Date: 04/17/22 Time: 21:39
Sample (adjusted): 3 9360
Included observations: 9358 after adjustments

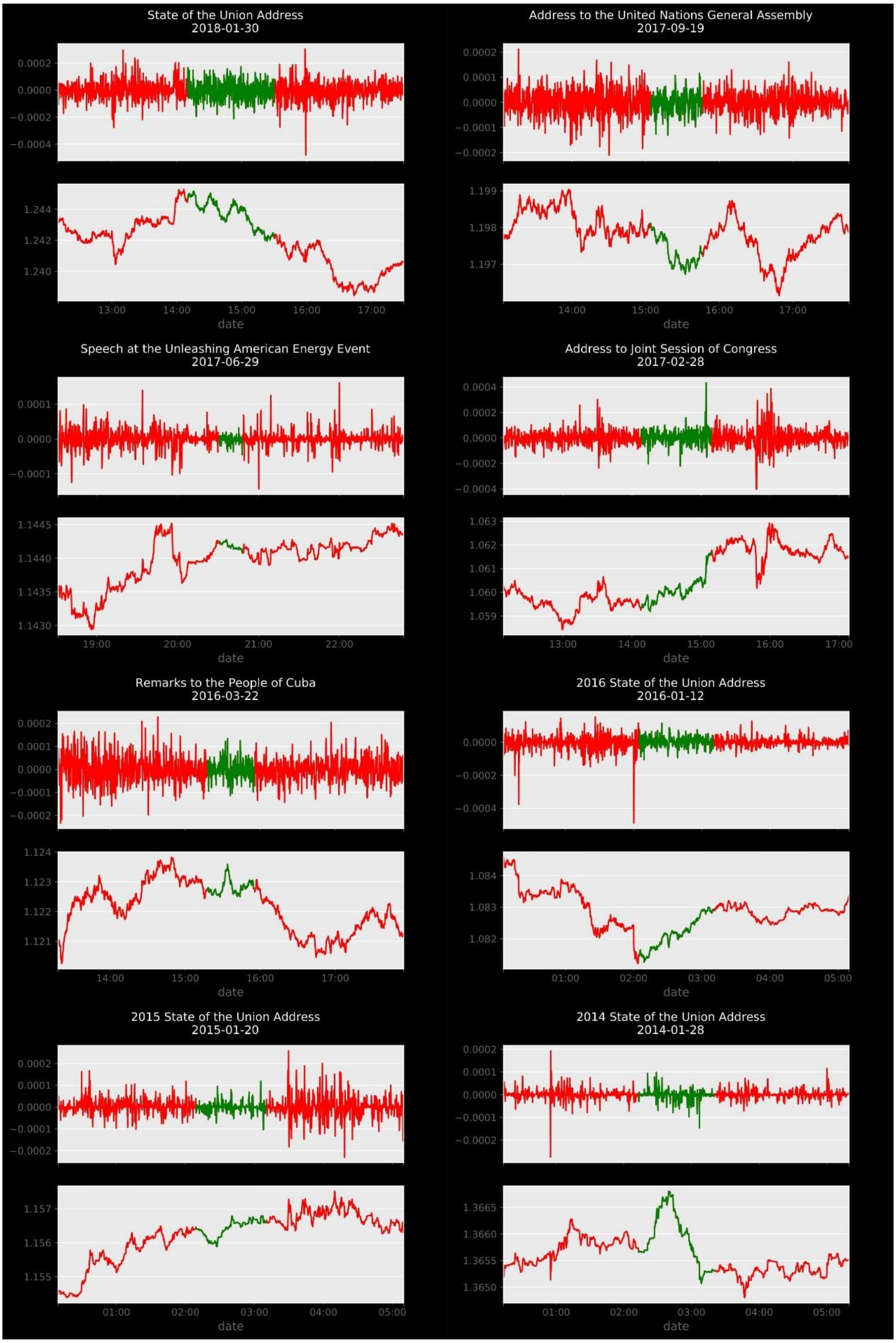
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	80.38520	8.915602	9.016239	0.0000
RETURN(-1)	0.009806	0.010269	0.954891	0.3397
RETURN(-2)	-0.119289	0.010258	-11.62872	0.0000
LOG(MARKET_CAP(-1))	-2.449585	0.346614	-7.067193	0.0000

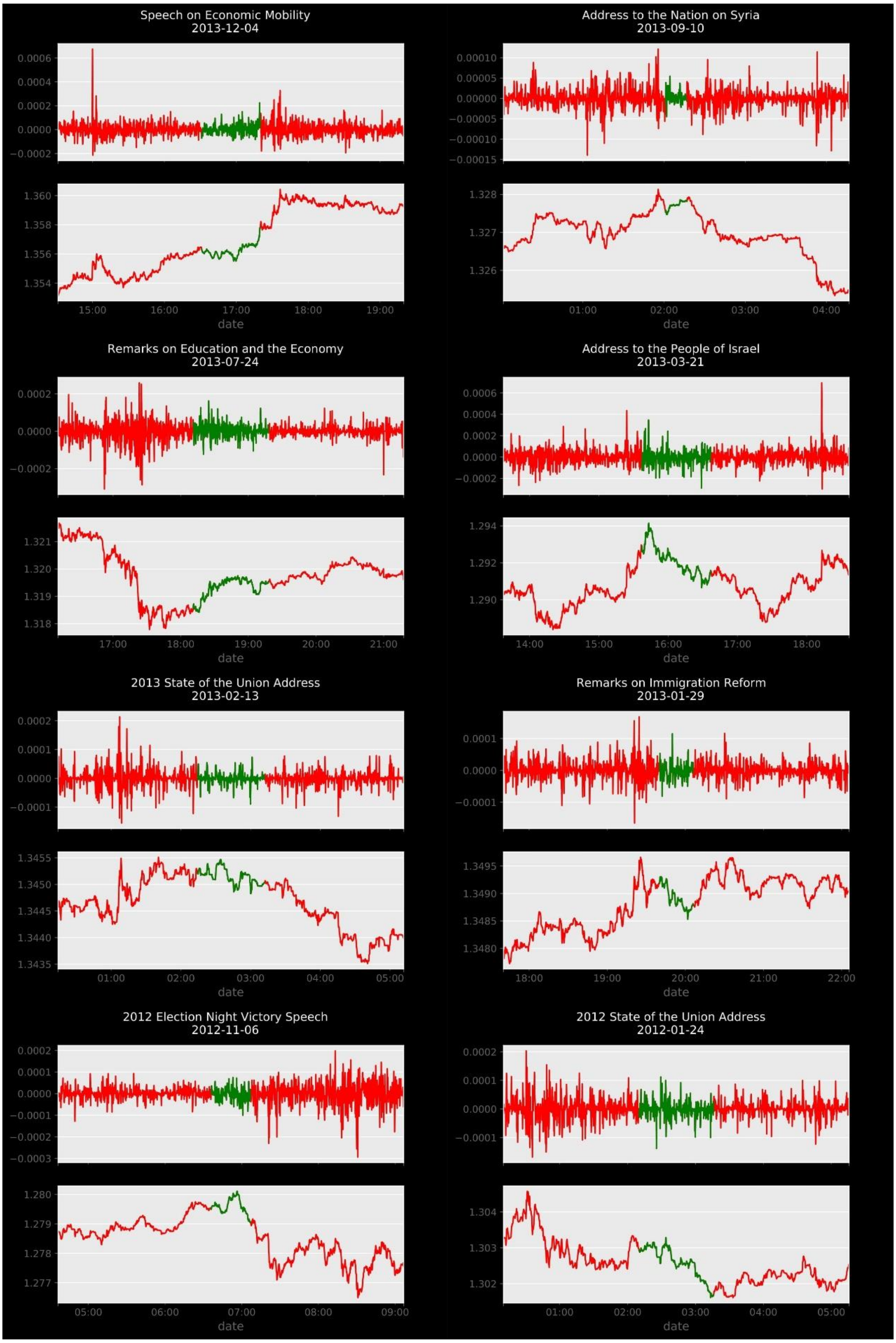
R-squared	0.021092	Mean dependent var	15.76723
Adjusted R-squared	0.020778	S.D. dependent var	46.80688
S.E. of regression	46.31805	Akaike info criterion	10.50937
Sum squared resid	20067716	Schwarz criterion	10.51242
Log likelihood	-49169.33	Hannan-Quinn criter.	10.51041
F-statistic	67.18123	Durbin-Watson stat	2.026719
Prob(F-statistic)	0.000000		

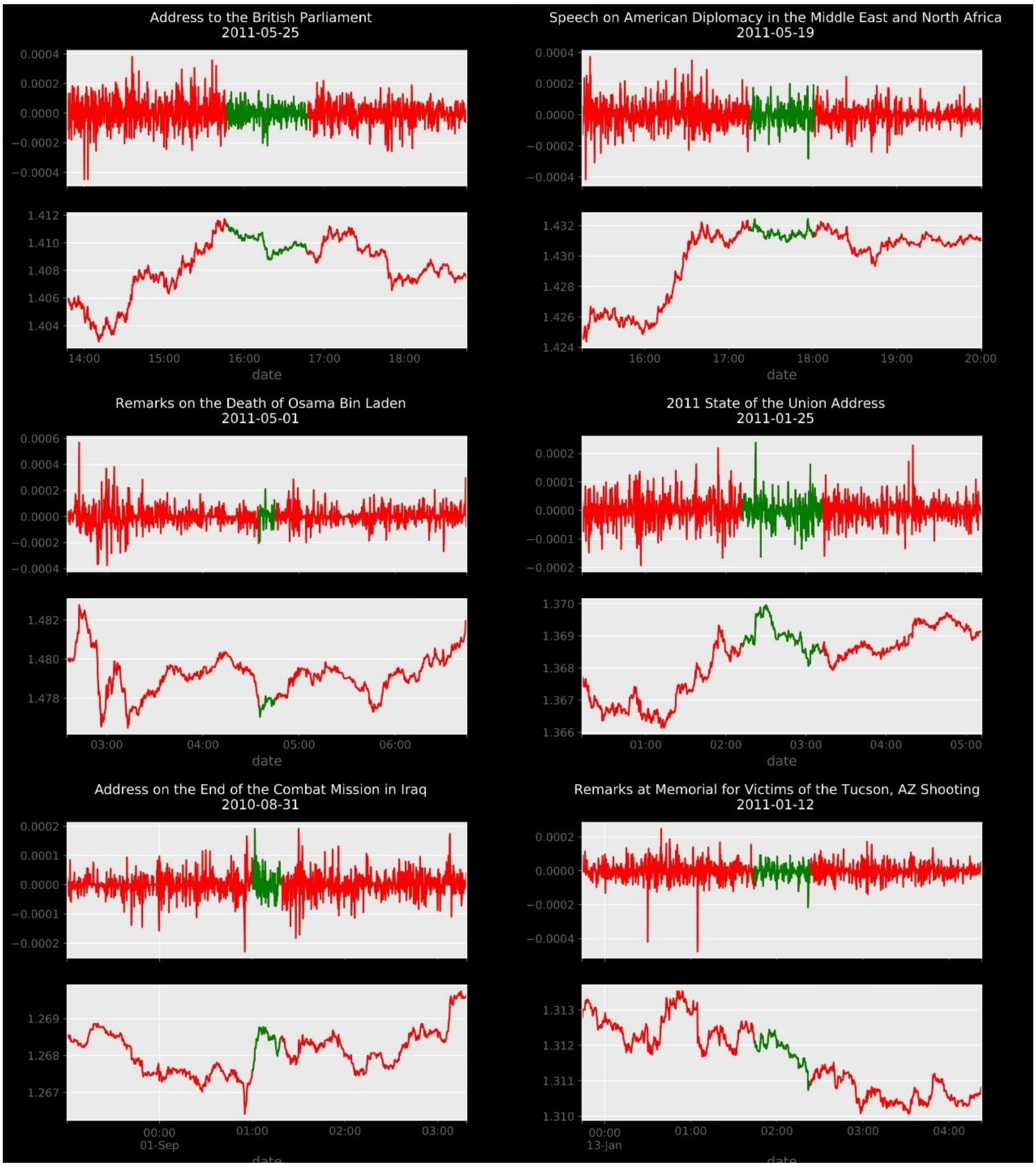
Appendix B:

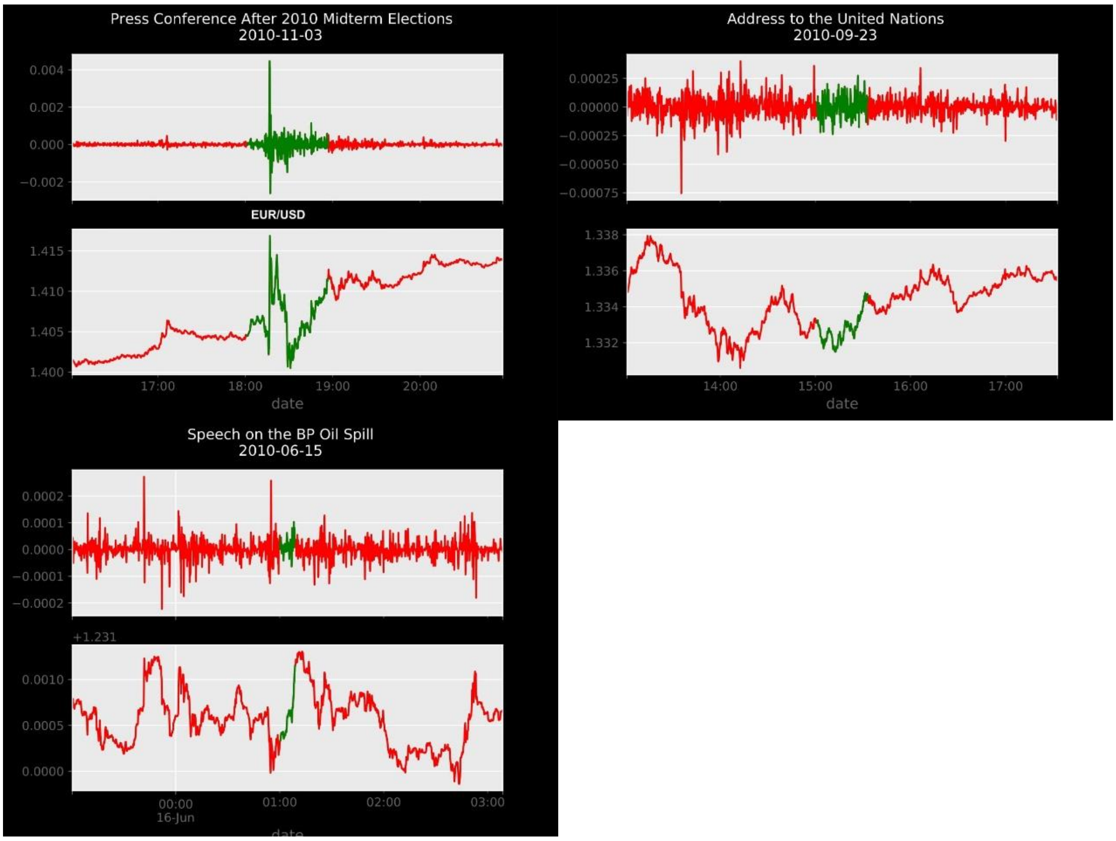
EUR/USDT



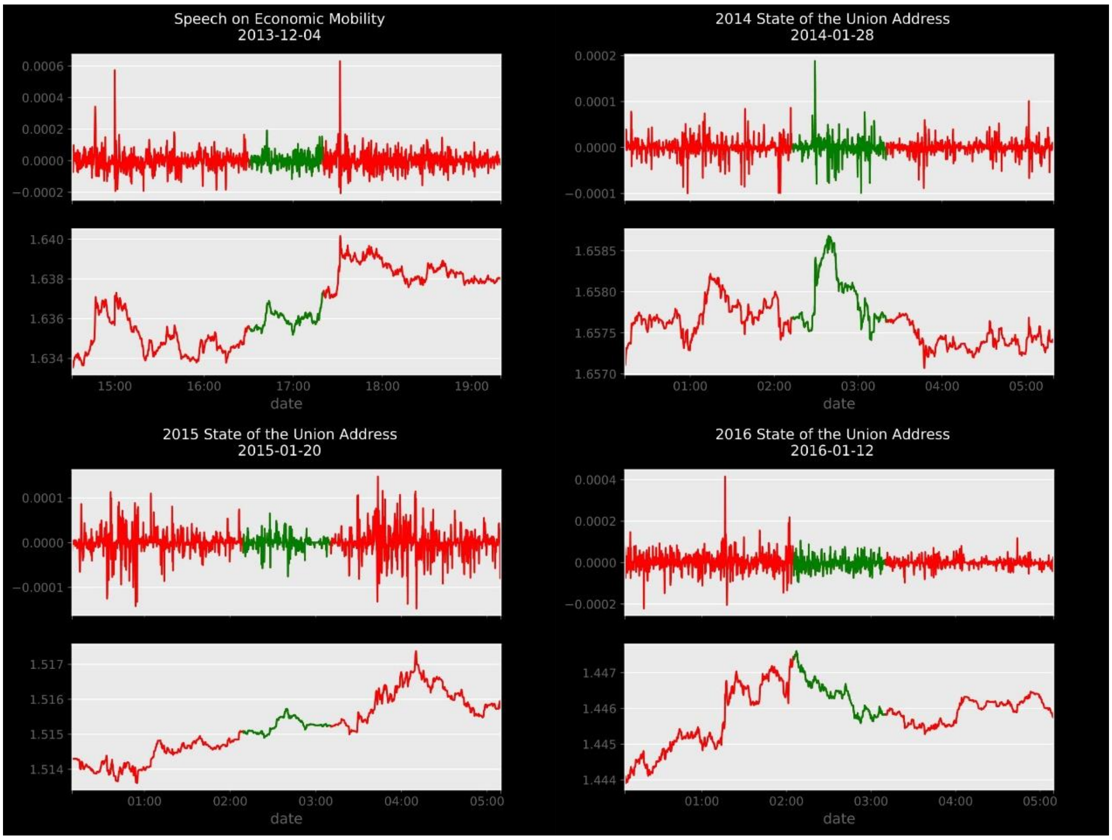

State of the Union Address
2018-01-30
Address to the United Nations General Assembly
2017-09-19
Speech at the Unleashing American Energy Event
2017-06-29
Address to Joint Session of Congress
2017-02-28
Remarks to the People of Cuba
2016-03-22
2016 State of the Union Address
2016-01-12
2015 State of the Union Address
2015-01-20
2014 State of the Union Address
2014-01-28
date

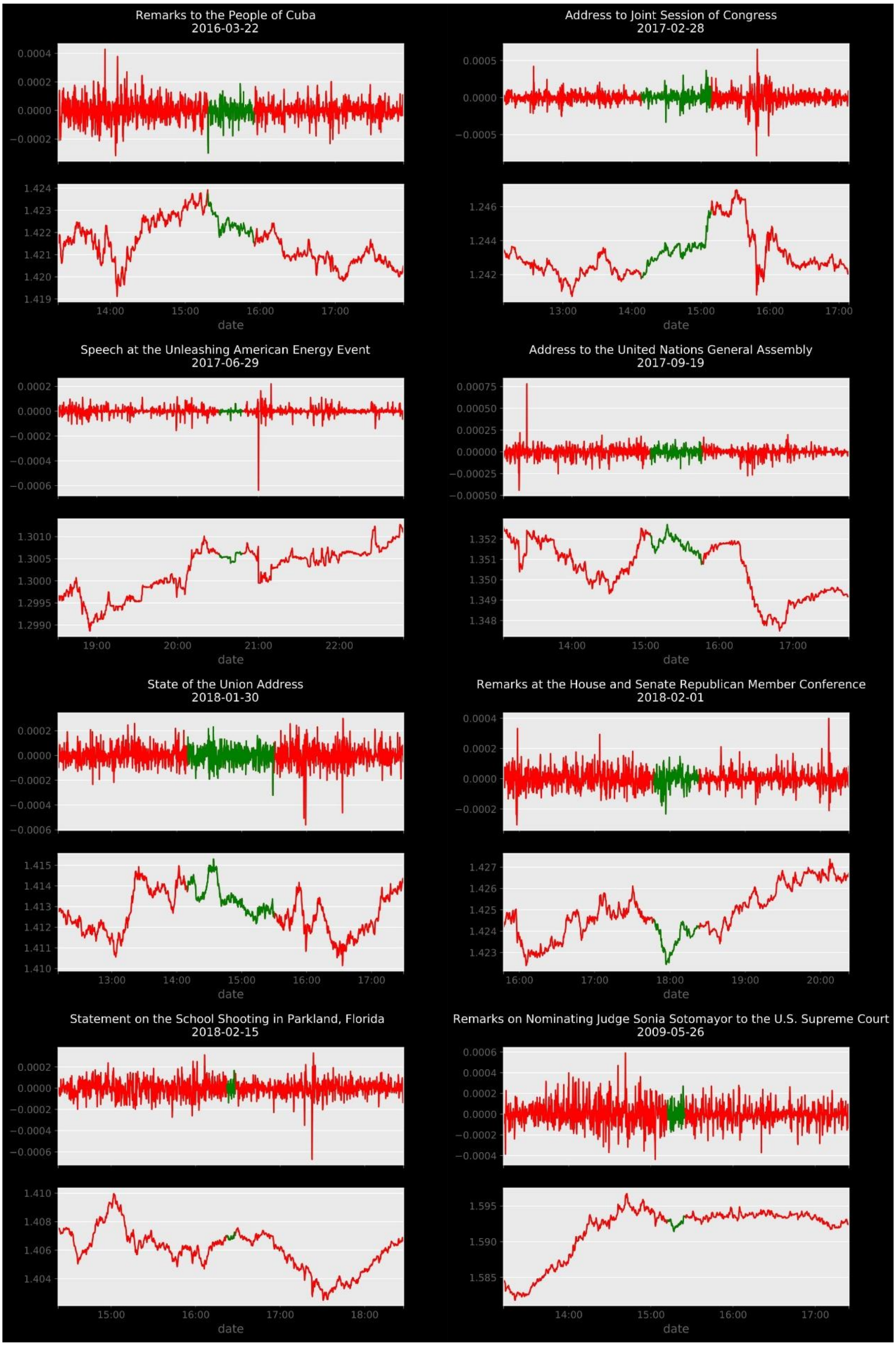

Speech on Economic Mobility
2013-12-04
Address to the Nation on Syria
2013-09-10
Remarks on Education and the Economy
2013-07-24
Address to the People of Israel
2013-03-21
2013 State of the Union Address
2013-02-13
Remarks on Immigration Reform
2013-01-29
2012 Election Night Victory Speech
2012-11-06
2012 State of the Union Address
2012-01-24
date

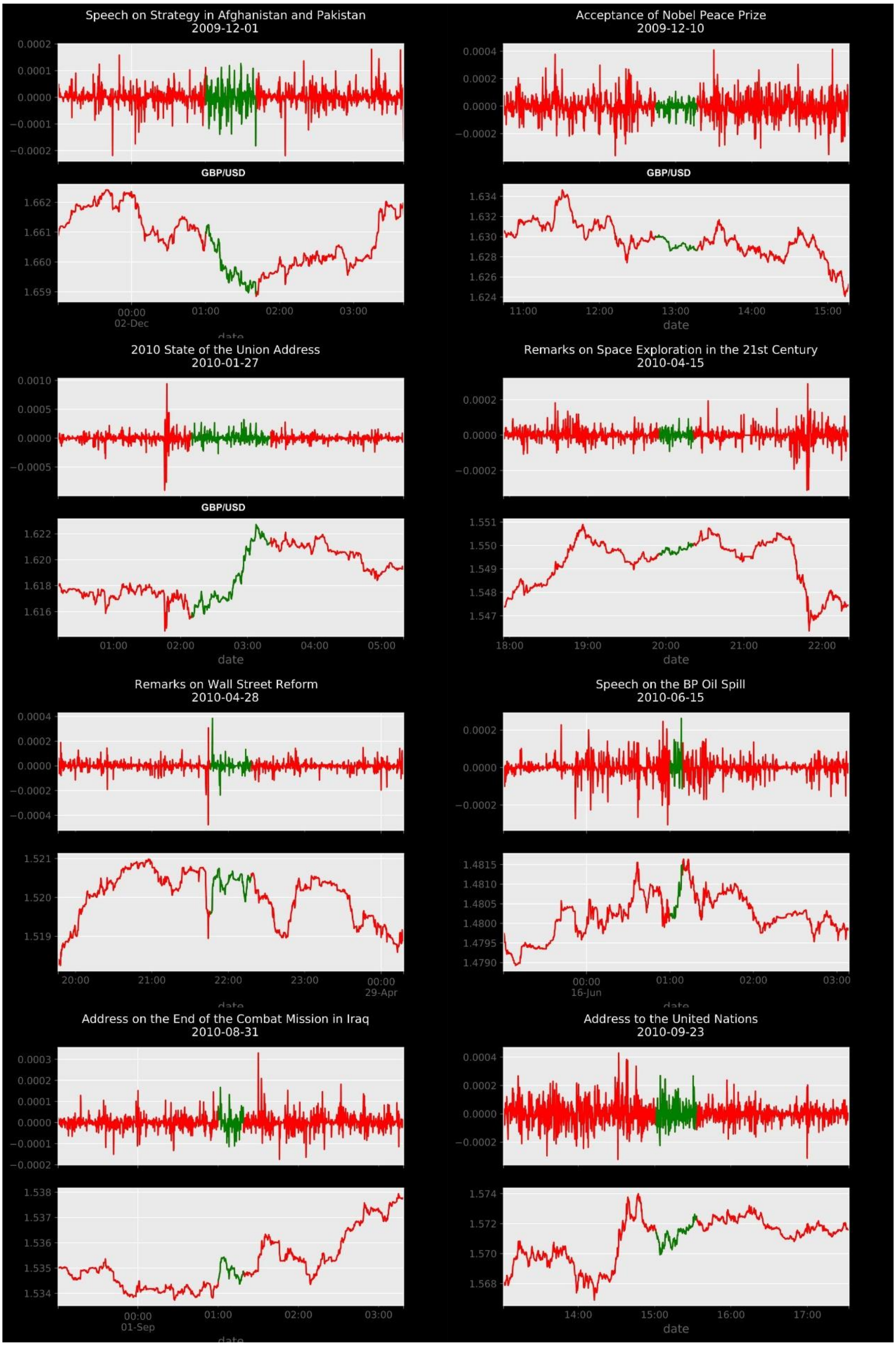

Address to the British Parliament
2011-05-25
Speech on American Diplomacy in the Middle East and North Africa
2011-05-19
Remarks on the Death of Osama Bin Laden
2011-05-01
2011 State of the Union Address
2011-01-25
Address on the End of the Combat Mission in Iraq
2010-08-31
Remarks at Memorial for Victims of the Tucson, AZ Shooting
2011-01-12
date


Press Conference After 2010 Midterm Elections
2010-11-03
EUR/USD
Address to the United Nations
2010-09-23
Speech on the BP Oil Spill
2010-06-15
date

GBP/USDT


Speech on Economic Mobility
2013-12-04
2014 State of the Union Address
2014-01-28
2015 State of the Union Address
2015-01-20
2016 State of the Union Address
2016-01-12
date


Remarks to the People of Cuba
2016-03-22
Address to Joint Session of Congress
2017-02-28
Speech at the Unleashing American Energy Event
2017-06-29
Address to the United Nations General Assembly
2017-09-19
State of the Union Address
2018-01-30
Remarks at the House and Senate Republican Member Conference
2018-02-01
Statement on the School Shooting in Parkland, Florida
2018-02-15
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court
2009-05-26
date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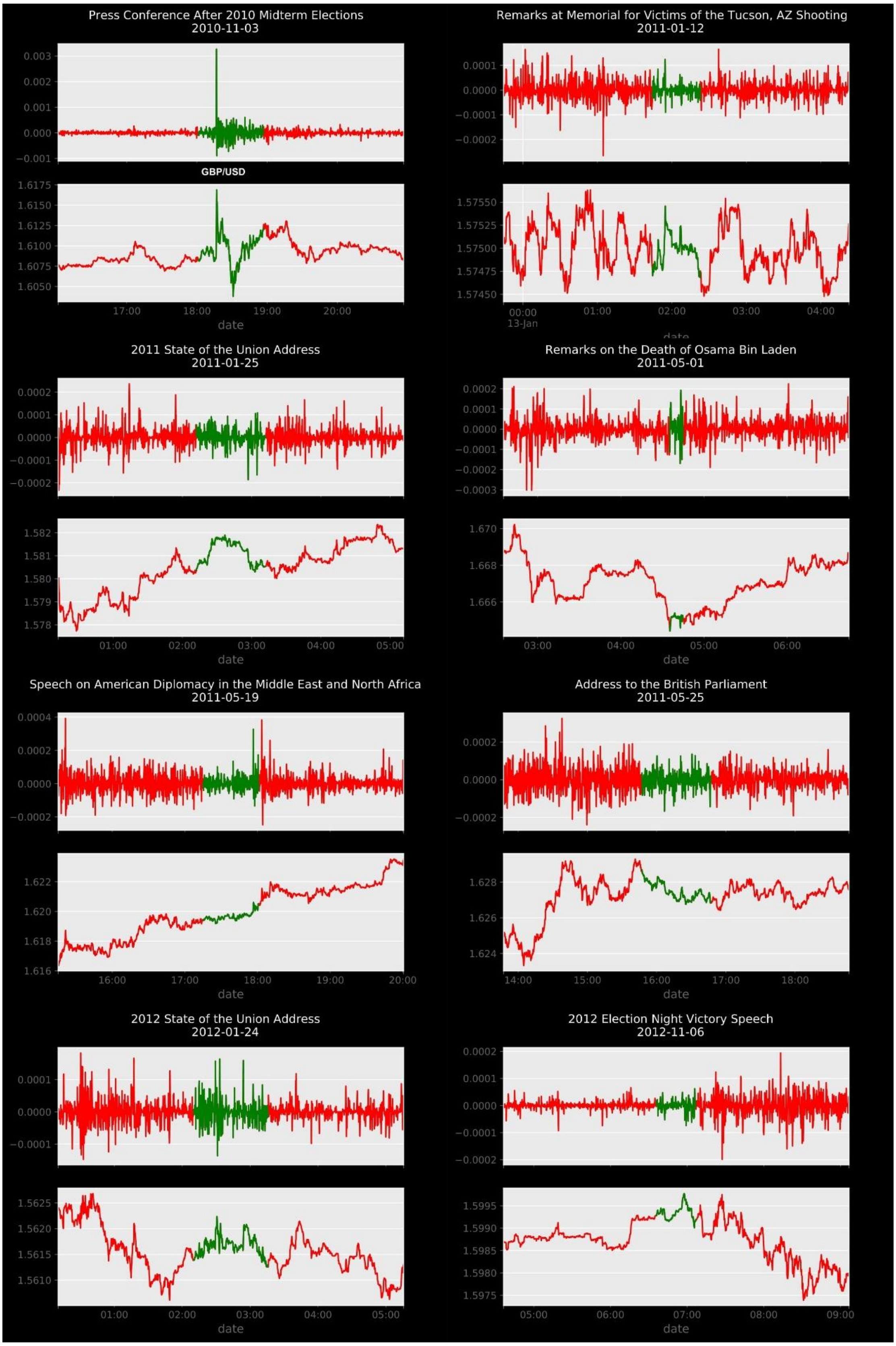
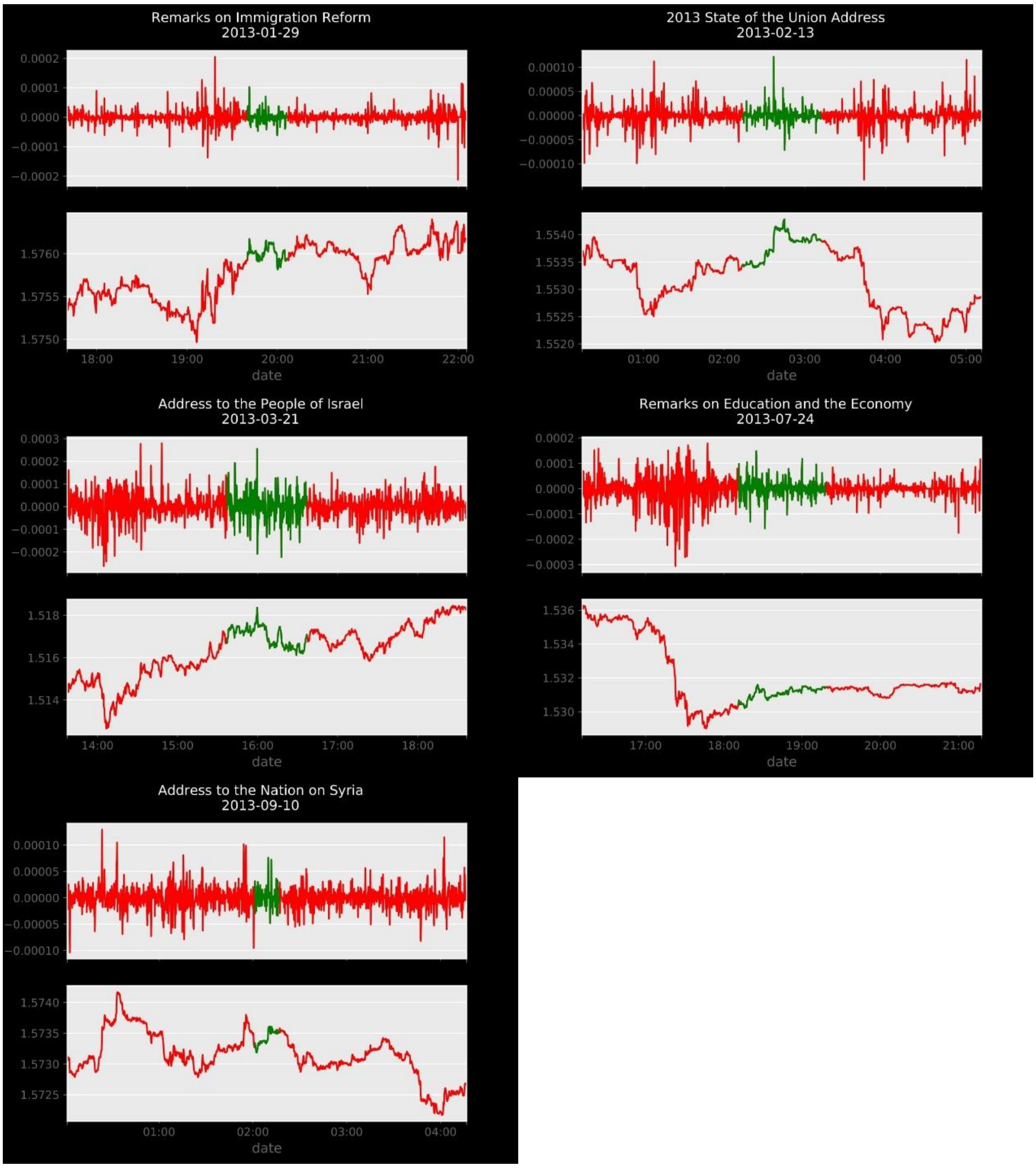
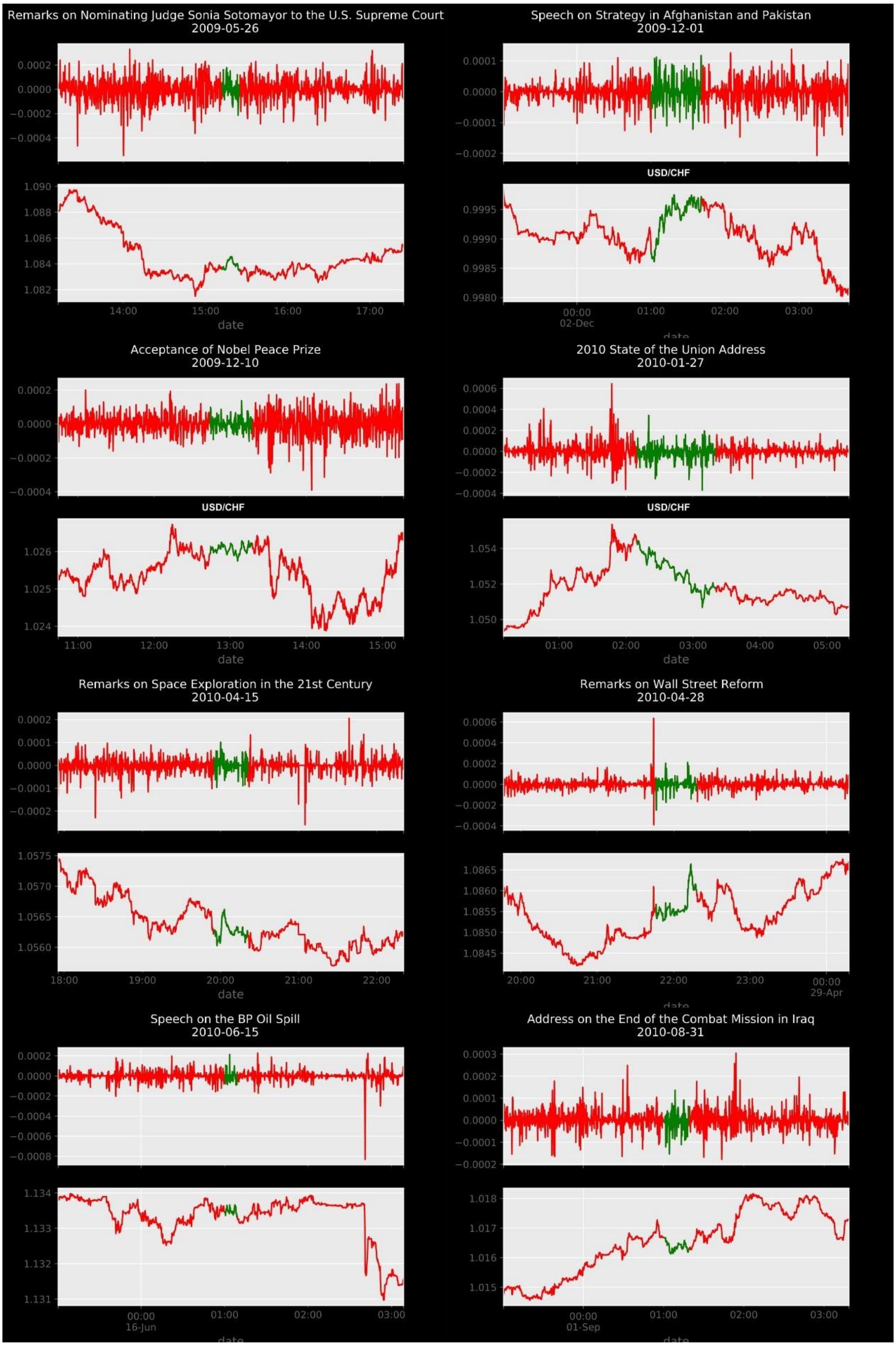
GBP/USD
date
Acceptance of Nobel Peace Prize
2009-12-10
GBP/USD
date
2010 State of the Union Address
2010-01-27
GBP/USD
date
Remarks on Space Exploration in the 21st Century
2010-04-15
date
Remarks on Wall Street Reform
2010-04-28
Speech on the BP Oil Spill
2010-06-15
Address on the End of the Combat Mission in Iraq
2010-08-31
Address to the United Nations
2010-09-23
date


Press Conference After 2010 Midterm Elections
2010-11-03
GBP/USD
date
Remarks at Memorial for Victims of the Tucson, AZ Shooting
2011-01-12
2011 State of the Union Address
2011-01-25
Remarks on the Death of Osama Bin Laden
2011-05-01
Speech on American Diplomacy in the Middle East and North Africa
2011-05-19
Address to the British Parliament
2011-05-25
2012 State of the Union Address
2012-01-24
2012 Election Night Victory Speech
2012-11-06


Remarks on Immigration Reform
2013-01-29
2013 State of the Union Address
2013-02-13
Address to the People of Israel
2013-03-21
Remarks on Education and the Economy
2013-07-24
Address to the Nation on Syria
2013-09-10
date

USD/CHF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USD/CHF
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03:00
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Speech on the BP Oil Spill
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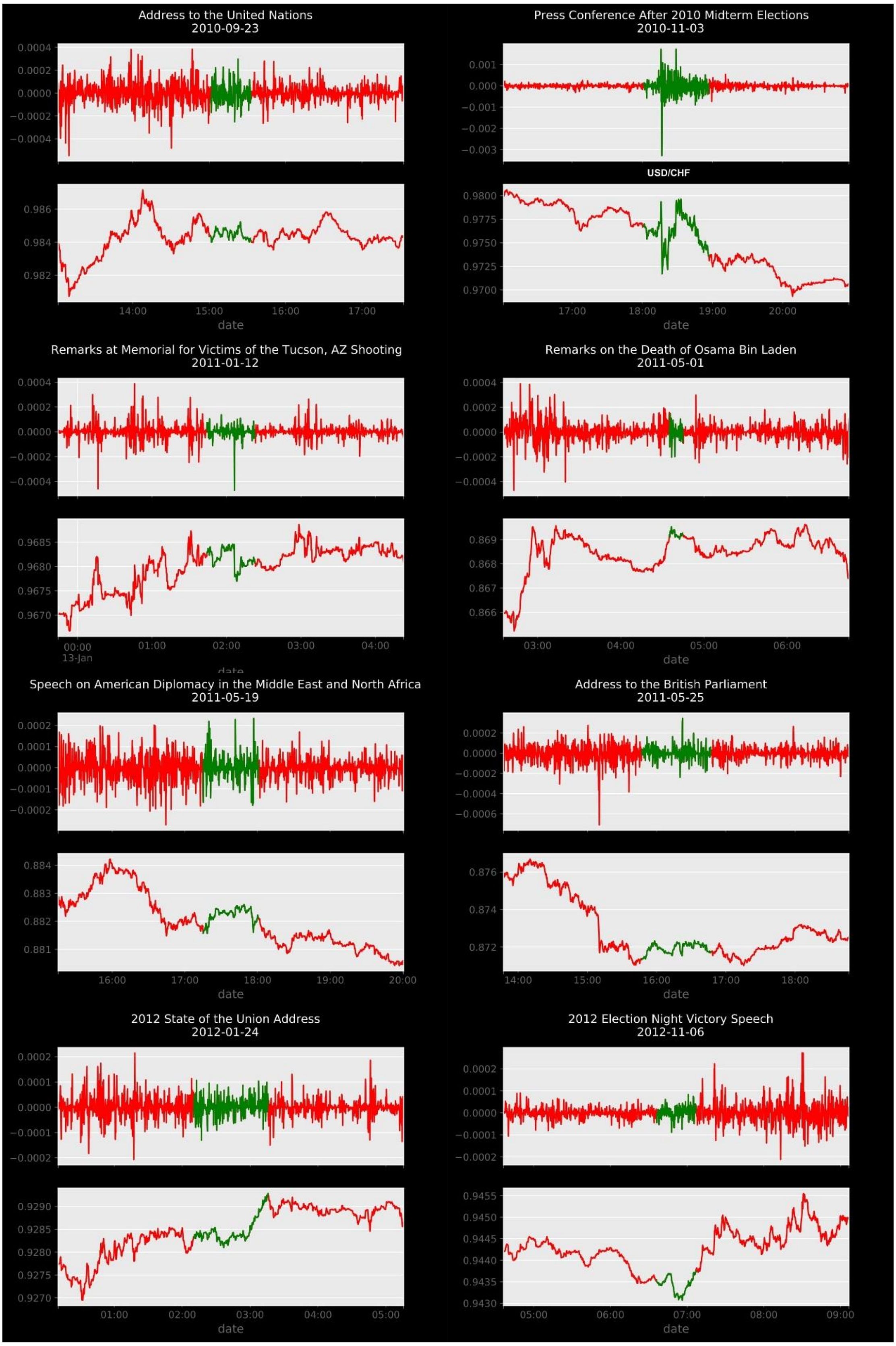
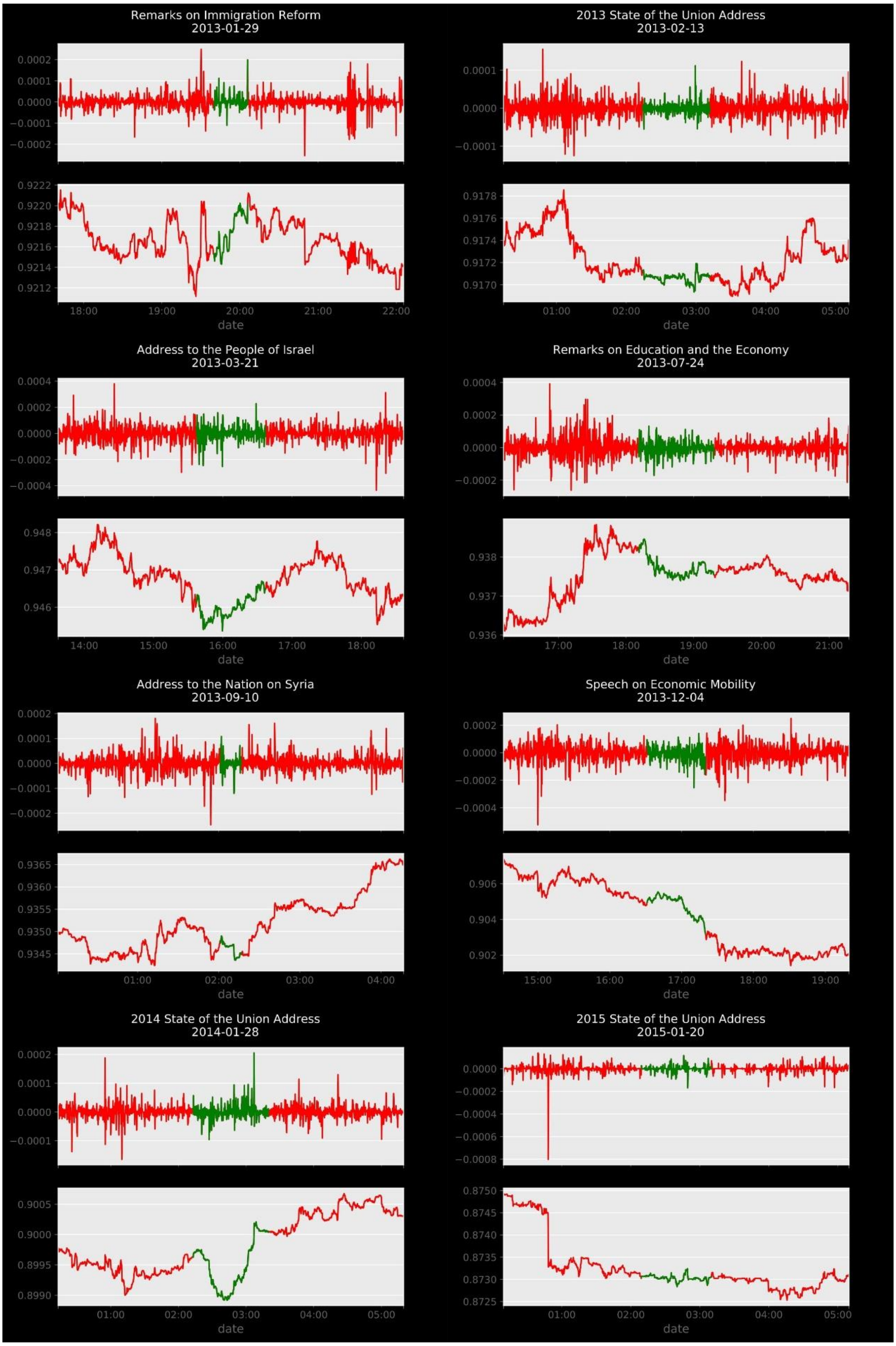

Address to the United Nations
2010-09-23
Press Conference After 2010 Midterm Elections
2010-11-03
USD/CHF
date
Remarks at Memorial for Victims of the Tucson, AZ Shooting
2011-01-12
Remarks on the Death of Osama Bin Laden
2011-05-01
Speech on American Diplomacy in the Middle East and North Africa
2011-05-19
Address to the British Parliament
2011-05-25
2012 State of the Union Address
2012-01-24
2012 Election Night Victory Speech
2012-11-06
date


Remarks on Immigration Reform
2013-01-29
2013 State of the Union Address
2013-02-13
Address to the People of Israel
2013-03-21
Remarks on Education and the Economy
2013-07-24
Address to the Nation on Syria
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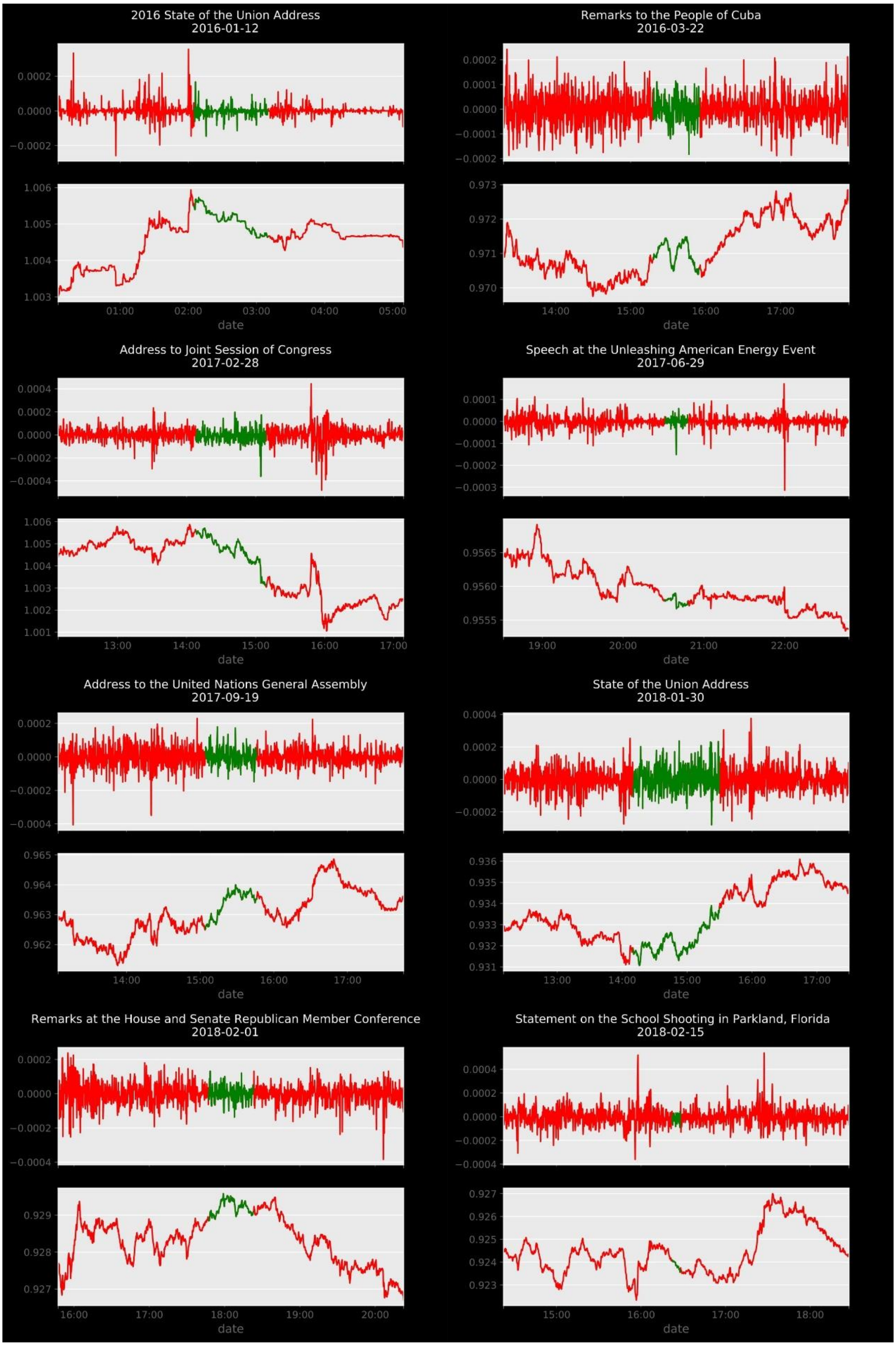
Speech on Economic Mobility
2013-12-04
2014 State of the Union Address
2014-01-28
2015 State of the Union Address
2015-01-20
date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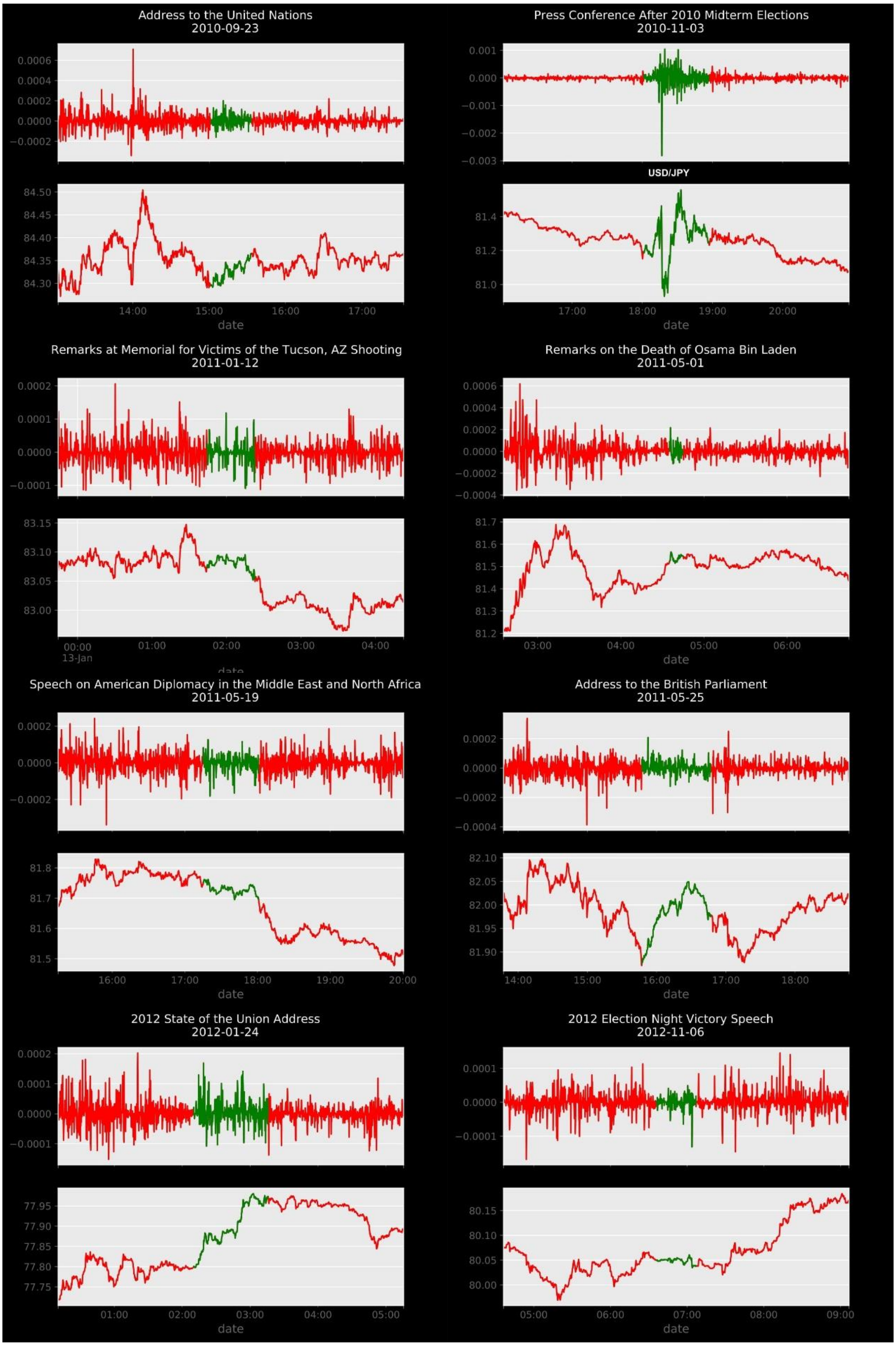
2016-01-12
Remarks to the People of Cuba
2016-03-22
Address to Joint Session of Congress
2017-02-28
Speech at the Unleashing American Energy Event
2017-06-29
Address to the United Nations General Assembly
2017-09-19
State of the Union Address
2018-01-30
Remarks at the House and Senate Republican Member Conference
2018-02-01
Statement on the School Shooting in Parkland, Florida
2018-02-15
date

USD/JPY


Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court
2009-05-26
Acceptance of Nobel Peace Prize
2009-12-10
USD/JPY
date
Speech on Strategy in Afghanistan and Pakistan
2009-12-01
2010 State of the Union Address
2010-01-27
USD/JPY
USD/JPY
Remarks on Space Exploration in the 21st Century
2010-04-15
Remarks on Wall Street Reform
2010-04-28
Speech on the BP Oil Spill
2010-06-15
Address on the End of the Combat Mission in Iraq
2010-08-31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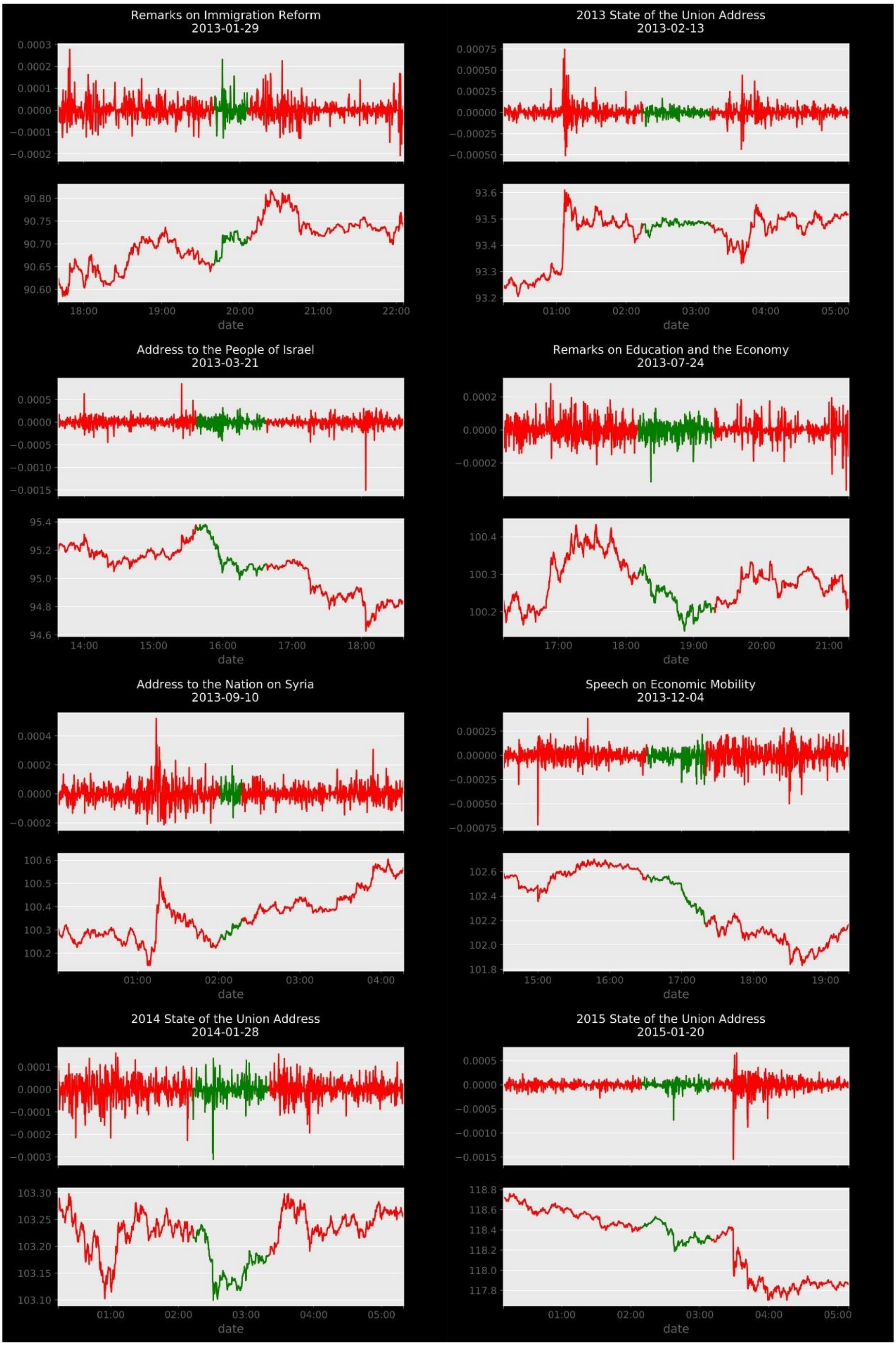
Press Conference After 2010 Midterm Elections
2010-11-03
USD/JPY
date
Remarks at Memorial for Victims of the Tucson, AZ Shooting
2011-01-12
Remarks on the Death of Osama Bin Laden
2011-05-01
Speech on American Diplomacy in the Middle East and North Africa
2011-05-19
Address to the British Parliament
2011-05-25
2012 State of the Union Address
2012-01-24
2012 Election Night Victory Speech
2012-11-06
date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Address to the People of Israel
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Remarks on Education and the Economy
2013-07-24
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Speech on Economic Mobility
2013-12-04
2014 State of the Union Address
2014-01-28
2015 State of the Union Address
2015-01-20
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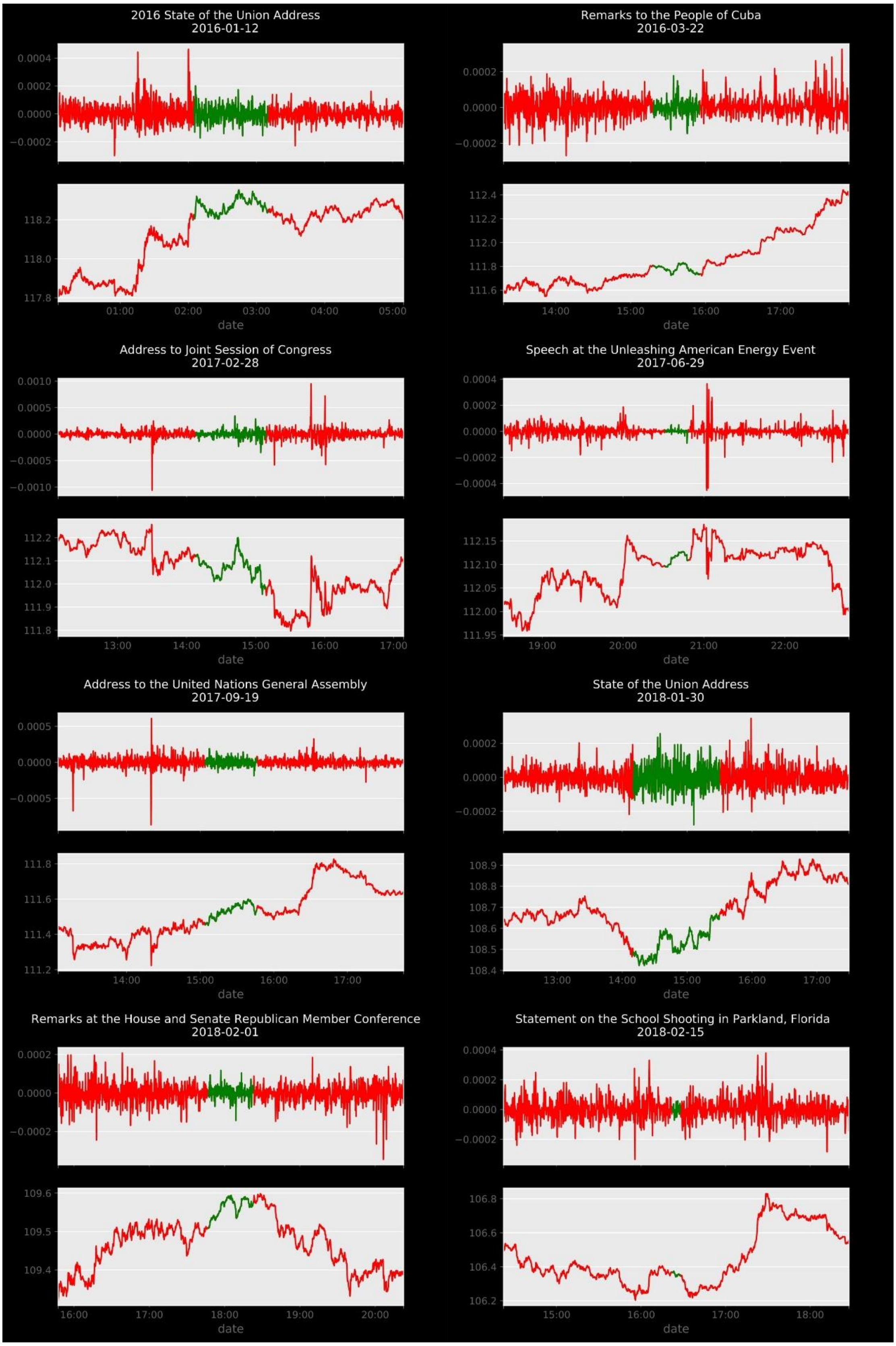
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Appendix C:

P-value of Augmented Dickey–Fuller test 60 min ± speech duration

topic	adfuller_EURUSD	adfuller_GBPUSD	adfuller_USDJPY	adfuller_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	1.03884E-12	4.31354E-15	0.000472228	1.49071E-13
Speech on Strategy in Afghanistan and Pakistan	4.11E-21	3.04358E-20	1.67914E-15	1.53667E-13
Acceptance of Nobel Peace Prize	9.19605E-07	4.47149E-14	2.03604E-14	1.77487E-07
2010 State of the Union Address	2.88483E-14	6.91275E-25	2.1564E-20	8.63169E-14
Remarks on Space Exploration in the 21st Century	1.41902E-14	9.57705E-13	2.14384E-07	5.06619E-14
Remarks on Wall Street Reform	1.18375E-14	1.14987E-06	0.004018213	1.83137E-15
Speech on the BP Oil Spill	1.45788E-10	2.30656E-11	6.36551E-06	2.87037E-11
Address on the End of the Combat Mission in Iraq	1.25985E-10	5.90227E-11	1.59116E-06	0.039715936
Address to the United Nations	1.15913E-14	1.53406E-05	1.27526E-23	4.37025E-17
Press Conference After 2010 Midterm Elections	2.67182E-14	5.06771E-19	6.89633E-07	6.73536E-14
Remarks at Memorial for Victims of the Tucson, AZ Shooting	9.05504E-14	9.97985E-05	1.40508E-16	7.18086E-19
2011 State of the Union Address	3.52592E-05	2.85729E-21		
Remarks on the Death of Osama Bin Laden	1.13496E-08	3.32231E-13	1.3205E-12	1.85166E-08
Speech on American Diplomacy in the Middle East and North Africa	1.05358E-21	2.6907E-15	5.25577E-19	2.43417E-16
Address to the British Parliament	3.97112E-19	2.63583E-18	5.65829E-20	6.06769E-20
2012 State of the Union Address	2.55046E-06	1.81835E-19	2.28132E-18	1.17246E-05
2012 Election Night Victory Speech	1.99285E-12	1.72364E-12	1.9432E-15	9.71858E-16
Remarks on Immigration Reform	1.42695E-10	5.77018E-24	6.85231E-21	1.65436E-10
2013 State of the Union Address	7.83224E-17	5.06023E-17	2.12179E-15	8.40745E-24
Address to the People of Israel	7.32103E-18	4.68898E-13	6.22169E-22	4.62571E-12
Remarks on Education and the Economy	6.30898E-21	4.5069E-05	7.88529E-22	1.10252E-10
Address to the Nation on Syria	9.67631E-09	2.69452E-09	8.4306E-16	6.75327E-15
Speech on Economic Mobility	7.73244E-13	4.06689E-17	2.38654E-15	4.3433E-15
2014 State of the Union Address	0.002606495	1.3261E-20	1.03839E-25	5.26461E-16
2015 State of the Union Address	2.37431E-05	1.43982E-20	4.33111E-13	2.97647E-07
2016 State of the Union Address	4.35823E-20	2.36967E-17	1.23515E-20	2.57685E-11
Remarks to the People of Cuba	9.78173E-17	0.010130453	2.28187E-15	5.50343E-13
Address to Joint Session of Congress	5.29367E-19	5.33352E-20	5.74713E-22	2.05248E-13
Speech at the Unleashing American Energy Event	1.45611E-14	1.4264E-22	7.99949E-09	6.6151E-17
Address to the United Nations General Assembly	1.32166E-05	3.67027E-18	1.05802E-21	8.86598E-06
State of the Union Address	5.02948E-19	3.09975E-05	8.45442E-23	1.30043E-22
Remarks at the House and Senate Republican Member Conference	6.66692E-15	0.030212326	2.65545E-13	3.4562E-19
Â Statement on the School Shooting in Parkland, Florida	2.24484E-12	6.47801E-06	3.89206E-10	5.80382E-11

P-value of Augmented Dickey–Fuller test the day of speech

topic	adfuller_EURUSD	adfuller_GBPUSD	adfuller_USDJPY	adfuller_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	3.43504E-12	0	0	2.19324E-25
Speech on Strategy in Afghanistan and Pakistan	0	0	0	1.13112E-12
Acceptance of Nobel Peace Prize	0	1.08593E-27	3.91191E-29	0
2010 State of the Union Address	1.05133E-18	1.1351E-18	0	0
Remarks on Space Exploration in the 21st Century	0	0	0	0
Remarks on Wall Street Reform	6.63512E-30	3.61944E-30	0	7.85055E-26
Speech on the BP Oil Spill	0	0	1.18257E-22	0
Address on the End of the Combat Mission in Iraq	0	0	5.15864E-18	7.02666E-25
Address to the United Nations	0	2.55588E-13	0	0
Press Conference After 2010 Midterm Elections	1.43069E-16	1.44849E-21	1.14941E-10	5.06777E-16
Remarks at Memorial for Victims of the Tucson, AZ Shooting	0	0	3.95736E-14	0
2011 State of the Union Address	1.65573E-26	0		
Remarks on the Death of Osama Bin Laden	7.85565E-11	0	8.72571E-19	9.25632E-11
Speech on American Diplomacy in the Middle East and North Africa	5.28316E-22	0	1.06549E-13	0
Address to the British Parliament	1.14378E-18	0	5.7321E-19	1.76001E-11
2012 State of the Union Address	0	0	1.55077E-08	6.68126E-30
2012 Election Night Victory Speech	0	0	0	0
Remarks on Immigration Reform	0	0	0	4.95766E-30
2013 State of the Union Address	1.07395E-29	1.79427E-17	1.58024E-28	0
Address to the People of Israel	0	2.87154E-24	1.01526E-17	0
Remarks on Education and the Economy	2.57432E-30	4.6443E-22	6.54715E-30	1.08759E-25
Address to the Nation on Syria	0	2.31447E-21	1.70928E-29	2.11787E-30
Speech on Economic Mobility	2.97208E-13	1.14806E-27	2.4225E-18	6.37613E-14
2014 State of the Union Address	3.06962E-09	1.7124E-27	1.21698E-10	4.50969E-17
2015 State of the Union Address	4.13483E-14	4.17205E-14	5.15567E-19	0
2016 State of the Union Address	0	0	0	7.93782E-23
Remarks to the People of Cuba	0	2.03737E-30	0	1.15101E-09
Address to Joint Session of Congress	0	1.86935E-22	6.3485E-24	0
Speech at the Unleashing American Energy Event	0	0	1.31056E-22	5.79429E-29
Address to the United Nations General Assembly	2.03086E-29	5.02082E-23	3.72749E-20	0
State of the Union Address	0	0	0	0
Remarks at the House and Senate Republican Member Conference	0	0	0	3.52536E-15
Â Statement on the School Shooting in Parkland, Florida	0	0	0	0

R squared, Autoregressive order 1 60 min ± speech duration

topic	r2_with_EURUSD	r2_without_EURUSD	r2_with_GBPUSD	r2_without_GBPUSD	r2_with_USDJPY	r2_without_USDJPY	r2_with_USDCHF	r2_without_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	0.001197106	0.000742885	0.019591601	0.006477217	0.020355483	0.003606417	0.001107054	0.000149975
Speech on Strategy in Afghanistan and Pakistan	0.044122715	0.022179899	0.046657314	0.012432895	0.014962252	0.005105812	0.040583878	0.02171383
Acceptance of Nobel Peace Prize	0.009272703	0.000246053	0.018082017	0.008185675	0.005741553	0.005513575	0.007128297	0.000140244
2010 State of the Union Address	0.081688595	0.060577312	0.047826654	0.026695072	0.007796948	3.86911E-05	0.01210914	0.002188965
Remarks on Space Exploration in the 21st Century	0.000746842	0.000743264	0.018679841	0.013790641	0.024036469	0.017254215	0.002625204	0.002633924
Remarks on Wall Street Reform	0.001433368	0.001305158	0.033503798	0.019937274	0.004774122	0.001934464	0.001558918	-1.79639E-05
Speech on the BP Oil Spill	0.099853046	0.011255312	0.040182	0.008792805	0.024765	0.020819067	0.09556709	0.086448701
Address on the End of the Combat Mission in Iraq	0.045274538	0.030784074	0.027883084	0.024582288	0.010127266	6.09375E-05	0.011240405	0.000136717
Address to the United Nations	0.010419247	0.004088279	0.016405525	0.01639402	0.129675207	0.084445674	0.002031669	0.000359496
Press Conference After 2010 Midterm Elections	0.039814942	0.038268078	0.084533517	0.08172184	0.092197422	0.09073479	0.042426138	0.042360498
Remarks at Memorial for Victims of the Tucson, AZ Shooting	0.013492648	0.001432392	0.005339656	2.14529E-06	0.002959882	0.000271042	0.012084003	0.005842903
Remarks on the Death of Osama Bin Laden	0.049368066	0.048238635	0.005909847	0.000557591	0.002974652	9.76012E-05	0.057343955	0.055386783
Speech on American Diplomacy in the Middle East and North Africa	0.023472819	0.021783628	0.106245803	0.104921843	0.007328578	0.002210345	0.005525282	0.003747417
Address to the British Parliament	0.030677209	0.000162313	0.019657343	0.001963641	0.034100176	0.000111381	0.005397198	0.000221879
2012 State of the Union Address	0.026702144	0.003208657	0.030726904	0.024823843	0.031302283	0.004316465	0.021391748	0.000617035
2012 Election Night Victory Speech	0.024821976	0.024677146	0.025376544	0.022749184	0.020951356	1.22945E-05	0.000404247	3.11711E-05
Remarks on Immigration Reform	0.031352133	0.020805941	0.063598266	0.062248418	0.046587925	0.040487523	0.025471013	0.011573497
2013 State of the Union Address	0.00756811	0.005858873	-0.202535073	-0.147675066	0.063471813	0.053762669	-0.104449914	-0.114644336
Address to the People of Israel	0.010272225	0.003787279	0.005794012	0.005540269	0.045252703	0.008376321	0.00157442	0.000213644
Remarks on Education and the Economy	0.003727375	0.000700522	0.002312527	5.57242E-05	0.00836766	0.002557326	0.009994124	0.000759695
Address to the Nation on Syria	0.073314394	0.068466983	0.058896499	0.05349903	0.046949621	0.006444894	0.011649796	0.002349101
Speech on Economic Mobility	0.009613878	0.007151117	0.001713287	0.001518479	0.014618952	0.007211933	0.021604808	0.021576725
2014 State of the Union Address	0.050032143	0.051713489	0.001237641	-0.000165038	0.05440997	0.043205962	0.026948645	0.025425954
2015 State of the Union Address	0.001095933	0.001011882	-0.005988207	-0.005030142	0.038395707	0.037946589	-0.00545744	-0.003968083
2016 State of the Union Address	0.017198787	5.27778E-07	0.031977403	0.010880151	0.000405113	0.000372719	0.022314011	0.011207584
Remarks to the People of Cuba	0.014868251	0.000679076	0.03069298	0.007822803	0.041011128	0.002139765	0.035941253	0.028075486
Address to Joint Session of Congress	0.015732708	0.000235764	0.026318868	0.000838953	0.008357058	0.00812213	0.031402511	0.007284439
Speech at the Unleashing American Energy Event	0.006291133	-0.003224235	0.110435143	0.109557591	0.054628529	0.054998522	-0.016391909	0.002422886
Address to the United Nations General Assembly	0.013324185	0.003119206	0.070387763	0.001020572	0.028050723	0.026639416	0.030023395	0.002986248
State of the Union Address	0.010727642	0.00764296	0.006217423	0.006025839	0.004708408	0.002550771	0.003623194	0.001999788
Remarks at the House and Senate Republican Member Conference	0.005943129	0.00486989	0.002398067	0.000406038	0.031912324	0.018535071	0.01094091	0.010753671
Â Statement on the School Shooting in Parkland, Florida	0.004555078	9.117E-05	0.010946921	0.009746927	0.01529187	0.012712973	0.016142993	0.004061391

R Squared, Autoregressive order 1 the day of speech

topic	r2_with_EURUSD	r2_without_EURUSD	r2_with_GBPUSD	r2_without_GBPUSD	r2_with_USDJPY	r2_without_USDJPY	r2_with_USDCHF	r2_without_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	0.000190857	0.000114872	0.000499649	0.000273085	0.002366604	0.000917692	0.001404918	0.00136825
Speech on Strategy in Afghanistan and Pakistan	0.002183676	0.00138182	0.001090755	5.19797E-05	6.08399E-05	1.33876E-05	0.000616149	2.2274E-05
Acceptance of Nobel Peace Prize	0.000156813	2.44504E-05	0.006625845	0.006275704	0.00429906	0.00409769	0.000210568	0.00016449
2010 State of the Union Address	0.009105487	0.005013807	0.010945243	0.00661759	0.00105263	0.00103139	0.002541221	0.00027313
Remarks on Space Exploration in the 21st Century	0.003970522	0.003932517	0.001674142	0.001598181	6.19307E-05	6.08418E-05	0.001480359	0.001464441
Remarks on Wall Street Reform	0.017431733	0.017398537	0.001794243	0.001569679	0.00077313	0.000710501	0.009526204	0.009480071
Speech on the BP Oil Spill	0.001567873	0.000125036	0.001765767	0.000573858	0.012783866	0.012622482	6.29279E-05	2.71617E-05
Address on the End of the Combat Mission in Iraq	0.00075236	0.000138909	0.003263153	0.003126428	0.006790654	0.006740112	0.001815147	0.001686207
Address to the United Nations	0.002021187	0.000855092	0.000208783	7.97784E-06	0.003000064	0.00216124	0.001230456	0.001152601
Press Conference After 2010 Midterm Elections	0.032310377	0.02951318	0.032835866	0.031610233	0.0317727	0.031681975	0.015395169	0.013943161
Remarks at Memorial for Victims of the Tucson, AZ Shooting	0.002074995	0.001080094	5.95613E-05	2.504E-06	0.001732211	0.001730253	0.004779242	0.0047784
Remarks on the Death of Osama Bin Laden	0.003440393	0.003358307	0.004493687	0.004444141	0.003767387	0.00335288	0.004365319	0.004287572
Speech on American Diplomacy in the Middle East and North Africa	0.001037642	0.00097407	0.00075241	0.000564953	0.001106798	0.00084656	0.000169189	0.000111465
Address to the British Parliament	0.000907243	0.000464134	0.001444424	0.000321722	0.001744794	0.000647215	0.001832435	0.001577802
2012 State of the Union Address	0.000473433	2.45914E-05	0.00010788	9.40641E-05	0.002096016	0.000352149	0.000664644	8.13379E-05
2012 Election Night Victory Speech	0.004181739	0.003948477	0.004471322	0.004449128	0.000461428	0.000362873	0.005093523	0.004996976
Remarks on Immigration Reform	0.000738626	0.000541039	1.02433E-05	4.12103E-06	0.006991169	0.006632788	0.003240294	0.002634424
2013 State of the Union Address	0.003048495	0.003035192	0.002667426	0.00251139	5.1452E-05	4.24014E-05	0.002987672	0.002947844
Address to the People of Israel	0.00312091	0.002645439	0.000760655	0.000759214	0.005362085	0.003925545	0.001554565	0.001448826
Remarks on Education and the Economy	0.002327674	0.001792242	0.000648873	8.31994E-06	0.001068921	0.000411963	0.001675034	0.001297634
Address to the Nation on Syria	0.000152396	6.6366E-05	0.024865916	0.024855768	0.001666316	5.60594E-07	0.000265381	0.000170257
Speech on Economic Mobility	0.001979588	0.000610762	0.003506258	0.002257037	0.00645347	0.000153492	0.00271886	0.00049046
2014 State of the Union Address	0.001537741	0.001470096	0.002426659	0.002426629	0.003379785	0.003379381	0.006569445	0.006390622
2015 State of the Union Address	0.00726785	0.007265645	0.0011742	0.001170097	0.002626214	0.002517066	0.004172313	0.004144755
2016 State of the Union Address	0.002240997	0.001636963	0.002068379	0.001410468	0.002039143	0.002005824	0.003495721	0.003078159
Remarks to the People of Cuba	0.005190183	0.005190876	0.00277474	0.001697016	0.000377023	7.87381E-06	0.000211051	9.64403E-05
Address to Joint Session of Congress	0.004337464	0.000354525	0.005885349	5.21681E-05	0.000726978	4.13285E-05	0.005557108	0.001689374
Speech at the Unleashing American Energy Event	0.000194876	8.3884E-05	8.38128E-05	7.35776E-05	0.000413565	0.000371115	0.000174693	0.000173367
Address to the United Nations General Assembly	0.001427108	0.000925652	0.005894338	0.005179979	0.000690342	0.000331031	0.001089719	3.75915E-10
State of the Union Address	0.006644768	0.005364589	0.000379155	1.6626E-05	0.001548398	0.000649496	0.003188678	0.001341621
Remarks at the House and Senate Republican Member Conference	0.000857167	0.000800358	8.14456E-05	1.60939E-05	0.000410891	5.1512E-05	0.011691652	0.01162441
Â Statement on the School Shooting in Parkland, Florida	0.000271749	0.000190453	0.00046793	0.000448701	0.004406357	0.004360931	0.006866958	0.006075958

Mean Squared Error, Autoregressive order 1 60 min ± speech duration

topic	mse_with_EURUSD	mse_without_EURUSD	mse_with_GBPUSD	mse_without_GBPUSD	mse_with_USDJPY	mse_without_USDJPY	mse_with_USDCHF	mse_without_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	1.49E-09	1.49E-09	1.90E-09	1.93E-09	1.22E-09	1.24E-09	1.84E-09	1.84E-09
Speech on Strategy in Afghanistan and Pakistan	3.50E-10	3.58E-10	3.39E-10	3.51E-10	7.57E-10	7.65E-10	3.76E-10	3.84E-10
Acceptance of Nobel Peace Prize	8.97E-10	9.05E-10	1.27E-09	1.29E-09	3.21E-09	3.21E-09	8.40E-10	8.45E-10
2010 State of the Union Address	2.31E-09	2.36E-09	2.13E-09	2.18E-09	1.06E-09	1.07E-09	1.84E-09	1.86E-09
Remarks on Space Exploration in the 21st Century	2.00E-10	2.00E-10	1.35E-10	1.35E-10	2.08E-10	2.09E-10	1.61E-10	1.61E-10
Remarks on Wall Street Reform	6.99E-10	6.99E-10	3.86E-10	3.92E-10	5.47E-10	5.49E-10	4.75E-10	4.76E-10
Speech on the BP Oil Spill	2.61E-10	2.86E-10	6.42E-10	6.63E-10	3.75E-10	3.76E-10	2.72E-10	2.74E-10
Address on the End of the Combat Mission in Iraq	3.74E-10	3.79E-10	3.65E-10	3.66E-10	1.48E-09	1.50E-09	4.53E-10	4.58E-10
Address to the United Nations	1.52E-09	1.53E-09	1.40E-09	1.40E-09	4.11E-10	4.32E-10	1.76E-09	1.77E-09
Press Conference After 2010 Midterm Elections	3.92E-08	3.92E-08	1.25E-08	1.26E-08	1.08E-08	1.09E-08	2.07E-08	2.07E-08
Remarks at Memorial for Victims of the Tucson, AZ Shooting	4.31E-10	4.36E-10	1.52E-10	1.53E-10	2.45E-10	2.46E-10	4.03E-10	4.06E-10
Remarks on the Death of Osama Bin Laden	6.47E-10	6.48E-10	5.35E-10	5.38E-10	8.22E-10	8.24E-10	5.21E-10	5.22E-10
Speech on American Diplomacy in the Middle East and North Africa	7.07E-10	7.08E-10	4.38E-10	4.38E-10	4.72E-10	4.74E-10	5.58E-10	5.59E-10
Address to the British Parliament	1.13E-09	1.16E-09	4.73E-10	4.81E-10	4.96E-10	5.13E-10	7.47E-10	7.51E-10
2012 State of the Union Address	1.83E-10	1.87E-10	2.17E-10	2.18E-10	2.85E-10	2.92E-10	1.79E-10	1.83E-10
2012 Election Night Victory Speech	3.25E-10	3.25E-10	1.18E-10	1.18E-10	1.29E-10	1.31E-10	3.20E-10	3.20E-10
Remarks on Immigration Reform	2.43E-10	2.45E-10	1.02E-10	1.02E-10	4.84E-10	4.87E-10	3.39E-10	3.43E-10
2013 State of the Union Address	1.00E-10	1.00E-10	5.36E-11	5.11E-11	6.36E-10	6.43E-10	5.01E-11	5.05E-11
Address to the People of Israel	1.04E-09	1.05E-09	5.62E-10	5.62E-10	1.48E-09	1.54E-09	5.80E-10	5.81E-10
Remarks on Education and the Economy	2.20E-10	2.21E-10	2.50E-10	2.51E-10	5.31E-10	5.34E-10	2.99E-10	3.02E-10
Address to the Nation on Syria	9.59E-11	9.64E-11	5.69E-11	5.72E-11	5.66E-10	5.90E-10	3.08E-10	3.11E-10
Speech on Economic Mobility	7.34E-10	7.36E-10	8.49E-10	8.49E-10	1.56E-09	1.57E-09	9.27E-10	9.27E-10
2014 State of the Union Address	8.20E-11	8.19E-11	9.47E-11	9.48E-11	4.70E-10	4.76E-10	1.21E-10	1.21E-10
2015 State of the Union Address	3.17E-10	3.17E-10	8.27E-11	8.26E-11	5.22E-09	5.22E-09	8.25E-11	8.24E-11
2016 State of the Union Address	3.71E-10	3.78E-10	2.11E-10	2.16E-10	7.79E-10	7.79E-10	2.75E-10	2.78E-10
Remarks to the People of Cuba	4.77E-10	4.84E-10	6.92E-10	7.09E-10	4.75E-10	4.94E-10	4.94E-10	4.98E-10
Address to Joint Session of Congress	6.72E-10	6.82E-10	1.07E-09	1.09E-09	1.16E-09	1.16E-09	7.12E-10	7.29E-10
Speech at the Unleashing American Energy Event	8.09E-11	8.17E-11	2.68E-10	2.68E-10	2.87E-10	2.87E-10	7.40E-11	7.26E-11
Address to the United Nations General Assembly	4.13E-10	4.18E-10	4.09E-10	4.40E-10	5.23E-10	5.24E-10	4.84E-10	4.98E-10
State of the Union Address	9.30E-10	9.33E-10	1.23E-09	1.23E-09	1.07E-09	1.07E-09	1.34E-09	1.34E-09
Remarks at the House and Senate Republican Member Conference	4.22E-10	4.22E-10	6.87E-10	6.88E-10	2.98E-10	3.02E-10	5.00E-10	5.00E-10
Â Statement on the School Shooting in Parkland, Florida	9.41E-10	9.46E-10	9.92E-10	9.93E-10	9.65E-10	9.68E-10	1.68E-09	1.70E-09

Mean Squared Error, Autoregressive order 1 the day of speech

topic	mse_with_EURUSD	mse_without_EURUSD	mse_with_GBPUSD	mse_without_GBPUSD	mse_with_USDJPY	mse_without_USDJPY	mse_with_USDCHF	mse_without_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	1.49E-09	1.49E-09	1.90E-09	1.93E-09	1.22E-09	1.24E-09	1.84E-09	1.84E-09
Speech on Strategy in Afghanistan and Pakistan	3.50E-10	3.58E-10	3.39E-10	3.51E-10	7.57E-10	7.65E-10	3.76E-10	3.84E-10
Acceptance of Nobel Peace Prize	8.97E-10	9.05E-10	1.27E-09	1.29E-09	3.21E-09	3.21E-09	8.40E-10	8.45E-10
2010 State of the Union Address	2.31E-09	2.36E-09	2.13E-09	2.18E-09	1.06E-09	1.07E-09	1.84E-09	1.86E-09
Remarks on Space Exploration in the 21st Century	2.00E-10	2.00E-10	1.35E-10	1.35E-10	2.08E-10	2.09E-10	1.61E-10	1.61E-10
Remarks on Wall Street Reform	6.99E-10	6.99E-10	3.86E-10	3.92E-10	5.47E-10	5.49E-10	4.75E-10	4.76E-10
Speech on the BP Oil Spill	2.61E-10	2.86E-10	6.42E-10	6.63E-10	3.75E-10	3.76E-10	2.72E-10	2.74E-10
Address on the End of the Combat Mission in Iraq	3.74E-10	3.79E-10	3.65E-10	3.66E-10	1.48E-09	1.50E-09	4.53E-10	4.58E-10
Address to the United Nations	1.52E-09	1.53E-09	1.40E-09	1.40E-09	4.11E-10	4.32E-10	1.76E-09	1.77E-09
Press Conference After 2010 Midterm Elections	3.92E-08	3.92E-08	1.25E-08	1.26E-08	1.08E-08	1.09E-08	2.07E-08	2.07E-08
Remarks at Memorial for Victims of the Tucson, AZ Shooting	4.31E-10	4.36E-10	1.52E-10	1.53E-10	2.45E-10	2.46E-10	4.03E-10	4.06E-10
Remarks on the Death of Osama Bin Laden	6.47E-10	6.48E-10	5.35E-10	5.38E-10	8.22E-10	8.24E-10	5.21E-10	5.22E-10
Speech on American Diplomacy in the Middle East and North Africa	7.07E-10	7.08E-10	4.38E-10	4.38E-10	4.72E-10	4.74E-10	5.58E-10	5.59E-10
Address to the British Parliament	1.13E-09	1.16E-09	4.73E-10	4.81E-10	4.96E-10	5.13E-10	7.47E-10	7.51E-10
2012 State of the Union Address	1.83E-10	1.87E-10	2.17E-10	2.18E-10	2.85E-10	2.92E-10	1.79E-10	1.83E-10
2012 Election Night Victory Speech	3.25E-10	3.25E-10	1.18E-10	1.18E-10	1.29E-10	1.31E-10	3.20E-10	3.20E-10
Remarks on Immigration Reform	2.43E-10	2.45E-10	1.02E-10	1.02E-10	4.84E-10	4.87E-10	3.39E-10	3.43E-10
2013 State of the Union Address	1.00E-10	1.00E-10	5.36E-11	5.11E-11	6.36E-10	6.43E-10	5.01E-11	5.05E-11
Address to the People of Israel	1.04E-09	1.05E-09	5.62E-10	5.62E-10	1.48E-09	1.54E-09	5.80E-10	5.81E-10
Remarks on Education and the Economy	2.20E-10	2.21E-10	2.50E-10	2.51E-10	5.31E-10	5.34E-10	2.99E-10	3.02E-10
Address to the Nation on Syria	9.59E-11	9.64E-11	5.69E-11	5.72E-11	5.66E-10	5.90E-10	3.08E-10	3.11E-10
Speech on Economic Mobility	7.34E-10	7.36E-10	8.49E-10	8.49E-10	1.56E-09	1.57E-09	9.27E-10	9.27E-10
2014 State of the Union Address	8.20E-11	8.19E-11	9.47E-11	9.48E-11	4.70E-10	4.76E-10	1.21E-10	1.21E-10
2015 State of the Union Address	3.17E-10	3.17E-10	8.27E-11	8.26E-11	5.22E-09	5.22E-09	8.25E-11	8.24E-11
2016 State of the Union Address	3.71E-10	3.78E-10	2.11E-10	2.16E-10	7.79E-10	7.79E-10	2.75E-10	2.78E-10
Remarks to the People of Cuba	4.77E-10	4.84E-10	6.92E-10	7.09E-10	4.75E-10	4.94E-10	4.94E-10	4.98E-10
Address to Joint Session of Congress	6.72E-10	6.82E-10	1.07E-09	1.09E-09	1.16E-09	1.16E-09	7.12E-10	7.29E-10
Speech at the Unleashing American Energy Event	8.09E-11	8.17E-11	2.68E-10	2.68E-10	2.87E-10	2.87E-10	7.40E-11	7.26E-11
Address to the United Nations General Assembly	4.13E-10	4.18E-10	4.09E-10	4.40E-10	5.23E-10	5.24E-10	4.84E-10	4.98E-10
State of the Union Address	9.30E-10	9.33E-10	1.23E-09	1.23E-09	1.07E-09	1.07E-09	1.34E-09	1.34E-09
Remarks at the House and Senate Republican Member Conference	4.22E-10	4.22E-10	6.87E-10	6.88E-10	2.98E-10	3.02E-10	5.00E-10	5.00E-10
Â Statement on the School Shooting in Parkland, Florida	9.41E-10	9.46E-10	9.92E-10	9.93E-10	9.65E-10	9.68E-10	1.68E-09	1.70E-09

P value of Dummy variable, Autoregressive order 1 60 min ± speech duration

topic	pvalues_EURUSD	pvalues_GBPUSD	pvalues_USDJPY	pvalues_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	0.87838736	0.328808214	0.290750862	0.837586748
Speech on Strategy in Afghanistan and Pakistan	0.101656792	0.044546645	0.311534046	0.129216589
Acceptance of Nobel Peace Prize	0.578644693	0.591124483	0.938179146	0.593922364
2010 State of the Union Address	0.219567014	0.170038932	0.32033925	0.273555082
Remarks on Space Exploration in the 21st Century	0.993705908	0.568412648	0.552779403	0.924489122
Remarks on Wall Street Reform	0.889920796	0.240576439	0.745367147	0.695336312
Speech on the BP Oil Spill	0.007716349	0.246464807	0.640254986	0.362048904
Address on the End of the Combat Mission in Iraq	0.236352308	0.686081066	0.335006313	0.407835755
Address to the United Nations	0.456496444	0.967254588	0.029006447	0.693624329
Press Conference After 2010 Midterm Elections	0.862909242	0.748598818	0.839327978	0.958388807
Remarks at Memorial for Victims of the Tucson, AZ Shooting	0.266267846	0.472990271	0.660676955	0.423859931
Remarks on the Death of Osama Bin Laden	0.751866785	0.44879826	0.648006729	0.805341019
Speech on American Diplomacy in the Middle East and North Africa	0.627693564	0.750852393	0.476097584	0.638798758
Address to the British Parliament	0.079024182	0.1458121	0.040236827	0.435468716
2012 State of the Union Address	0.075511796	0.415665475	0.101216745	0.101062307
2012 Election Night Victory Speech	0.913335736	0.569944535	0.221547578	0.888866727
Remarks on Immigration Reform	0.346497475	0.791402657	0.359781322	0.312192976
2013 State of the Union Address	0.658285672	0.885121922	0.4024621	0.649174597
Address to the People of Israel	0.398808018	0.793383024	0.060487445	0.696524302
Remarks on Education and the Economy	0.543222059	0.600485547	0.391932474	0.2803367
Address to the Nation on Syria	0.53075586	0.762374195	0.084623576	0.412456025
Speech on Economic Mobility	0.616074548	0.878924252	0.366706746	0.973190478
2014 State of the Union Address	0.843083893	0.72394908	0.22179976	0.664542985
2015 State of the Union Address	0.939641848	0.624990534	0.905292729	0.871748203
2016 State of the Union Address	0.180231912	0.112820848	0.953086765	0.274912974
Remarks to the People of Cuba	0.198919665	0.111459438	0.051789233	0.283648545
Address to Joint Session of Congress	0.203662625	0.076535264	0.874695059	0.101537602
Speech at the Unleashing American Energy Event	0.751267281	0.885740907	0.945944189	0.883889494
Address to the United Nations General Assembly	0.303974125	0.003968409	0.719410076	0.094977869
State of the Union Address	0.469505221	0.827380962	0.623378367	0.65623514
Remarks at the House and Senate Republican Member Conference	0.731673134	0.650474731	0.288937234	0.919424247
Â Statement on the School Shooting in Parkland, Florida	0.664176027	0.910482564	0.861035636	0.841351027

P value of Dummy variable, Autoregressive order 1 the day of speech

topic	pvalues_EURUSD	pvalues_GBPUSD	pvalues_USDJPY	pvalues_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	0.730668894	0.502343824	0.142311286	0.82039484
Speech on Strategy in Afghanistan and Pakistan	0.25186048	0.305626559	0.818187389	0.355515971
Acceptance of Nobel Peace Prize	0.789759015	0.729091142	0.642881266	0.872370515
2010 State of the Union Address	0.009909779	0.003344387	0.892548367	0.024021426
Remarks on Space Exploration in the 21st Century	0.881646488	0.91440474	0.985753091	0.93348662
Remarks on Wall Street Reform	0.808451642	0.73458141	0.905808833	0.848842481
Speech on the BP Oil Spill	0.378337147	0.486391166	0.775900353	0.87406049
Address on the End of the Combat Mission in Iraq	0.392431568	0.719798422	0.664767694	0.820897524
Address to the United Nations	0.07311802	0.556919943	0.271604472	0.666096731
Press Conference After 2010 Midterm Elections	5.11268E-05	0.001896622	0.418920091	0.000334208
Remarks at Memorial for Victims of the Tucson, AZ Shooting	0.465075725	0.902934816	0.980369286	0.983554742
Remarks on the Death of Osama Bin Laden	0.749752188	0.665647295	0.352388671	0.796466895
Speech on American Diplomacy in the Middle East and North Africa	0.8189778	0.718564848	0.642909264	0.831624621
Address to the British Parliament	0.548550821	0.291642671	0.272714561	0.559857432
2012 State of the Union Address	0.742911141	0.9237057	0.257882081	0.708104935
2012 Election Night Victory Speech	0.674353519	0.900380454	0.805084886	0.782217718
Remarks on Immigration Reform	0.723103353	0.96295151	0.502773484	0.455649557
2013 State of the Union Address	0.946116296	0.847176161	0.950918578	0.935847289
Address to the People of Israel	0.312742563	0.972443445	0.121934315	0.668256313
Remarks on Education and the Economy	0.541893621	0.483261226	0.367203692	0.588951439
Address to the Nation on Syria	0.865668845	0.969282346	0.180147717	0.745443963
Speech on Economic Mobility	0.069254852	0.131630014	0.000294704	0.04255799
2014 State of the Union Address	0.875444259	0.99824107	0.985499885	0.810501667
2015 State of the Union Address	0.988510914	0.987610432	0.683912177	0.976706196
2016 State of the Union Address	0.57557967	0.57012025	0.805583238	0.711039219
Remarks to the People of Cuba	0.969060821	0.286931385	0.566315228	0.645759313
Address to Joint Session of Congress	0.000749529	0.000138139	0.260875075	0.001809956
Speech at the Unleashing American Energy Event	0.952992256	0.970243598	0.938818183	0.981876344
Address to the United Nations General Assembly	0.431753191	0.358484979	0.418569838	0.204443082
State of the Union Address	0.09647881	0.429292357	0.104210337	0.026937092
Remarks at the House and Senate Republican Member Conference	0.80347716	0.74320379	0.624163727	0.830302283
Â Statement on the School Shooting in Parkland, Florida	0.731627829	0.934141453	0.921794936	0.727422036

R squared, Random Forest 60 min ± speech duration

topic	r_squared_with_EURUSD	r_squared_without_EURUSD	r_squared_with_GBPUSD	r_squared_without_GBPUSD	r_squared_with_USDJPY	r_squared_without_USDJPY	r_squared_with_USDCHF	r_squared_without_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	0.764292761	0.754105086	0.734534378	0.738959024	0.668244441	0.647891271	0.769755014	0.768024857
Speech on Strategy in Afghanistan and Pakistan	0.773971633	0.67905618	0.7166254	0.633626057	0.670362078	0.606406179	0.727225014	0.688674947
Acceptance of Nobel Peace Prize	0.731568952	0.705434655	0.735750216	0.704751765	0.712376025	0.688927938	0.775050608	0.725259133
2010 State of the Union Address	0.775686036	0.77405954	0.749910955	0.70790784	0.765776774	0.710318175	0.786310227	0.73516323
Remarks on Space Exploration in the 21st Century	0.591045201	0.551166529	0.638805517	0.607041963	0.733876426	0.731003294	0.713707303	0.631038461
Remarks on Wall Street Reform	0.731228094	0.701451097	0.7182385	0.483882633	0.646436032	0.617437232	0.765765824	0.701262148
Speech on the BP Oil Spill	0.64837453	0.615425739	0.772926459	0.765121223	0.553177178	0.557499674	0.721927429	0.664958189
Address on the End of the Combat Mission in Iraq	0.709930972	0.659199216	0.758749397	0.722134295	0.716860289	0.705247143	0.71342483	0.675812987
Address to the United Nations	0.788546729	0.726424631	0.631811887	0.640455794	0.747553771	0.7079924	0.745596209	0.712415919
Press Conference After 2010 Midterm Elections	0.811735302	0.820476927	0.792841985	0.761896148	0.761876746	0.75835187	0.784623615	0.790122316
Remarks at Memorial for Victims of the Tucson, AZ Shooting	0.795056701	0.739086009	0.687657381	0.607764023	0.709055169	0.665641838	0.691279881	0.662718053
Remarks on the Death of Osama Bin Laden	0.709502595	0.70610864	0.72398199	0.668603222	0.712091957	0.68723825	0.706810761	0.661989877
Speech on American Diplomacy in the Middle East and North Africa	0.725431398	0.663603456	0.773975542	0.719640544	0.668652049	0.643657123	0.688713065	0.655225079
Address to the British Parliament	0.740221364	0.734594979	0.659346538	0.612945081	0.713641469	0.699263488	0.828494659	0.766548815
2012 State of the Union Address	0.701377683	0.609336865	0.601809759	0.54030698	0.740087473	0.619487775	0.578075377	0.474838645
2012 Election Night Victory Speech	0.66998894	0.612271351	0.66572084	0.5679197	0.602716748	0.485341112	0.78586043	0.775066641
Remarks on Immigration Reform	0.65987841	0.625286297	0.59719	0.554748768	0.63304974	0.567992103	0.604768676	0.585485931
2013 State of the Union Address	0.677882981	0.566435653	0.541297264	0.445088594	0.735762207	0.691446362	0.540931744	0.479450953
Address to the People of Israel	0.765856188	0.745845586	0.757454614	0.702390213	0.761658236	0.729473627	0.679120621	0.657151482
Remarks on Education and the Economy	0.723328422	0.675979934	0.682077936	0.610074087	0.734680899	0.674370057	0.77969395	0.729144765
Address to the Nation on Syria	0.601423076	0.56712929	0.614684451	0.595355853	0.802377282	0.787093573	0.6911427	0.701578534
Speech on Economic Mobility	0.742480383	0.63640165	0.741688853	0.677583054	0.754007581	0.699177573	0.794233341	0.750803722
2014 State of the Union Address	0.674147974	0.580939543	0.697491002	0.613551244	0.759705303	0.698465971	0.601499956	0.570186971
2015 State of the Union Address	0.774685092	0.736411241	0.661247272	0.609387967	0.53154043	0.460113108	0.639062472	0.551742086
2016 State of the Union Address	0.702347119	0.635339219	0.616045996	0.567046342	0.781507669	0.710457383	0.775306898	0.721648344
Remarks to the People of Cuba	0.691366216	0.651094951	0.73902811	0.676706758	0.672612835	0.644422293	0.737164307	0.736764871
Address to Joint Session of Congress	0.739123962	0.721449957	0.814759176	0.729059472	0.744318203	0.727999405	0.718276454	0.695776382
Speech at the Unleashing American Energy Event	0.597978668	0.558490745	0.639082184	0.631547301	0.651086708	0.655253458	0.523510317	0.489349479
Address to the United Nations General Assembly	0.773572669	0.753884155	0.726109561	0.701448432	0.728135848	0.683307099	0.774512698	0.752444538
State of the Union Address	0.781764556	0.712864523	0.755210975	0.729395227	0.74278341	0.718279338	0.801787669	0.75208173
Remarks at the House and Senate Republican Member Conference	0.675533696	0.671305165	0.716584484	0.643631973	0.798405887	0.766013824	0.74283903	0.658351829
Â Statement on the School Shooting in Parkland, Florida	0.693647726	0.688217295	0.712245414	0.727962734	0.745082436	0.780045558	0.756591449	0.789627133

R Squared, Random Forest the day of speech

topic	r_squared_with_EURUSD	r_squared_without_EURUSD	r_squared_with_GBPUSD	r_squared_without_GBPUSD	r_squared_with_USDJPY	r_squared_without_USDJPY	r_squared_with_USDCHF	r_squared_without_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	0.383870864	0.381500512	0.380711882	0.370906877	0.353753844	0.357799388	0.358032359	0.352860614
Speech on Strategy in Afghanistan and Pakistan	0.301028012	0.27959509	0.337657737	0.320597624	0.345118101	0.338267328	0.30678848	0.287557097
Acceptance of Nobel Peace Prize	0.365762792	0.356597284	0.42859911	0.420305278	0.386838431	0.376451057	0.378357622	0.367683217
2010 State of the Union Address	0.457101526	0.422865786	0.439739274	0.399197651	0.387216244	0.373288722	0.435210253	0.389759779
Remarks on Space Exploration in the 21st Century	0.323898777	0.32138488	0.345696706	0.339183989	0.291147285	0.288931796	0.325499093	0.319623501
Remarks on Wall Street Reform	0.450548327	0.432638728	0.401158929	0.38980382	0.376269001	0.368430755	0.44912868	0.449435349
Speech on the BP Oil Spill	0.340980333	0.340504294	0.369966253	0.373687156	0.373382719	0.377976334	0.359761142	0.354227667
Address on the End of the Combat Mission in Iraq	0.336764469	0.332802734	0.326681573	0.317210312	0.472621685	0.457247506	0.392782325	0.393092976
Address to the United Nations	0.40373348	0.388708614	0.336003871	0.33026872	0.311219908	0.293847979	0.378730873	0.361228677
Press Conference After 2010 Midterm Elections	0.762915944	0.743905482	0.609049202	0.516512949	0.590828725	0.556642645	0.651969592	0.599157332
Remarks at Memorial for Victims of the Tucson, AZ Shooting	0.400528023	0.38951409	0.326722566	0.319292668	0.31212477	0.315466342	0.4592947	0.455560429
Remarks on the Death of Osama Bin Laden	0.404608905	0.40451619	0.295716923	0.278181216	0.385342035	0.383579168	0.352949703	0.355392995
Speech on American Diplomacy in the Middle East and North Africa	0.35108302	0.328994001	0.34862152	0.335824166	0.369825883	0.365828351	0.365625576	0.351450177
Address to the British Parliament	0.385828353	0.368840541	0.28934938	0.2630475	0.32548985	0.30215485	0.414269185	0.382124295
2012 State of the Union Address	0.437465115	0.432682875	0.395016047	0.374559325	0.377300493	0.348673016	0.404562517	0.401158979
2012 Election Night Victory Speech	0.315265655	0.304630391	0.224365132	0.21714489	0.194683019	0.18476115	0.302921293	0.297881448
Remarks on Immigration Reform	0.341049865	0.340996394	0.235987351	0.234352558	0.304894981	0.289642895	0.323513055	0.312222776
2013 State of the Union Address	0.374230148	0.36025125	0.321962284	0.306835132	0.373041606	0.356403409	0.258537103	0.255148601
Address to the People of Israel	0.453376517	0.421057193	0.279090234	0.255640015	0.519376644	0.482701075	0.357908151	0.334782978
Remarks on Education and the Economy	0.399357865	0.39696066	0.324070704	0.312869679	0.329935998	0.30184369	0.391248988	0.378188362
Address to the Nation on Syria	0.300983827	0.299321968	0.551993866	0.614407193	0.338351129	0.332389407	0.29741949	0.29682436
Speech on Economic Mobility	0.338328745	0.306479975	0.300202366	0.277813118	0.413276848	0.403775113	0.376630257	0.352914526
2014 State of the Union Address	0.356193117	0.34783536	0.315963092	0.305380173	0.418699249	0.402446411	0.39314101	0.379240373
2015 State of the Union Address	0.503408118	0.478673255	0.509128692	0.524179077	0.31530213	0.295784405	0.522513414	0.517944875
2016 State of the Union Address	0.32270504	0.308156786	0.298595886	0.282677775	0.315310425	0.291244699	0.382400052	0.372265929
Remarks to the People of Cuba	0.4312336	0.415717558	0.475100651	0.468559974	0.317692294	0.299223801	0.340688691	0.321447393
Address to Joint Session of Congress	0.338969061	0.289575996	0.42686691	0.393201276	0.365728819	0.341335639	0.384339717	0.356390811
Speech at the Unleashing American Energy Event	0.25104623	0.248837902	0.299645981	0.299579105	0.254055053	0.253772127	0.273322091	0.274105806
Address to the United Nations General Assembly	0.334384662	0.315985565	0.362809878	0.35312923	0.327261605	0.315269799	0.334180327	0.318991871
State of the Union Address	0.352417425	0.31976824	0.362744973	0.32877873	0.35034408	0.299805683	0.387938922	0.329850969
Remarks at the House and Senate Republican Member Conference	0.279603017	0.27018123	0.310784851	0.29050477	0.29356678	0.286289001	0.424163763	0.414188801
Â Statement on the School Shooting in Parkland, Florida	0.305650613	0.30820287	0.323976131	0.323002061	0.348869603	0.345894063	0.362633794	0.35867873

Mean Squared Error, Random Forest 60 min ± speech duration

topic	mse_with_EURUSD	mse_without_EURUSD	mse_with_GBPUSD	mse_without_GBPUSD	mse_with_USDJPY	mse_without_USDJPY	mse_with_USDCHF	mse_without_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	4.02E-10	4.19E-10	6.40E-10	6.29E-10	4.20E-10	4.46E-10	4.20E-10	4.23E-10
Speech on Strategy in Afghanistan and Pakistan	7.35E-11	1.04E-10	9.01E-11	1.16E-10	3.25E-10	3.88E-10	9.55E-11	1.09E-10
Acceptance of Nobel Peace Prize	2.41E-10	2.64E-10	3.65E-10	4.08E-10	7.14E-10	7.72E-10	2.07E-10	2.53E-10
2010 State of the Union Address	4.49E-10	4.53E-10	4.33E-10	5.06E-10	2.26E-10	2.80E-10	3.24E-10	4.02E-10
Remarks on Space Exploration in the 21st Century	8.05E-11	8.84E-11	5.20E-11	5.65E-11	8.01E-11	8.10E-11	4.39E-11	5.66E-11
Remarks on Wall Street Reform	1.48E-10	1.64E-10	8.28E-11	1.52E-10	2.00E-10	2.16E-10	8.99E-11	1.15E-10
Speech on the BP Oil Spill	9.40E-11	1.03E-10	1.19E-10	1.23E-10	1.44E-10	1.42E-10	7.98E-11	9.61E-11
Address on the End of the Combat Mission in Iraq	9.00E-11	1.06E-10	8.01E-11	9.23E-11	2.77E-10	2.89E-10	1.18E-10	1.33E-10
Address to the United Nations	3.79E-10	4.90E-10	5.05E-10	4.94E-10	1.52E-10	1.75E-10	4.56E-10	5.16E-10
Press Conference After 2010 Midterm Elections	5.22E-09	4.98E-09	1.99E-09	2.29E-09	1.95E-09	1.98E-09	3.26E-09	3.18E-09
Remarks at Memorial for Victims of the Tucson, AZ Shooting	1.04E-10	1.33E-10	5.31E-11	6.66E-11	6.16E-11	7.08E-11	1.97E-10	2.15E-10
Remarks on the Death of Osama Bin Laden	1.63E-10	1.65E-10	1.05E-10	1.26E-10	2.38E-10	2.59E-10	1.30E-10	1.50E-10
Speech on American Diplomacy in the Middle East and North Africa	2.99E-10	3.67E-10	1.07E-10	1.33E-10	1.29E-10	1.39E-10	1.97E-10	2.19E-10
Address to the British Parliament	3.45E-10	3.52E-10	2.04E-10	2.32E-10	1.66E-10	1.75E-10	2.00E-10	2.72E-10
2012 State of the Union Address	5.34E-11	6.99E-11	8.66E-11	1.00E-10	7.40E-11	1.08E-10	8.70E-11	1.08E-10
2012 Election Night Victory Speech	9.32E-11	1.09E-10	4.37E-11	5.64E-11	6.16E-11	7.97E-11	5.55E-11	5.83E-11
Remarks on Immigration Reform	7.56E-11	8.33E-11	3.37E-11	3.73E-11	1.66E-10	1.95E-10	1.14E-10	1.20E-10
2013 State of the Union Address	3.30E-11	4.44E-11	3.13E-11	3.78E-11	2.35E-10	2.74E-10	2.52E-11	2.86E-11
Address to the People of Israel	2.17E-10	2.35E-10	1.29E-10	1.59E-10	3.60E-10	4.08E-10	1.80E-10	1.92E-10
Remarks on Education and the Economy	9.64E-11	1.13E-10	1.68E-10	2.06E-10	1.61E-10	1.98E-10	9.69E-11	1.19E-10
Address to the Nation on Syria	5.23E-11	5.68E-11	3.17E-11	3.33E-11	2.50E-10	2.69E-10	9.97E-11	9.64E-11
Speech on Economic Mobility	1.63E-10	2.30E-10	1.96E-10	2.45E-10	3.83E-10	4.68E-10	1.83E-10	2.22E-10
2014 State of the Union Address	2.75E-11	3.54E-11	2.51E-11	3.20E-11	1.11E-10	1.39E-10	4.46E-11	4.81E-11
2015 State of the Union Address	7.62E-11	8.92E-11	4.44E-11	5.12E-11	2.35E-09	2.71E-09	3.88E-11	4.82E-11
2016 State of the Union Address	9.90E-11	1.21E-10	1.15E-10	1.30E-10	1.98E-10	2.62E-10	6.37E-11	7.90E-11
Remarks to the People of Cuba	1.64E-10	1.86E-10	2.07E-10	2.57E-10	1.93E-10	2.09E-10	1.42E-10	1.42E-10
Address to Joint Session of Congress	3.05E-10	3.26E-10	4.02E-10	5.88E-10	6.05E-10	6.43E-10	3.65E-10	3.95E-10
Speech at the Unleashing American Energy Event	5.09E-11	5.59E-11	8.11E-11	8.28E-11	8.11E-11	8.02E-11	3.52E-11	3.77E-11
Address to the United Nations General Assembly	1.17E-10	1.28E-10	1.68E-10	1.84E-10	2.14E-10	2.50E-10	1.61E-10	1.77E-10
State of the Union Address	2.26E-10	2.97E-10	3.12E-10	3.45E-10	2.53E-10	2.77E-10	2.65E-10	3.32E-10
Remarks at the House and Senate Republican Member Conference	1.75E-10	1.78E-10	2.03E-10	2.55E-10	7.68E-11	8.92E-11	1.58E-10	2.10E-10
Â Statement on the School Shooting in Parkland, Florida	2.86E-10	2.91E-10	4.25E-10	4.02E-10	3.18E-10	2.74E-10	4.31E-10	3.72E-10

Mean Squared Error, Random Forest the day of speech

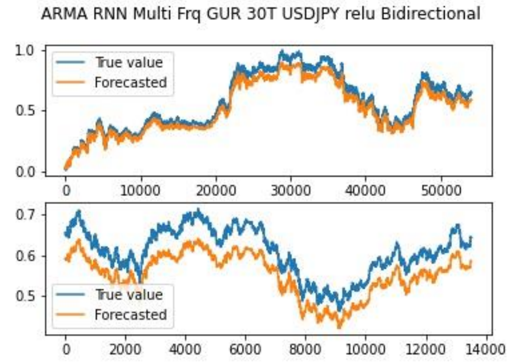
topic	mse_with_EURUSD	mse_without_EURUSD	mse_with_GBPUSD	mse_without_GBPUSD	mse_with_USDJPY	mse_without_USDJPY	mse_with_USDCHF	mse_without_USDCHF
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	6.20E-10	6.22E-10	8.19E-10	8.32E-10	6.82E-10	6.78E-10	6.69E-10	6.75E-10
Speech on Strategy in Afghanistan and Pakistan	3.05E-10	3.14E-10	4.33E-10	4.44E-10	6.57E-10	6.64E-10	3.17E-10	3.26E-10
Acceptance of Nobel Peace Prize	4.03E-10	4.09E-10	6.69E-10	6.79E-10	7.13E-10	7.25E-10	4.38E-10	4.46E-10
2010 State of the Union Address	4.57E-10	4.86E-10	5.75E-10	6.16E-10	7.28E-10	7.44E-10	4.71E-10	5.09E-10
Remarks on Space Exploration in the 21st Century	3.83E-10	3.84E-10	4.25E-10	4.29E-10	4.29E-10	4.30E-10	4.29E-10	4.33E-10
Remarks on Wall Street Reform	8.21E-10	8.48E-10	7.22E-10	7.36E-10	6.48E-10	6.56E-10	7.72E-10	7.72E-10
Speech on the BP Oil Spill	5.50E-10	5.50E-10	7.33E-10	7.29E-10	4.65E-10	4.62E-10	5.57E-10	5.62E-10
Address on the End of the Combat Mission in Iraq	4.66E-10	4.69E-10	4.46E-10	4.53E-10	7.51E-10	7.73E-10	7.07E-10	7.07E-10
Address to the United Nations	5.34E-10	5.48E-10	5.49E-10	5.54E-10	3.44E-10	3.52E-10	5.34E-10	5.49E-10
Press Conference After 2010 Midterm Elections	9.29E-10	1.00E-09	6.97E-10	8.62E-10	6.28E-10	6.80E-10	9.09E-10	1.05E-09
Remarks at Memorial for Victims of the Tucson, AZ Shooting	6.90E-10	7.03E-10	5.17E-10	5.23E-10	3.93E-10	3.91E-10	7.99E-10	8.05E-10
Remarks on the Death of Osama Bin Laden	4.47E-10	4.47E-10	2.97E-10	3.04E-10	4.24E-10	4.25E-10	4.81E-10	4.79E-10
Speech on American Diplomacy in the Middle East and North Africa	5.57E-10	5.75E-10	3.57E-10	3.64E-10	3.94E-10	3.96E-10	5.97E-10	6.10E-10
Address to the British Parliament	6.80E-10	6.99E-10	3.99E-10	4.14E-10	3.34E-10	3.46E-10	5.66E-10	5.97E-10
2012 State of the Union Address	5.83E-10	5.88E-10	3.75E-10	3.87E-10	5.12E-10	5.36E-10	5.71E-10	5.74E-10
2012 Election Night Victory Speech	2.13E-10	2.16E-10	1.23E-10	1.24E-10	1.55E-10	1.57E-10	1.92E-10	1.93E-10
Remarks on Immigration Reform	2.65E-10	2.65E-10	1.71E-10	1.72E-10	4.88E-10	4.98E-10	2.82E-10	2.87E-10
2013 State of the Union Address	3.01E-10	3.08E-10	2.27E-10	2.32E-10	6.54E-10	6.72E-10	3.41E-10	3.42E-10
Address to the People of Israel	3.71E-10	3.93E-10	3.90E-10	4.03E-10	7.43E-10	8.00E-10	2.79E-10	2.89E-10
Remarks on Education and the Economy	2.97E-10	2.99E-10	2.84E-10	2.89E-10	4.67E-10	4.87E-10	3.83E-10	3.92E-10
Address to the Nation on Syria	1.65E-10	1.65E-10	2.56E-10	2.20E-10	4.20E-10	4.23E-10	2.74E-10	2.74E-10
Speech on Economic Mobility	2.16E-10	2.27E-10	2.80E-10	2.89E-10	5.31E-10	5.39E-10	3.21E-10	3.34E-10
2014 State of the Union Address	2.56E-10	2.60E-10	2.45E-10	2.49E-10	7.49E-10	7.70E-10	4.25E-10	4.35E-10
2015 State of the Union Address	6.90E-10	7.25E-10	5.66E-10	5.48E-10	1.07E-09	1.10E-09	2.25E-09	2.27E-09
2016 State of the Union Address	4.32E-10	4.41E-10	3.39E-10	3.47E-10	4.16E-10	4.31E-10	4.64E-10	4.71E-10
Remarks to the People of Cuba	3.14E-10	3.22E-10	4.81E-10	4.87E-10	4.64E-10	4.77E-10	3.16E-10	3.26E-10
Address to Joint Session of Congress	2.79E-10	2.99E-10	3.73E-10	3.95E-10	5.56E-10	5.77E-10	2.77E-10	2.90E-10
Speech at the Unleashing American Energy Event	3.39E-10	3.40E-10	3.21E-10	3.21E-10	4.33E-10	4.33E-10	2.88E-10	2.88E-10
Address to the United Nations General Assembly	3.00E-10	3.08E-10	3.79E-10	3.85E-10	2.95E-10	3.00E-10	2.95E-10	3.02E-10
State of the Union Address	3.60E-10	3.78E-10	4.71E-10	4.96E-10	3.76E-10	4.06E-10	4.30E-10	4.71E-10
Remarks at the House and Senate Republican Member Conference	3.86E-10	3.91E-10	4.87E-10	5.01E-10	3.24E-10	3.28E-10	5.03E-10	5.12E-10
Â Statement on the School Shooting in Parkland, Florida	4.14E-10	4.12E-10	4.86E-10	4.87E-10	6.85E-10	6.88E-10	4.83E-10	4.86E-10

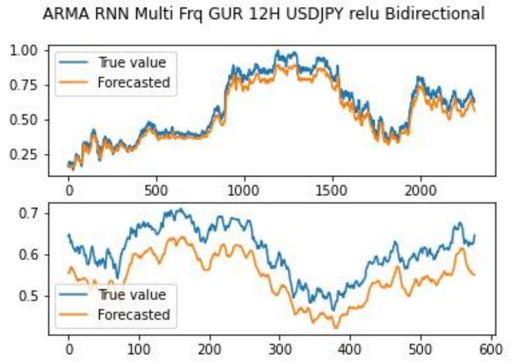
Feature importance, Random Forest

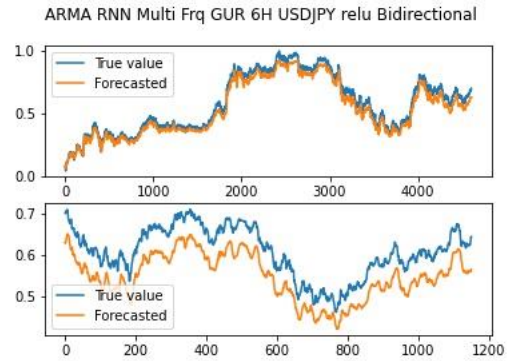
topics	EURUSD		GBPUSD		USDCHF		USDJPY	
	60+-	1_day	60+-	1_day	60+-	1_day	60+-	1_day
2010 State of the Union Address	4.342965146	3.047532639	8.96558161	3.978489476	8.016665306	5.644706901	9.377458572	2.623243115
2012 Election Night Victory Speech	6.441034924	2.522109196	8.415585311	2.042907727	4.212213727	1.950603947	7.108440857	1.761085143
2012 State of the Union Address	8.269561781	0.715266422	11.41863399	3.17609251	7.684214148	1.026692867	7.785204929	2.795667804
2013 State of the Union Address	9.879158628	1.21802438	10.57643498	0.879201851	12.63338073	1.268142403	4.499215591	2.122414199
2014 State of the Union Address	9.582349886	2.650690412	10.95703934	2.229940907	10.55562001	1.635996344	8.747669373	1.989296231
2015 State of the Union Address	5.420061749	0.497090241	5.817694352	0.330229422	9.672807008	0.48402314	8.175495356	5.206586379
2016 State of the Union Address	6.542153401	2.037715241	6.677451021	2.843293296	5.704283733	1.912909635	7.354891962	5.322370189
Â Statement on the School Shooting in Parkland, Florida	2.9920888	0.813367309	1.00486451	0.269801115	0.608479843	0.322690119	1.178707732	0.210473468
Acceptance of Nobel Peace Prize	4.758831169	1.422975131	5.82550043	1.430321848	4.478371346	1.641381181	2.640313581	1.819090711
Address on the End of the Combat Mission in Iraq	8.155330997	1.691314949	7.667989678	1.361146153	5.49456147	0.628898029	10.50414184	2.055027547
Address to Joint Session of Congress	4.9351429	5.342692078	7.838442766	5.892863131	5.671693566	3.074978079	3.903494206	4.252325541
Address to the British Parliament	5.674973282	2.454154125	7.038931679	3.283739244	5.457026752	3.452270368	5.405139594	4.034694927
Address to the Nation on Syria	4.305840479	0.795594991	4.800881627	0.217318401	2.957479046	0.775431137	3.079670094	1.237418578
Address to the People of Israel	7.085846103	3.313807081	7.320365566	4.99753646	6.331238035	3.432219761	7.108065671	2.564288504
Address to the United Nations	7.015862082	2.984388881	5.181875025	3.011094164	6.096960973	3.720081059	7.322388158	2.842313463
Address to the United Nations General Assembly	6.721703841	2.526866975	5.784436471	2.64398926	4.492389998	3.672296595	6.887251161	2.941851399
Press Conference After 2010 Midterm Elections	2.745031524	3.310171033	5.272619022	4.060552768	4.46633005	5.786469664	4.063673601	5.981758197
Remarks at Memorial for Victims of the Tucson, AZ Shooting	5.802572905	1.113029764	8.564222699	1.125870427	5.884376644	0.780903733	6.428333134	1.055564145
Remarks at the House and Senate Republican Member Conference	6.888972662	2.839635082	9.544843986	3.953196336	9.436467139	1.650405975	4.946470915	1.707823868
Remarks on Education and the Economy	6.080202389	2.56613099	9.827162791	2.883912243	6.818754993	2.655606435	9.641599528	3.90562043
Remarks on Immigration Reform	5.335466353	1.119629129	4.969298584	0.755789964	7.157571296	1.852556536	6.961344572	1.749788411
Remarks on Nominating Judge Sonia Sotomayor to the U.S. Supreme Court	4.443401662	1.255651453	3.016207951	1.10556724	3.368664354	0.983927637	3.825754438	0.827600254
Remarks on Space Exploration in the 21st Century	9.609176454	1.31293498	5.760264514	0.564323625	10.43735207	1.071519591	4.255863991	0.584204531
Remarks on the Death of Osama Bin Laden	7.061970505	1.616118281	10.34074437	3.030188146	7.346676297	0.850842771	3.98491045	1.119301963
Remarks on Wall Street Reform	8.014696671	1.443684225	14.05912928	1.057181458	10.38229843	1.272891154	4.533161316	0.823681087
Remarks to the People of Cuba	6.872168031	2.294283229	8.003484881	2.04604063	6.358104612	3.228501803	6.944666698	2.984178599
Speech at the Unleashing American Energy Event	3.368503134	0.262595645	3.082670028	0.190179247	5.096108063	0.579387669	3.032053019	0.413013887
Speech on American Diplomacy in the Middle East and North Africa	7.575153751	3.062012379	6.721374876	2.120311917	6.272712999	2.287751365	7.050486229	2.094793739
Speech on Economic Mobility	9.820091716	4.820762039	7.427889712	4.783560209	6.630394816	3.968905705	6.784750154	3.307667489
Speech on Strategy in Afghanistan and Pakistan	9.544182362	3.44765135	9.476305221	2.713228209	8.651195933	3.922762763	6.187463418	2.359415694
Speech on the BP Oil Spill	3.510490848	0.378500879	2.221203086	0.239647441	4.404897458	0.49752166	3.554813837	0.432166942
State of the Union Address	7.515695618	5.302998106	7.554330624	5.586696417	6.753576158	5.925256126	6.811543347	6.073715837

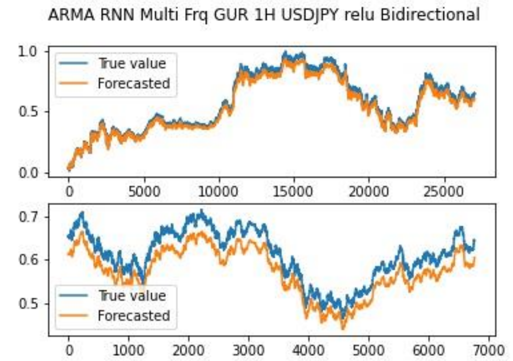
Appendix D:

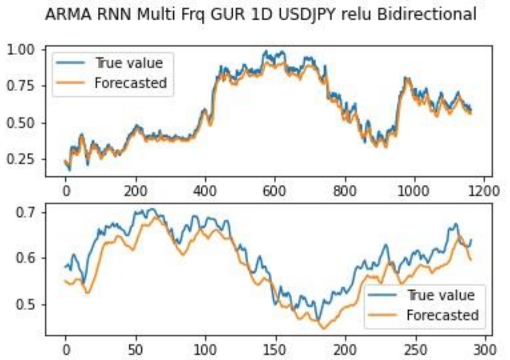
Upper plot represents in-sample data sets and lower plots shows out of sample performance.

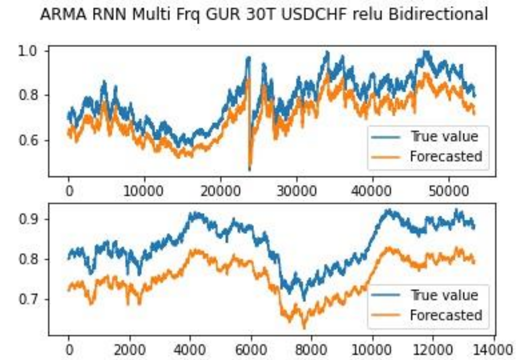


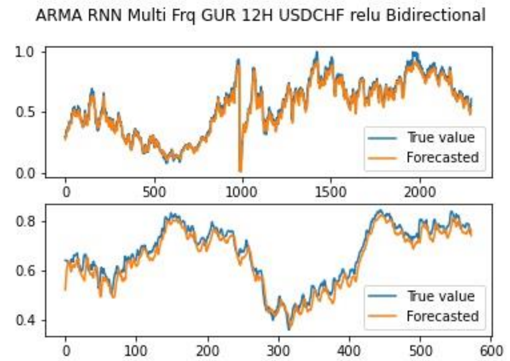


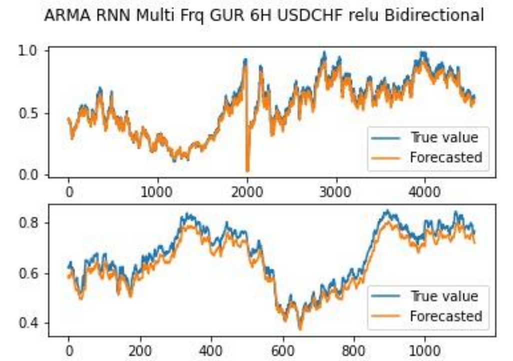


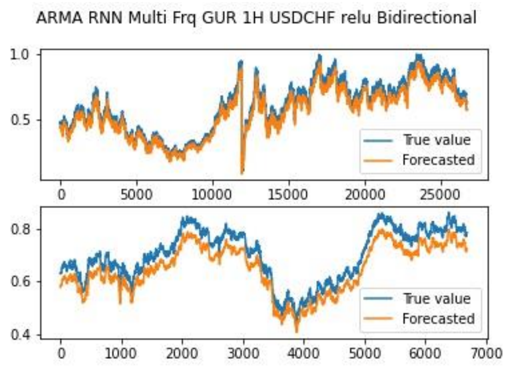


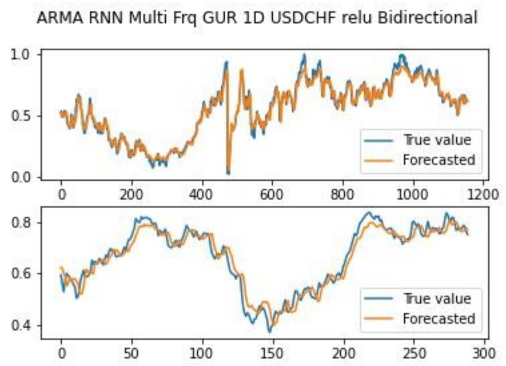









ARMA RNN Multi Frq GUR 1H USDCHF relu Bidirectional
True value
Forecasted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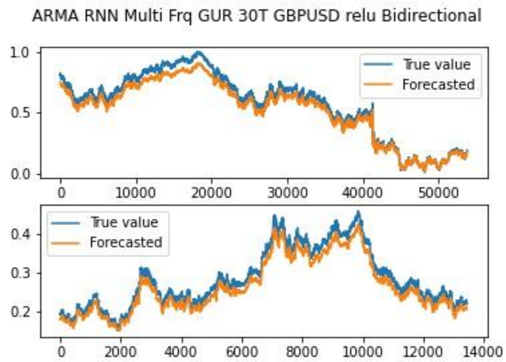
True value
Forecasted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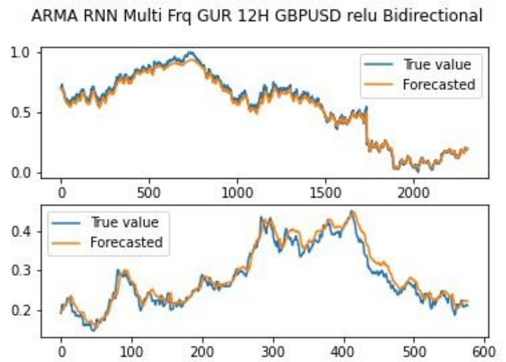
True value
Forecasted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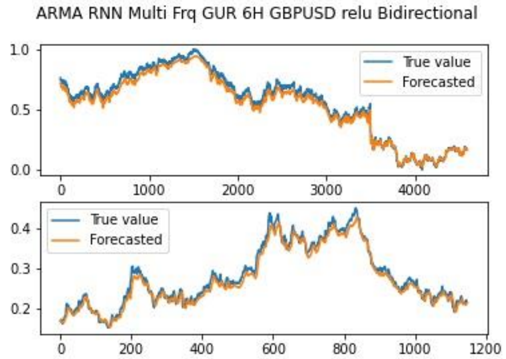
True value
Forecasted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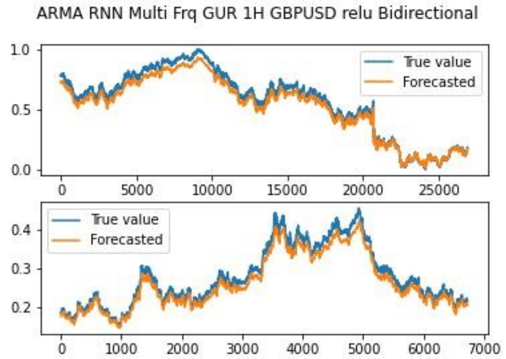
True value
Forecasted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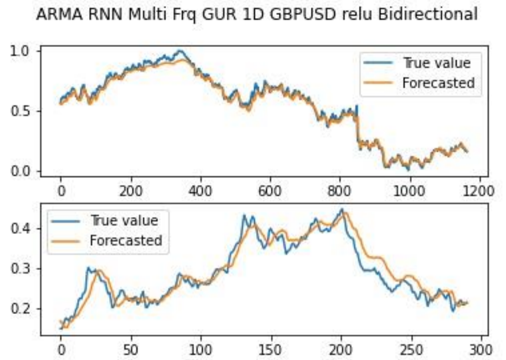
True value
Forecasted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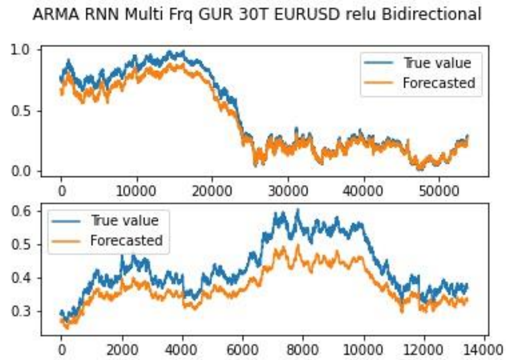
True value
Forecasted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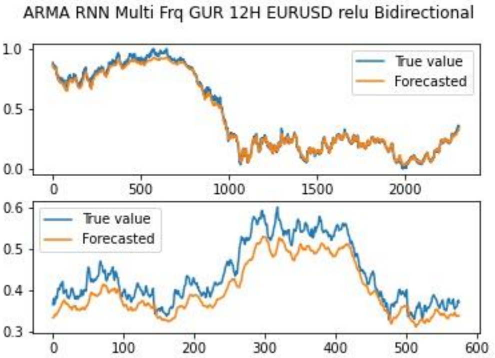
True value
Forecasted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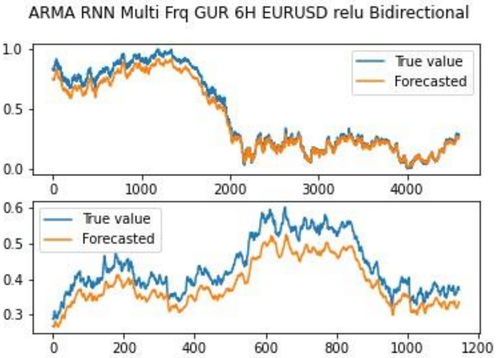
True value
Forecasted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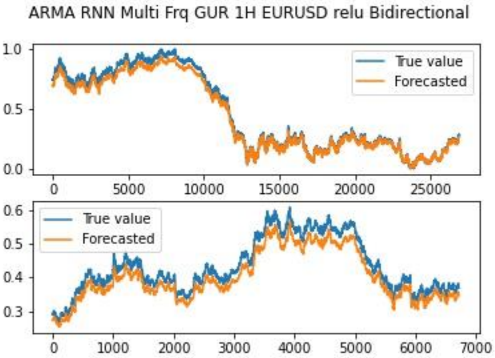
Forecasted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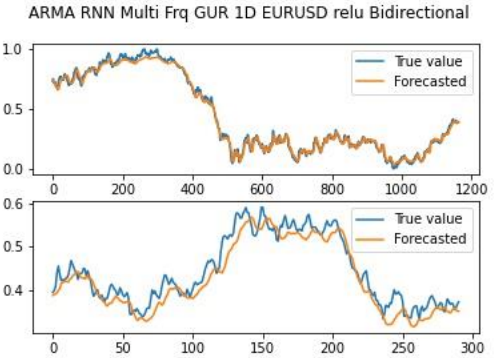
True value
Forecasted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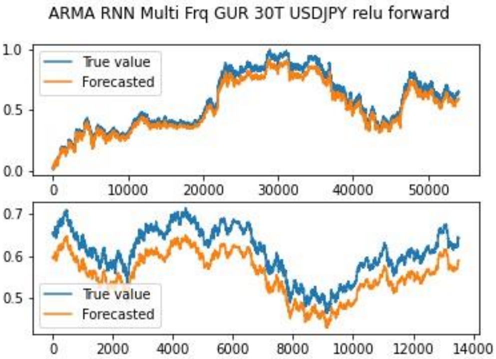
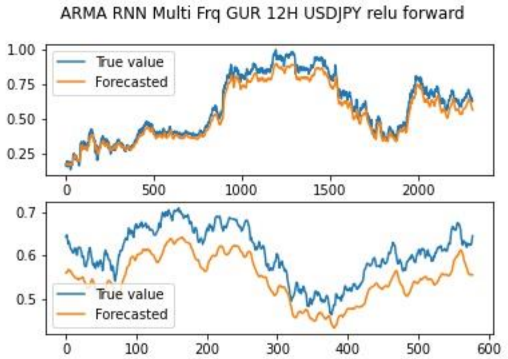
True value
Forecasted


ARMA RNN Multi Frq GUR 30T USDJPY relu forward
True value
Forecasted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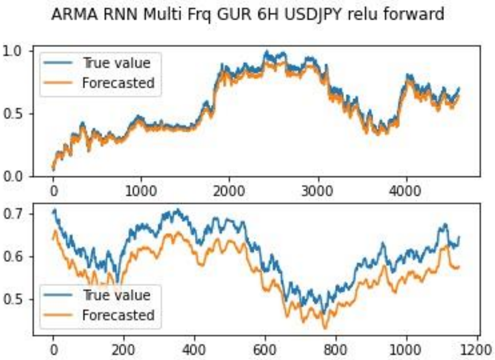
True value
Forecasted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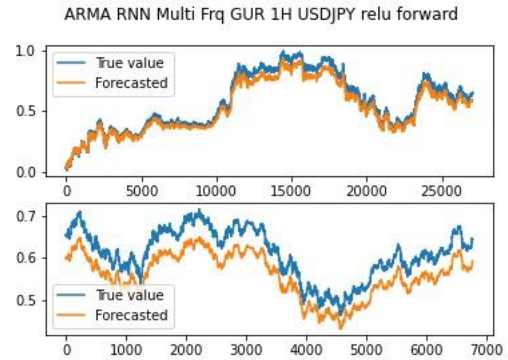
True value
Forecasted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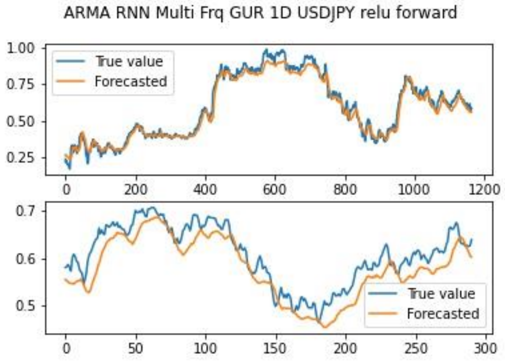
Forecasted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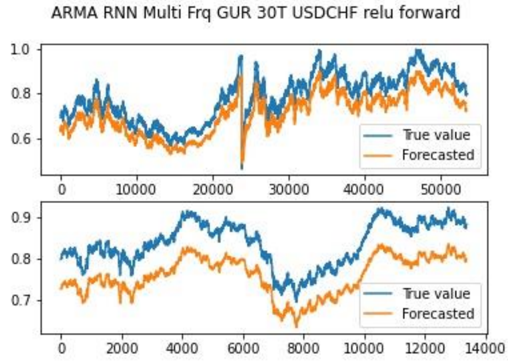
True value
Forecasted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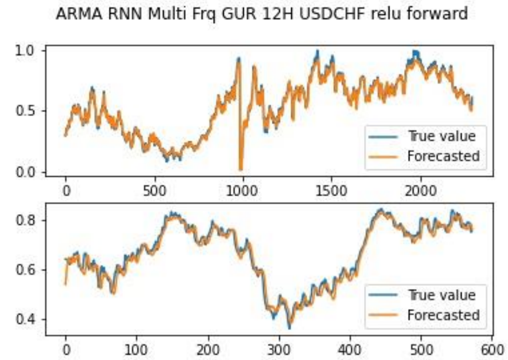
True value
Forecasted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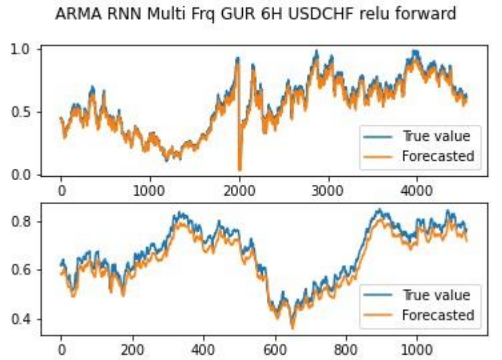
True value
Forecasted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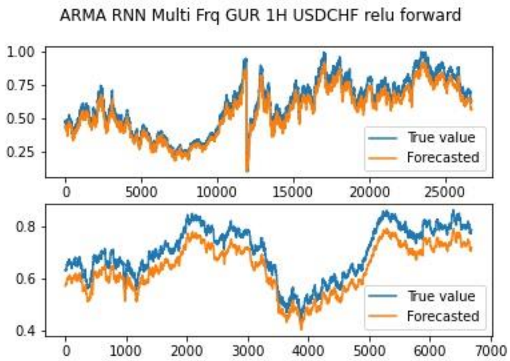
True value
Forecasted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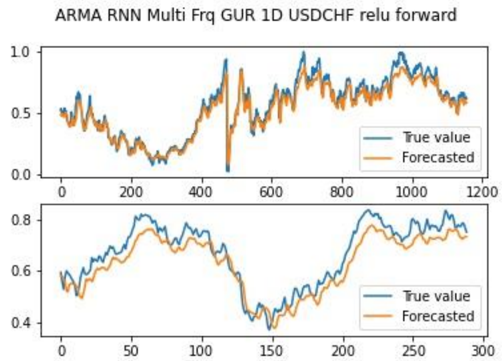
True value
Forecasted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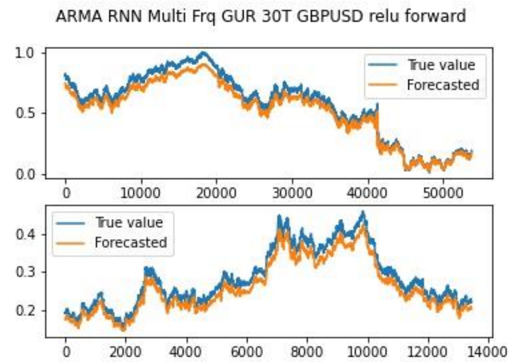
True value
Forecasted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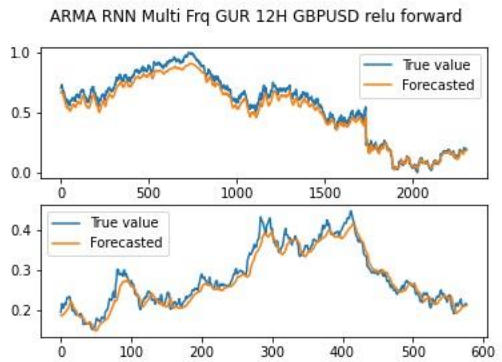
True value
Forecasted


ARMA RNN Multi Frq GUR 12H GBPUSD relu forward
True value
Forecasted

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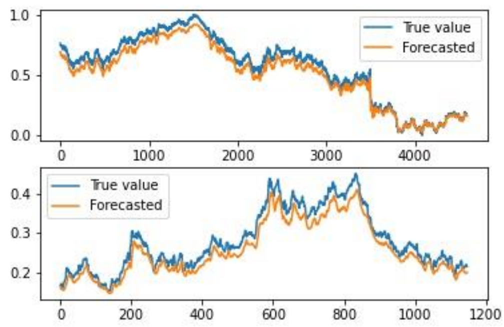

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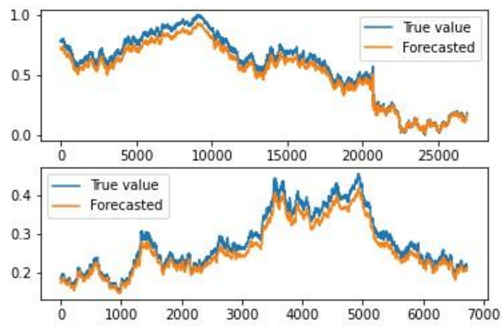

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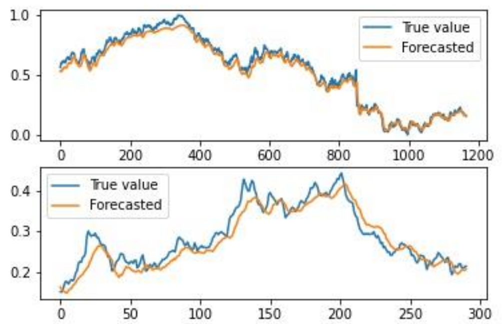

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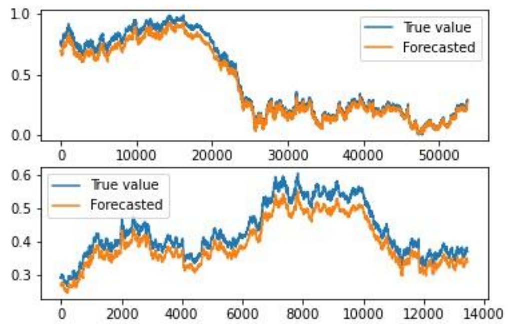

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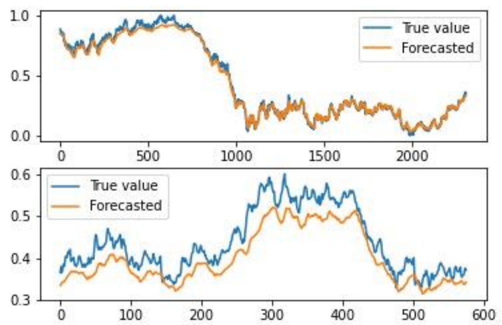

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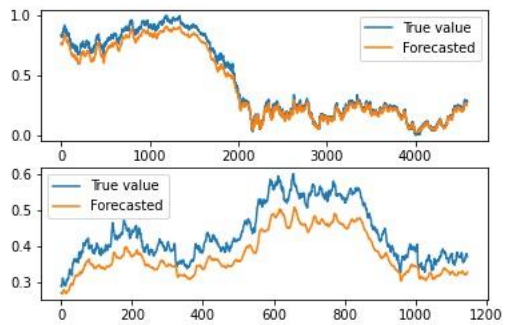

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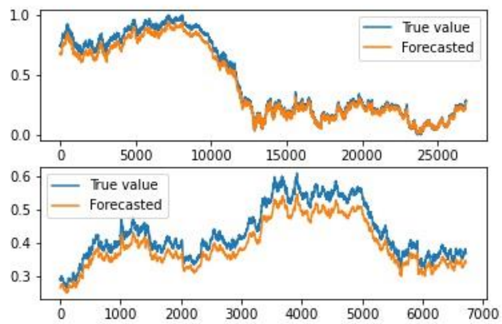

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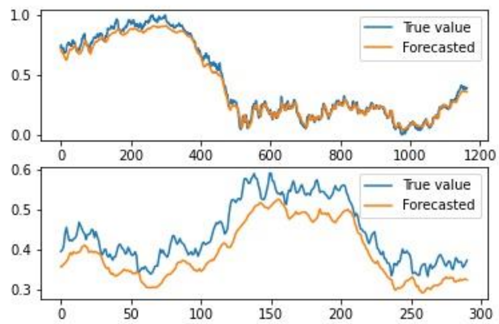
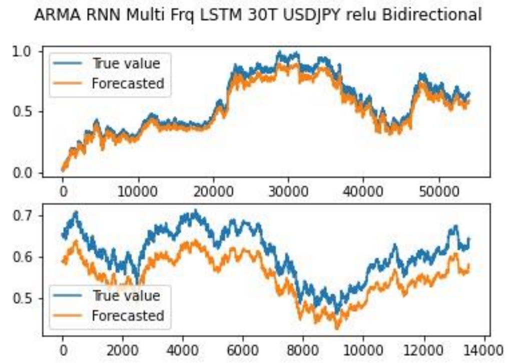
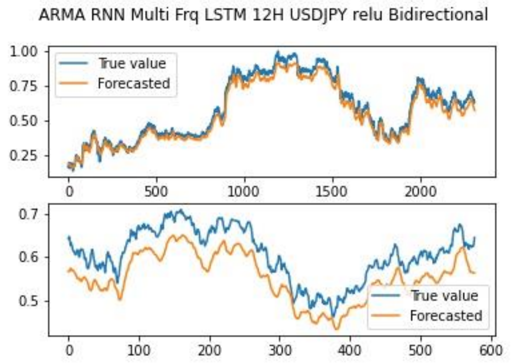



ARMA RNN Multi Frq LSTM 30T USDJPY relu Bidirectional
True value
Forecasted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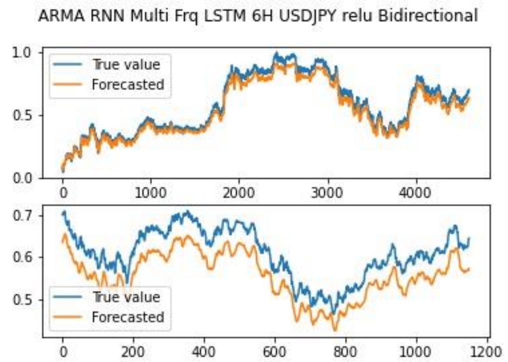
True value
Forecasted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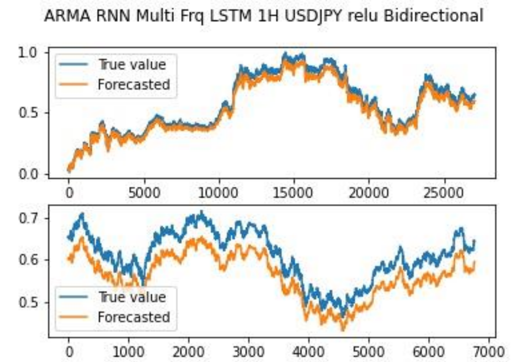
True value
Forecasted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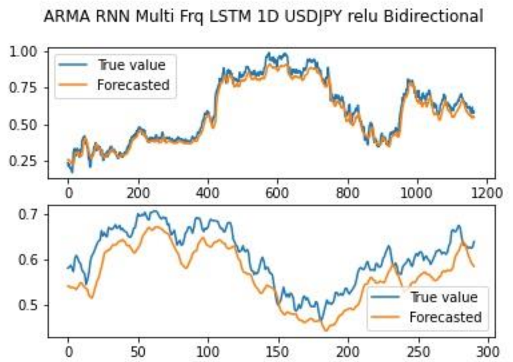
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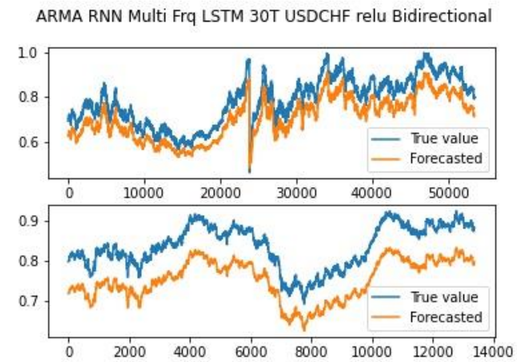
Forecasted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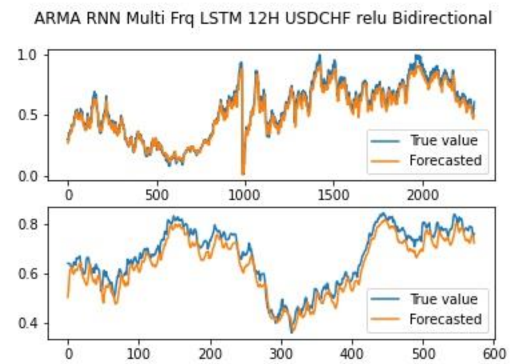
True value
Forecasted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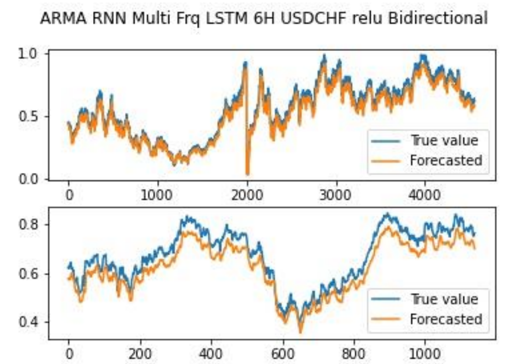
True value
Forecasted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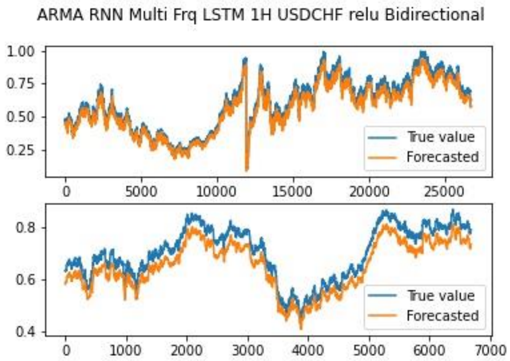
Forecasted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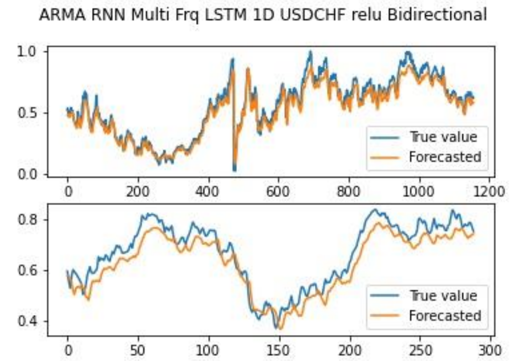
True value
Forecasted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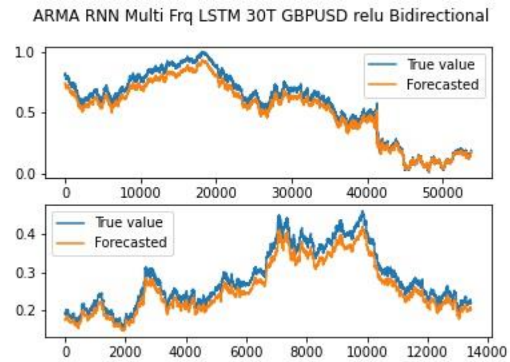
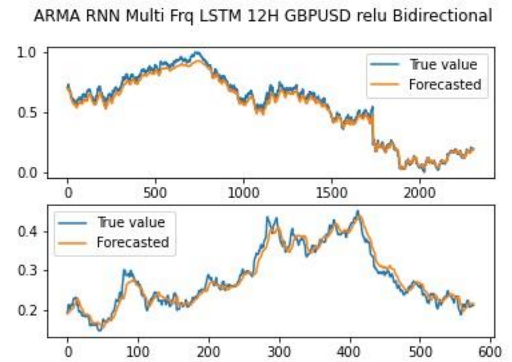
True value
Forecasted


ARMA RNN Multi Frq LSTM 30T GBPUSD relu Bidirectional
True value
Forecasted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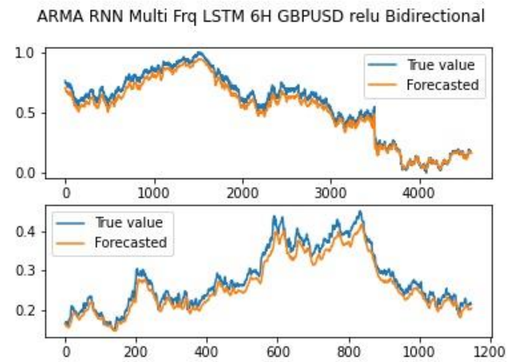
True value
Forecasted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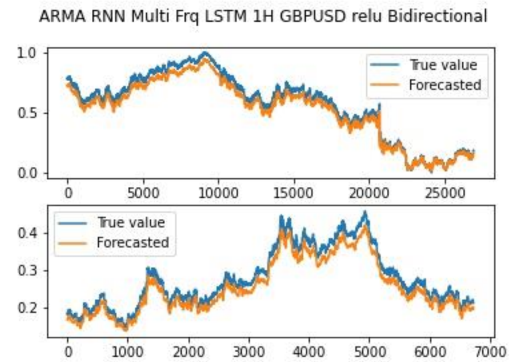
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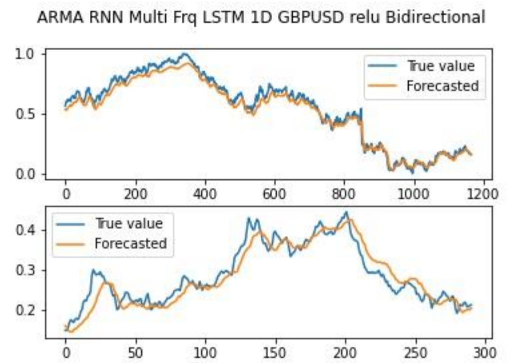
True value
Forecasted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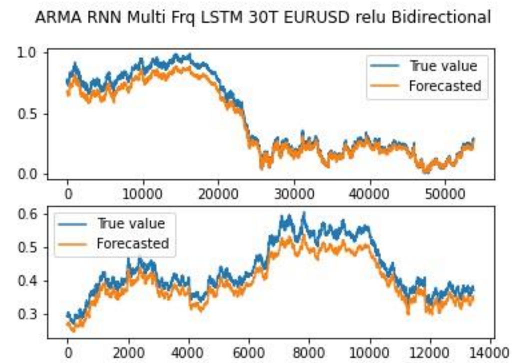
True value
Forecasted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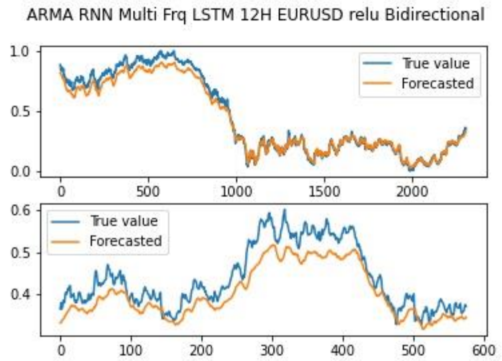
True value
Forecasted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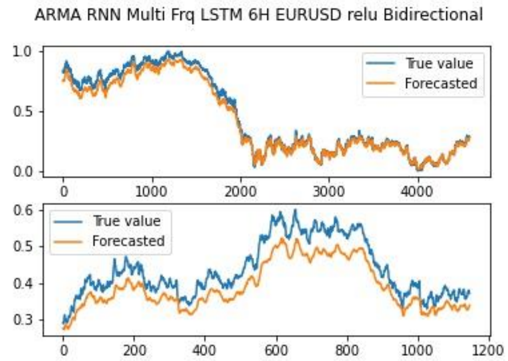
True value
Forecasted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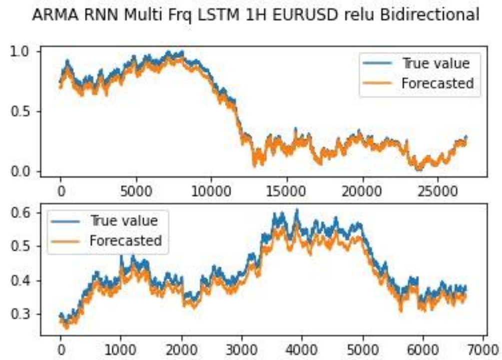
Forecasted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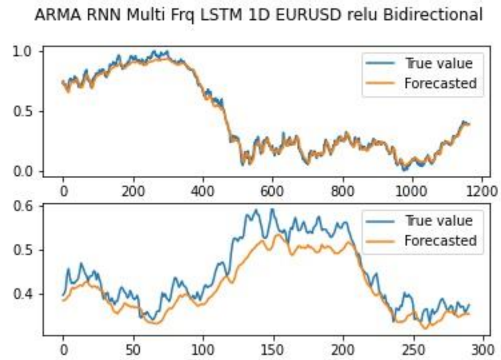
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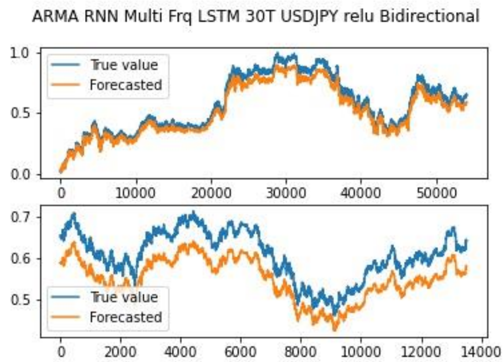
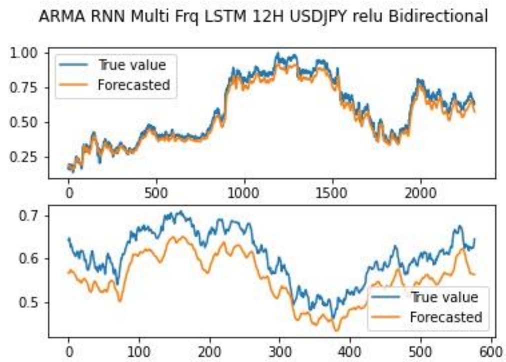
Forecasted


ARMA RNN Multi Frq LSTM 30T USDJPY relu Bidirectional
True value
Forecasted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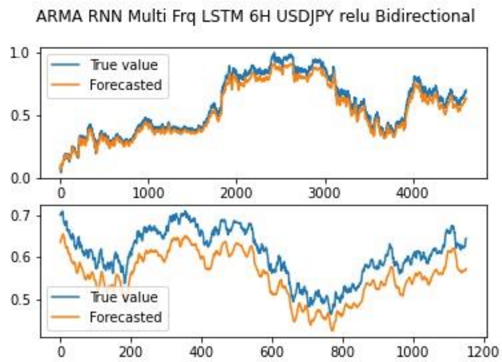
True value
Forecasted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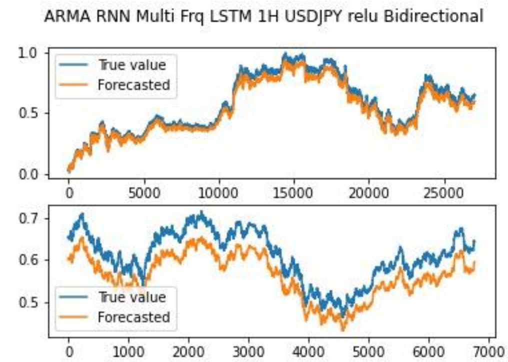
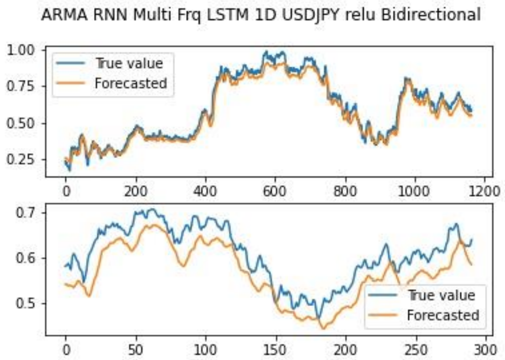
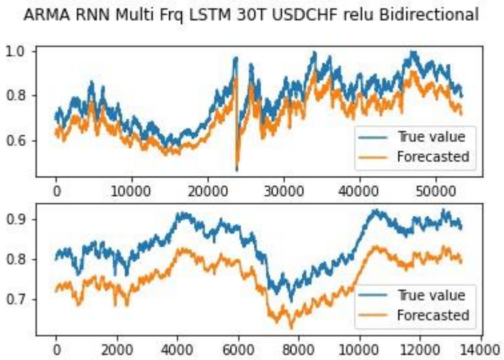
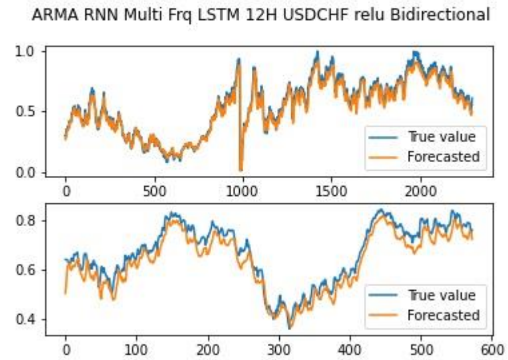
True value
Forecasted


ARMA RNN Multi Frq LSTM 1H USDJPY relu Bidirectional
True value
Forecasted


ARMA RNN Multi Frq LSTM 1D USDJPY relu Bidirectional
True value
Forecasted


ARMA RNN Multi Frq LSTM 30T USDCHF relu Bidirectional
True value
Forecasted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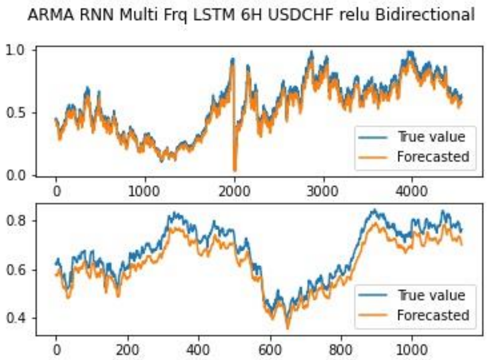
True value
Forecasted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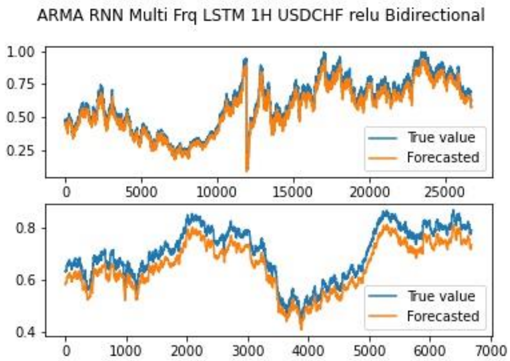
True value
Forecasted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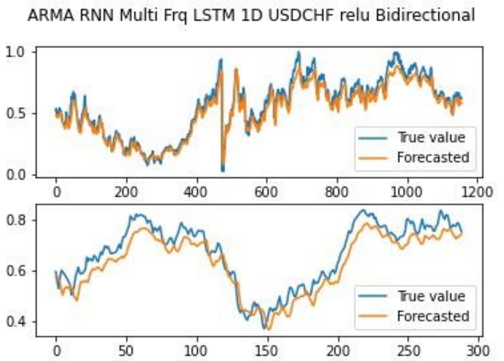
True value
Forecasted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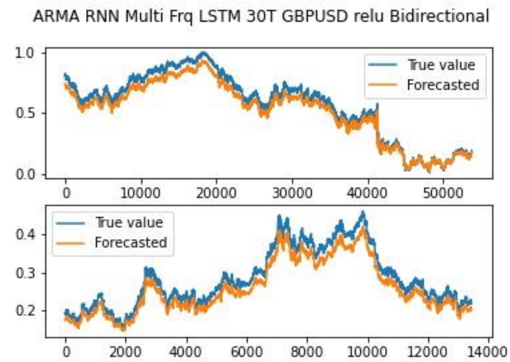
True value
Forecasted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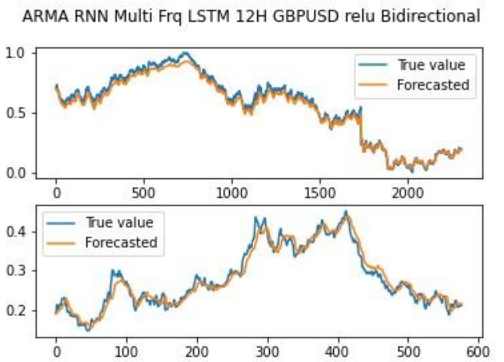
True value
Forecasted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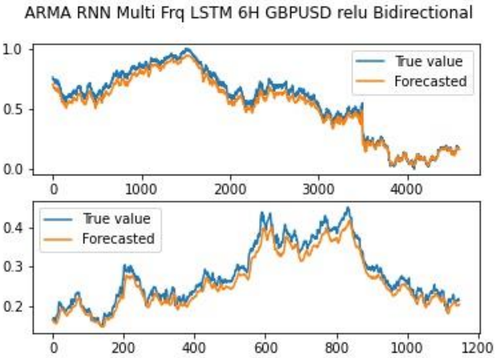
True value
Forecasted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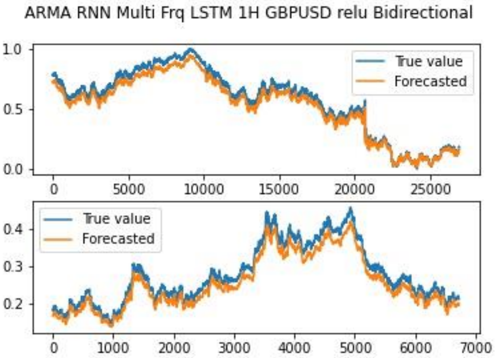
Forecasted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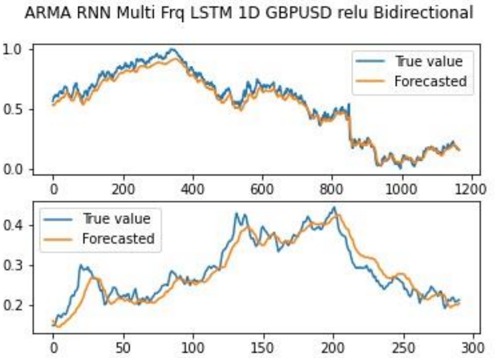
True value
Forecasted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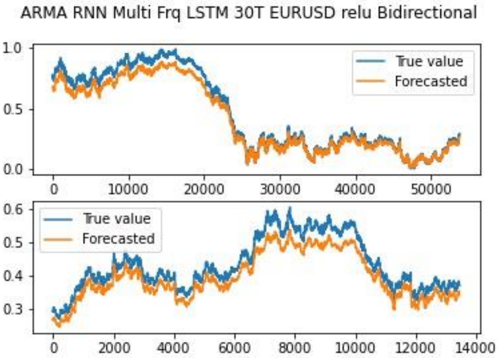
True value
Forecasted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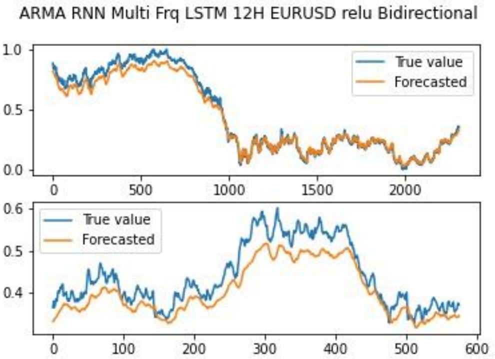
True value
Forecasted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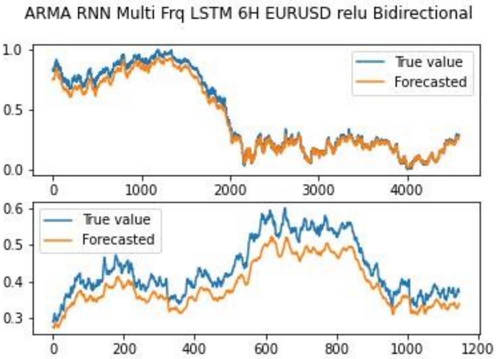
True value
Forecasted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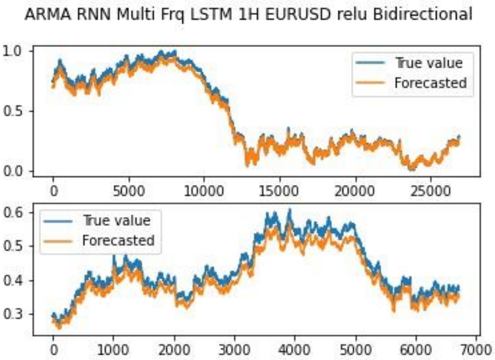
True value
Forecasted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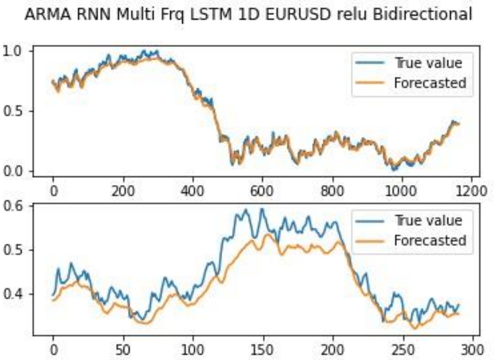
Forecasted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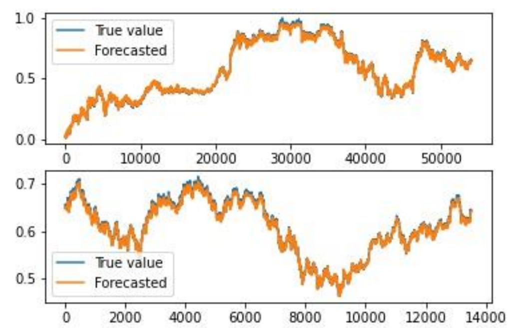
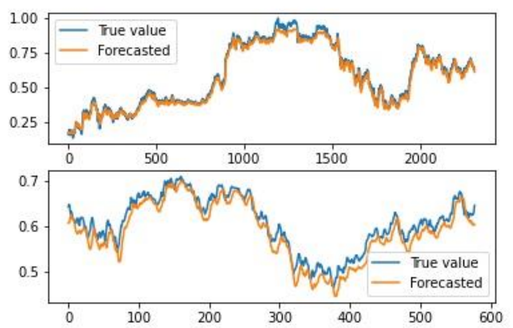
True value
Forecasted



ARMA RNN Multi Frq GUR 30T USDJPY tanh Bidirectional



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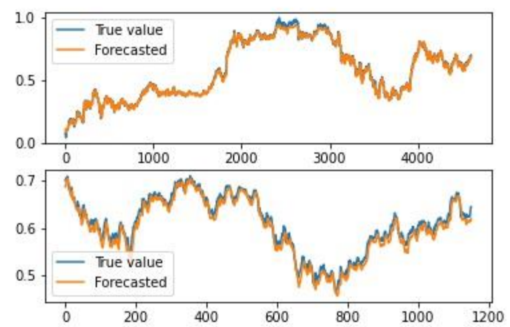

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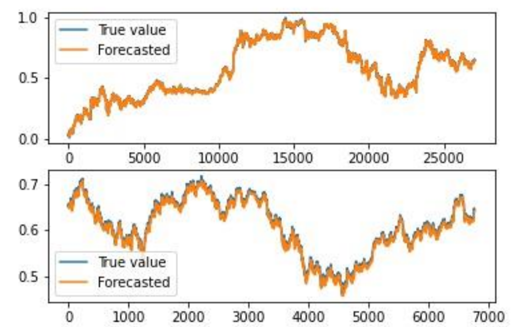

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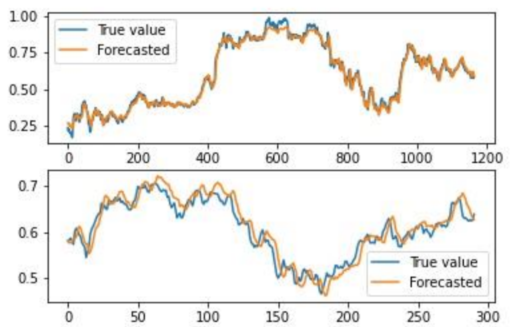

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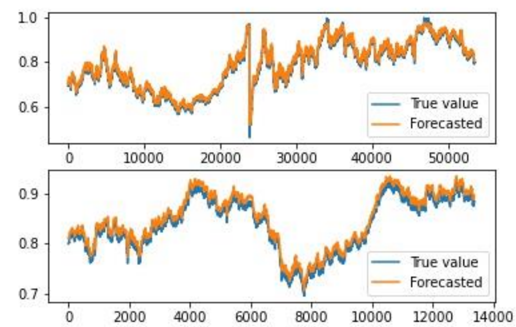

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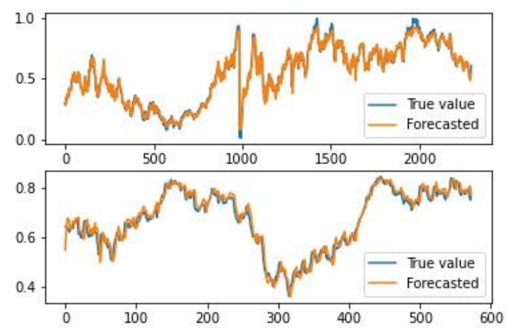

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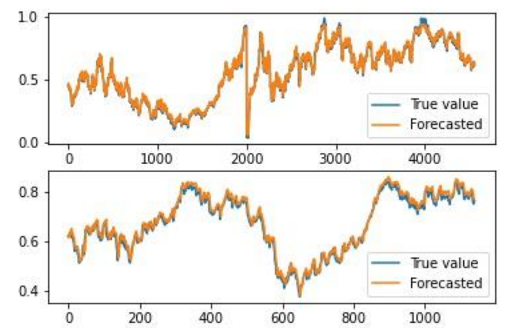

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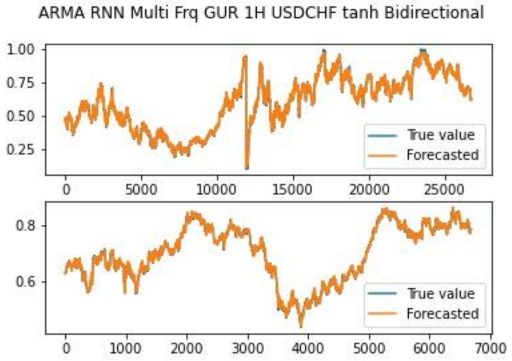
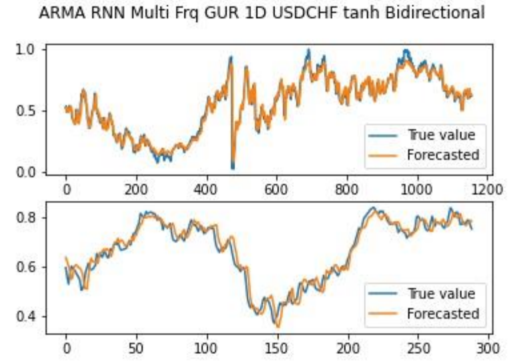

ARMA RNN Multi Frq GUR 1H USDCHF tanh Bidirectional
True value
Forecasted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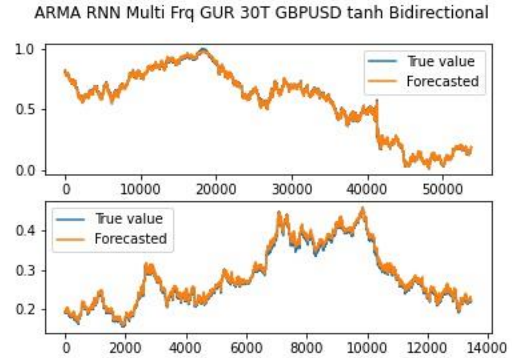
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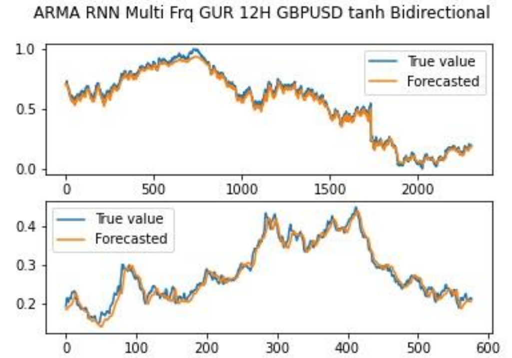
Forecasted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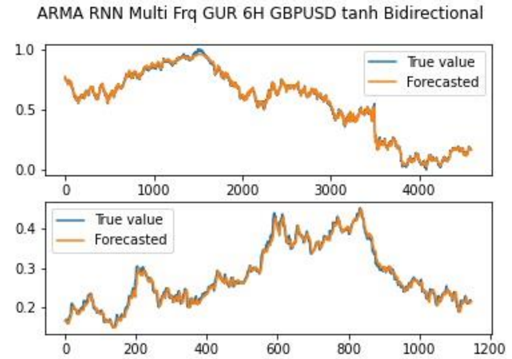
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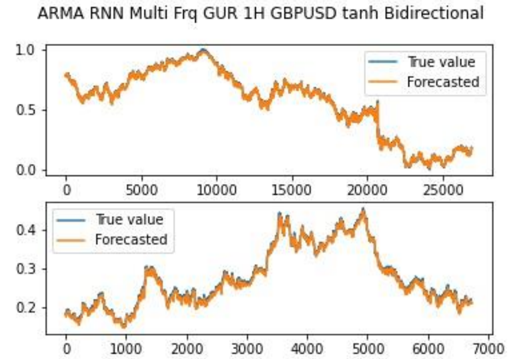
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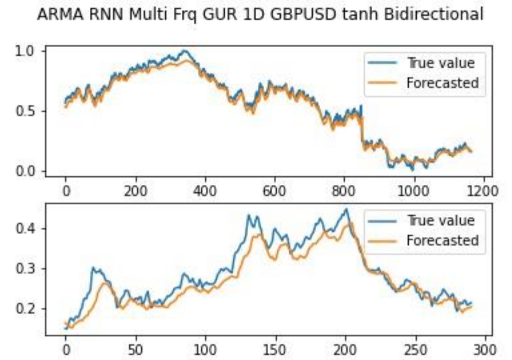
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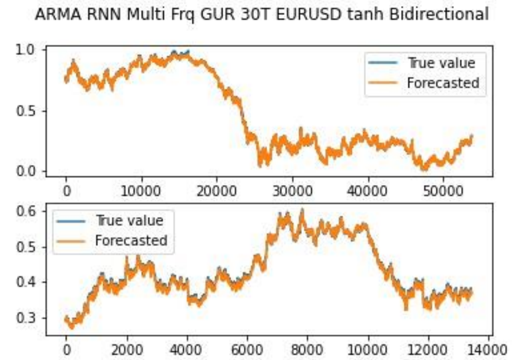
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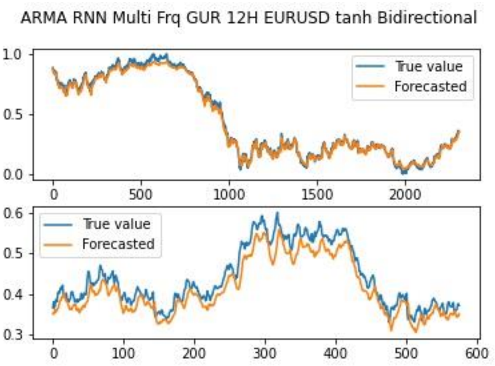
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Forecasted
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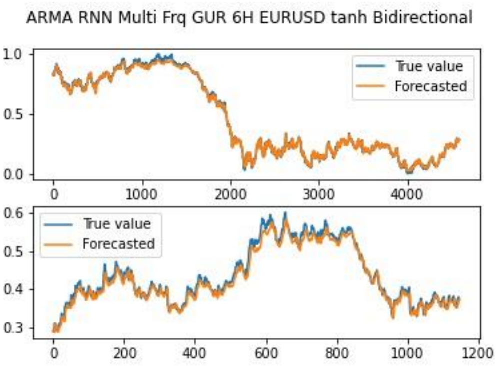
Forecasted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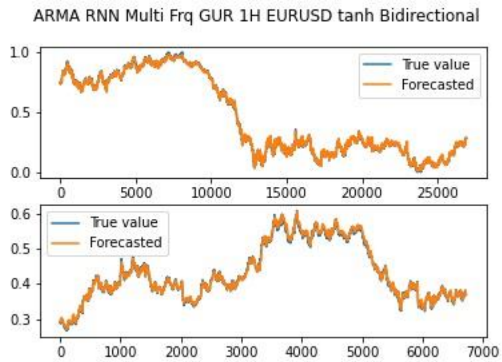
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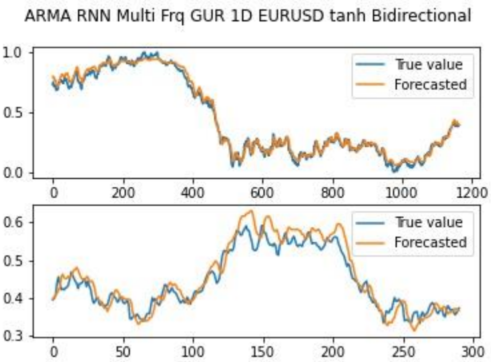
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Forecasted
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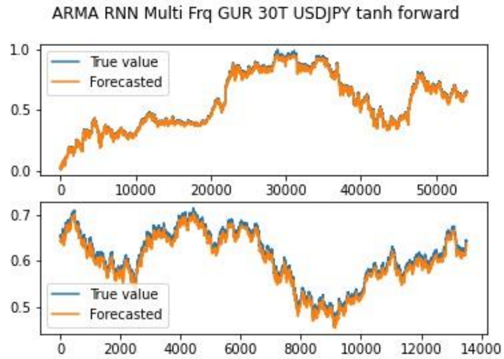
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Forecasted
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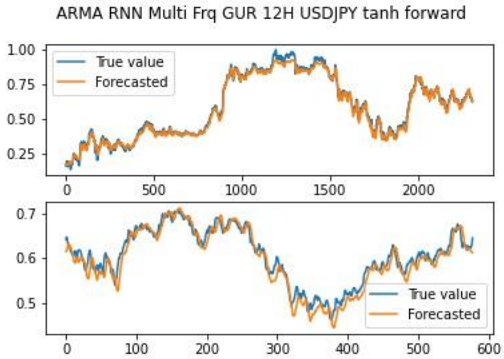
Forecasted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Forecasted
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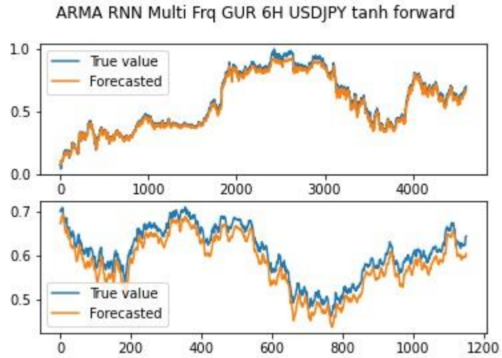
Forecasted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Forecasted
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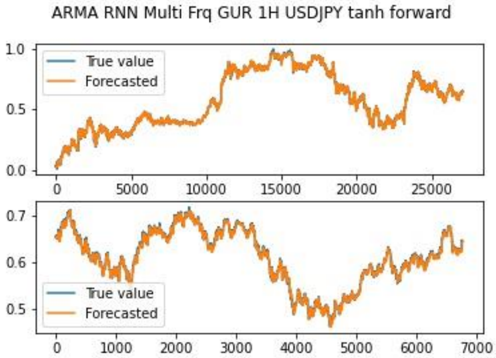
Forecasted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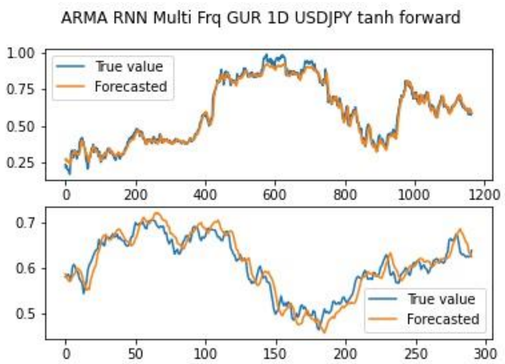
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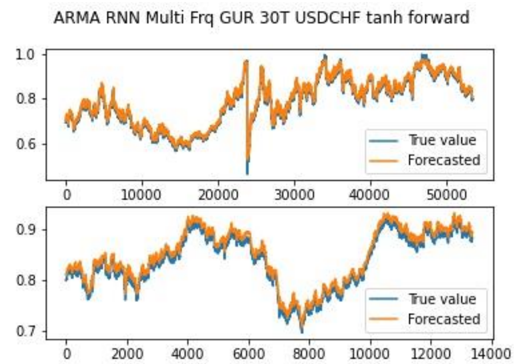
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Forecasted
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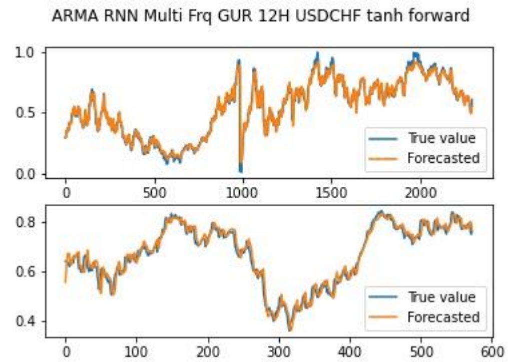
Forecasted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Forecasted
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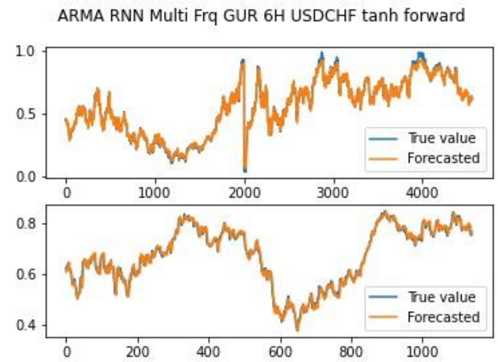
Forecasted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Forecasted
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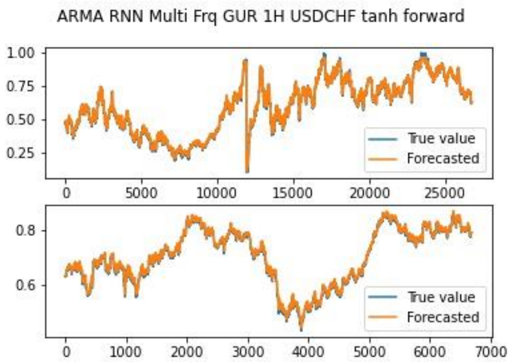
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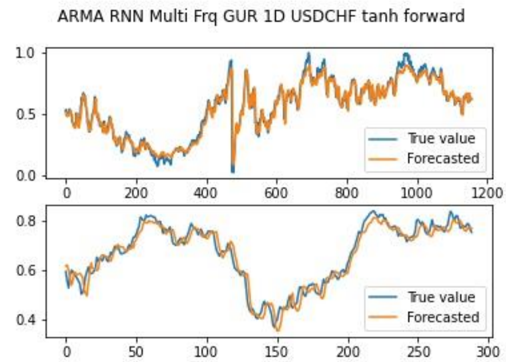
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Forecasted
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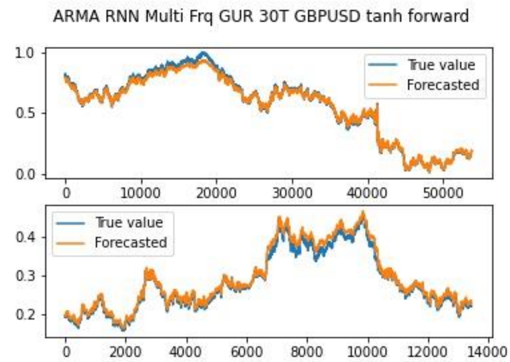
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Forecasted
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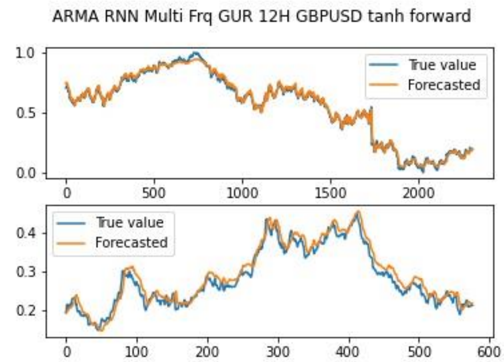
Forecasted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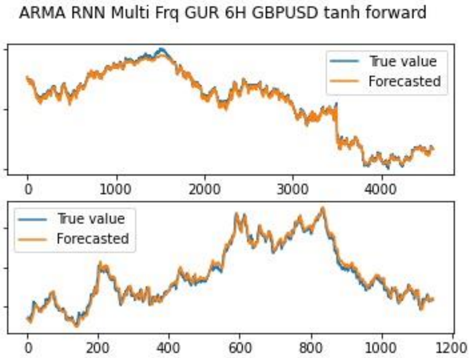
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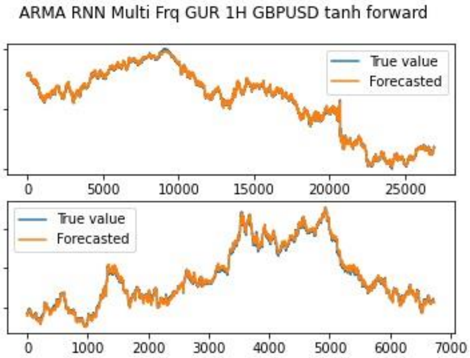
Forecasted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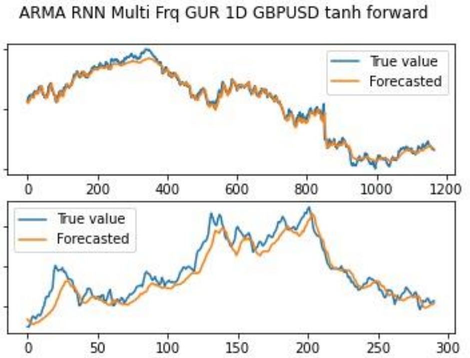
Forecasted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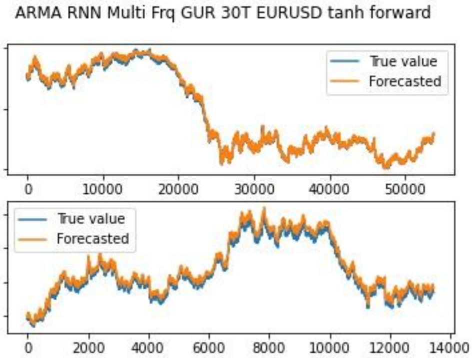
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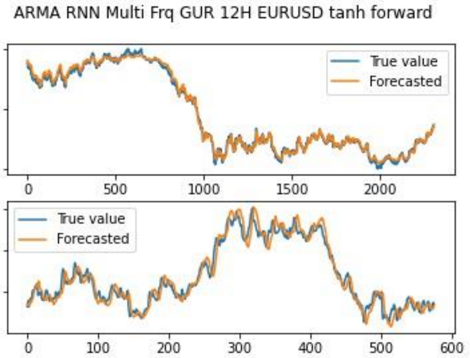
Forecasted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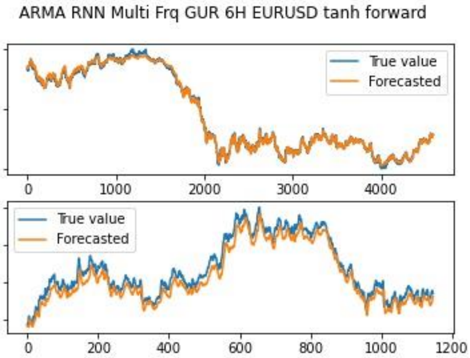
Forecasted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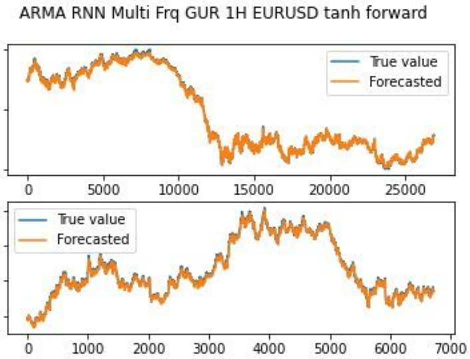
Forecasted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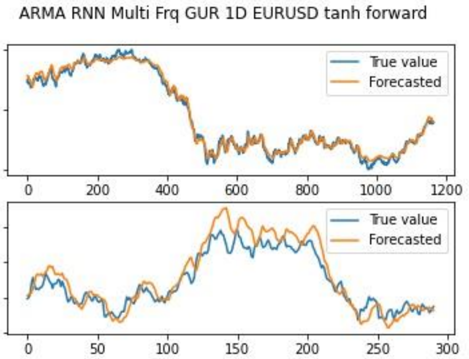
True value
Forecasted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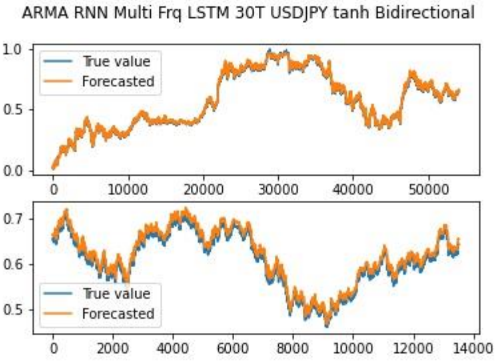
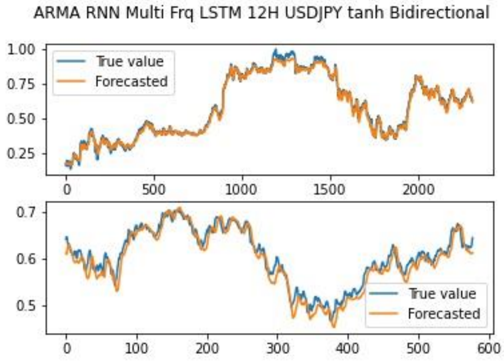
True value
Forecasted


ARMA RNN Multi Frq LSTM 30T USDJPY tanh Bidirectional
True value
Forecasted
True value
Forecasted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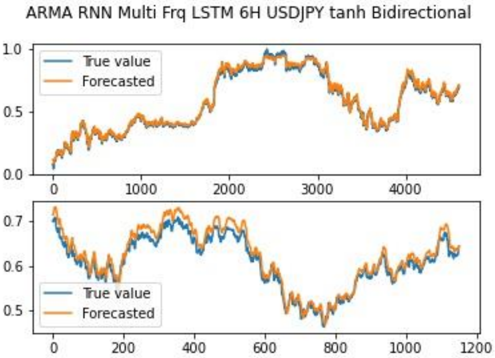
Forecasted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Forecasted
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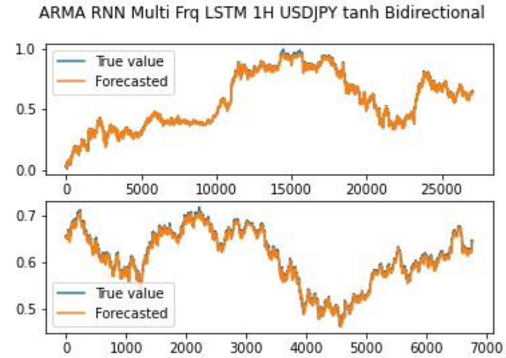
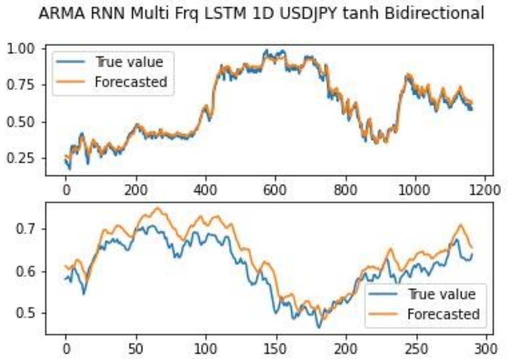
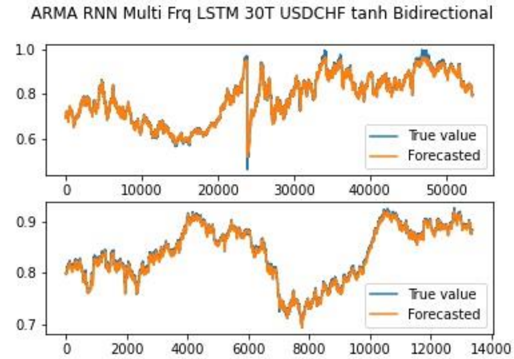
Forecasted


ARMA RNN Multi Frq LSTM 1H USDJPY tanh Bidirectional
True value
Forecasted
True value
Forecasted


ARMA RNN Multi Frq LSTM 1D USDJPY tanh Bidirectional
True value
Forecasted
True value
Forecasted


ARMA RNN Multi Frq LSTM 30T USDCHF tanh Bidirectional
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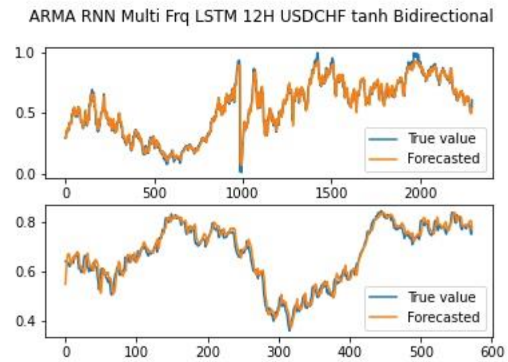
Forecasted
True value
Forecasted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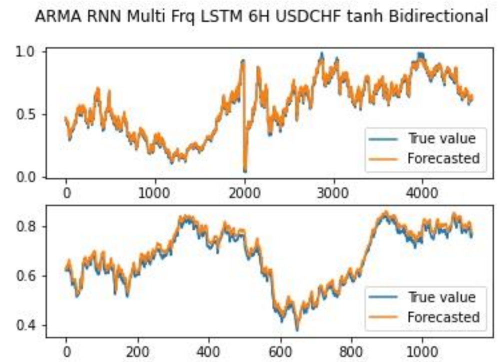
Forecasted
True value
Forecasted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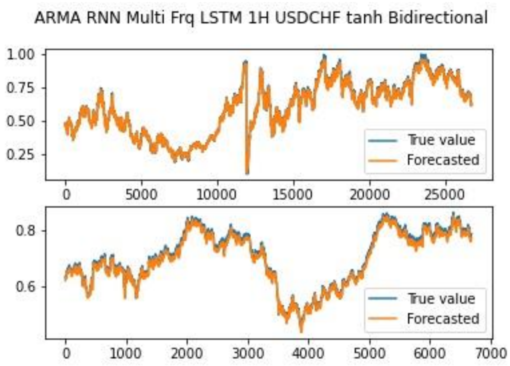
Forecasted
True value
Forecasted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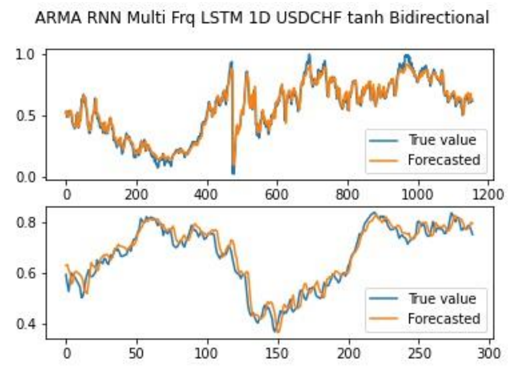
Forecasted
True value
Forecasted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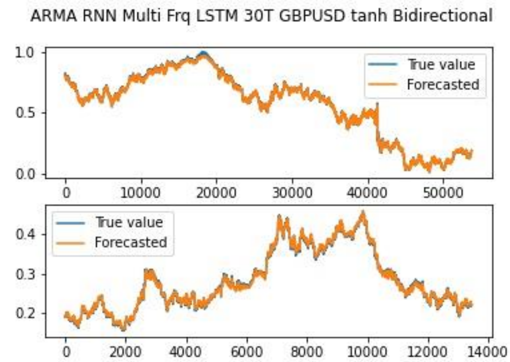
Forecasted
True value
Forecasted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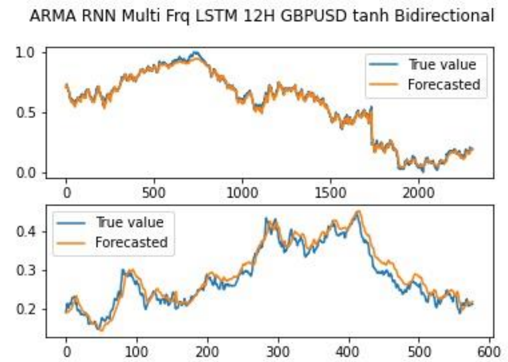
Forecasted
True value
Forecasted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Forecasted
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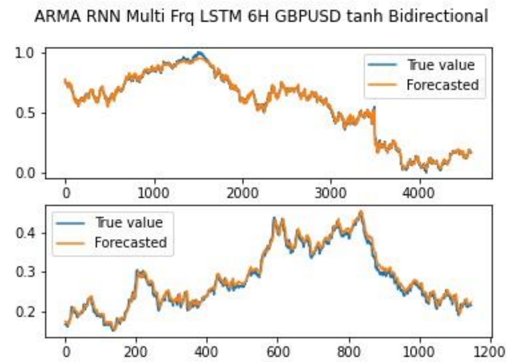
Forecasted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Forecasted
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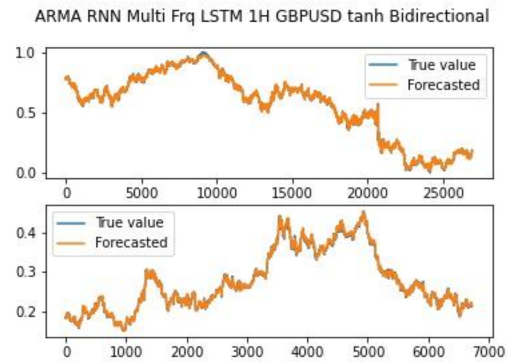
Forecasted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Forecasted
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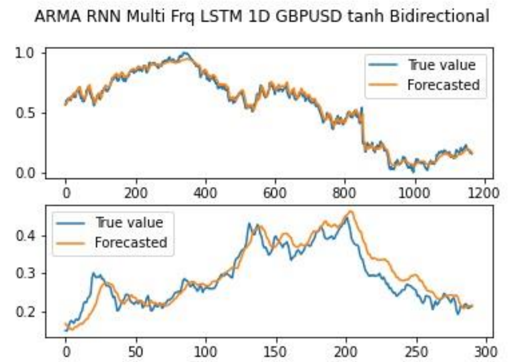
Forecasted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Forecasted
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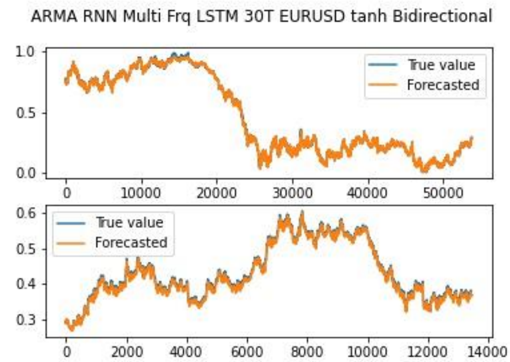
Forecasted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Forecasted
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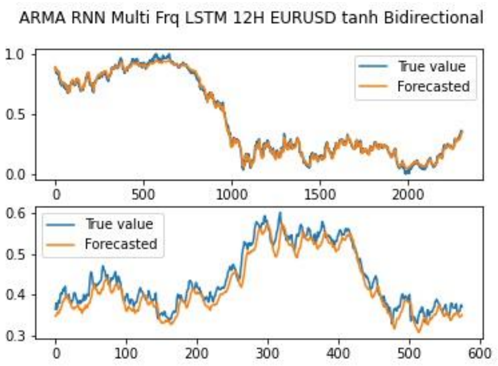
Forecasted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Forecasted
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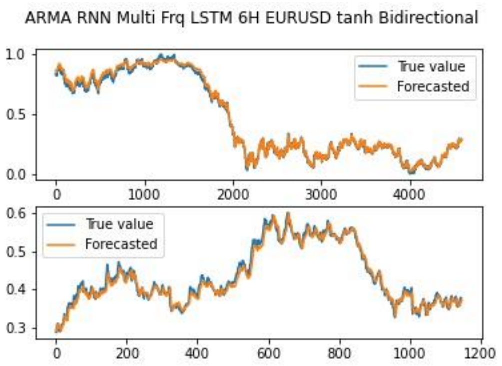
Forecasted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Forecasted
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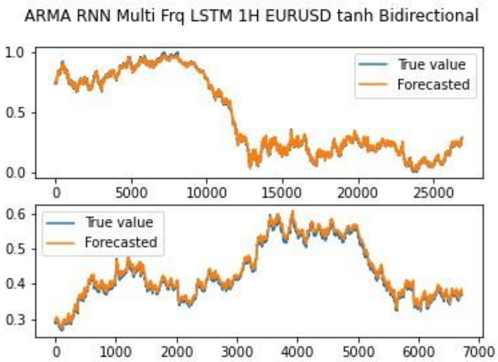
Forecasted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Forecasted
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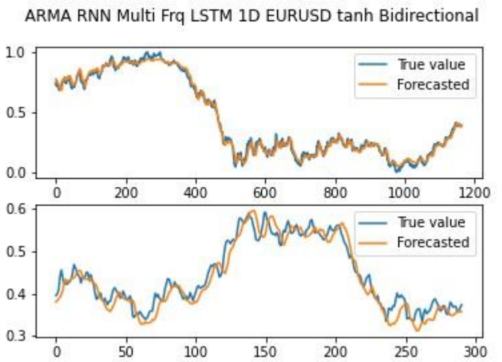
Forecasted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Forecasted
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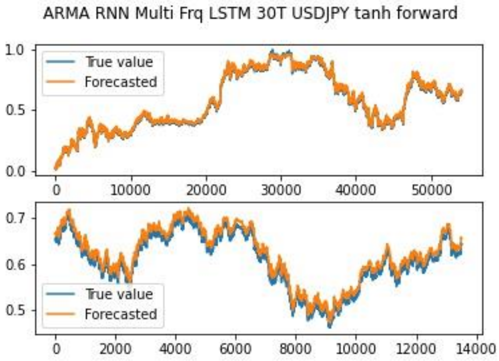
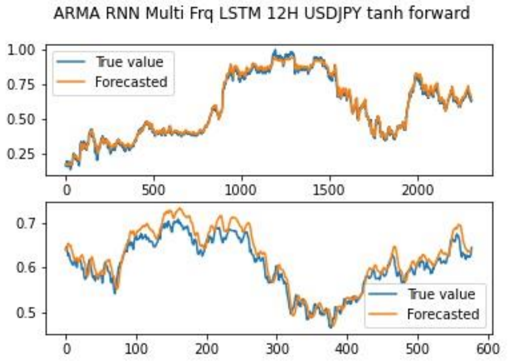
Forecasted


ARMA RNN Multi Frq LSTM 30T USDJPY tanh forward
True value
Forecasted
True value
Forecasted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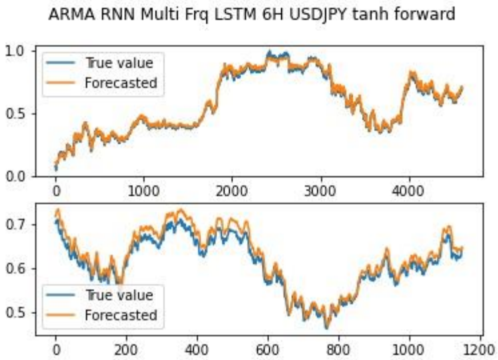
True value
Forecasted
True value
Forecasted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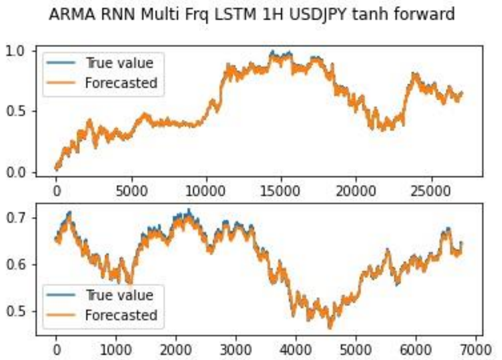
Forecasted
True value
Forecasted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True value
Forecasted
True value
Forecasted

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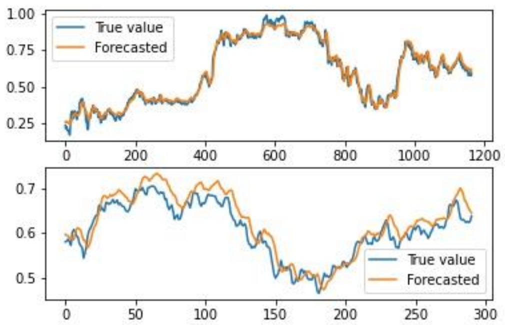

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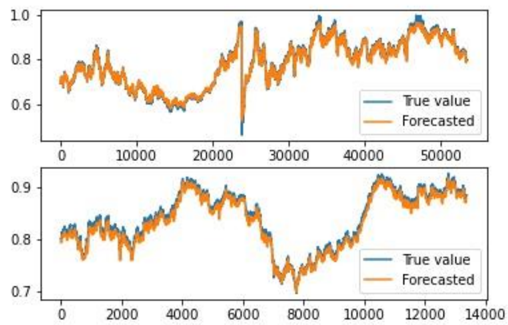
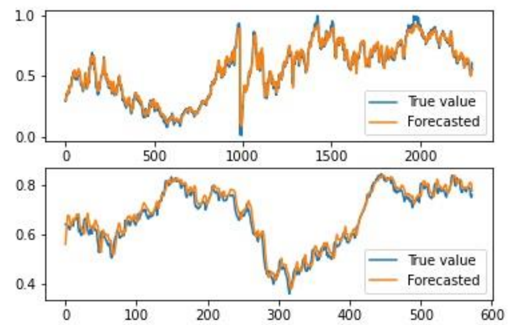


ARMA RNN Multi Frq LSTM 12H USDCHF tanh forward



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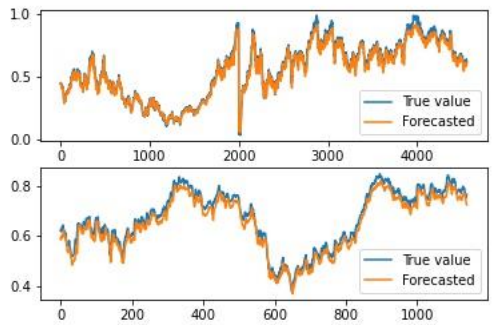

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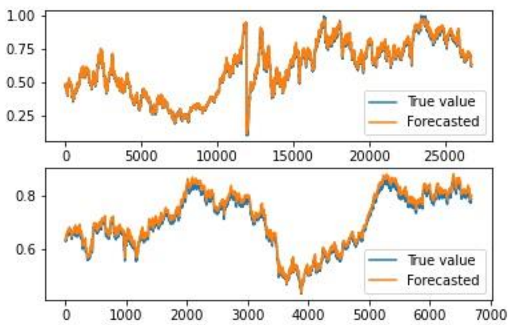
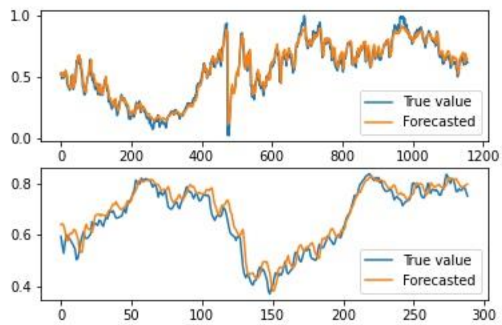
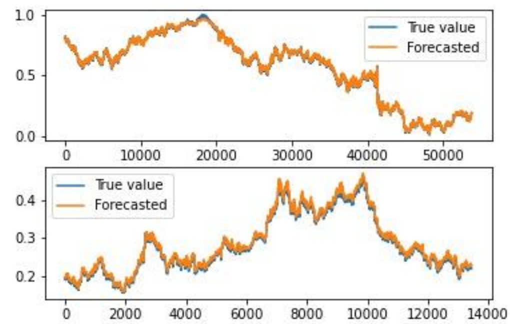


ARMA RNN Multi Frq LSTM 1D USDCHF tanh forward



ARMA RNN Multi Frq LSTM 30T GBPUSD tanh forward



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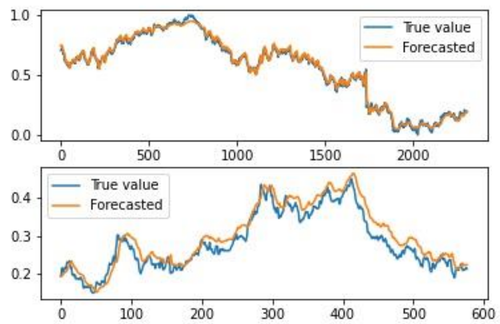

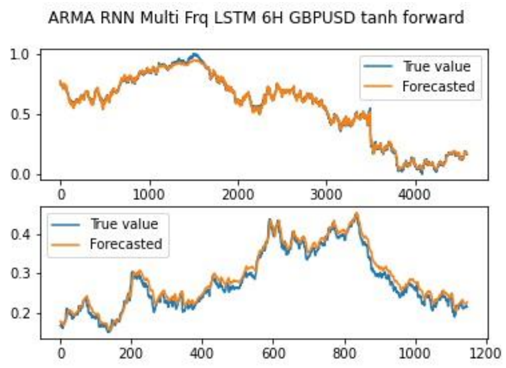
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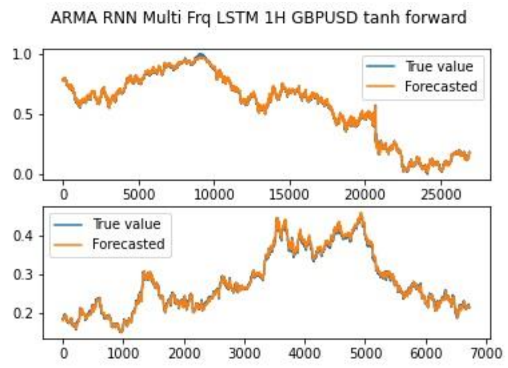
True value
Forecasted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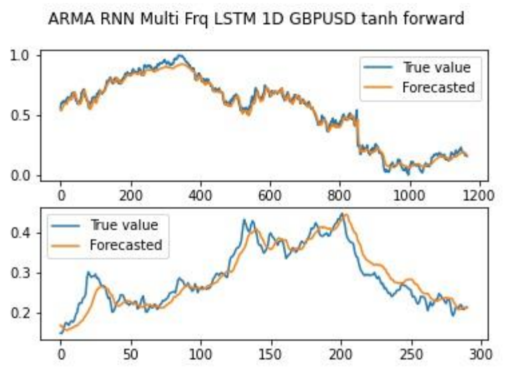
True value
Forecasted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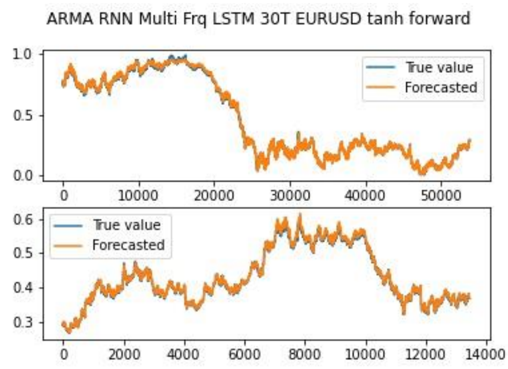
True value
Forecasted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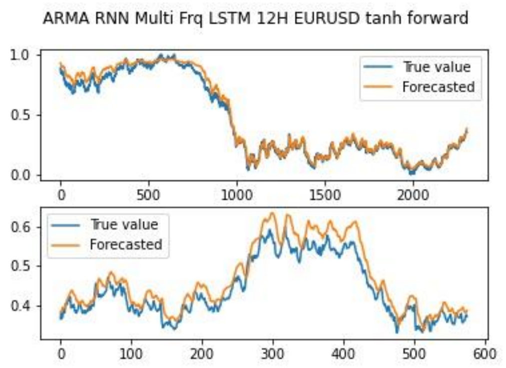
True value
Forecasted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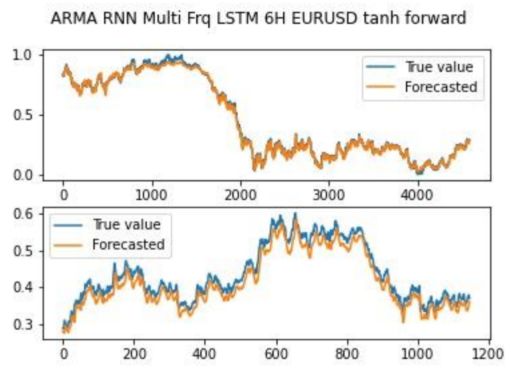
Forecasted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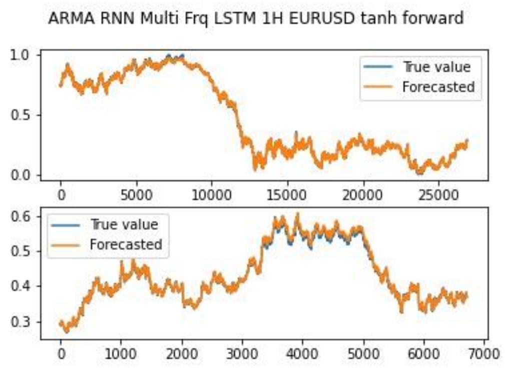
Forecasted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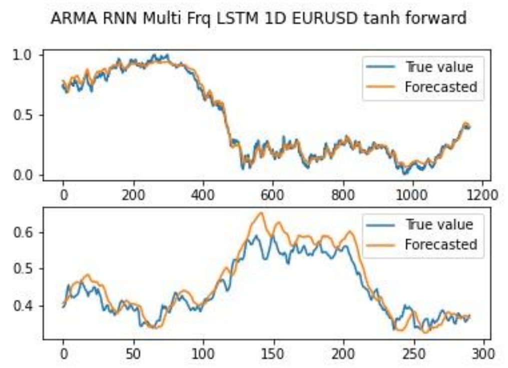
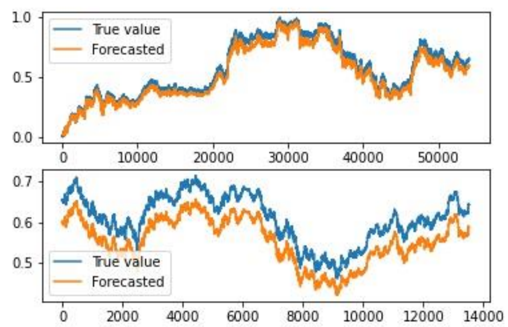
Forecasted


ARMA RNN Multi Frq LSTM 1D EURUSD tanh forward
True value
Forecasted

ARMA RNN Singel Frq GUR 30T USDJPY relu Bidirectional



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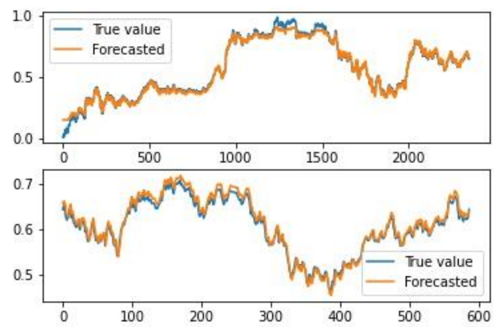

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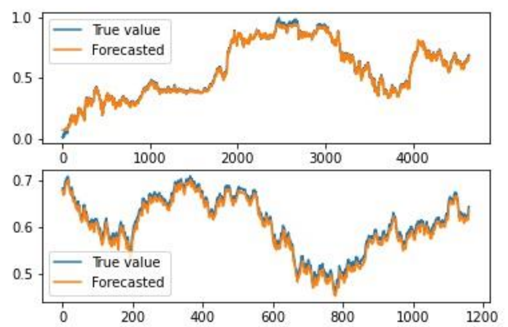

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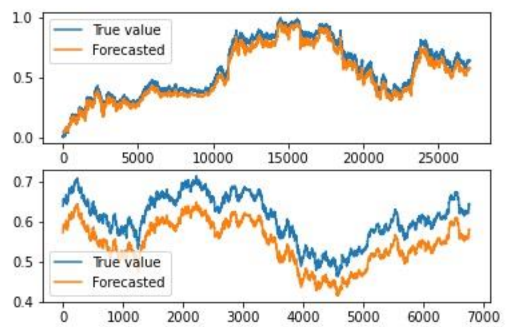

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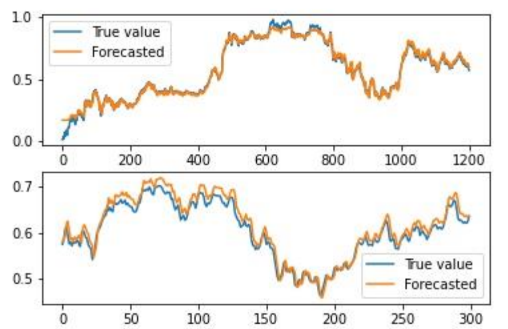

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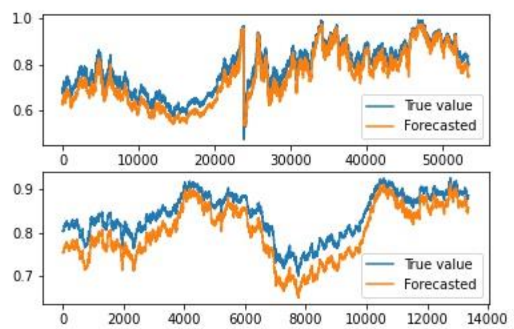

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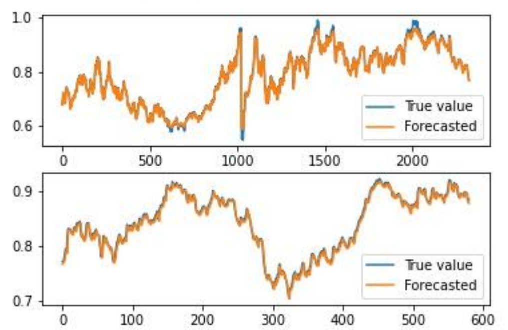

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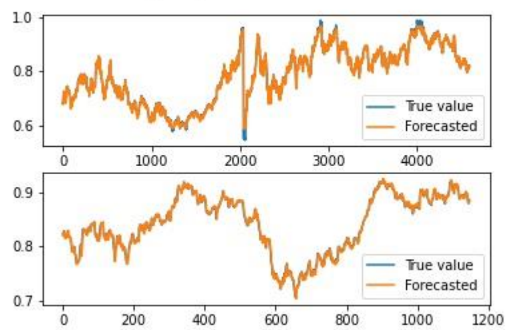

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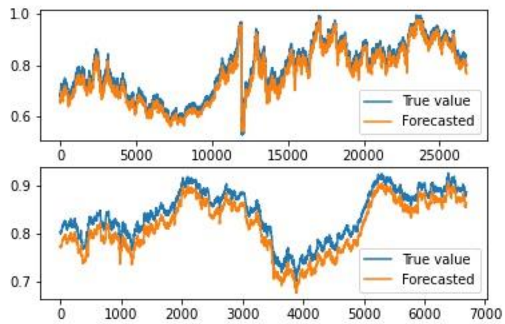

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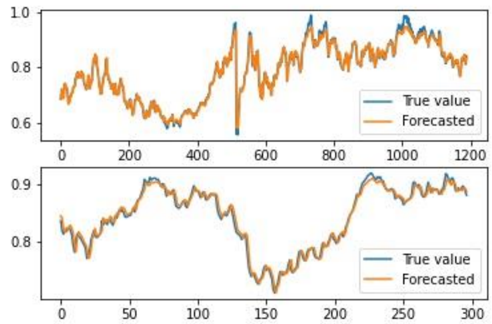

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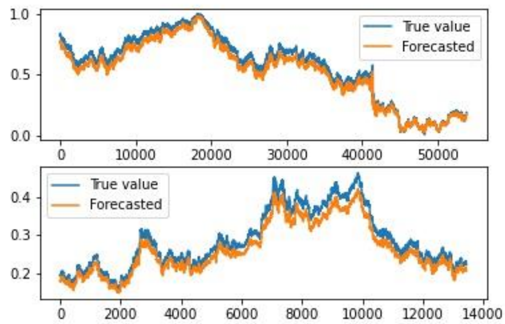

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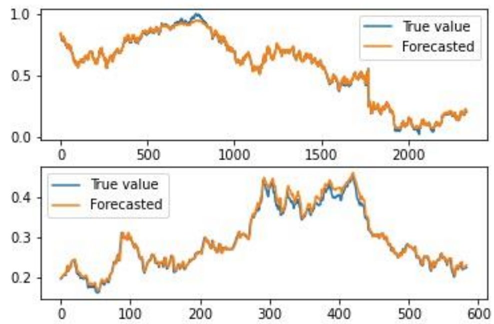

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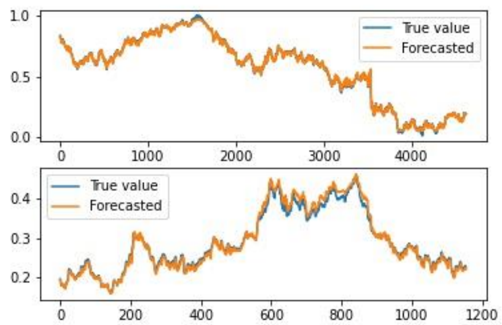

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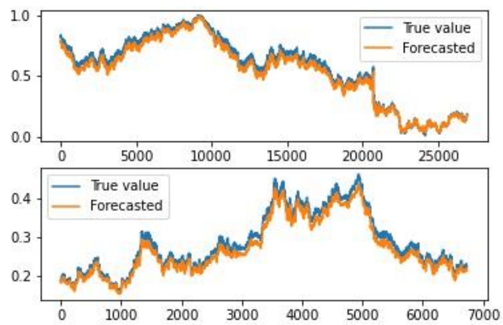

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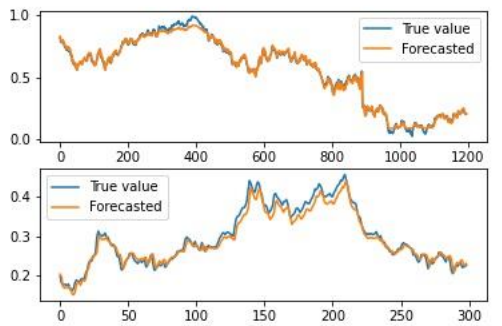
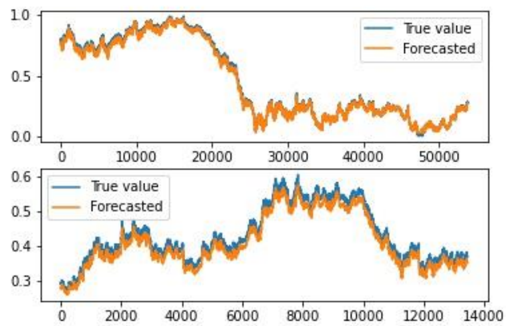
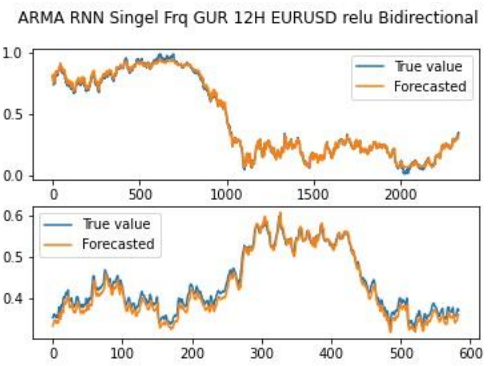
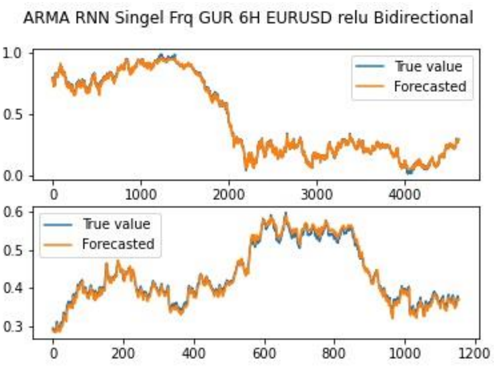


ARMA RNN Singel Frq GUR 30T EURUSD relu Bidirectional




ARMA RNN Singel Frq GUR 12H EURUSD relu Bidirectional
True value
Forecasted
True value
Forecasted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True value
Forecasted
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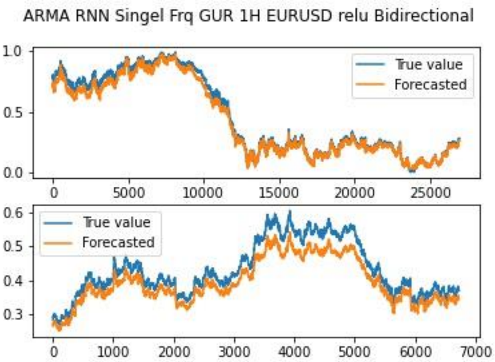
Forecasted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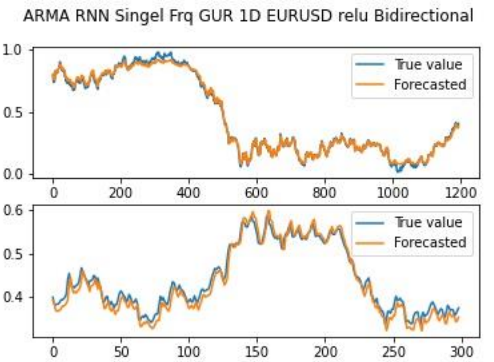
True value
Forecasted
True value
Forecasted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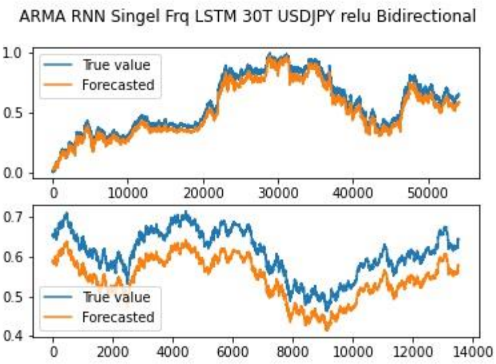
Forecasted
True value
Forecasted


ARMA RNN Singel Frq LSTM 30T USDJPY relu Bidirectional
True value
Forecasted
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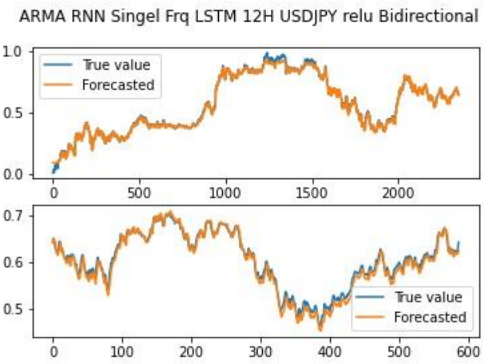
Forecasted


ARMA RNN Singel Frq LSTM 12H USDJPY relu Bidirectional
True value
Forecasted
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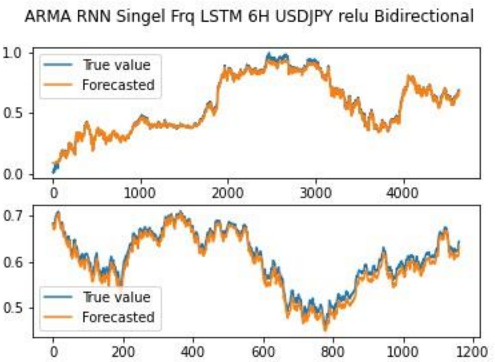
Forecasted


ARMA RNN Singel Frq LSTM 6H USDJPY relu Bidirectional
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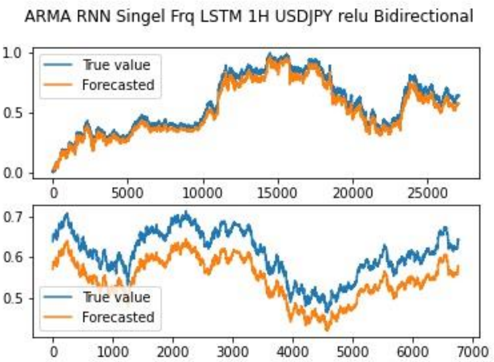
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Forecasted
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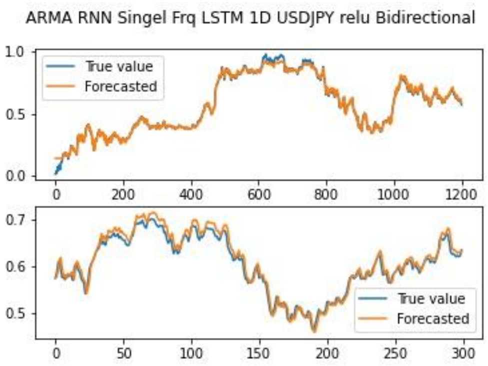
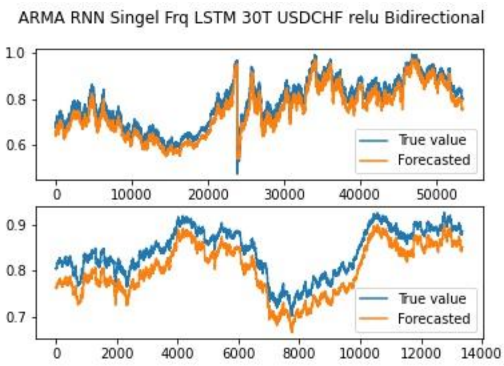
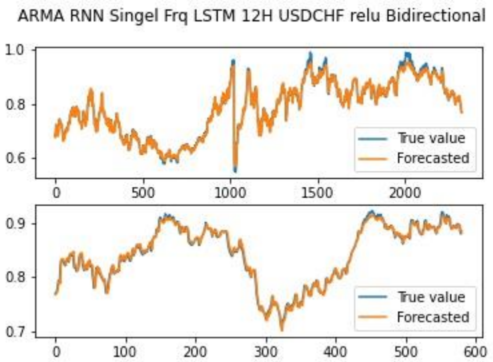
Forecasted


ARMA RNN Singel Frq LSTM 1D USDJPY relu Bidirectional
True value
Forecasted


ARMA RNN Singel Frq LSTM 30T USDCHF relu Bidirectional
True value
Forecasted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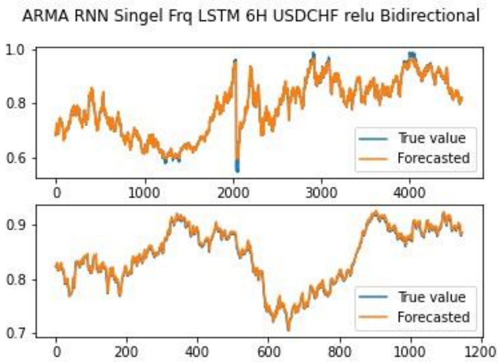
True value
Forecasted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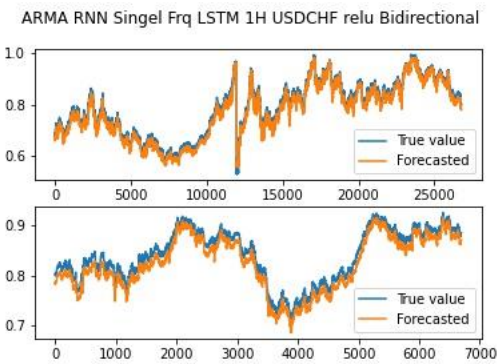
True value
Forecasted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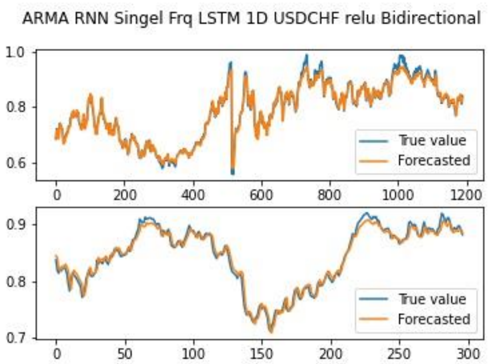
True value
Forecasted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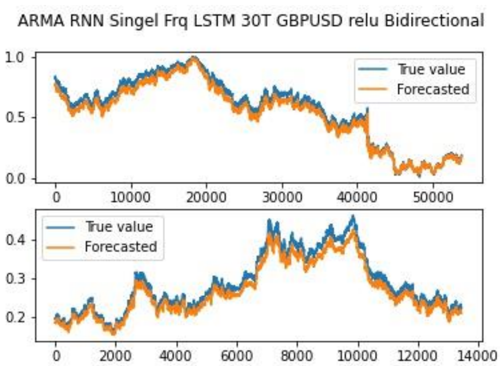
True value
Forecasted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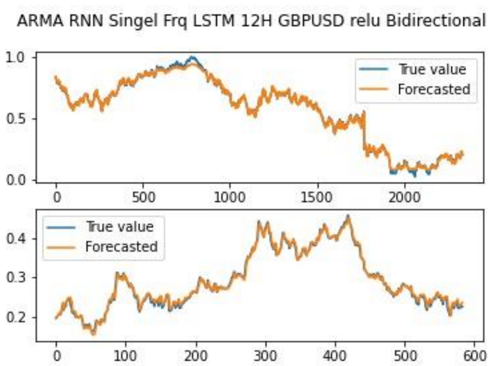
True value
Forecasted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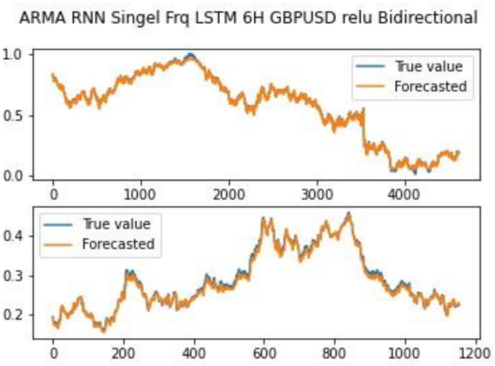
True value
Forecasted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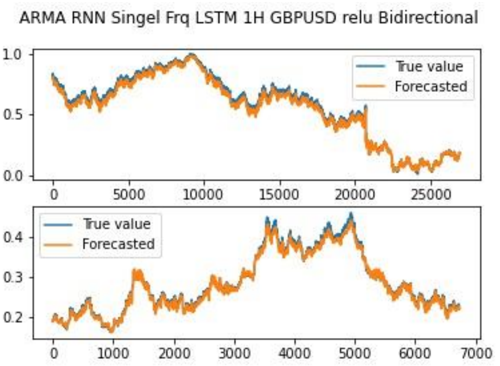
True value
Forecasted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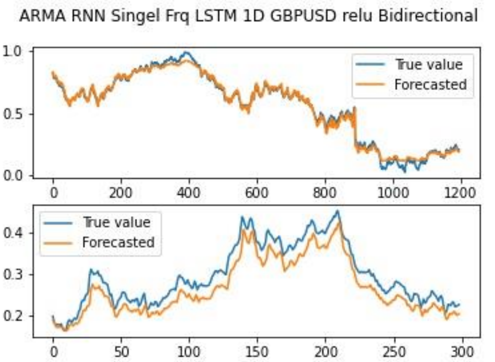
True value
Forecasted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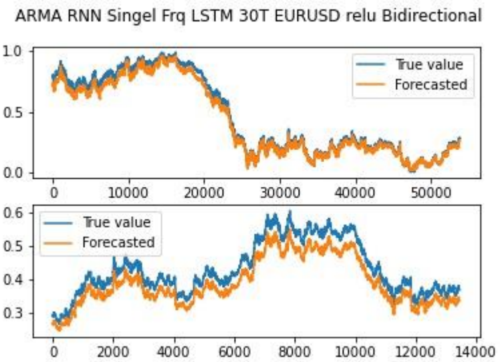
True value
Forecasted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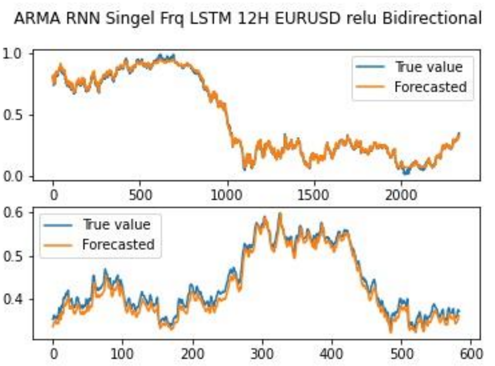
True value
Forecasted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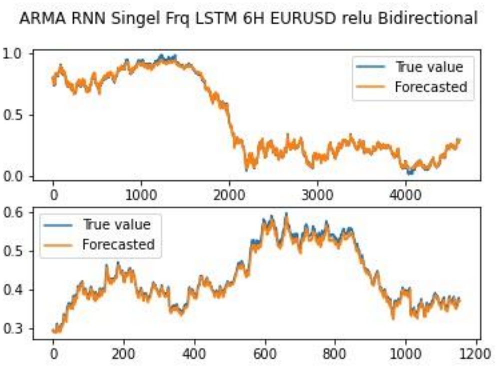
Forecasted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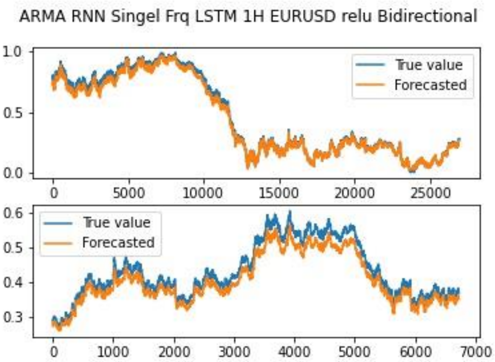
Forecasted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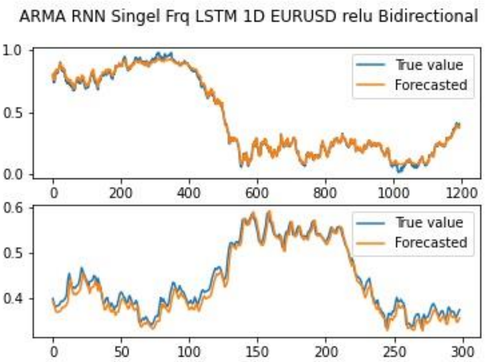
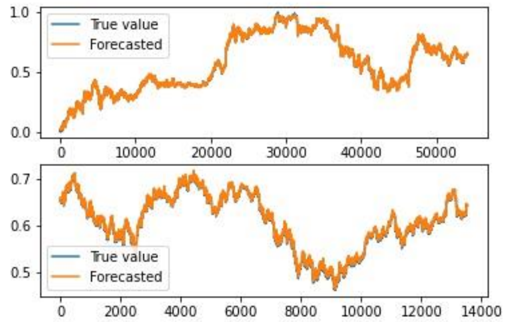
True value
Forecasted


ARMA RNN Singel Frq LSTM 1D EURUSD relu Bidirectional
True value
Forecasted

ARMA RNN Singel Frq LSTM 30T USDJPY tanh forward



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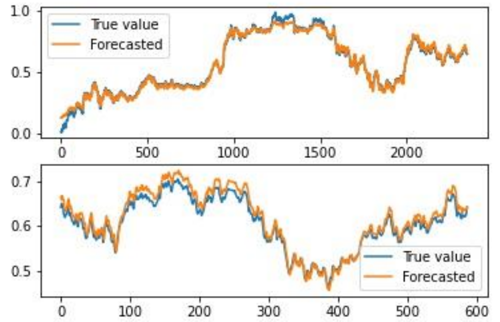

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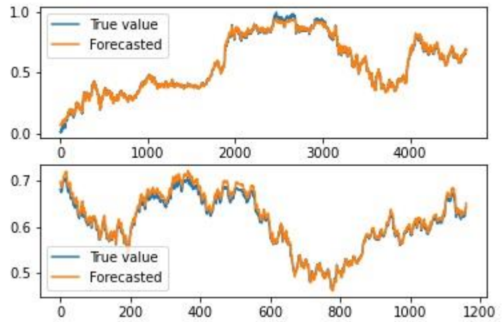
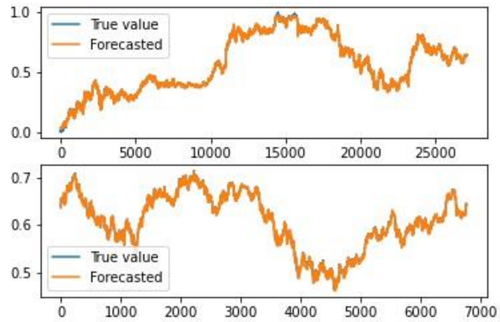


ARMA RNN Singel Frq LSTM 1H USDJPY tanh forward



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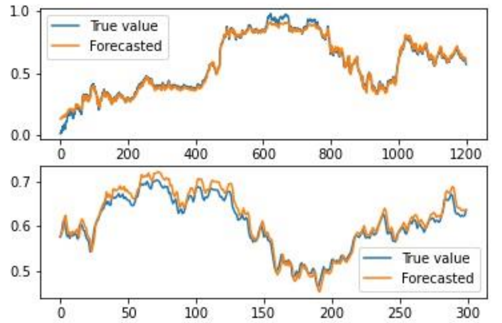

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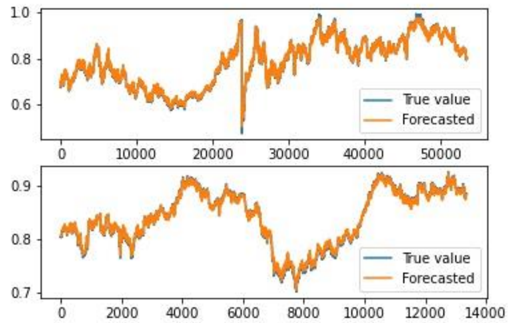

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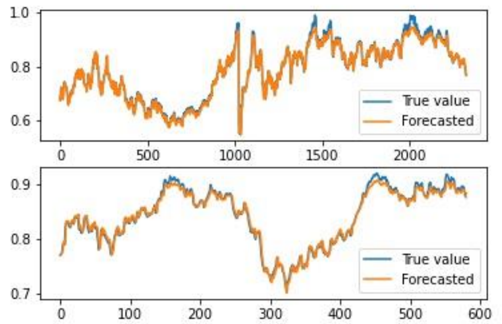

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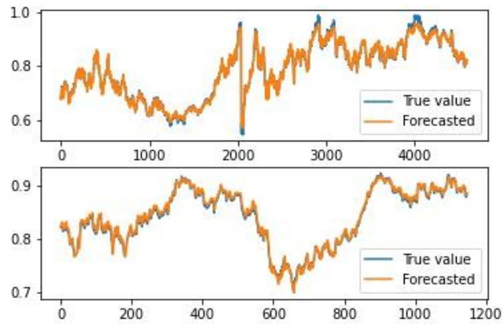
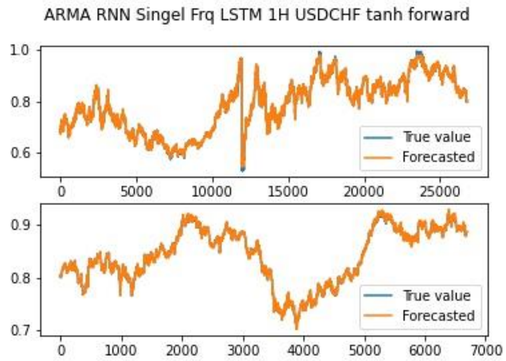
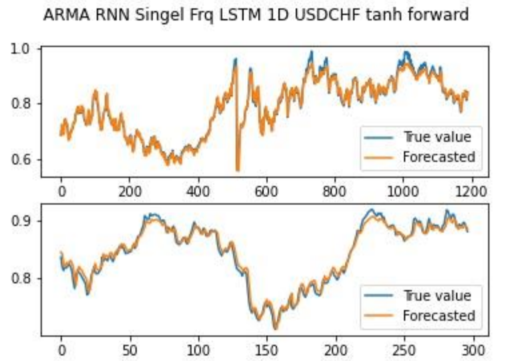



ARMA RNN Singel Frq LSTM 1H USDCHF tanh forward
True value
Forecasted
True value
Forecasted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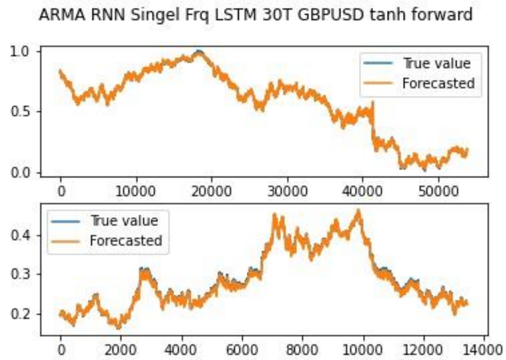
True value
Forecasted
True value
Forecasted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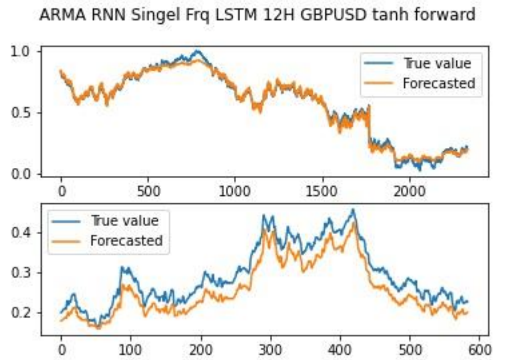
True value
Forecasted
True value
Forecasted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Forecasted
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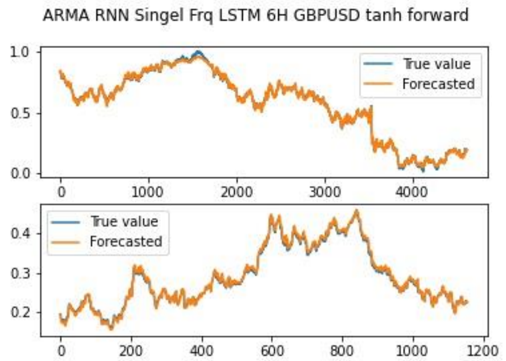
Forecasted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True value
Forecasted
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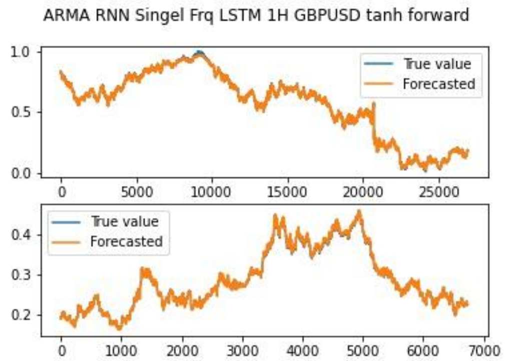
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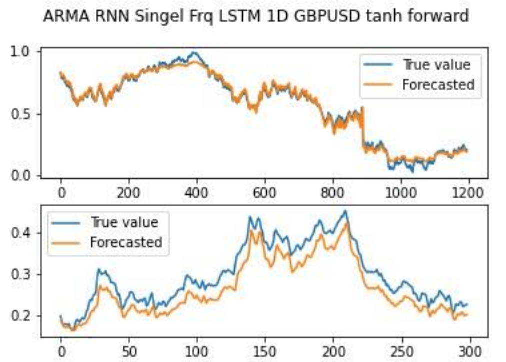
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Forecasted
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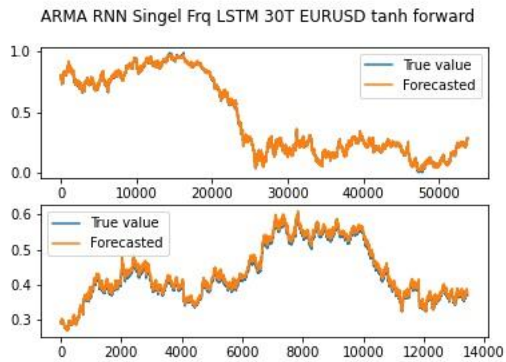
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Forecasted
True value
Forecasted

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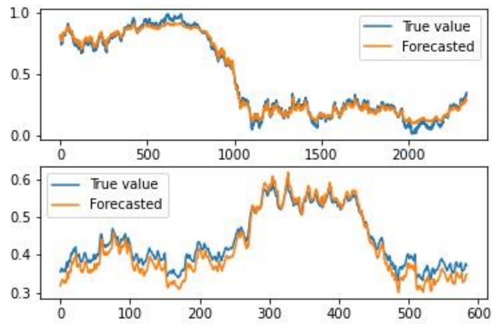

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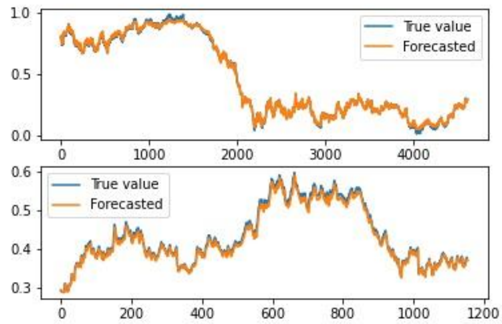

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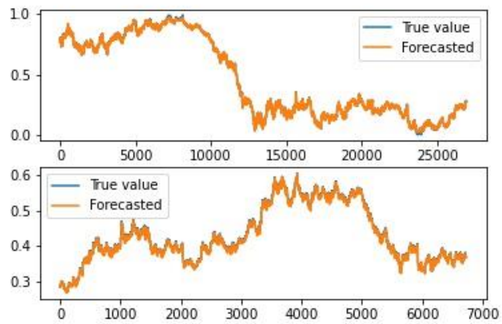

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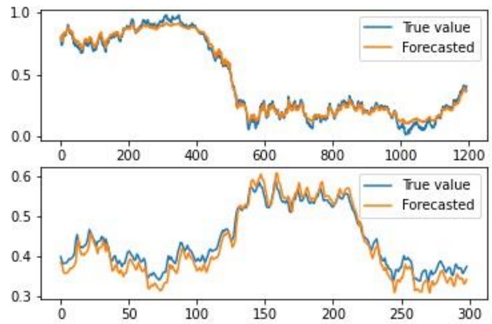
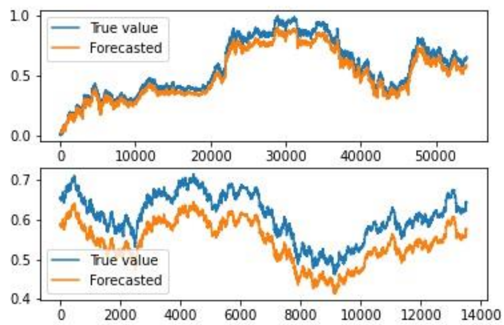


ARMA RNN Singel Frq GUR 30T USDJPY relu forward



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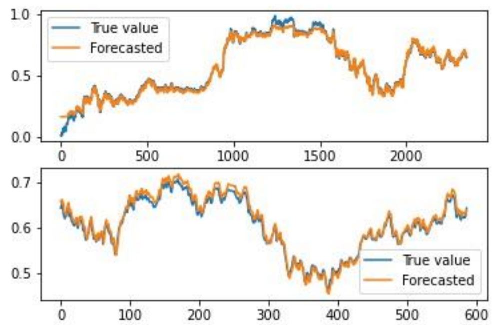

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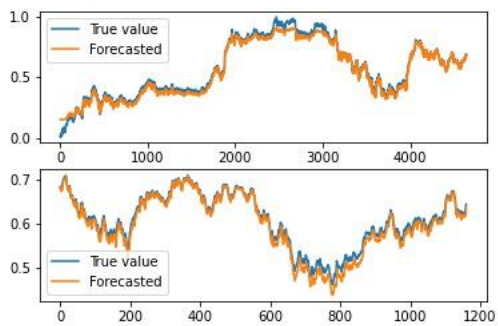

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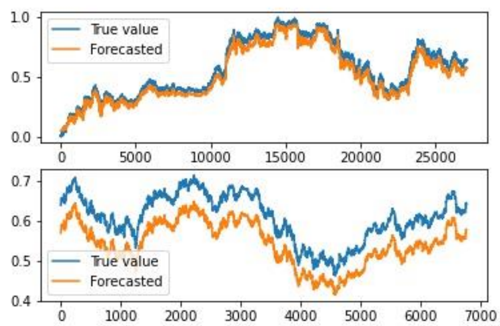
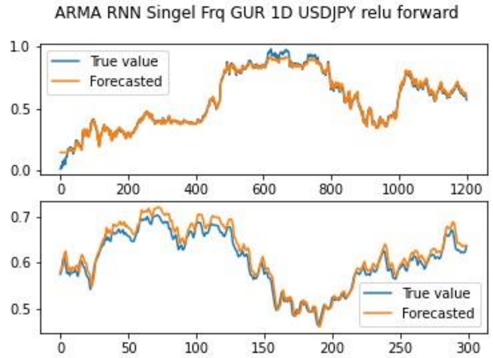
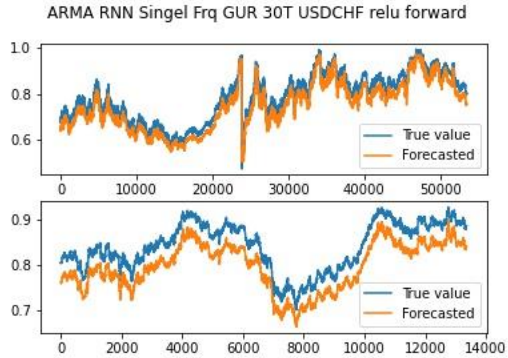



ARMA RNN Singel Frq GUR 1D USDJPY relu forward
True value
Forecasted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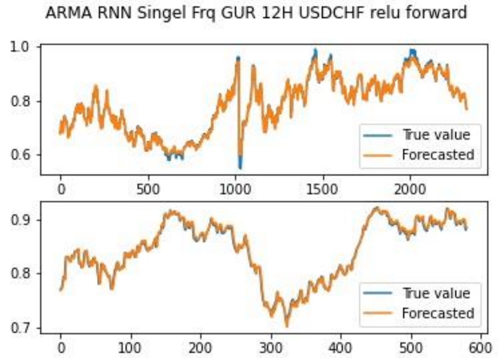
True value
Forecasted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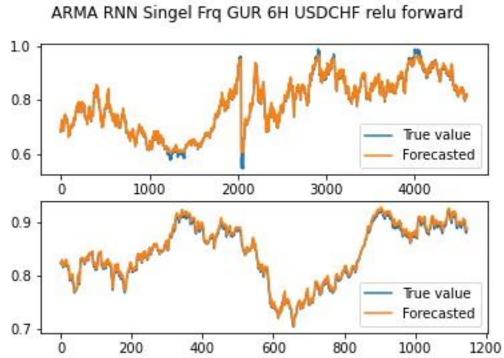
True value
Forecasted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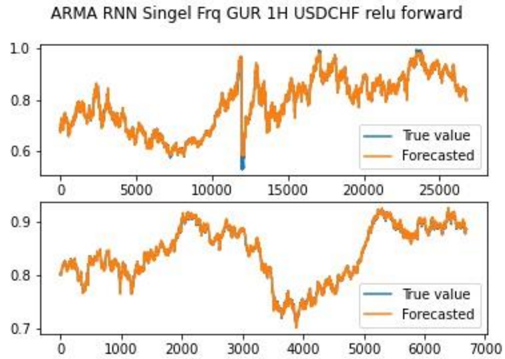
Forecasted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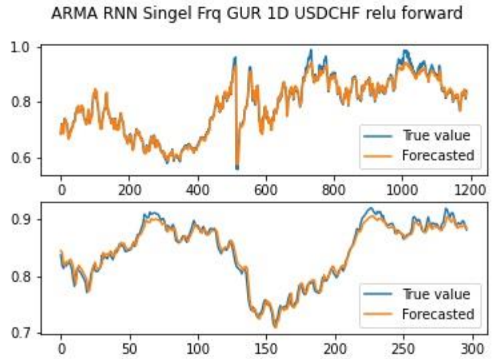
Forecasted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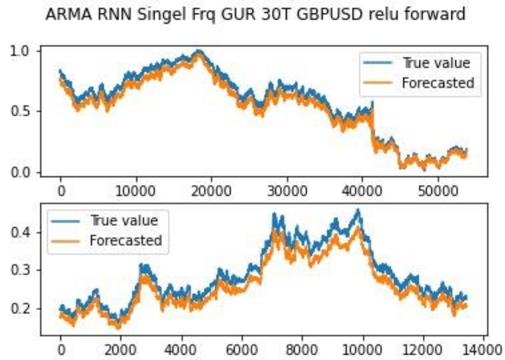
Forecasted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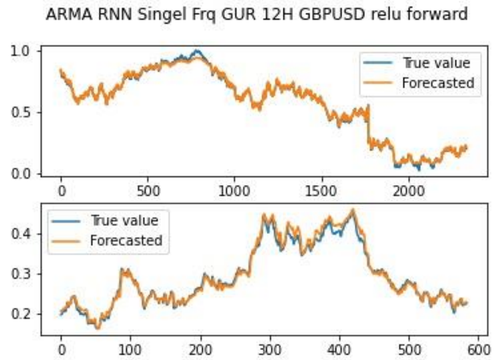
True value
Forecasted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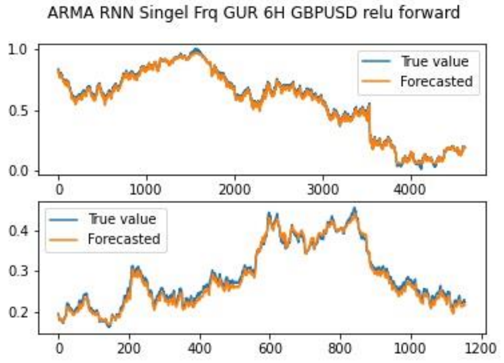
True value
Forecasted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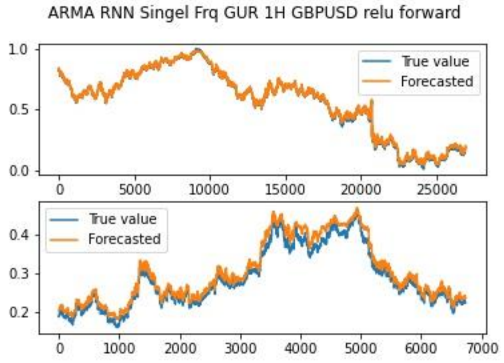
Forecasted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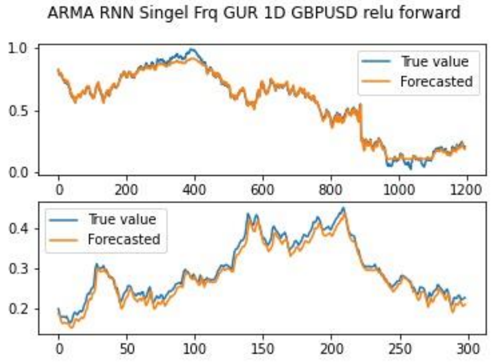
Forecasted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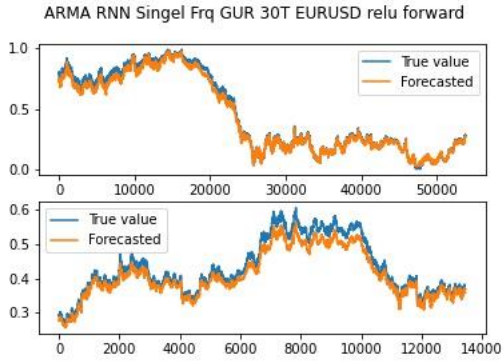
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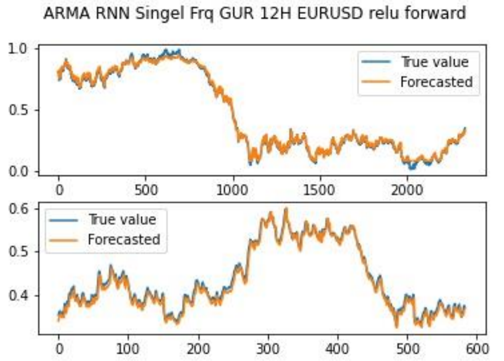
Forecasted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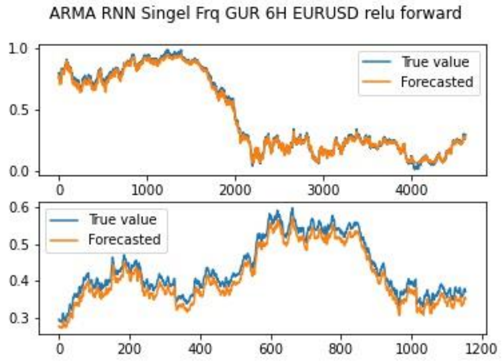
Forecasted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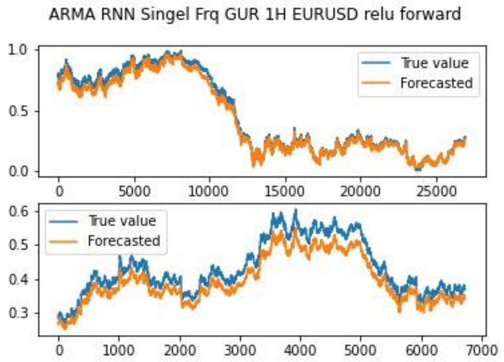
Forecasted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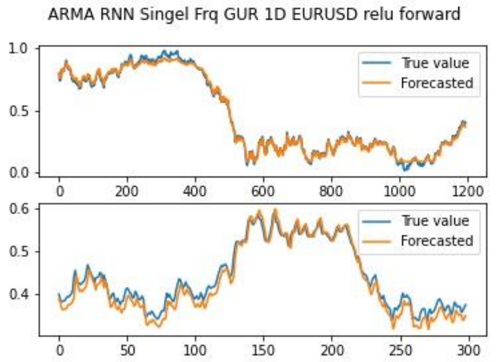
True value
Forecasted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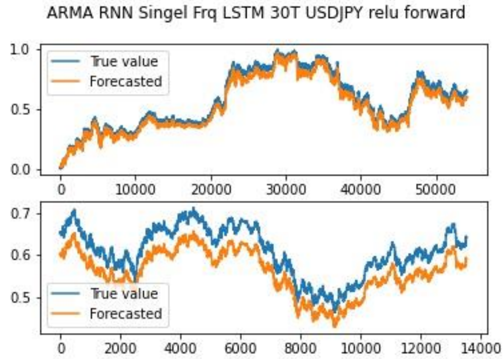
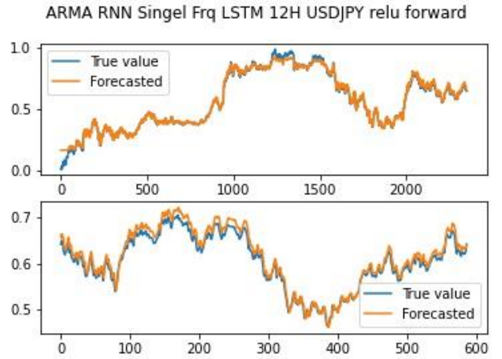
True value
Forecasted


ARMA RNN Singel Frq LSTM 30T USDJPY relu forward
True value
Forecasted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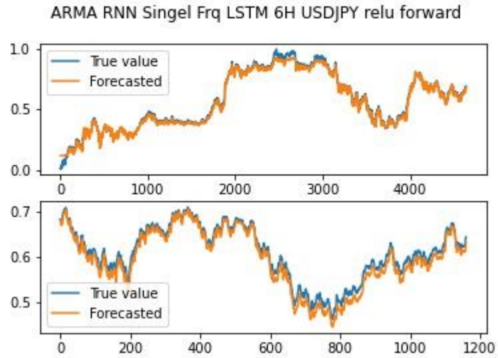
True value
Forecasted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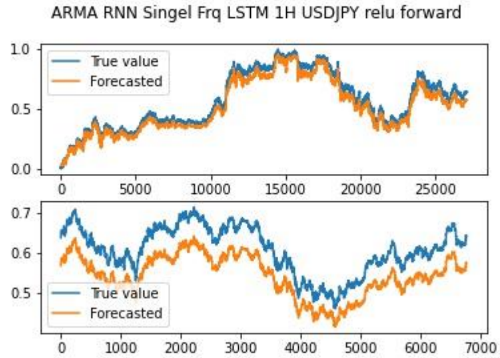
True value
Forecasted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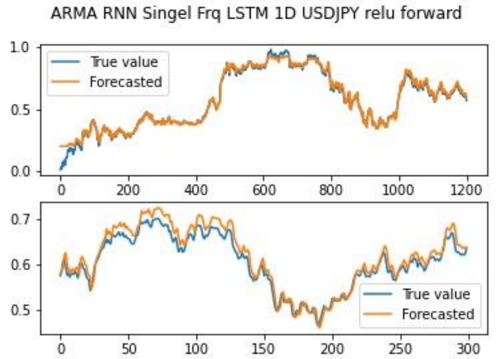
True value
Forecasted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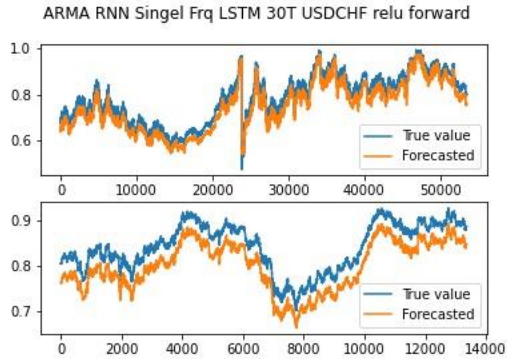
Forecasted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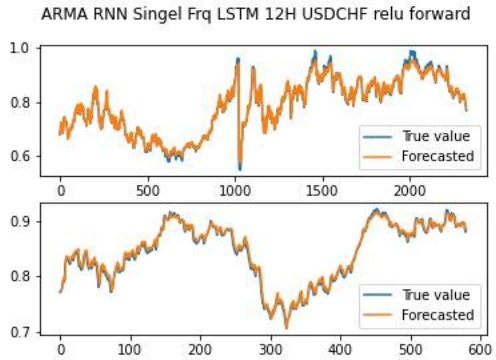
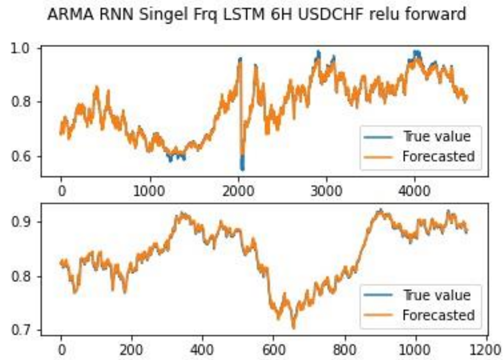
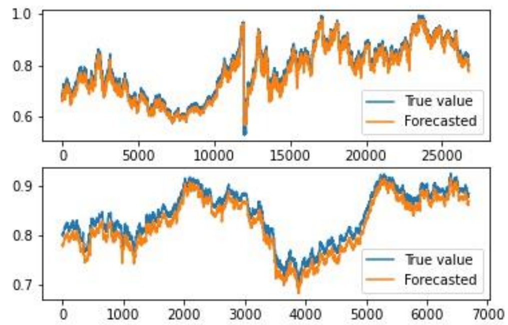
True value
Forecasted

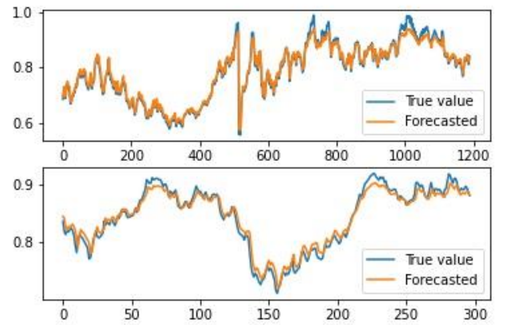

ARMA RNN Singel Frq LSTM 12H USDCHF relu forward
True value
Forecasted


ARMA RNN Singel Frq LSTM 6H USDCHF relu forward
True value
Forecasted

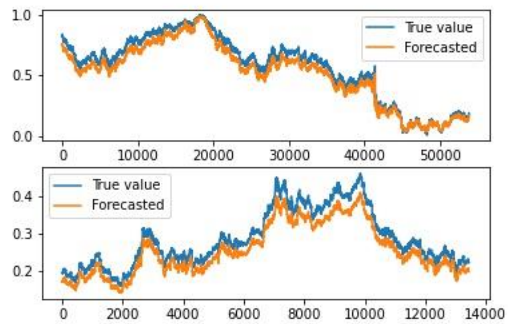
ARMA RNN Singel Frq LSTM 1H USDCHF relu forward



ARMA RNN Singel Frq LSTM 1D USDCHF relu forward



ARMA RNN Singel Frq LSTM 30T GBPUSD relu forward



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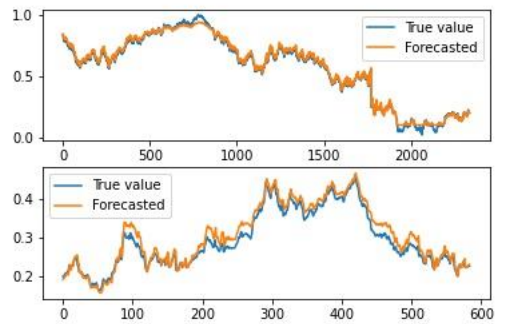

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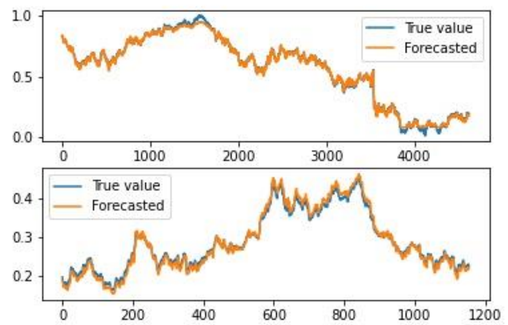

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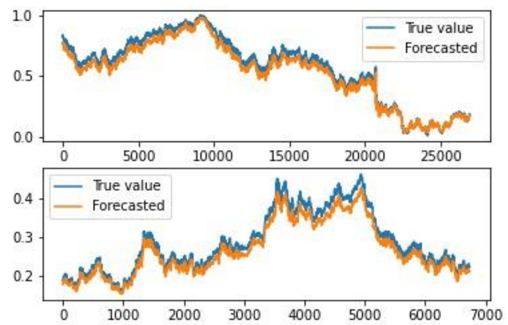

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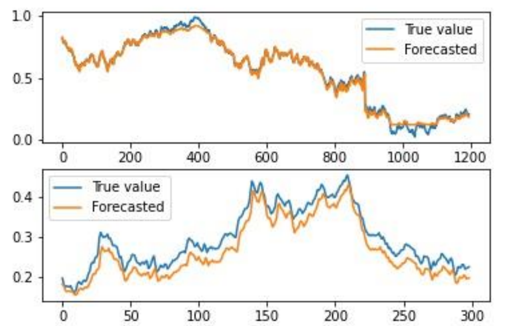

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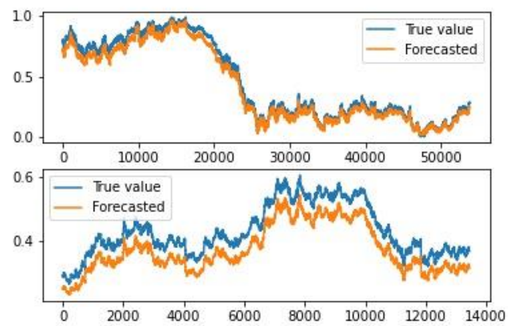
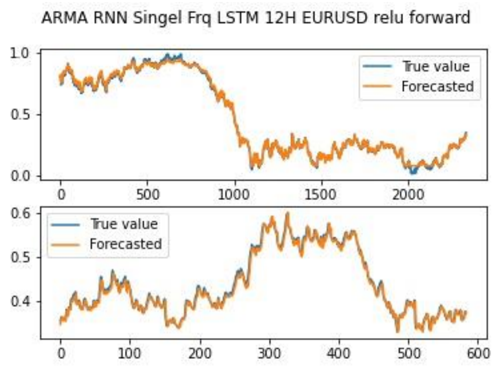
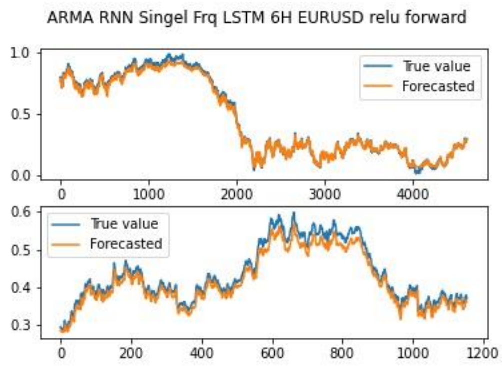



ARMA RNN Singel Frq LSTM 12H EURUSD relu forward
True value
Forecasted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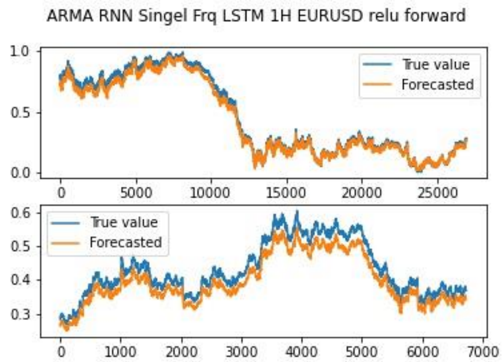
True value
Forecasted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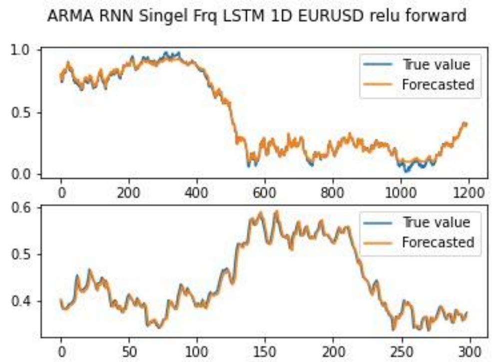
Forecasted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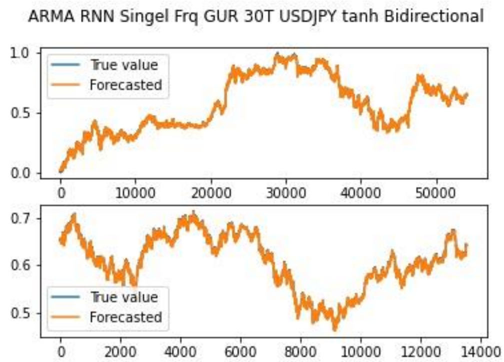
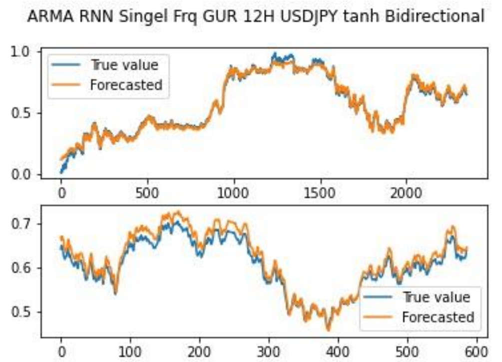
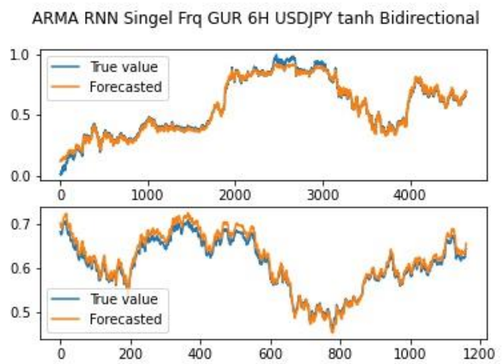
True value
Forecasted


ARMA RNN Singel Frq GUR 30T USDJPY tanh Bidirectional
True value
Forecasted


ARMA RNN Singel Frq GUR 12H USDJPY tanh Bidirectional
True value
Forecasted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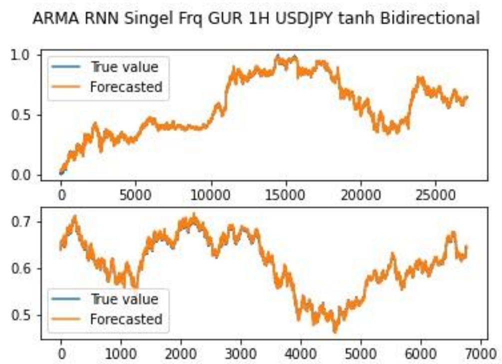
True value
Forecasted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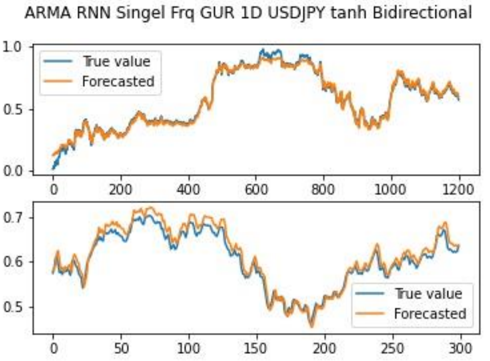
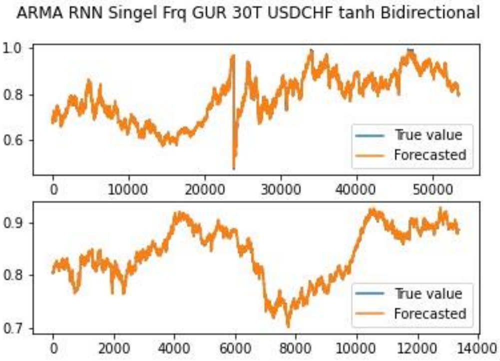
True value
Forecasted


ARMA RNN Singel Frq GUR 1D USDJPY tanh Bidirectional
True value
Forecasted
True value
Forecasted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True value
Forecasted
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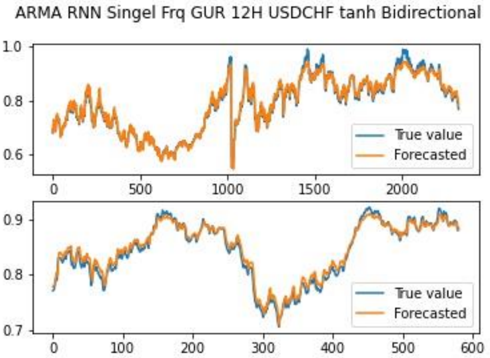
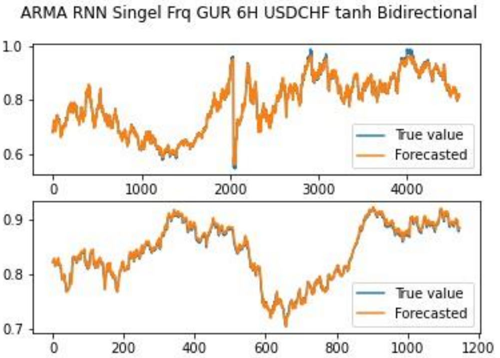
Forecasted


ARMA RNN Singel Frq GUR 12H USDCHF tanh Bidirectional
True value
Forecasted
True value
Forecasted


ARMA RNN Singel Frq GUR 6H USDCHF tanh Bidirectional
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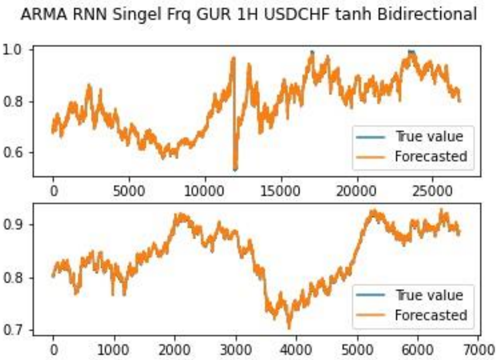
Forecasted
True value
Forecasted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Forecasted
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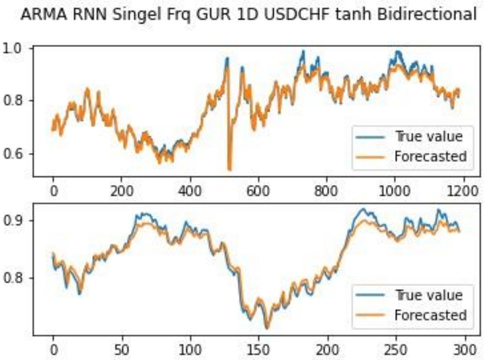
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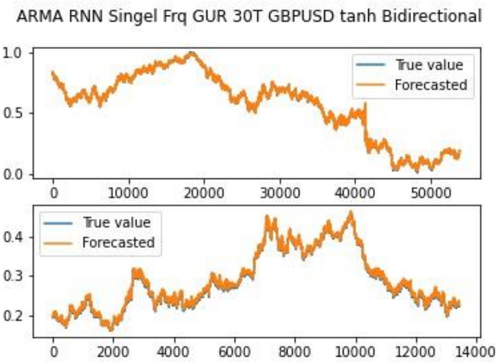
Forecasted
True value
Forecasted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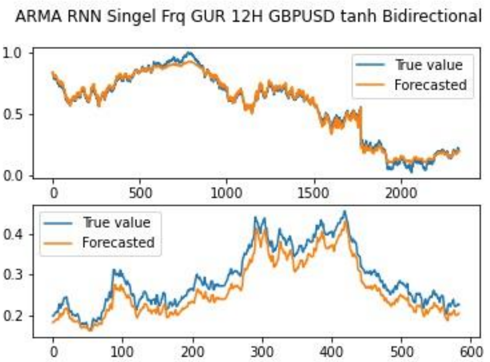
True value
Forecasted
True value
Forecasted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True value
Forecasted
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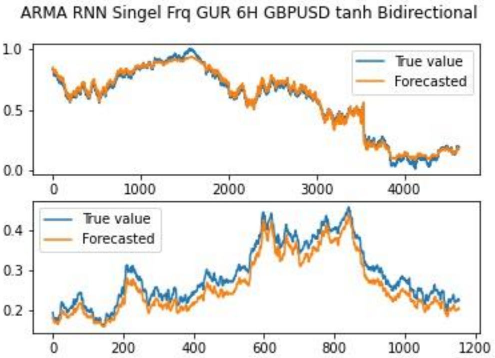
Forecasted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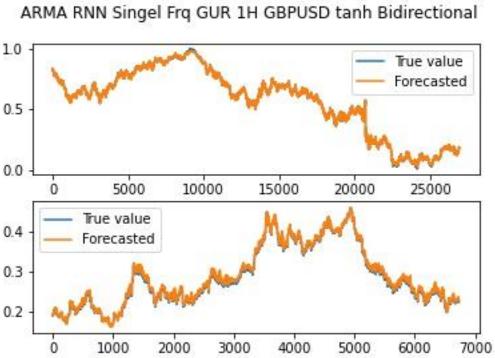
Forecasted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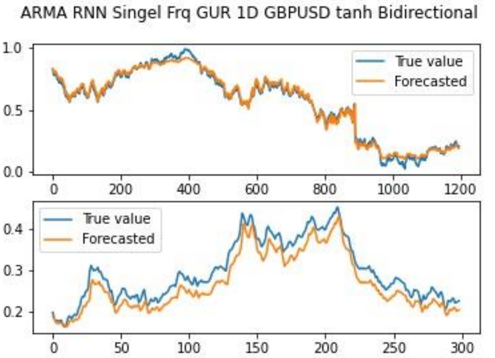
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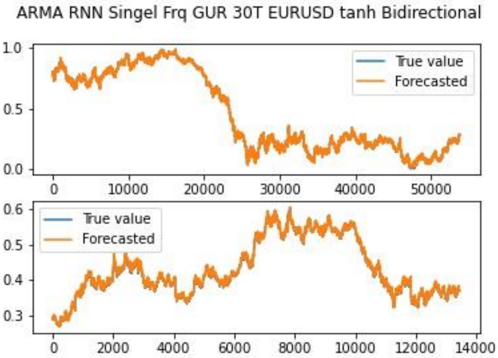
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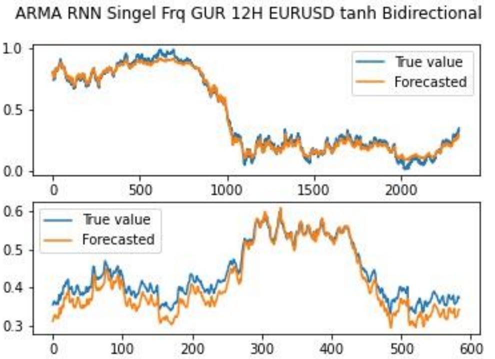
Forecasted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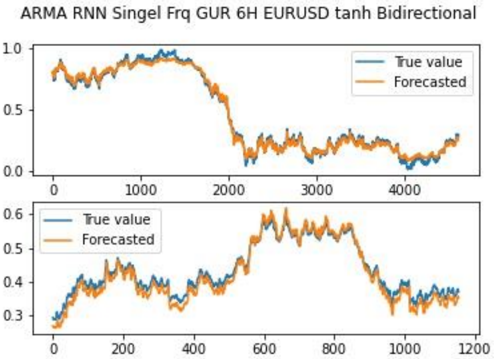
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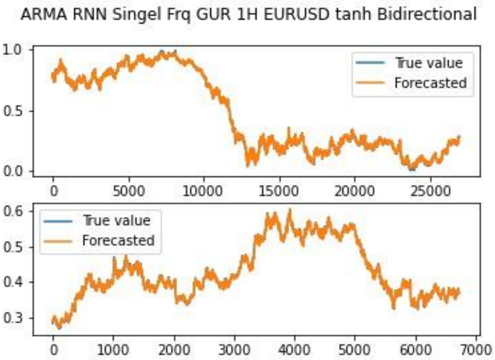
Forecasted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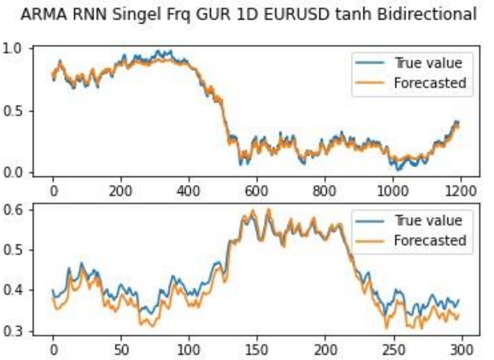
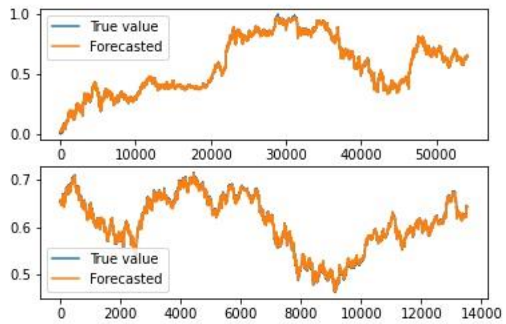
True value
Forecasted


ARMA RNN Singel Frq GUR 1D EURUSD tanh Bidirectional
True value
Forecasted

ARMA RNN Singel Frq GUR 30T USDJPY tanh forward



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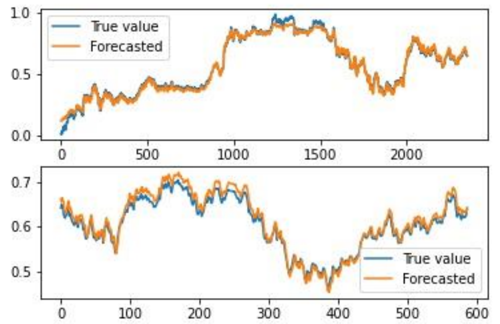

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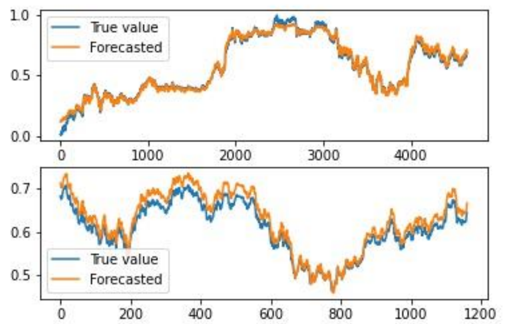

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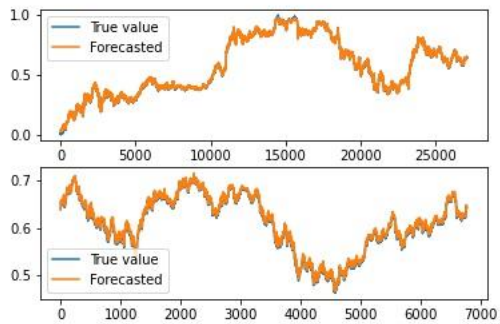

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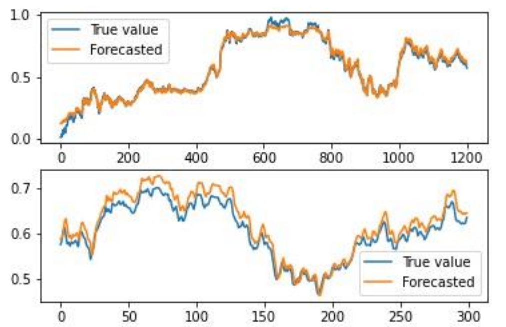

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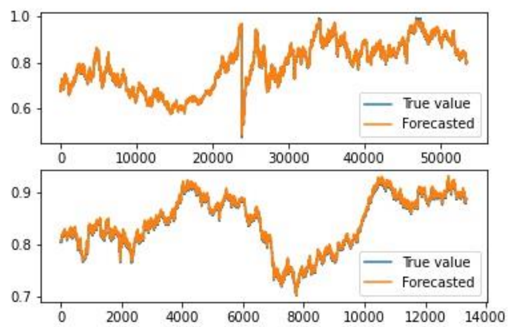
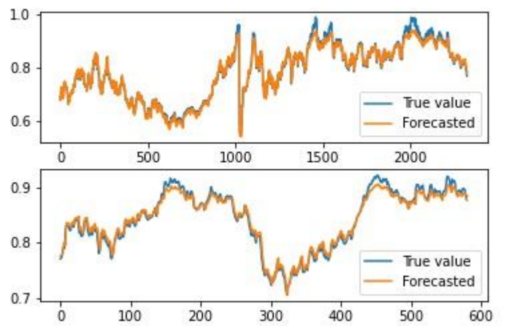


ARMA RNN Singel Frq GUR 12H USDCHF tanh forward



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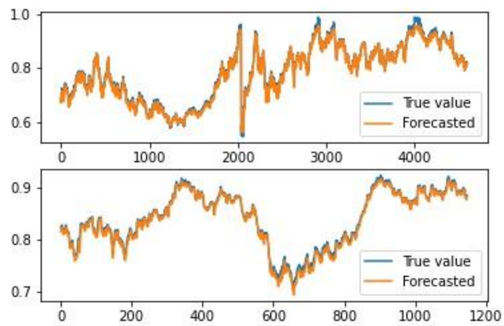
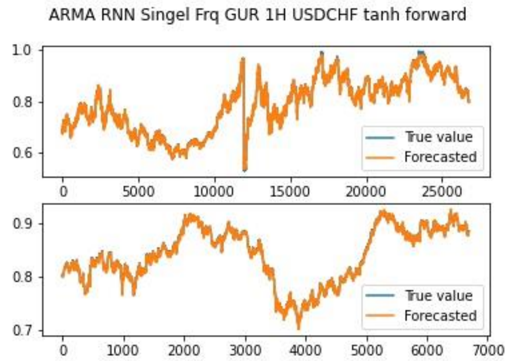
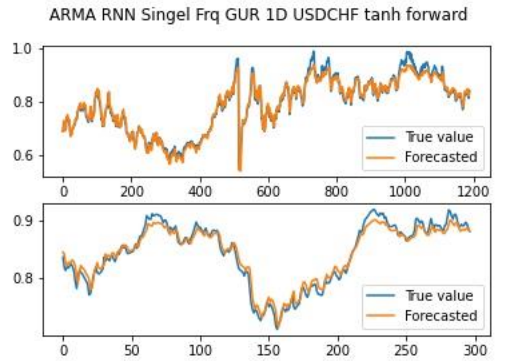



ARMA RNN Singel Frq GUR 1H USDCHF tanh forward
True value
Forecasted
True value
Forecasted


ARMA RNN Singel Frq GUR 1D USDCHF tanh forward
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Forecasted
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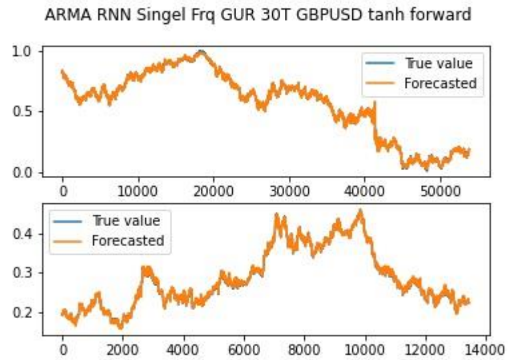
Forecasted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Forecasted
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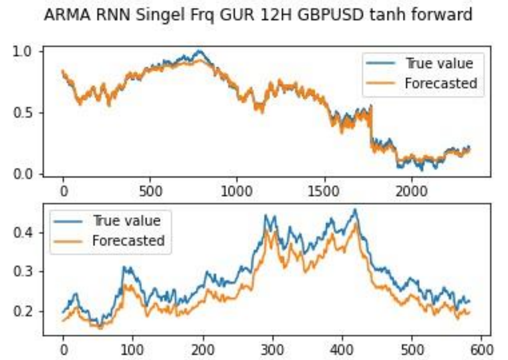
Forecasted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Forecasted
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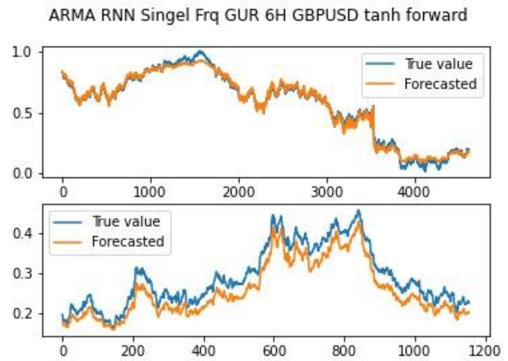
Forecasted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Forecasted
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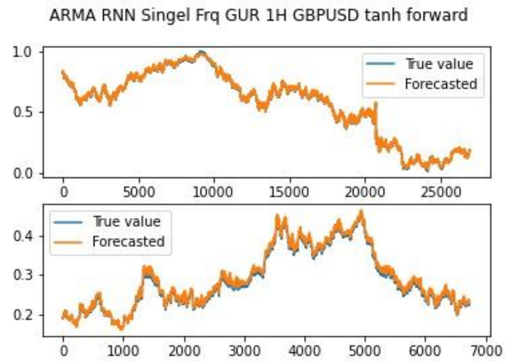
Forecasted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Forecasted
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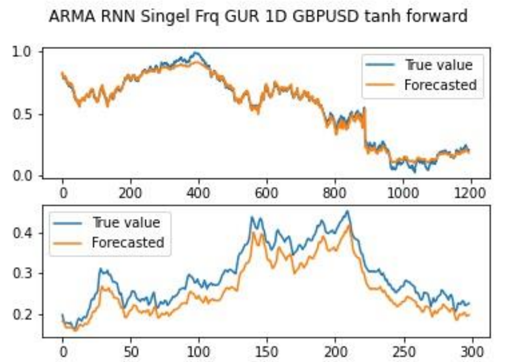
Forecasted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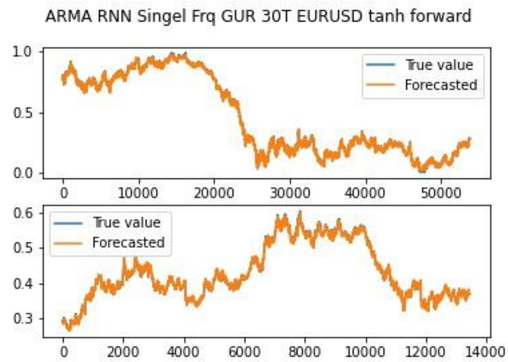
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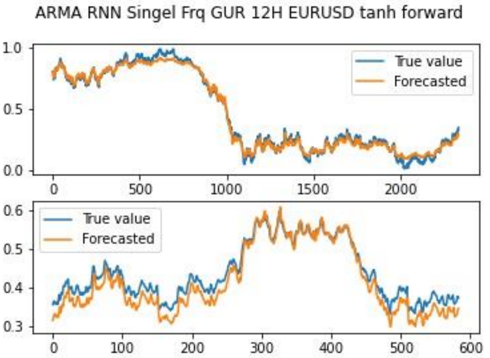
True value
Forecasted
True value
Forecasted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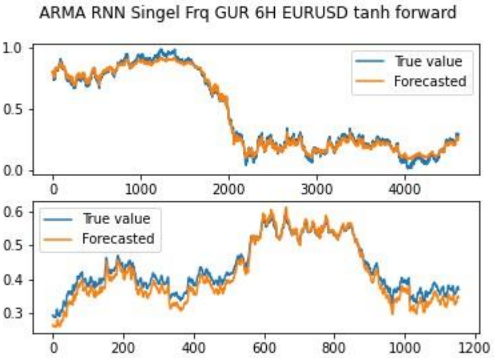
True value
Forecasted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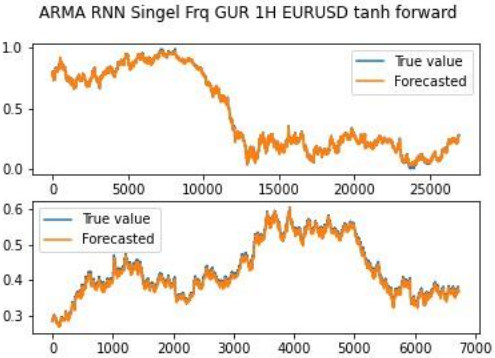
Forecasted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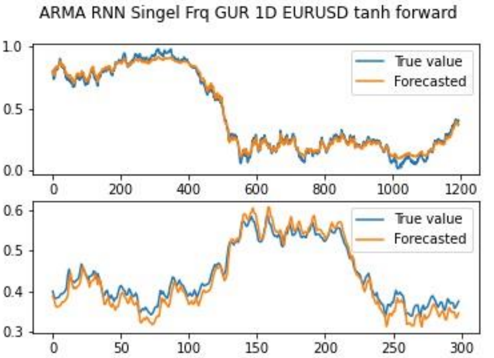
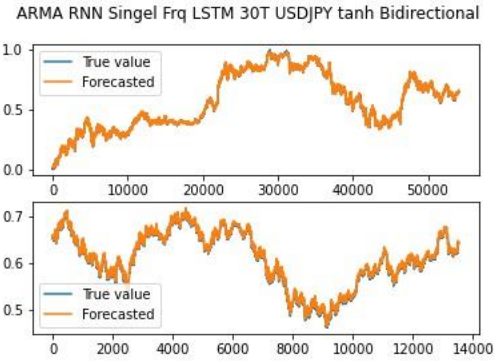
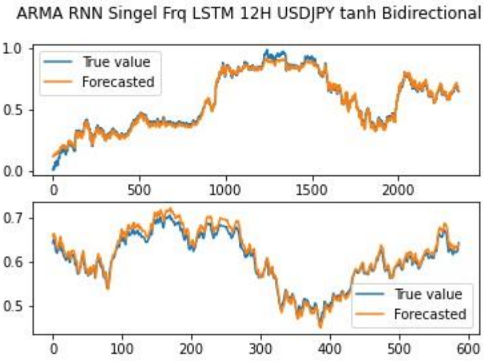
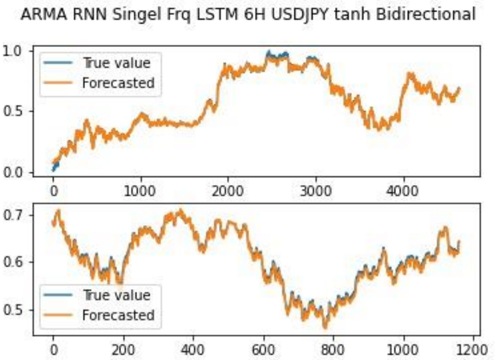
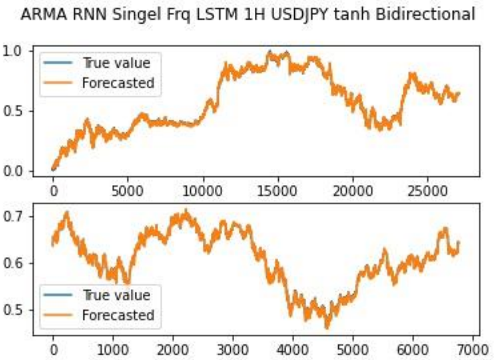
True value
Forecasted


ARMA RNN Singel Frq GUR 1D EURUSD tanh forward
True value
Forecasted


ARMA RNN Singel Frq LSTM 30T USDJPY tanh Bidirectional
True value
Forecasted


ARMA RNN Singel Frq LSTM 12H USDJPY tanh Bidirectional
True value
Forecasted


ARMA RNN Singel Frq LSTM 6H USDJPY tanh Bidirectional
True value
Forecasted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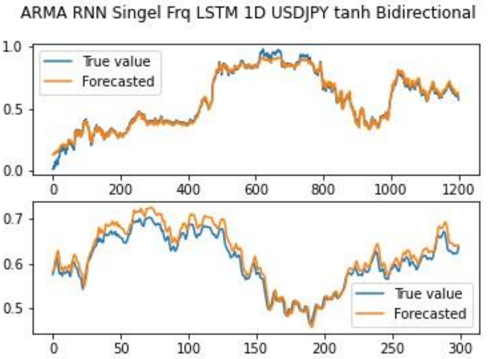
True value
Forecasted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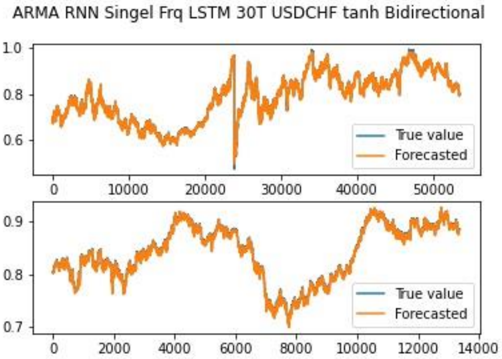
True value
Forecasted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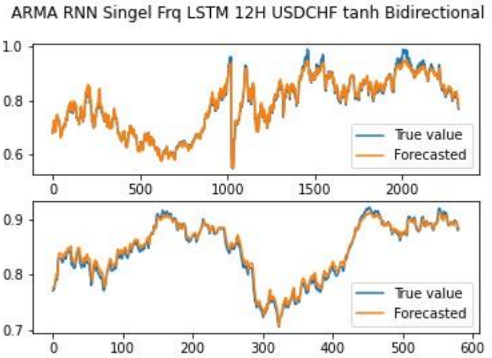
True value
Forecasted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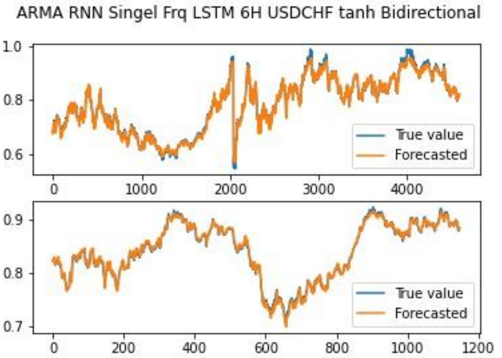
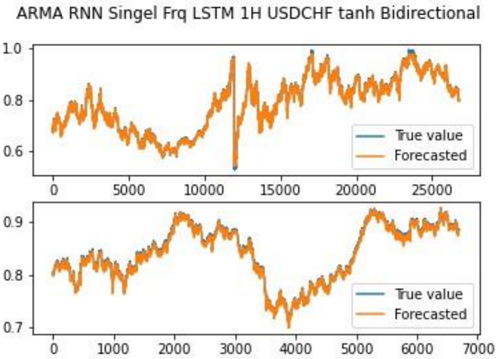
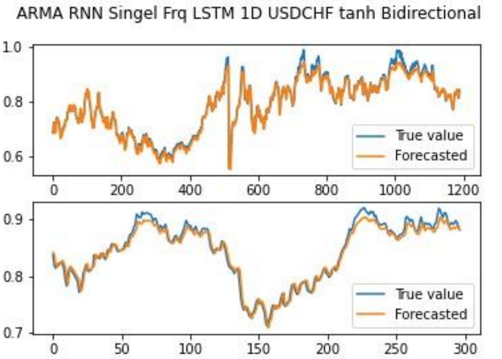
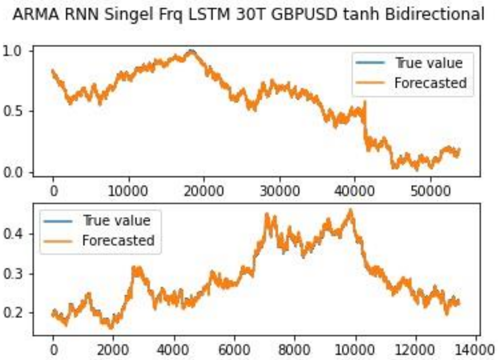
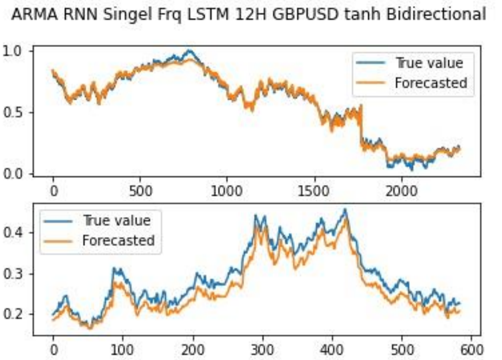
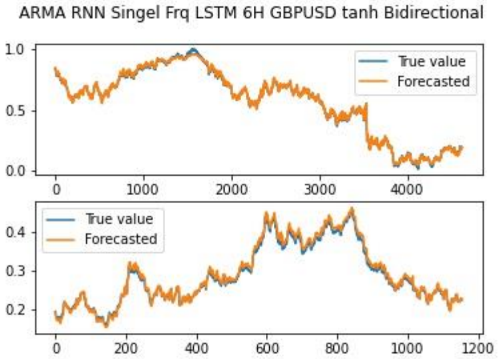

ARMA RNN Singel Frq LSTM 6H USDCHF tanh Bidirectional
True value
Forecasted

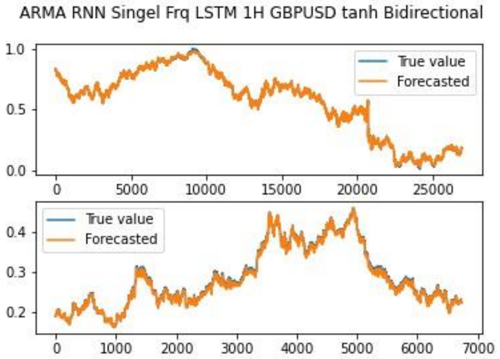

ARMA RNN Singel Frq LSTM 1H USDCHF tanh Bidirectional
True value
Forecasted

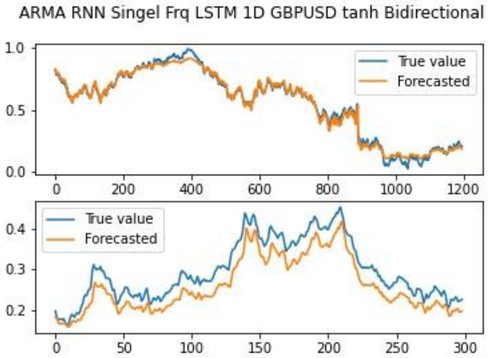

ARMA RNN Singel Frq LSTM 1D USDCHF tanh Bidirectional
True value
Forecasted

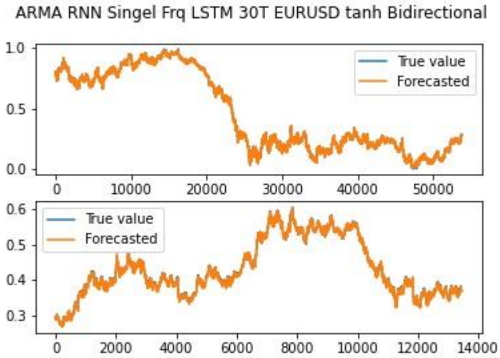

ARMA RNN Singel Frq LSTM 30T GBPUSD tanh Bidirectional
True value
Forecasted

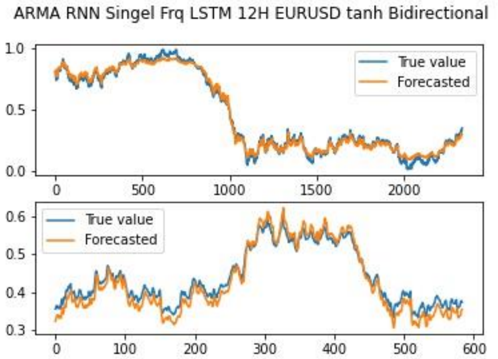

ARMA RNN Singel Frq LSTM 12H GBPUSD tanh Bidirectional
True value
Forecasted

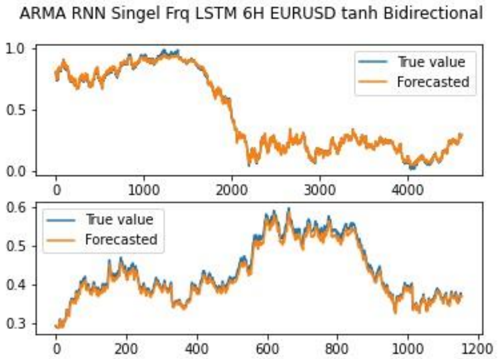

ARMA RNN Singel Frq LSTM 6H GBPUSD tanh Bidirectional
True value
Forecasted

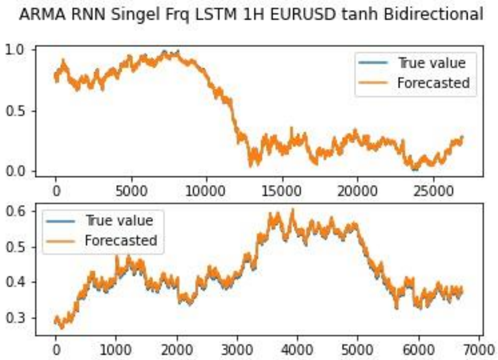

ARMA RNN Singel Frq LSTM 1H GBPUSD tanh Bidirectional
True value
Forecasted

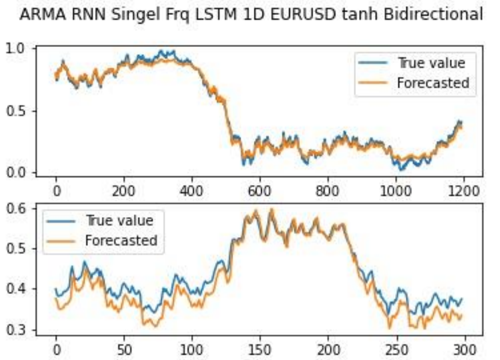

ARMA RNN Singel Frq LSTM 1D GBPUSD tanh Bidirectional
True value
Forecasted


ARMA RNN Singel Frq LSTM 30T EURUSD tanh Bidirectional
True value
Forecasted


ARMA RNN Singel Frq LSTM 12H EURUSD tanh Bidirectional
True value
Forecasted


ARMA RNN Singel Frq LSTM 6H EURUSD tanh Bidirectional
True value
Forecasted


ARMA RNN Singel Frq LSTM 1H EURUSD tanh Bidirectional
True value
Forecasted


ARMA RNN Singel Frq LSTM 1D EURUSD tanh Bidirectional
True value
Forecasted

Appendix E:

Recurrent neural single frequency network Mean Square Error (MSE) GRU vs LSTM

Currency and frequency	GRU Relu Bidirectional		LSTM Relu Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.003264418	0.002508793	0.000646601	0.000477242
EURUSD_12H	0.001804951	0.001976188	0.001781473	0.002271858
EURUSD_6H	0.003681875	0.002461885	0.000484017	0.000572836
EURUSD_1H	0.002070203	0.000625061	0.001236252	0.000782335
EURUSD_30T	0.002019272	0.001011214	0.000651753	0.000410656
GBPUSD_1D	0.003268477	0.001078161	0.000899452	0.000476266
GBPUSD_12H	0.004628441	0.00077614	0.000584252	0.000189026
GBPUSD_6H	0.003690071	0.000304833	0.001402092	0.000108173
GBPUSD_1H	0.003498528	0.000116116	0.001538053	0.000120323
GBPUSD_30T	0.002436929	0.000274796	0.001448046	0.000179853
USDCHF_1D	0.003381599	0.003802104	0.001500302	0.000838828
USDCHF_12H	0.005414608	0.006338591	0.001532165	0.001369681
USDCHF_6H	0.00229487	0.002524693	0.0017615	0.00192644
USDCHF_1H	0.00311218	0.003806221	0.003380316	0.004217774
USDCHF_30T	0.002605188	0.003176072	0.00263084	0.00293319
USDJPY_1D	0.003850373	0.002772214	0.000767427	0.000329108
USDJPY_12H	0.004921299	0.004387937	0.001434876	0.001372796
USDJPY_6H	0.003069344	0.00267188	0.000896078	0.000700275
USDJPY_1H	0.002900043	0.002304077	0.00228328	0.00216007
USDJPY_30T	0.00224058	0.001590825	0.002166076	0.002411678
Mean	0.003207662	0.00222539	0.001451243	0.00119242

Currency and frequency	GRU Relu forward		LSTM Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.004515877	0.003002102	0.000956876	0.000701727
EURUSD_12H	0.003761206	0.003486629	0.002376047	0.002850674
EURUSD_6H	0.003921711	0.002497948	0.001537763	0.002085426
EURUSD_1H	0.004403116	0.003055279	0.002679884	0.001083536
EURUSD_30T	0.003890968	0.002241523	0.002620105	0.001305268
GBPUSD_1D	0.004125347	0.000723338	0.003149294	0.001065977
GBPUSD_12H	0.001596336	0.00035417	0.002440605	0.000622988
GBPUSD_6H	0.005500077	0.00064289	0.001911535	0.000276965
GBPUSD_1H	0.003083498	0.000604044	0.002309129	0.000156728
GBPUSD_30T	0.002898972	0.000148486	0.002320939	0.000288851
USDCHF_1D	0.009482416	0.011774896	0.005184083	0.006166027
USDCHF_12H	0.006215273	0.007890506	0.002781219	0.002570386
USDCHF_6H	0.003654939	0.004146543	0.002841884	0.003254781
USDCHF_1H	0.00258969	0.003090261	0.00214713	0.00261582
USDCHF_30T	0.002781555	0.003499343	0.002359283	0.002592896
USDJPY_1D	0.002742899	0.002404767	0.001821802	0.001161809
USDJPY_12H	0.002443389	0.002344669	0.001791801	0.0014219
USDJPY_6H	0.003449132	0.002884945	0.000809604	0.000592112
USDJPY_1H	0.003270028	0.003171229	0.001876947	0.001784609
USDJPY_30T	0.002303494	0.002172991	0.002118625	0.001985001
Mean	0.003831496	0.003006828	0.002301728	0.001729174

Currency and frequency	GRU Tanh Bidirectional		LSTM Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000550794	0.000538757	0.000534389	0.000368498
EURUSD_12H	0.002389571	0.002087286	0.000314574	0.000174082
EURUSD_6H	0.000154944	0.000102952	0.000259049	0.000508039
EURUSD_1H	0.000262996	3.08E-05	0.000101767	8.29E-05
EURUSD_30T	8.90E-05	9.10E-05	0.000216816	0.000125221
GBPUSD_1D	0.00040952	0.000186909	0.00138551	0.000275364
GBPUSD_12H	0.000425576	0.000104514	0.000406774	0.000118637
GBPUSD_6H	0.000133072	5.87E-05	0.000264347	6.48E-05
GBPUSD_1H	2.74E-05	1.76E-05	6.13E-05	3.45E-05
GBPUSD_30T	0.000102446	1.08E-05	6.25E-05	4.72E-05
USDCHF_1D	0.001419555	0.001377875	0.00102671	0.000563364
USDCHF_12H	0.000235081	0.000122869	0.000289928	0.000105889
USDCHF_6H	0.000117892	6.00E-05	0.000665103	0.000651929
USDCHF_1H	4.53E-05	3.73E-05	0.000108804	9.14E-05
USDCHF_30T	1.63E-05	6.90E-06	1.38E-05	4.95E-06
USDJPY_1D	0.00040242	0.000200462	0.000626735	0.000486395
USDJPY_12H	0.000251021	0.000202049	0.000329364	0.000254369
USDJPY_6H	0.000108625	6.03E-05	0.000146509	9.05E-05
USDJPY_1H	4.01E-05	2.30E-05	2.49E-05	1.12E-05
USDJPY_30T	4.04E-05	8.09E-06	9.92E-05	9.09E-06
Mean	0.000361102	0.000266408	0.000346904	0.000203416

Currency and frequency	GRU Tanh forward		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000547363	0.000294357	0.000741205	0.000512807
EURUSD_12H	0.00037586	0.000366956	0.000345858	0.000367943
EURUSD_6H	0.000156339	0.000169519	0.000283605	0.000114141
EURUSD_1H	8.26E-05	3.27E-05	7.07E-05	2.23E-05
EURUSD_30T	0.000133514	0.0001726	0.000270454	0.000301993
GBPUSD_1D	0.000863967	0.000231997	0.000873749	0.000429257
GBPUSD_12H	0.000832904	0.000274174	0.000516829	0.000141321
GBPUSD_6H	0.000289487	7.91E-05	0.000127112	6.52E-05
GBPUSD_1H	4.71E-05	3.52E-05	9.95E-05	9.19E-05
GBPUSD_30T	8.15E-05	4.17E-05	2.72E-05	7.53E-05
USDCHF_1D	0.001034684	0.000865974	0.000826196	0.000277496
USDCHF_12H	0.000294718	0.000144912	0.001229451	0.001052051
USDCHF_6H	0.000614527	0.000541701	0.000182393	0.00010063
USDCHF_1H	3.27E-05	2.31E-05	0.000159003	0.000160018
USDCHF_30T	1.69E-05	4.73E-06	5.61E-05	6.92E-05
USDJPY_1D	0.000566972	0.00020133	0.001275144	0.00089141
USDJPY_12H	0.000294898	0.000188022	0.000923487	0.001247426
USDJPY_6H	0.000182391	0.000170614	0.000215203	0.000118273
USDJPY_1H	0.000197502	9.20E-05	0.00014967	8.11E-05
USDJPY_30T	7.77E-05	3.91E-05	3.52E-05	1.54E-05
Mean	0.000336184	0.000198495	0.000420407	0.000306762

Unidirectional Vs Bidirectional

Currency and frequency	GRU Relu Bidirectional		GRU Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.003264418	0.002508793	0.004515877	0.003002102
EURUSD_12H	0.001804951	0.001976188	0.003761206	0.003486629
EURUSD_6H	0.003681875	0.002461885	0.003921711	0.002497948
EURUSD_1H	0.002070203	0.000625061	0.004403116	0.003055279
EURUSD_30T	0.002019272	0.001011214	0.003890968	0.002241523
GBPUSD_1D	0.003268477	0.001078161	0.004125347	0.000723338
GBPUSD_12H	0.004628441	0.00077614	0.001596336	0.00035417
GBPUSD_6H	0.003690071	0.000304833	0.005500077	0.00064289
GBPUSD_1H	0.003498528	0.000116116	0.003083498	0.000604044
GBPUSD_30T	0.002436929	0.000274796	0.002898972	0.000148486
USDCHF_1D	0.003381599	0.003802104	0.009482416	0.011774896
USDCHF_12H	0.005414608	0.006338591	0.006215273	0.007890506
USDCHF_6H	0.00229487	0.002524693	0.003654939	0.004146543
USDCHF_1H	0.00311218	0.003806221	0.00258969	0.003090261
USDCHF_30T	0.002605188	0.003176072	0.002781555	0.003499343
USDJPY_1D	0.003850373	0.002772214	0.002742899	0.002404767
USDJPY_12H	0.004921299	0.004387937	0.002443389	0.002344669
USDJPY_6H	0.003069344	0.00267188	0.003449132	0.002884945
USDJPY_1H	0.002900043	0.002304077	0.003270028	0.003171229
USDJPY_30T	0.00224058	0.001590825	0.002303494	0.002172991
Mean	0.003207662	0.00222539	0.003831496	0.003006828

Currency and frequency	LSTM Relu Bidirectional		LSTM Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000646601	0.000477242	0.000956876	0.000701727
EURUSD_12H	0.001781473	0.002271858	0.002376047	0.002850674
EURUSD_6H	0.000484017	0.000572836	0.001537763	0.002085426
EURUSD_1H	0.001236252	0.000782335	0.002679884	0.001083536
EURUSD_30T	0.000651753	0.000410656	0.002620105	0.001305268
GBPUSD_1D	0.000899452	0.000476266	0.003149294	0.001065977
GBPUSD_12H	0.000584252	0.000189026	0.002440605	0.000622988
GBPUSD_6H	0.001402092	0.000108173	0.001911535	0.000276965
GBPUSD_1H	0.001538053	0.000120323	0.002309129	0.000156728
GBPUSD_30T	0.001448046	0.000179853	0.002320939	0.000288851
USDCHF_1D	0.001500302	0.000838828	0.005184083	0.006166027
USDCHF_12H	0.001532165	0.001369681	0.002781219	0.002570386
USDCHF_6H	0.0017615	0.00192644	0.002841884	0.003254781
USDCHF_1H	0.003380316	0.004217774	0.00214713	0.00261582
USDCHF_30T	0.00263084	0.00293319	0.002359283	0.002592896
USDJPY_1D	0.000767427	0.000329108	0.001821802	0.001161809
USDJPY_12H	0.001434876	0.001372796	0.001791801	0.0014219
USDJPY_6H	0.000896078	0.000700275	0.000809604	0.000592112
USDJPY_1H	0.00228328	0.00216007	0.001876947	0.001784609
USDJPY_30T	0.002166076	0.002411678	0.002118625	0.001985001
Mean	0.001451243	0.00119242	0.002301728	0.001729174

Currency and frequency	GRU Tanh Bidirectional		GRU Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000550794	0.000538757	0.000547363	0.000294357
EURUSD_12H	0.002389571	0.002087286	0.00037586	0.000366956
EURUSD_6H	0.000154944	0.000102952	0.000156339	0.000169519
EURUSD_1H	0.000262996	3.08E-05	8.26E-05	3.27E-05
EURUSD_30T	8.90E-05	9.10E-05	0.000133514	0.0001726
GBPUSD_1D	0.00040952	0.000186909	0.000863967	0.000231997
GBPUSD_12H	0.000425576	0.000104514	0.000832904	0.000274174
GBPUSD_6H	0.000133072	5.87E-05	0.000289487	7.91E-05
GBPUSD_1H	2.74E-05	1.76E-05	4.71E-05	3.52E-05
GBPUSD_30T	0.000102446	1.08E-05	8.15E-05	4.17E-05
USDCHF_1D	0.001419555	0.001377875	0.001034684	0.000865974
USDCHF_12H	0.000235081	0.000122869	0.000294718	0.000144912
USDCHF_6H	0.000117892	6.00E-05	0.000614527	0.000541701
USDCHF_1H	4.53E-05	3.73E-05	3.27E-05	2.31E-05
USDCHF_30T	1.63E-05	6.90E-06	1.69E-05	4.73E-06
USDJPY_1D	0.00040242	0.000200462	0.000566972	0.00020133
USDJPY_12H	0.000251021	0.000202049	0.000294898	0.000188022
USDJPY_6H	0.000108625	6.03E-05	0.000182391	0.000170614
USDJPY_1H	4.01E-05	2.30E-05	0.000197502	9.20E-05
USDJPY_30T	4.04E-05	8.09E-06	7.77E-05	3.91E-05
Mean	0.000361102	0.000266408	0.000336184	0.000198495

Currency and frequency	LSTM Tanh Bidirectional		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000534389	0.000368498	0.000741205	0.000512807
EURUSD_12H	0.000314574	0.000174082	0.000345858	0.000367943
EURUSD_6H	0.000259049	0.000508039	0.000283605	0.000114141
EURUSD_1H	0.000101767	8.29E-05	7.07E-05	2.23E-05
EURUSD_30T	0.000216816	0.000125221	0.000270454	0.000301993
GBPUSD_1D	0.00138551	0.000275364	0.000873749	0.000429257
GBPUSD_12H	0.000406774	0.000118637	0.000516829	0.000141321
GBPUSD_6H	0.000264347	6.48E-05	0.000127112	6.52E-05
GBPUSD_1H	6.13E-05	3.45E-05	9.95E-05	9.19E-05
GBPUSD_30T	6.25E-05	4.72E-05	2.72E-05	7.53E-05
USDCHF_1D	0.00102671	0.000563364	0.000826196	0.000277496
USDCHF_12H	0.000289928	0.000105889	0.001229451	0.001052051
USDCHF_6H	0.000665103	0.000651929	0.000182393	0.00010063
USDCHF_1H	0.000108804	9.14E-05	0.000159003	0.000160018
USDCHF_30T	1.38E-05	4.95E-06	5.61E-05	6.92E-05
USDJPY_1D	0.000626735	0.000486395	0.001275144	0.00089141
USDJPY_12H	0.000329364	0.000254369	0.000923487	0.001247426
USDJPY_6H	0.000146509	9.05E-05	0.000215203	0.000118273
USDJPY_1H	2.49E-05	1.12E-05	0.00014967	8.11E-05
USDJPY_30T	9.92E-05	9.09E-06	3.52E-05	1.54E-05
Mean	0.000346904	0.000203416	0.000420407	0.000306762

Relu Vs Tanh

Currency and frequency	GRU Relu Bidirectional		GRU Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.003264418	0.002508793	0.000550794	0.000538757
EURUSD_12H	0.001804951	0.001976188	0.002389571	0.002087286
EURUSD_6H	0.003681875	0.002461885	0.000154944	0.000102952
EURUSD_1H	0.002070203	0.000625061	0.000262996	3.08E-05
EURUSD_30T	0.002019272	0.001011214	8.90E-05	9.10E-05
GBPUSD_1D	0.003268477	0.001078161	0.00040952	0.000186909
GBPUSD_12H	0.004628441	0.00077614	0.000425576	0.000104514
GBPUSD_6H	0.003690071	0.000304833	0.000133072	5.87E-05
GBPUSD_1H	0.003498528	0.000116116	2.74E-05	1.76E-05
GBPUSD_30T	0.002436929	0.000274796	0.000102446	1.08E-05
USDCHF_1D	0.003381599	0.003802104	0.001419555	0.001377875
USDCHF_12H	0.005414608	0.006338591	0.000235081	0.000122869
USDCHF_6H	0.00229487	0.002524693	0.000117892	6.00E-05
USDCHF_1H	0.00311218	0.003806221	4.53E-05	3.73E-05
USDCHF_30T	0.002605188	0.003176072	1.63E-05	6.90E-06
USDJPY_1D	0.003850373	0.002772214	0.00040242	0.000200462
USDJPY_12H	0.004921299	0.004387937	0.000251021	0.000202049
USDJPY_6H	0.003069344	0.00267188	0.000108625	6.03E-05
USDJPY_1H	0.002900043	0.002304077	4.01E-05	2.30E-05
USDJPY_30T	0.00224058	0.001590825	4.04E-05	8.09E-06
Mean	0.003207662	0.00222539	0.000361102	0.000266408

Currency and frequency	GRU Relu forward		GRU Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000478781	0.000325808	0.000547363	0.000294357
EURUSD_12H	0.000299871	0.000111475	0.00037586	0.000366956
EURUSD_6H	3.11E-04	5.64E-04	0.000156339	0.000169519
EURUSD_1H	0.001307133	0.001379669	8.26E-05	3.27E-05
EURUSD_30T	0.000821247	0.000545807	0.000133514	0.0001726
GBPUSD_1D	0.000564528	0.00024966	0.000863967	0.000231997
GBPUSD_12H	0.000242298	0.000121673	0.000832904	0.000274174
GBPUSD_6H	2.25E-04	1.03E-04	0.000289487	7.91E-05
GBPUSD_1H	6.68587E-05	0.000297834	4.71E-05	3.52E-05
GBPUSD_30T	0.002804412	0.000812502	8.15E-05	4.17E-05
USDCHF_1D	0.000241978	7.86E-05	0.001034684	0.000865974
USDCHF_12H	0.000130659	3.93E-05	0.000294718	0.000144912
USDCHF_6H	6.89E-05	3.33E-05	0.000614527	0.000541701
USDCHF_1H	1.35391E-05	4.8413E-06	3.27E-05	2.31E-05
USDCHF_30T	0.001499633	0.001870315	1.69E-05	4.73E-06
USDJPY_1D	0.000532539	0.000234369	0.000566972	0.00020133
USDJPY_12H	0.000594708	0.000113337	0.000294898	0.000188022
USDJPY_6H	0.000816494	0.000147291	0.000182391	0.000170614
USDJPY_1H	0.002497351	0.00413478	0.000197502	9.20E-05
USDJPY_30T	0.003598446	0.004151132	7.77E-05	3.91E-05
Mean	0.000855766	0.000765944	0.000336184	0.000198495

Currency and frequency	LSTM Relu Bidirectional		LSTM Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000646601	0.000477242	0.000534389	0.000368498
EURUSD_12H	0.001781473	0.002271858	0.000314574	0.000174082
EURUSD_6H	0.000484017	0.000572836	0.000259049	0.000508039
EURUSD_1H	0.001236252	0.000782335	0.000101767	8.29E-05
EURUSD_30T	0.000651753	0.000410656	0.000216816	0.000125221
GBPUSD_1D	0.000899452	0.000476266	0.00138551	0.000275364
GBPUSD_12H	0.000584252	0.000189026	0.000406774	0.000118637
GBPUSD_6H	0.001402092	0.000108173	0.000264347	6.48E-05
GBPUSD_1H	0.001538053	0.000120323	6.13E-05	3.45E-05
GBPUSD_30T	0.001448046	0.000179853	6.25E-05	4.72E-05
USDCHF_1D	0.001500302	0.000838828	0.00102671	0.000563364
USDCHF_12H	0.001532165	0.001369681	0.000289928	0.000105889
USDCHF_6H	0.0017615	0.00192644	0.000665103	0.000651929
USDCHF_1H	0.003380316	0.004217774	0.000108804	9.14E-05
USDCHF_30T	0.00263084	0.00293319	1.38E-05	4.95E-06
USDJPY_1D	0.000767427	0.000329108	0.000626735	0.000486395
USDJPY_12H	0.001434876	0.001372796	0.000329364	0.000254369
USDJPY_6H	0.000896078	0.000700275	0.000146509	9.05E-05
USDJPY_1H	0.00228328	0.00216007	2.49E-05	1.12E-05
USDJPY_30T	0.002166076	0.002411678	9.92E-05	9.09E-06
Mean	0.001451243	0.00119242	0.000346904	0.000203416

Currency and frequency	LSTM Relu forward		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000956876	0.000701727	0.000741205	0.000512807
EURUSD_12H	0.002376047	0.002850674	0.000345858	0.000367943
EURUSD_6H	0.001537763	0.002085426	0.000283605	0.000114141
EURUSD_1H	0.002679884	0.001083536	7.07E-05	2.23E-05
EURUSD_30T	0.002620105	0.001305268	0.000270454	0.000301993
GBPUSD_1D	0.003149294	0.001065977	0.000873749	0.000429257
GBPUSD_12H	0.002440605	0.000622988	0.000516829	0.000141321
GBPUSD_6H	0.001911535	0.000276965	0.000127112	6.52E-05
GBPUSD_1H	0.002309129	0.000156728	9.95E-05	9.19E-05
GBPUSD_30T	0.002320939	0.000288851	2.72E-05	7.53E-05
USDCHF_1D	0.005184083	0.006166027	0.000826196	0.000277496
USDCHF_12H	0.002781219	0.002570386	0.001229451	0.001052051
USDCHF_6H	0.002841884	0.003254781	0.000182393	0.00010063
USDCHF_1H	0.00214713	0.00261582	0.000159003	0.000160018
USDCHF_30T	0.002359283	0.002592896	5.61E-05	6.92E-05
USDJPY_1D	0.001821802	0.001161809	0.001275144	0.00089141
USDJPY_12H	0.001791801	0.0014219	0.000923487	0.001247426
USDJPY_6H	0.000809604	0.000592112	0.000215203	0.000118273
USDJPY_1H	0.001876947	0.001784609	0.00014967	8.11E-05
USDJPY_30T	0.002118625	0.001985001	3.52E-05	1.54E-05
Mean	0.002301728	0.001729174	0.000420407	0.000306762

Model with lowest MSE

Currency and frequency	GRU Tanh forward	
	In Sample	Out of Sample
EURUSD_1D	0.000547363	0.000294357
EURUSD_12H	0.00037586	0.000366956
EURUSD_6H	0.000156339	0.000169519
EURUSD_1H	8.26E-05	3.27E-05
EURUSD_30T	0.000133514	0.0001726
GBPUSD_1D	0.000863967	0.000231997
GBPUSD_12H	0.000832904	0.000274174
GBPUSD_6H	0.000289487	7.91E-05
GBPUSD_1H	4.71E-05	3.52E-05
GBPUSD_30T	8.15E-05	4.17E-05
USDCHF_1D	0.001034684	0.000865974
USDCHF_12H	0.000294718	0.000144912
USDCHF_6H	0.000614527	0.000541701
USDCHF_1H	3.27E-05	2.31E-05
USDCHF_30T	1.69E-05	4.73E-06
USDJPY_1D	0.000566972	0.00020133
USDJPY_12H	0.000294898	0.000188022
USDJPY_6H	0.000182391	0.000170614
USDJPY_1H	0.000197502	9.20E-05
USDJPY_30T	7.77E-05	3.91E-05
Mean	0.000336184	0.000198495

Recurrent neural multifrequency network Mean Square Error (MSE) GRU vs LSTM

Currency and frequency	GRU Relu Bidirectional		LSTM Relu Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.001600192	0.00141451	0.003282524	0.004266454
EURUSD_12H	0.001315873	0.002558812	0.000581833	0.000464477
EURUSD_6H	0.005572165	0.004675283	0.002801754	0.002336874
EURUSD_1H	0.002809075	0.000842808	0.002109197	0.001493156
EURUSD_30T	0.007909591	0.003631255	0.008684234	0.00489835
GBPUSD_1D	0.007566556	0.001922606	0.001208502	0.000589517
GBPUSD_12H	0.002002741	0.000287993	0.00299204	0.000497529
GBPUSD_6H	0.004973769	0.000842679	0.003755517	0.000627497
GBPUSD_1H	0.002858165	0.000145563	0.002576424	0.000185838
GBPUSD_30T	0.01060341	0.000917182	0.010552931	0.001112045
USDCHF_1D	0.004018882	0.002693601	0.003942629	0.002327312
USDCHF_12H	0.004200715	0.004029691	0.001422351	0.000614392
USDCHF_6H	0.001252894	0.000885794	0.004677046	0.005481635
USDCHF_1H	0.00377987	0.005021711	0.002225646	0.002765861
USDCHF_30T	0.011548418	0.014116974	0.01172267	0.014279066
USDJPY_1D	0.003833288	0.003126358	0.001809655	0.001249284
USDJPY_12H	0.003415277	0.003284397	0.000567307	0.000328786
USDJPY_6H	0.006328044	0.007032551	0.003817865	0.003804151
USDJPY_1H	0.00301213	0.002265188	0.003300674	0.00316756
USDJPY_30T	0.01140475	0.010427575	0.008832768	0.007614164
Mean	0.00500029	0.003506127	0.004043178	0.002905197

Currency and frequency	GRU Relu forward		LSTM Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.004905307	0.003372196	0.002001242	0.002526855
EURUSD_12H	0.006595444	0.005606485	0.001255424	0.001495186
EURUSD_6H	0.008169597	0.006435292	0.003059928	0.002443466
EURUSD_1H	0.003977727	0.001507072	0.002747494	0.001132335
EURUSD_30T	0.007350246	0.003578599	0.007836731	0.003807934
GBPUSD_1D	0.007110231	0.00164177	0.003045818	0.001106883
GBPUSD_12H	0.004951344	0.000993578	0.002869006	0.000436751
GBPUSD_6H	0.003443115	0.000304046	0.002398119	0.000354773
GBPUSD_1H	0.005017692	0.000312495	0.002530077	0.000524187
GBPUSD_30T	0.013053786	0.002405268	0.010909613	0.00135342
USDCHF_1D	0.003322871	0.001350411	0.003747551	0.00126575
USDCHF_12H	0.002446723	0.001716367	0.002749496	0.001831999
USDCHF_6H	0.00506943	0.006273679	0.001736477	0.001623693
USDCHF_1H	0.002720264	0.003457188	0.002660172	0.003065953
USDCHF_30T	0.010586558	0.013447225	0.012781013	0.015651133
USDJPY_1D	0.005166901	0.004357106	0.003915742	0.003173063
USDJPY_12H	0.003087702	0.002599103	0.002761174	0.002726422
USDJPY_6H	0.003969108	0.004816965	0.004630488	0.005103915
USDJPY_1H	0.003561468	0.002557045	0.003214747	0.002780813
USDJPY_30T	0.008715298	0.007954829	0.013963149	0.012238441
Mean	0.005661041	0.003734336	0.004540673	0.003232149

Currency and frequency	GRU Tanh Bidirectional		LSTM Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000806388	0.000650794	0.001143026	0.000945469
EURUSD_12H	0.000422621	0.000299481	0.003292629	0.002335385
EURUSD_6H	0.000377615	0.000151466	0.000794375	0.000224627
EURUSD_1H	0.000318452	0.000259541	0.000215043	5.11E-05
EURUSD_30T	0.000152552	9.68E-05	0.002133258	0.000660647
GBPUSD_1D	0.000619897	0.000518153	0.001104585	0.001218729
GBPUSD_12H	0.005478862	0.001164701	0.001867613	0.000342936
GBPUSD_6H	0.000222009	0.000138404	0.000174885	0.000118608
GBPUSD_1H	0.000241073	0.000169746	7.39E-05	9.56E-05
GBPUSD_30T	4.02E-05	1.65E-05	7.20E-05	1.74E-05
USDCHF_1D	0.003309961	0.002171862	0.003076095	0.001534717
USDCHF_12H	0.00149262	0.00076994	0.001338639	0.000594794
USDCHF_6H	0.000625067	0.000269836	0.000610207	0.000260116
USDCHF_1H	0.000622972	0.000719392	0.000138868	7.89E-05
USDCHF_30T	4.11E-05	4.15E-05	4.34E-05	3.25E-05
USDJPY_1D	0.001356887	0.000712293	0.000911141	0.000334355
USDJPY_12H	0.000524949	0.00024101	0.000648458	0.000746725
USDJPY_6H	0.000367799	0.000208181	0.001134261	0.000742271
USDJPY_1H	0.000226138	0.000175771	4.90E-05	2.17E-05
USDJPY_30T	0.000250732	0.000255995	4.06E-05	1.69E-05
Mean	0.000874897	0.000451567	0.000943099	0.000518672

Currency and frequency	GRU Tanh forward		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000779434	0.000498998	0.001034733	0.001049399
EURUSD_12H	0.000900803	0.000739943	0.000639042	0.001011705
EURUSD_6H	0.000304427	0.000168922	0.000488054	0.00016185
EURUSD_1H	5.80E-05	6.78E-05	0.000186525	0.000453624
EURUSD_30T	0.000544223	0.00015724	0.000106624	0.000116367
GBPUSD_1D	0.000946543	0.00105262	0.000876884	0.000825538
GBPUSD_12H	0.000387108	0.000217407	0.001490421	0.00035002
GBPUSD_6H	0.000210813	0.000108503	0.000208925	0.000121069
GBPUSD_1H	6.71E-05	2.31E-05	0.000129024	7.15E-05
GBPUSD_30T	0.000107711	7.67E-05	5.84E-05	2.22E-05
USDCHF_1D	0.002757218	0.001303155	0.002828265	0.00129066
USDCHF_12H	0.003139904	0.002862081	0.001424879	0.000555466
USDCHF_6H	0.000681481	0.00025657	0.005040801	0.00612983
USDCHF_1H	0.000233971	0.000176866	0.000204839	0.000198912
USDCHF_30T	4.96E-05	5.02E-05	0.000417516	0.000445191
USDJPY_1D	0.001257887	0.001158159	0.001064862	0.000925865
USDJPY_12H	0.002211989	0.001772744	0.000656764	0.000316547
USDJPY_6H	0.000255254	0.000101026	0.000317779	0.000156973
USDJPY_1H	0.000101651	2.50E-05	3.99E-05	1.79E-05
USDJPY_30T	3.75E-05	3.69E-05	0.000212989	0.000133231
Mean	0.000751633	0.000542694	0.000871359	0.000717691

Unidirectional Vs Bidirectional

Currency and Frequency	GRU Relu Bidirectional		GRU Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.001600192	0.00141451	0.004905307	0.003372196
EURUSD_12H	0.001315873	0.002558812	0.006595444	0.005606485
EURUSD_6H	0.005572165	0.004675283	0.008169597	0.006435292
EURUSD_1H	0.002809075	0.000842808	0.003977727	0.001507072
EURUSD_30T	0.007909591	0.003631255	0.007350246	0.003578599
GBPUSD_1D	0.007566556	0.001922606	0.007110231	0.00164177
GBPUSD_12H	0.002002741	0.000287993	0.004951344	0.000993578
GBPUSD_6H	0.004973769	0.000842679	0.003443115	0.000304046
GBPUSD_1H	0.002858165	0.000145563	0.005017692	0.000312495
GBPUSD_30T	0.01060341	0.000917182	0.013053786	0.002405268
USDCHF_1D	0.004018882	0.002693601	0.003322871	0.001350411
USDCHF_12H	0.004200715	0.004029691	0.002446723	0.001716367
USDCHF_6H	0.001252894	0.000885794	0.00506943	0.006273679
USDCHF_1H	0.00377987	0.005021711	0.002720264	0.003457188
USDCHF_30T	0.011548418	0.014116974	0.010586558	0.013447225
USDJPY_1D	0.003833288	0.003126358	0.005166901	0.004357106
USDJPY_12H	0.003415277	0.003284397	0.003087702	0.002599103
USDJPY_6H	0.006328044	0.007032551	0.003969108	0.004816965
USDJPY_1H	0.00301213	0.002265188	0.003561468	0.002557045
USDJPY_30T	0.01140475	0.010427575	0.008715298	0.007954829
Mean	0.00500029	0.003506127	0.005661041	0.003734336

Currency and Frequency	LSTM Relu Bidirectional		LSTM Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.003282524	0.004266454	0.002001242	0.002526855
EURUSD_12H	0.000581833	0.000464477	0.001255424	0.001495186
EURUSD_6H	0.002801754	0.002336874	0.003059928	0.002443466
EURUSD_1H	0.002109197	0.001493156	0.002747494	0.001132335
EURUSD_30T	0.008684234	0.00489835	0.007836731	0.003807934
GBPUSD_1D	0.001208502	0.000589517	0.003045818	0.001106883
GBPUSD_12H	0.00299204	0.000497529	0.002869006	0.000436751
GBPUSD_6H	0.003755517	0.000627497	0.002398119	0.000354773
GBPUSD_1H	0.002576424	0.000185838	0.002530077	0.000524187
GBPUSD_30T	0.010552931	0.001112045	0.010909613	0.00135342
USDCHF_1D	0.003942629	0.002327312	0.003747551	0.00126575
USDCHF_12H	0.001422351	0.000614392	0.002749496	0.001831999
USDCHF_6H	0.004677046	0.005481635	0.001736477	0.001623693
USDCHF_1H	0.002225646	0.002765861	0.002660172	0.003065953
USDCHF_30T	0.01172267	0.014279066	0.012781013	0.015651133
USDJPY_1D	0.001809655	0.001249284	0.003915742	0.003173063
USDJPY_12H	0.000567307	0.000328786	0.002761174	0.002726422
USDJPY_6H	0.003817865	0.003804151	0.004630488	0.005103915
USDJPY_1H	0.003300674	0.00316756	0.003214747	0.002780813
USDJPY_30T	0.008832768	0.007614164	0.013963149	0.012238441
Mean	0.004043178	0.002905197	0.004540673	0.003232149

Currency and Frequency	GRU Tanh Bidirectional		GRU Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000806388	0.000650794	0.000779434	0.000498998
EURUSD_12H	0.000422621	0.000299481	0.000900803	0.000739943
EURUSD_6H	0.000377615	0.000151466	0.000304427	0.000168922
EURUSD_1H	0.000318452	0.000259541	5.80E-05	6.78E-05
EURUSD_30T	0.000152552	9.68E-05	0.000544223	0.00015724
GBPUSD_1D	0.000619897	0.000518153	0.000946543	0.00105262
GBPUSD_12H	0.005478862	0.001164701	0.000387108	0.000217407
GBPUSD_6H	0.000222009	0.000138404	0.000210813	0.000108503
GBPUSD_1H	0.000241073	0.000169746	6.71E-05	2.31E-05
GBPUSD_30T	4.02E-05	1.65E-05	0.000107711	7.67E-05
USDCHF_1D	0.003309961	0.002171862	0.002757218	0.001303155
USDCHF_12H	0.00149262	0.00076994	0.003139904	0.002862081
USDCHF_6H	0.000625067	0.000269836	0.000681481	0.00025657
USDCHF_1H	0.000622972	0.000719392	0.000233971	0.000176866
USDCHF_30T	4.11E-05	4.15E-05	4.96E-05	5.02E-05
USDJPY_1D	0.001356887	0.000712293	0.001257887	0.001158159
USDJPY_12H	0.000524949	0.00024101	0.002211989	0.001772744
USDJPY_6H	0.000367799	0.000208181	0.000255254	0.000101026
USDJPY_1H	0.000226138	0.000175771	0.000101651	2.50E-05
USDJPY_30T	0.000250732	0.000255995	3.75E-05	3.69E-05
Mean	0.000874897	0.000451567	0.000751633	0.000542694

Currency and Frequency	LSTM Tanh Bidirectional		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.001143026	0.000945469	0.001034733	0.001049399
EURUSD_12H	0.003292629	0.002335385	0.000639042	0.001011705
EURUSD_6H	0.000794375	0.000224627	0.000488054	0.00016185
EURUSD_1H	0.000215043	5.11E-05	0.000186525	0.000453624
EURUSD_30T	0.002133258	0.000660647	0.000106624	0.000116367
GBPUSD_1D	0.001104585	0.001218729	0.000876884	0.000825538
GBPUSD_12H	0.001867613	0.000342936	0.001490421	0.00035002
GBPUSD_6H	0.000174885	0.000118608	0.000208925	0.000121069
GBPUSD_1H	7.39E-05	9.56E-05	0.000129024	7.15E-05
GBPUSD_30T	7.20E-05	1.74E-05	5.84E-05	2.22E-05
USDCHF_1D	0.003076095	0.001534717	0.002828265	0.00129066
USDCHF_12H	0.001338639	0.000594794	0.001424879	0.000555466
USDCHF_6H	0.000610207	0.000260116	0.005040801	0.00612983
USDCHF_1H	0.000138868	7.89E-05	0.000204839	0.000198912
USDCHF_30T	4.34E-05	3.25E-05	0.000417516	0.000445191
USDJPY_1D	0.000911141	0.000334355	0.001064862	0.000925865
USDJPY_12H	0.000648458	0.000746725	0.000656764	0.000316547
USDJPY_6H	0.001134261	0.000742271	0.000317779	0.000156973
USDJPY_1H	4.90E-05	2.17E-05	3.99E-05	1.79E-05
USDJPY_30T	4.06E-05	1.69E-05	0.000212989	0.000133231
Mean	0.000943099	0.000518672	0.000871359	0.000717691

Relu Vs Tanh

Currency and Frequency	GRU Relu Bidirectional		GRU Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.001600192	0.00141451	0.000806388	0.000650794
EURUSD_12H	0.001315873	0.002558812	0.000422621	0.000299481
EURUSD_6H	0.005572165	0.004675283	0.000377615	0.000151466
EURUSD_1H	0.002809075	0.000842808	0.000318452	0.000259541
EURUSD_30T	0.007909591	0.003631255	0.000152552	9.68E-05
GBPUSD_1D	0.007566556	0.001922606	0.000619897	0.000518153
GBPUSD_12H	0.002002741	0.000287993	0.005478862	0.001164701
GBPUSD_6H	0.004973769	0.000842679	0.000222009	0.000138404
GBPUSD_1H	0.002858165	0.000145563	0.000241073	0.000169746
GBPUSD_30T	0.01060341	0.000917182	4.02E-05	1.65E-05
USDCHF_1D	0.004018882	0.002693601	0.003309961	0.002171862
USDCHF_12H	0.004200715	0.004029691	0.00149262	0.00076994
USDCHF_6H	0.001252894	0.000885794	0.000625067	0.000269836
USDCHF_1H	0.00377987	0.005021711	0.000622972	0.000719392
USDCHF_30T	0.011548418	0.014116974	4.11E-05	4.15E-05
USDJPY_1D	0.003833288	0.003126358	0.001356887	0.000712293
USDJPY_12H	0.003415277	0.003284397	0.000524949	0.00024101
USDJPY_6H	0.006328044	0.007032551	0.000367799	0.000208181
USDJPY_1H	0.00301213	0.002265188	0.000226138	0.000175771
USDJPY_30T	0.01140475	0.010427575	0.000250732	0.000255995
Mean	0.00500029	0.003506127	0.000874897	0.000451567

Currency and Frequency	GRU Relu forward		GRU Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.004905307	0.003372196	0.000779434	0.000498998
EURUSD_12H	0.006595444	0.005606485	0.000900803	0.000739943
EURUSD_6H	0.008169597	0.006435292	0.000304427	0.000168922
EURUSD_1H	0.003977727	0.001507072	5.80E-05	6.78E-05
EURUSD_30T	0.007350246	0.003578599	0.000544223	0.00015724
GBPUSD_1D	0.007110231	0.00164177	0.000946543	0.00105262
GBPUSD_12H	0.004951344	0.000993578	0.000387108	0.000217407
GBPUSD_6H	0.003443115	0.000304046	0.000210813	0.000108503
GBPUSD_1H	0.005017692	0.000312495	6.71E-05	2.31E-05
GBPUSD_30T	0.013053786	0.002405268	0.000107711	7.67E-05
USDCHF_1D	0.003322871	0.001350411	0.002757218	0.001303155
USDCHF_12H	0.002446723	0.001716367	0.003139904	0.002862081
USDCHF_6H	0.00506943	0.006273679	0.000681481	0.00025657
USDCHF_1H	0.002720264	0.003457188	0.000233971	0.000176866
USDCHF_30T	0.010586558	0.013447225	4.96E-05	5.02E-05
USDJPY_1D	0.005166901	0.004357106	0.001257887	0.001158159
USDJPY_12H	0.003087702	0.002599103	0.002211989	0.001772744
USDJPY_6H	0.003969108	0.004816965	0.000255254	0.000101026
USDJPY_1H	0.003561468	0.002557045	0.000101651	2.50E-05
USDJPY_30T	0.008715298	0.007954829	3.75E-05	3.69E-05
Mean	0.005661041	0.003734336	0.000751633	0.000542694

Currency and Frequency	LSTM Relu Bidirectional		LSTM Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.003282524	0.004266454	0.001143026	0.000945469
EURUSD_12H	0.000581833	0.000464477	0.003292629	0.002335385
EURUSD_6H	0.002801754	0.002336874	0.000794375	0.000224627
EURUSD_1H	0.002109197	0.001493156	0.000215043	5.11E-05
EURUSD_30T	0.008684234	0.00489835	0.002133258	0.000660647
GBPUSD_1D	0.001208502	0.000589517	0.001104585	0.001218729
GBPUSD_12H	0.00299204	0.000497529	0.001867613	0.000342936
GBPUSD_6H	0.003755517	0.000627497	0.000174885	0.000118608
GBPUSD_1H	0.002576424	0.000185838	7.39E-05	9.56E-05
GBPUSD_30T	0.010552931	0.001112045	7.20E-05	1.74E-05
USDCHF_1D	0.003942629	0.002327312	0.003076095	0.001534717
USDCHF_12H	0.001422351	0.000614392	0.001338639	0.000594794
USDCHF_6H	0.004677046	0.005481635	0.000610207	0.000260116
USDCHF_1H	0.002225646	0.002765861	0.000138868	7.89E-05
USDCHF_30T	0.01172267	0.014279066	4.34E-05	3.25E-05
USDJPY_1D	0.001809655	0.001249284	0.000911141	0.000334355
USDJPY_12H	0.000567307	0.000328786	0.000648458	0.000746725
USDJPY_6H	0.003817865	0.003804151	0.001134261	0.000742271
USDJPY_1H	0.003300674	0.00316756	4.90E-05	2.17E-05
USDJPY_30T	0.008832768	0.007614164	4.06E-05	1.69E-05
Mean	0.004043178	0.002905197	0.000943099	0.000518672

Currency and Frequency	LSTM Relu forward		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.002001242	0.002526855	0.001034733	0.001049399
EURUSD_12H	0.001255424	0.001495186	0.000639042	0.001011705
EURUSD_6H	0.003059928	0.002443466	0.000488054	0.00016185
EURUSD_1H	0.002747494	0.001132335	0.000186525	0.000453624
EURUSD_30T	0.007836731	0.003807934	0.000106624	0.000116367
GBPUSD_1D	0.003045818	0.001106883	0.000876884	0.000825538
GBPUSD_12H	0.002869006	0.000436751	0.001490421	0.00035002
GBPUSD_6H	0.002398119	0.000354773	0.000208925	0.000121069
GBPUSD_1H	0.002530077	0.000524187	0.000129024	7.15E-05
GBPUSD_30T	0.010909613	0.00135342	5.84E-05	2.22E-05
USDCHF_1D	0.003747551	0.00126575	0.002828265	0.00129066
USDCHF_12H	0.002749496	0.001831999	0.001424879	0.000555466
USDCHF_6H	0.001736477	0.001623693	0.005040801	0.00612983
USDCHF_1H	0.002660172	0.003065953	0.000204839	0.000198912
USDCHF_30T	0.012781013	0.015651133	0.000417516	0.000445191
USDJPY_1D	0.003915742	0.003173063	0.001064862	0.000925865
USDJPY_12H	0.002761174	0.002726422	0.000656764	0.000316547
USDJPY_6H	0.004630488	0.005103915	0.000317779	0.000156973
USDJPY_1H	0.003214747	0.002780813	3.99E-05	1.79E-05
USDJPY_30T	0.013963149	0.012238441	0.000212989	0.000133231
Mean	0.004540673	0.003232149	0.000871359	0.000717691

ARMA-RNN single frequency network Mean Square Error (MSE) GRU vs LSTM

Currency and Frequency	GRU Relu Bidirectional		LSTM Relu Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000443229	0.000248624	0.000359513	0.000222005
EURUSD_12H	0.000246072	0.000207135	0.000209114	0.000238781
EURUSD_6H	9.82E-05	8.61E-05	0.00013009	9.80E-05
EURUSD_1H	0.001422648	0.001465934	0.000686673	0.000697724
EURUSD_30T	0.000212351	0.000385776	0.001430812	0.001593241
GBPUSD_1D	0.000455889	0.000191745	0.000678704	0.000999973
GBPUSD_12H	0.000185123	0.00010604	0.000233745	6.32E-05
GBPUSD_6H	8.01E-05	9.80E-05	8.30E-05	5.71E-05
GBPUSD_1H	0.001315384	0.000239831	0.000607485	4.18E-05
GBPUSD_30T	0.002286183	0.000567917	0.001903209	0.0003751
USDCHF_1D	0.000214338	6.21E-05	0.000226745	7.22E-05
USDCHF_12H	0.000127273	4.34E-05	0.000136928	3.92E-05
USDCHF_6H	5.37E-05	1.96E-05	5.78E-05	2.40E-05
USDCHF_1H	0.000611334	0.000678887	0.00025325	0.000266383
USDCHF_30T	0.001831243	0.001667874	0.001340398	0.001507544
USDJPY_1D	0.000622524	0.000235766	0.000442852	0.000150672
USDJPY_12H	0.000561153	0.000109292	0.000247441	0.000100865
USDJPY_6H	0.000145129	0.000110513	0.000214591	0.000175966
USDJPY_1H	0.002438919	0.003875681	0.002436554	0.003920583
USDJPY_30T	0.002069871	0.00283074	0.00273299	0.004034094
Mean	0.000771031	0.000661549	0.000720595	0.000733927

Currency and Frequency	GRU Relu forward		LSTM Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000478781	0.000325808	0.000423136	0.000112108
EURUSD_12H	0.000299871	0.000111475	0.000252757	8.13296E-05
EURUSD_6H	3.11E-04	5.64E-04	0.000398169	3.75E-04
EURUSD_1H	0.001307133	0.001379669	0.001151242	0.001100398
EURUSD_30T	0.000821247	0.000545807	0.002061276	0.003077799
GBPUSD_1D	0.000564528	0.00024966	0.000656902	0.000922847
GBPUSD_12H	0.000242298	0.000121673	0.000452352	3.36E-04
GBPUSD_6H	2.25E-04	1.03E-04	1.85E-04	9.93E-05
GBPUSD_1H	6.68587E-05	0.000297834	0.001920513	3.73E-04
GBPUSD_30T	0.002804412	0.000812502	0.003358092	0.000926624
USDCHF_1D	0.000241978	7.86E-05	0.000284187	1.12E-04
USDCHF_12H	0.000130659	3.93E-05	0.000142711	4.54E-05
USDCHF_6H	6.89E-05	3.33E-05	7.61E-05	2.17E-05
USDCHF_1H	1.35391E-05	4.8413E-06	0.000304521	0.000349454
USDCHF_30T	0.001499633	0.001870315	0.00141902	0.001642298
USDJPY_1D	0.000532539	0.000234369	0.000773043	0.000290484
USDJPY_12H	0.000594708	0.000113337	0.000460177	0.000157911
USDJPY_6H	0.000816494	0.000147291	0.00034687	0.000203352
USDJPY_1H	0.002497351	0.00413478	0.00258046	0.00402606
USDJPY_30T	0.003598446	0.004151132	0.001765896	0.002346142
Mean	0.000855766	0.000765944	0.000950635	0.000829964

Currency and Frequency	GRU Tanh Bidirectional		LSTM Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000817883	0.000613922	0.000883073	0.000751868
EURUSD_12H	0.000799897	0.000807952	0.000774773	0.00041462
EURUSD_6H	6.14E-04	3.46E-04	0.000128633	1.31E-04
EURUSD_1H	1.62025E-05	7.35916E-06	1.61315E-05	3.35139E-05
EURUSD_30T	5.96473E-06	6.10171E-06	6.7174E-06	5.26913E-06
GBPUSD_1D	0.000753472	0.000868242	0.000762349	0.001442196
GBPUSD_12H	0.000655454	0.00095846	0.000667682	8.30E-04
GBPUSD_6H	6.89E-04	7.34E-04	1.13E-04	7.66E-05
GBPUSD_1H	1.40918E-05	2.02938E-05	1.42706E-05	1.64E-05
GBPUSD_30T	8.76448E-06	1.38679E-05	7.53079E-06	5.21931E-06
USDCHF_1D	0.000320668	1.19E-04	0.000263464	8.90E-05
USDCHF_12H	0.000187766	7.94E-05	0.000165185	6.45E-05
USDCHF_6H	5.61E-05	2.41E-05	8.23E-05	2.46E-05
USDCHF_1H	1.02644E-05	4.9056E-06	1.81946E-05	1.24335E-05
USDCHF_30T	8.54269E-06	1.9787E-06	1.25902E-05	5.74303E-06
USDJPY_1D	0.000596614	0.000236436	0.000613552	0.000320303
USDJPY_12H	0.000503548	0.000307388	0.000523591	0.000153092
USDJPY_6H	0.000452433	0.000145749	0.000135167	4.84964E-05
USDJPY_1H	1.68939E-05	7.71428E-06	1.98276E-05	6.12584E-06
USDJPY_30T	8.95691E-06	4.13637E-06	1.11556E-05	1.1947E-05
Mean	0.000326801	0.000265346	0.00026095	0.000222159

Currency and Frequency	GRU Tanh forward		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000825085	0.000425665	0.000921075	0.000500184
EURUSD_12H	0.000809513	0.000703693	0.000838533	0.000545776
EURUSD_6H	6.85E-04	5.28E-04	0.0001392	8.32E-05
EURUSD_1H	1.9086E-05	3.22617E-05	1.64012E-05	1.40897E-05
EURUSD_30T	1.2301E-05	5.02138E-06	1.34702E-05	4.64395E-05
GBPUSD_1D	0.000759216	0.001430547	0.000803939	0.001190406
GBPUSD_12H	0.000685633	0.001484101	0.000691056	1.41E-03
GBPUSD_6H	5.93E-04	1.10E-03	1.09E-04	4.11E-05
GBPUSD_1H	3.24528E-05	3.96889E-05	2.08546E-05	6.94E-06
GBPUSD_30T	8.6649E-06	4.32029E-06	1.21474E-05	1.32562E-05
USDCHF_1D	0.000306888	1.15E-04	0.000238018	7.79E-05
USDCHF_12H	0.000205567	7.13E-05	0.000172735	5.09E-05
USDCHF_6H	1.03E-04	4.42E-05	7.96E-05	2.98E-05
USDCHF_1H	1.11013E-05	4.64768E-06	1.11076E-05	4.27527E-06
USDCHF_30T	1.3905E-05	9.19175E-06	2.02237E-05	7.89123E-06
USDJPY_1D	0.000627763	0.000466593	0.000642689	0.000229469
USDJPY_12H	0.00053215	0.000169876	0.00053522	0.00021895
USDJPY_6H	0.000463676	0.000412657	0.000173661	8.40341E-05
USDJPY_1H	2.45675E-05	1.57034E-05	1.5461E-05	5.22589E-06
USDJPY_30T	9.05783E-06	4.44978E-06	1.0288E-05	9.67407E-06
Mean	0.000336399	0.000353389	0.000273248	0.0002283

Unidirectional Vs Bidirectional

Currency and Frequency	GRU Relu Bidirectional		GRU Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000443229	0.000248624	0.000478781	0.000325808
EURUSD_12H	0.000246072	0.000207135	0.000299871	0.000111475
EURUSD_6H	9.82E-05	8.61E-05	0.000311012	5.64E-04
EURUSD_1H	0.001422648	0.001465934	0.001307133	0.001379669
EURUSD_30T	0.000212351	0.000385776	0.000821247	0.000545807
GBPUSD_1D	0.000455889	0.000191745	0.000564528	0.00024966
GBPUSD_12H	0.000185123	0.00010604	0.000242298	1.22E-04
GBPUSD_6H	8.01E-05	9.80E-05	2.25E-04	1.03E-04
GBPUSD_1H	0.001315384	0.000239831	6.68587E-05	2.98E-04
GBPUSD_30T	0.002286183	0.000567917	0.002804412	0.000812502
USDCHF_1D	0.000214338	6.21E-05	0.000241978	7.86E-05
USDCHF_12H	0.000127273	4.34E-05	0.000130659	3.93E-05
USDCHF_6H	5.37E-05	1.96E-05	6.89E-05	3.33E-05
USDCHF_1H	0.000611334	0.000678887	1.35391E-05	4.8413E-06
USDCHF_30T	0.001831243	0.001667874	0.001499633	0.001870315
USDJPY_1D	0.000622524	0.000235766	0.000532539	0.000234369
USDJPY_12H	0.000561153	0.000109292	0.000594708	0.000113337
USDJPY_6H	0.000145129	0.000110513	0.000816494	0.000147291
USDJPY_1H	0.002438919	0.003875681	0.002497351	0.00413478
USDJPY_30T	0.002069871	0.00283074	0.003598446	0.004151132
Mean	0.000771031	0.000661549	0.000855766	0.000765944

Currency and Frequency	LSTM Relu Bidirectional		LSTM Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000359513	0.000222005	0.000423136	0.000112108
EURUSD_12H	0.000209114	0.000238781	0.000252757	8.13296E-05
EURUSD_6H	1.30E-04	9.80E-05	0.000398169	3.75E-04
EURUSD_1H	0.000686673	0.000697724	0.001151242	0.001100398
EURUSD_30T	0.001430812	0.001593241	0.002061276	0.003077799
GBPUSD_1D	0.000678704	0.000999973	0.000656902	0.000922847
GBPUSD_12H	0.000233745	6.32114E-05	0.000452352	3.36E-04
GBPUSD_6H	8.30E-05	5.71E-05	1.85E-04	9.93E-05
GBPUSD_1H	0.000607485	4.18337E-05	0.001920513	3.73E-04
GBPUSD_30T	0.001903209	0.0003751	0.003358092	0.000926624
USDCHF_1D	0.000226745	7.22E-05	0.000284187	1.12E-04
USDCHF_12H	0.000136928	3.92E-05	0.000142711	4.54E-05
USDCHF_6H	5.78E-05	2.40E-05	7.61E-05	2.17E-05
USDCHF_1H	0.00025325	0.000266383	0.000304521	0.000349454
USDCHF_30T	0.001340398	0.001507544	0.00141902	0.001642298
USDJPY_1D	0.000442852	0.000150672	0.000773043	0.000290484
USDJPY_12H	0.000247441	0.000100865	0.000460177	0.000157911
USDJPY_6H	0.000214591	0.000175966	0.00034687	0.000203352
USDJPY_1H	0.002436554	0.003920583	0.00258046	0.00402606
USDJPY_30T	0.00273299	0.004034094	0.001765896	0.002346142
Mean	0.000720595	0.000733927	0.000950635	0.000829964

Currency and Frequency	GRU Tanh Bidirectional		GRU Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000817883	0.000613922	0.000825085	0.000425665
EURUSD_12H	0.000799897	0.000807952	0.000809513	0.000703693
EURUSD_6H	6.14E-04	3.46E-04	0.00068517	5.28E-04
EURUSD_1H	1.62025E-05	7.35916E-06	1.9086E-05	3.22617E-05
EURUSD_30T	5.96473E-06	6.10171E-06	1.2301E-05	5.02138E-06
GBPUSD_1D	0.000753472	0.000868242	0.000759216	0.001430547
GBPUSD_12H	0.000655454	0.00095846	0.000685633	1.48E-03
GBPUSD_6H	6.89E-04	7.34E-04	5.93E-04	1.10E-03
GBPUSD_1H	1.40918E-05	2.02938E-05	3.24528E-05	3.97E-05
GBPUSD_30T	8.76448E-06	1.38679E-05	8.6649E-06	4.32029E-06
USDCHF_1D	0.000320668	1.19E-04	0.000306888	1.15E-04
USDCHF_12H	0.000187766	7.94E-05	0.000205567	7.13E-05
USDCHF_6H	5.61E-05	2.41E-05	1.03E-04	4.42E-05
USDCHF_1H	1.02644E-05	4.9056E-06	1.11013E-05	4.64768E-06
USDCHF_30T	8.54269E-06	1.9787E-06	1.3905E-05	9.19175E-06
USDJPY_1D	0.000596614	0.000236436	0.000627763	0.000466593
USDJPY_12H	0.000503548	0.000307388	0.00053215	0.000169876
USDJPY_6H	0.000452433	0.000145749	0.000463676	0.000412657
USDJPY_1H	1.68939E-05	7.71428E-06	2.45675E-05	1.57034E-05
USDJPY_30T	8.95691E-06	4.13637E-06	9.05783E-06	4.44978E-06
Mean	0.000326801	0.000265346	0.000336399	0.000353389

Currency and Frequency	LSTM Tanh Bidirectional		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000883073	0.000751868	0.000921075	0.000500184
EURUSD_12H	0.000774773	0.00041462	0.000838533	0.000545776
EURUSD_6H	1.29E-04	1.31E-04	0.0001392	8.32E-05
EURUSD_1H	1.61315E-05	3.35139E-05	1.64012E-05	1.40897E-05
EURUSD_30T	6.7174E-06	5.26913E-06	1.34702E-05	4.64395E-05
GBPUSD_1D	0.000762349	0.001442196	0.000803939	0.001190406
GBPUSD_12H	0.000667682	0.00082987	0.000691056	1.41E-03
GBPUSD_6H	1.13E-04	7.66E-05	1.09E-04	4.11E-05
GBPUSD_1H	1.42706E-05	1.6364E-05	2.08546E-05	6.94E-06
GBPUSD_30T	7.53079E-06	5.21931E-06	1.21474E-05	1.32562E-05
USDCHF_1D	0.000263464	8.90E-05	0.000238018	7.79E-05
USDCHF_12H	0.000165185	6.45E-05	0.000172735	5.09E-05
USDCHF_6H	8.23E-05	2.46E-05	7.96E-05	2.98E-05
USDCHF_1H	1.81946E-05	1.24335E-05	1.11076E-05	4.27527E-06
USDCHF_30T	1.25902E-05	5.74303E-06	2.02237E-05	7.89123E-06
USDJPY_1D	0.000613552	0.000320303	0.000642689	0.000229469
USDJPY_12H	0.000523591	0.000153092	0.00053522	0.00021895
USDJPY_6H	0.000135167	4.84964E-05	0.000173661	8.40341E-05
USDJPY_1H	1.98276E-05	6.12584E-06	1.5461E-05	5.22589E-06
USDJPY_30T	1.11556E-05	1.1947E-05	1.0288E-05	9.67407E-06
Mean	0.00026095	0.000222159	0.000273248	0.0002283

Relu Vs Tanh

Currency and Frequency	GRU Relu Bidirectional		GRU Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000443229	0.000248624	0.000817883	0.000613922
EURUSD_12H	0.000246072	0.000207135	0.000799897	0.000807952
EURUSD_6H	9.82E-05	8.61E-05	0.000613668	3.46E-04
EURUSD_1H	0.001422648	0.001465934	1.62025E-05	7.35916E-06
EURUSD_30T	0.000212351	0.000385776	5.96473E-06	6.10171E-06
GBPUSD_1D	0.000455889	0.000191745	0.000753472	0.000868242
GBPUSD_12H	0.000185123	0.00010604	0.000655454	9.58E-04
GBPUSD_6H	8.01E-05	9.80E-05	6.89E-04	7.34E-04
GBPUSD_1H	0.001315384	0.000239831	1.40918E-05	2.03E-05
GBPUSD_30T	0.002286183	0.000567917	8.76448E-06	1.38679E-05
USDCHF_1D	0.000214338	6.21E-05	0.000320668	1.19E-04
USDCHF_12H	0.000127273	4.34E-05	0.000187766	7.94E-05
USDCHF_6H	5.37E-05	1.96E-05	5.61E-05	2.41E-05
USDCHF_1H	0.000611334	0.000678887	1.02644E-05	4.9056E-06
USDCHF_30T	0.001831243	0.001667874	8.54269E-06	1.9787E-06
USDJPY_1D	0.000622524	0.000235766	0.000596614	0.000236436
USDJPY_12H	0.000561153	0.000109292	0.000503548	0.000307388
USDJPY_6H	0.000145129	0.000110513	0.000452433	0.000145749
USDJPY_1H	0.002438919	0.003875681	1.68939E-05	7.71428E-06
USDJPY_30T	0.002069871	0.00283074	8.95691E-06	4.13637E-06
Mean	0.000771031	0.000661549	0.000326801	0.000265346

Currency and Frequency	GRU Relu forward		GRU Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000478781	0.000325808	0.000825085	0.000425665
EURUSD_12H	0.000299871	0.000111475	0.000809513	0.000703693
EURUSD_6H	3.11E-04	5.64E-04	0.00068517	5.28E-04
EURUSD_1H	0.001307133	0.001379669	1.9086E-05	3.22617E-05
EURUSD_30T	0.000821247	0.000545807	1.2301E-05	5.02138E-06
GBPUSD_1D	0.000564528	0.00024966	0.000759216	0.001430547
GBPUSD_12H	0.000242298	0.000121673	0.000685633	1.48E-03
GBPUSD_6H	2.25E-04	1.03E-04	5.93E-04	1.10E-03
GBPUSD_1H	6.68587E-05	0.000297834	3.24528E-05	3.97E-05
GBPUSD_30T	0.002804412	0.000812502	8.6649E-06	4.32029E-06
USDCHF_1D	0.000241978	7.86E-05	0.000306888	1.15E-04
USDCHF_12H	0.000130659	3.93E-05	0.000205567	7.13E-05
USDCHF_6H	6.89E-05	3.33E-05	1.03E-04	4.42E-05
USDCHF_1H	1.35391E-05	4.8413E-06	1.11013E-05	4.64768E-06
USDCHF_30T	0.001499633	0.001870315	1.3905E-05	9.19175E-06
USDJPY_1D	0.000532539	0.000234369	0.000627763	0.000466593
USDJPY_12H	0.000594708	0.000113337	0.00053215	0.000169876
USDJPY_6H	0.000816494	0.000147291	0.000463676	0.000412657
USDJPY_1H	0.002497351	0.00413478	2.45675E-05	1.57034E-05
USDJPY_30T	0.003598446	0.004151132	9.05783E-06	4.44978E-06
Mean	0.000855766	0.000765944	0.000336399	0.000353389

Currency and Frequency	LSTM Relu Bidirectional		LSTM Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000359513	0.000222005	0.000883073	0.000751868
EURUSD_12H	0.000209114	0.000238781	0.000774773	0.00041462
EURUSD_6H	1.30E-04	9.80E-05	0.000128633	1.31E-04
EURUSD_1H	0.000686673	0.000697724	1.61315E-05	3.35139E-05
EURUSD_30T	0.001430812	0.001593241	6.7174E-06	5.26913E-06
GBPUSD_1D	0.000678704	0.000999973	0.000762349	0.001442196
GBPUSD_12H	0.000233745	6.32114E-05	0.000667682	8.30E-04
GBPUSD_6H	8.30E-05	5.71E-05	1.13E-04	7.66E-05
GBPUSD_1H	0.000607485	4.18337E-05	1.42706E-05	1.64E-05
GBPUSD_30T	0.001903209	0.0003751	7.53079E-06	5.21931E-06
USDCHF_1D	0.000226745	7.22E-05	0.000263464	8.90E-05
USDCHF_12H	0.000136928	3.92E-05	0.000165185	6.45E-05
USDCHF_6H	5.78E-05	2.40E-05	8.23E-05	2.46E-05
USDCHF_1H	0.00025325	0.000266383	1.81946E-05	1.24335E-05
USDCHF_30T	0.001340398	0.001507544	1.25902E-05	5.74303E-06
USDJPY_1D	0.000442852	0.000150672	0.000613552	0.000320303
USDJPY_12H	0.000247441	0.000100865	0.000523591	0.000153092
USDJPY_6H	0.000214591	0.000175966	0.000135167	4.84964E-05
USDJPY_1H	0.002436554	0.003920583	1.98276E-05	6.12584E-06
USDJPY_30T	0.00273299	0.004034094	1.11556E-05	1.1947E-05
Mean	0.000720595	0.000733927	0.00026095	0.000222159

Currency and Frequency	LSTM Relu forward		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000423136	0.000112108	0.000921075	0.000500184
EURUSD_12H	0.000252757	8.13296E-05	0.000838533	0.000545776
EURUSD_6H	3.98E-04	3.75E-04	0.0001392	8.32E-05
EURUSD_1H	0.001151242	0.001100398	1.64012E-05	1.40897E-05
EURUSD_30T	0.002061276	0.003077799	1.34702E-05	4.64395E-05
GBPUSD_1D	0.000656902	0.000922847	0.000803939	0.001190406
GBPUSD_12H	0.000452352	0.000335552	0.000691056	1.41E-03
GBPUSD_6H	1.85E-04	9.93E-05	1.09E-04	4.11E-05
GBPUSD_1H	0.001920513	0.000373246	2.08546E-05	6.94E-06
GBPUSD_30T	0.003358092	0.000926624	1.21474E-05	1.32562E-05
USDCHF_1D	0.000284187	1.12E-04	0.000238018	7.79E-05
USDCHF_12H	0.000142711	4.54E-05	0.000172735	5.09E-05
USDCHF_6H	7.61E-05	2.17E-05	7.96E-05	2.98E-05
USDCHF_1H	0.000304521	0.000349454	1.11076E-05	4.27527E-06
USDCHF_30T	0.00141902	0.001642298	2.02237E-05	7.89123E-06
USDJPY_1D	0.000773043	0.000290484	0.000642689	0.000229469
USDJPY_12H	0.000460177	0.000157911	0.00053522	0.00021895
USDJPY_6H	0.00034687	0.000203352	0.000173661	8.40341E-05
USDJPY_1H	0.00258046	0.00402606	1.5461E-05	5.22589E-06
USDJPY_30T	0.001765896	0.002346142	1.0288E-05	9.67407E-06
Mean	0.000950635	0.000829964	0.000273248	0.0002283

Model with lowest MSE

LSTM Tanh Bidirectional	
In Sample	Out of Sample
0.000883073	0.000751868
0.000774773	0.00041462
0.000128633	1.31E-04
1.61315E-05	3.35139E-05
6.7174E-06	5.26913E-06
0.000762349	0.001442196
0.000667682	8.30E-04
1.13E-04	7.66E-05
1.42706E-05	1.64E-05
7.53079E-06	5.21931E-06
0.000263464	8.90E-05
0.000165185	6.45E-05
8.23E-05	2.46E-05
1.81946E-05	1.24335E-05
1.25902E-05	5.74303E-06
0.000613552	0.000320303
0.000523591	0.000153092
0.000135167	4.84964E-05
1.98276E-05	6.12584E-06
1.11556E-05	1.1947E-05
0.00026095	0.000222159
true	true

ARMA-RNN single frequency network Mean Square Error (MSE) GRU vs LSTM

Currency and Frequency	GRU Relu Bidirectional		LSTM Relu Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.003429689	0.003547061	0.000359513	0.000222005
EURUSD_12H	0.003287497	0.003457673	0.000209114	0.000238781
EURUSD_6H	0.003722039	0.004077045	0.00013009	9.80E-05
EURUSD_1H	0.00335705	0.00348906	0.000686673	0.000697724
EURUSD_30T	0.002307877	0.00249447	0.001430812	0.001593241
GBPUSD_1D	0.003350562	0.003568077	0.000678704	0.000999973
GBPUSD_12H	0.002336133	0.002572818	0.000233745	6.32E-05
GBPUSD_6H	0.003460433	0.00349242	8.30E-05	5.71E-05
GBPUSD_1H	0.003489793	0.003642495	0.000607485	4.18E-05
GBPUSD_30T	0.003141476	0.003037168	0.001903209	0.0003751
USDCHF_1D	0.003097447	0.00337742	0.000226745	7.22E-05
USDCHF_12H	0.002881237	0.002816247	0.000136928	3.92E-05
USDCHF_6H	0.003282983	0.003419336	5.78E-05	2.40E-05
USDCHF_1H	0.003463471	0.003653681	0.00025325	0.000266383
USDCHF_30T	0.003104656	0.003248023	0.001340398	0.001507544
USDJPY_1D	0.002507904	0.002555229	0.000442852	0.000150672
USDJPY_12H	0.003536348	0.003956326	0.000247441	0.000100865
USDJPY_6H	0.003215027	0.003236342	0.000214591	0.000175966
USDJPY_1H	0.003287777	0.003354308	0.002436554	0.003920583
USDJPY_30T	0.003296164	0.003734429	0.00273299	0.004034094
Mean	0.003177778	0.003336481	0.000720595	0.000733927

Currency and Frequency	GRU Relu forward		LSTM Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.003472925	0.003885241	0.003503378	0.00440255
EURUSD_12H	0.003353193	0.003510472	0.002733758	0.003159666
EURUSD_6H	0.003431621	0.003438744	0.003379449	0.003780143
EURUSD_1H	0.003524869	0.003599522	0.003436007	0.003905063
EURUSD_30T	0.002784439	0.003083456	0.002961357	0.003324533
GBPUSD_1D	0.003650885	0.00383935	0.003005217	0.003208342
GBPUSD_12H	0.003122506	0.004794059	0.00410272	0.00454216
GBPUSD_6H	0.004325496	0.004715901	0.003248394	0.003825904
GBPUSD_1H	0.002639441	0.0031225	0.003029602	0.003485614
GBPUSD_30T	0.00337372	0.003714608	0.00272345	0.003034605
USDCHF_1D	0.002248421	0.002664846	0.004245262	0.004650842
USDCHF_12H	0.003677499	0.003784244	0.00311891	0.003579296
USDCHF_6H	0.003806475	0.004443998	0.003770612	0.004197416
USDCHF_1H	0.003038703	0.003231939	0.002998889	0.003586926
USDCHF_30T	0.002966368	0.003224442	0.004242147	0.004884931
USDJPY_1D	0.002775881	0.002652472	0.003562141	0.003902761
USDJPY_12H	0.002782407	0.003016595	0.002570239	0.002607259
USDJPY_6H	0.003803581	0.003891136	0.003088803	0.003197659
USDJPY_1H	0.00309443	0.003340031	0.004036237	0.004127952
USDJPY_30T	0.004189656	0.004571453	0.002691402	0.003357787
Mean	0.003303126	0.003626251	0.003322399	0.00373807

Currency and Frequency	GRU Tanh Bidirectional		LSTM Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	7.40E-05	2.33E-05	9.76E-05	3.42E-05
EURUSD_12H	2.25E-05	9.35E-06	4.53E-05	5.92E-05
EURUSD_6H	4.31E-05	6.53E-05	4.00E-05	2.64E-05
EURUSD_1H	2.35E-05	1.19E-05	0.000206435	0.000224514
EURUSD_30T	2.58E-05	1.13E-05	2.85E-05	9.75E-06
GBPUSD_1D	3.29E-05	2.87E-05	2.35E-05	9.51E-06
GBPUSD_12H	3.29E-05	1.92E-05	4.36E-05	4.26E-05
GBPUSD_6H	0.00010088	9.68E-05	2.70E-05	8.97E-06
GBPUSD_1H	6.15E-05	3.69E-05	6.76E-05	4.14E-05
GBPUSD_30T	1.96E-05	1.29E-05	8.02E-05	9.04E-05
USDCHF_1D	5.57E-05	3.41E-05	7.87E-05	6.32E-05
USDCHF_12H	4.03E-05	1.16E-05	3.13E-05	1.21E-05
USDCHF_6H	4.04E-05	1.25E-05	3.00E-05	1.42E-05
USDCHF_1H	5.32E-05	5.85E-05	0.000134096	7.92E-05
USDCHF_30T	3.86E-05	5.36E-05	2.95E-05	9.29E-06
USDJPY_1D	2.89E-05	8.95E-06	2.51E-05	1.25E-05
USDJPY_12H	6.68E-05	4.80E-05	3.59E-05	2.81E-05
USDJPY_6H	1.95E-05	8.50E-06	2.91E-05	9.05E-06
USDJPY_1H	3.87E-05	1.70E-05	2.85E-05	8.44E-06
USDJPY_30T	3.90E-05	1.97E-05	0.000323364	0.000472566
Mean	4.28895E-05	2.94094E-05	7.0268E-05	6.27853E-05

Currency and Frequency	GRU Tanh forward		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	9.53E-05	0.000112663	0.000170002	6.75E-05
EURUSD_12H	5.25E-05	3.29E-05	0.000144563	9.29E-05
EURUSD_6H	3.98E-05	1.52E-05	4.84E-05	1.32E-05
EURUSD_1H	2.64E-05	1.82E-05	0.00011886	6.31E-05
EURUSD_30T	5.73E-05	1.35E-05	4.23E-05	3.42E-05
GBPUSD_1D	2.84E-05	8.56E-06	3.65E-05	1.63E-05
GBPUSD_12H	0.000144393	9.04E-05	0.000100814	6.13E-05
GBPUSD_6H	7.40E-05	1.35E-05	3.11E-05	8.69E-06
GBPUSD_1H	5.09E-05	2.57E-05	5.93E-05	3.23E-05
GBPUSD_30T	9.39E-05	8.31E-05	0.000114011	0.000195169
USDCHF_1D	6.76E-05	3.86E-05	7.83E-05	7.07E-05
USDCHF_12H	0.000156448	0.000124579	0.000166707	0.000125155
USDCHF_6H	7.12E-05	3.75E-05	0.000319247	0.000328318
USDCHF_1H	5.87E-05	1.93E-05	3.24E-05	1.51E-05
USDCHF_30T	6.80E-05	4.30E-05	4.11E-05	2.78E-05
USDJPY_1D	6.73E-05	4.33E-05	6.31E-05	1.49E-05
USDJPY_12H	2.78E-05	1.25E-05	5.14E-05	1.89E-05
USDJPY_6H	0.000222682	0.000167206	3.60E-05	1.36E-05
USDJPY_1H	0.000160916	7.09E-05	0.000159392	0.000210096
USDJPY_30T	2.44E-05	1.17E-05	3.13E-05	8.68E-06
Mean	7.93886E-05	4.91148E-05	9.22321E-05	7.08954E-05

Unidirectional Vs Bidirectional

Currency and Frequency	GRU Relu Bidirectional		GRU Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.003429689	0.003547061	0.003472925	0.003885241
EURUSD_12H	0.003287497	0.003457673	0.003353193	0.003510472
EURUSD_6H	0.003722039	0.004077045	0.003431621	0.003438744
EURUSD_1H	0.00335705	0.00348906	0.003524869	0.003599522
EURUSD_30T	0.002307877	0.00249447	0.002784439	0.003083456
GBPUSD_1D	0.003350562	0.003568077	0.003650885	0.00383935
GBPUSD_12H	0.002336133	0.002572818	0.003122506	0.004794059
GBPUSD_6H	0.003460433	0.00349242	0.004325496	0.004715901
GBPUSD_1H	0.003489793	0.003642495	0.002639441	0.0031225
GBPUSD_30T	0.003141476	0.003037168	0.00337372	0.003714608
USDCHF_1D	0.003097447	0.00337742	0.002248421	0.002664846
USDCHF_12H	0.002881237	0.002816247	0.003677499	0.003784244
USDCHF_6H	0.003282983	0.003419336	0.003806475	0.004443998
USDCHF_1H	0.003463471	0.003653681	0.003038703	0.003231939
USDCHF_30T	0.003104656	0.003248023	0.002966368	0.003224442
USDJPY_1D	0.002507904	0.002555229	0.002775881	0.002652472
USDJPY_12H	0.003536348	0.003956326	0.002782407	0.003016595
USDJPY_6H	0.003215027	0.003236342	0.003803581	0.003891136
USDJPY_1H	0.003287777	0.003354308	0.00309443	0.003340031
USDJPY_30T	0.003296164	0.003734429	0.004189656	0.004571453
Mean	0.003177778	0.003336481	0.003303126	0.003626251

Currency and Frequency	LSTM Relu Bidirectional		LSTM Relu forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000718228	0.000560193	0.003503378	0.00440255
EURUSD_12H	0.001446392	0.001445735	0.002733758	0.003159666
EURUSD_6H	0.001682895	0.001883556	0.003379449	0.003780143
EURUSD_1H	0.001171081	0.000381129	0.003436007	0.003905063
EURUSD_30T	0.002293806	0.000798304	0.002961357	0.003324533
GBPUSD_1D	0.001045356	0.000715109	0.003005217	0.003208342
GBPUSD_12H	0.001549193	0.000319063	0.00410272	0.00454216
GBPUSD_6H	0.003829324	0.000654547	0.003248394	0.003825904
GBPUSD_1H	0.001687875	0.000248019	0.003029602	0.003485614
GBPUSD_30T	0.003066537	0.000565708	0.00272345	0.003034605
USDCHF_1D	0.003204526	0.001579091	0.004245262	0.004650842
USDCHF_12H	0.001357506	0.000805546	0.00311891	0.003579296
USDCHF_6H	0.001945021	0.00230639	0.003770612	0.004197416
USDCHF_1H	0.003035085	0.0040915	0.002998889	0.003586926
USDCHF_30T	0.003423641	0.003930676	0.004242147	0.004884931
USDJPY_1D	0.001141303	0.00064809	0.003562141	0.003902761
USDJPY_12H	0.001890518	0.003042937	0.002570239	0.002607259
USDJPY_6H	0.001848987	0.002493375	0.003088803	0.003197659
USDJPY_1H	0.001617525	0.002109557	0.004036237	0.004127952
USDJPY_30T	0.002774728	0.00287565	0.002691402	0.003357787
Mean	0.002036476	0.001572709	0.003322399	0.00373807

[redacted]

Currency and Frequency	GRU Tanh Bidirectional		GRU Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	7.40E-05	2.33E-05	9.53E-05	0.000112663
EURUSD_12H	2.25E-05	9.35E-06	5.25E-05	3.29E-05
EURUSD_6H	4.31E-05	6.53E-05	3.98E-05	1.52E-05
EURUSD_1H	2.35E-05	1.19E-05	2.64E-05	1.82E-05
EURUSD_30T	2.58E-05	1.13E-05	5.73E-05	1.35E-05
GBPUSD_1D	3.29E-05	2.87E-05	2.84E-05	8.56E-06
GBPUSD_12H	3.29E-05	1.92E-05	0.000144393	9.04E-05
GBPUSD_6H	0.00010088	9.68E-05	7.40E-05	1.35E-05
GBPUSD_1H	6.15E-05	3.69E-05	5.09E-05	2.57E-05
GBPUSD_30T	1.96E-05	1.29E-05	9.39E-05	8.31E-05
USDCHF_1D	5.57E-05	3.41E-05	6.76E-05	3.86E-05
USDCHF_12H	4.03E-05	1.16E-05	0.000156448	0.000124579
USDCHF_6H	4.04E-05	1.25E-05	7.12E-05	3.75E-05
USDCHF_1H	5.32E-05	5.85E-05	5.87E-05	1.93E-05
USDCHF_30T	3.86E-05	5.36E-05	6.80E-05	4.30E-05
USDJPY_1D	2.89E-05	8.95E-06	6.73E-05	4.33E-05
USDJPY_12H	6.68E-05	4.80E-05	2.78E-05	1.25E-05
USDJPY_6H	1.95E-05	8.50E-06	0.000222682	0.000167206
USDJPY_1H	3.87E-05	1.70E-05	0.000160916	7.09E-05
USDJPY_30T	3.90E-05	1.97E-05	2.44E-05	1.17E-05
Mean	4.28895E-05	2.94094E-05	7.93886E-05	4.91148E-05

Currency and Frequency	LSTM Tanh Bidirectional		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	9.76E-05	3.42E-05	0.000170002	6.75E-05
EURUSD_12H	4.53E-05	5.92E-05	0.000144563	9.29E-05
EURUSD_6H	4.00E-05	2.64E-05	4.84E-05	1.32E-05
EURUSD_1H	0.000206435	0.000224514	0.00011886	6.31E-05
EURUSD_30T	2.85E-05	9.75E-06	4.23E-05	3.42E-05
GBPUSD_1D	2.35E-05	9.51E-06	3.65E-05	1.63E-05
GBPUSD_12H	4.36E-05	4.26E-05	0.000100814	6.13E-05
GBPUSD_6H	2.70E-05	8.97E-06	3.11E-05	8.69E-06
GBPUSD_1H	6.76E-05	4.14E-05	5.93E-05	3.23E-05
GBPUSD_30T	8.02E-05	9.04E-05	0.000114011	0.000195169
USDCHF_1D	7.87E-05	6.32E-05	7.83E-05	7.07E-05
USDCHF_12H	3.13E-05	1.21E-05	0.000166707	0.000125155
USDCHF_6H	3.00E-05	1.42E-05	0.000319247	0.000328318
USDCHF_1H	0.000134096	7.92E-05	3.24E-05	1.51E-05
USDCHF_30T	2.95E-05	9.29E-06	4.11E-05	2.78E-05
USDJPY_1D	2.51E-05	1.25E-05	6.31E-05	1.49E-05
USDJPY_12H	3.59E-05	2.81E-05	5.14E-05	1.89E-05
USDJPY_6H	2.91E-05	9.05E-06	3.60E-05	1.36E-05
USDJPY_1H	2.85E-05	8.44E-06	0.000159392	0.000210096
USDJPY_30T	0.000323364	0.000472566	3.13E-05	8.68E-06
Mean	7.0268E-05	6.27853E-05	9.22321E-05	7.08954E-05

Relu Vs Tanh

Currency and Frequency	GRU Relu Bidirectional		GRU Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.003429689	0.003547061	7.40E-05	2.33E-05
EURUSD_12H	0.003287497	0.003457673	2.25E-05	9.35E-06
EURUSD_6H	0.003722039	0.004077045	4.31E-05	6.53E-05
EURUSD_1H	0.00335705	0.00348906	2.35E-05	1.19E-05
EURUSD_30T	0.002307877	0.00249447	2.58E-05	1.13E-05
GBPUSD_1D	0.003350562	0.003568077	3.29E-05	2.87E-05
GBPUSD_12H	0.002336133	0.002572818	3.29E-05	1.92E-05
GBPUSD_6H	0.003460433	0.00349242	0.00010088	9.68E-05
GBPUSD_1H	0.003489793	0.003642495	6.15E-05	3.69E-05
GBPUSD_30T	0.003141476	0.003037168	1.96E-05	1.29E-05
USDCHF_1D	0.003097447	0.00337742	5.57E-05	3.41E-05
USDCHF_12H	0.002881237	0.002816247	4.03E-05	1.16E-05
USDCHF_6H	0.003282983	0.003419336	4.04E-05	1.25E-05
USDCHF_1H	0.003463471	0.003653681	5.32E-05	5.85E-05
USDCHF_30T	0.003104656	0.003248023	3.86E-05	5.36E-05
USDJPY_1D	0.002507904	0.002555229	2.89E-05	8.95E-06
USDJPY_12H	0.003536348	0.003956326	6.68E-05	4.80E-05
USDJPY_6H	0.003215027	0.003236342	1.95E-05	8.50E-06
USDJPY_1H	0.003287777	0.003354308	3.87E-05	1.70E-05
USDJPY_30T	0.003296164	0.003734429	3.90E-05	1.97E-05
Mean	0.003177778	0.003336481	4.28895E-05	2.94094E-05

Currency and Frequency	GRU Relu forward		GRU Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.003472925	0.003885241	0.000170002	6.75E-05
EURUSD_12H	0.003353193	0.003510472	0.000144563	9.29E-05
EURUSD_6H	0.003431621	0.003438744	4.84E-05	1.32E-05
EURUSD_1H	0.003524869	0.003599522	0.00011886	6.31E-05
EURUSD_30T	0.002784439	0.003083456	4.23E-05	3.42E-05
GBPUSD_1D	0.003650885	0.00383935	3.65E-05	1.63E-05
GBPUSD_12H	0.003122506	0.004794059	0.000100814	6.13E-05
GBPUSD_6H	0.004325496	0.004715901	3.11E-05	8.69E-06
GBPUSD_1H	0.002639441	0.0031225	5.93E-05	3.23E-05
GBPUSD_30T	0.00337372	0.003714608	0.000114011	0.000195169
USDCHF_1D	0.002248421	0.002664846	7.83E-05	7.07E-05
USDCHF_12H	0.003677499	0.003784244	0.000166707	0.000125155
USDCHF_6H	0.003806475	0.004443998	0.000319247	0.000328318
USDCHF_1H	0.003038703	0.003231939	3.24E-05	1.51E-05
USDCHF_30T	0.002966368	0.003224442	4.11E-05	2.78E-05
USDJPY_1D	0.002775881	0.002652472	6.31E-05	1.49E-05
USDJPY_12H	0.002782407	0.003016595	5.14E-05	1.89E-05
USDJPY_6H	0.003803581	0.003891136	3.60E-05	1.36E-05
USDJPY_1H	0.00309443	0.003340031	0.000159392	0.000210096
USDJPY_30T	0.004189656	0.004571453	3.13E-05	8.68E-06
Mean	0.003303126	0.003626251	9.22321E-05	7.08954E-05

Currency and Frequency	LSTM Relu Bidirectional		LSTM Tanh Bidirectional	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.000718228	0.000560193	9.76E-05	3.42E-05
EURUSD_12H	0.001446392	0.001445735	4.53E-05	5.92E-05
EURUSD_6H	0.001682895	0.001883556	4.00E-05	2.64E-05
EURUSD_1H	0.001171081	0.000381129	0.000206435	0.000224514
EURUSD_30T	0.002293806	0.000798304	2.85E-05	9.75E-06
GBPUSD_1D	0.001045356	0.000715109	2.35E-05	9.51E-06
GBPUSD_12H	0.001549193	0.000319063	4.36E-05	4.26E-05
GBPUSD_6H	0.003829324	0.000654547	2.70E-05	8.97E-06
GBPUSD_1H	0.001687875	0.000248019	6.76E-05	4.14E-05
GBPUSD_30T	0.003066537	0.000565708	8.02E-05	9.04E-05
USDCHF_1D	0.003204526	0.001579091	7.87E-05	6.32E-05
USDCHF_12H	0.001357506	0.000805546	3.13E-05	1.21E-05
USDCHF_6H	0.001945021	0.00230639	3.00E-05	1.42E-05
USDCHF_1H	0.003035085	0.0040915	0.000134096	7.92E-05
USDCHF_30T	0.003423641	0.003930676	2.95E-05	9.29E-06
USDJPY_1D	0.001141303	0.00064809	2.51E-05	1.25E-05
USDJPY_12H	0.001890518	0.003042937	3.59E-05	2.81E-05
USDJPY_6H	0.001848987	0.002493375	2.91E-05	9.05E-06
USDJPY_1H	0.001617525	0.002109557	2.85E-05	8.44E-06
USDJPY_30T	0.002774728	0.00287565	0.000323364	0.000472566
Mean	0.002036476	0.001572709	7.0268E-05	6.27853E-05

Currency and Frequency	LSTM Relu forward		LSTM Tanh forward	
	In Sample	Out of Sample	In Sample	Out of Sample
EURUSD_1D	0.003503378	0.00440255	0.000170002	6.75E-05
EURUSD_12H	0.002733758	0.003159666	0.000144563	9.29E-05
EURUSD_6H	0.003379449	0.003780143	4.84E-05	1.32E-05
EURUSD_1H	0.003436007	0.003905063	0.00011886	6.31E-05
EURUSD_30T	0.002961357	0.003324533	4.23E-05	3.42E-05
GBPUSD_1D	0.003005217	0.003208342	3.65E-05	1.63E-05
GBPUSD_12H	0.00410272	0.00454216	0.000100814	6.13E-05
GBPUSD_6H	0.003248394	0.003825904	3.11E-05	8.69E-06
GBPUSD_1H	0.003029602	0.003485614	5.93E-05	3.23E-05
GBPUSD_30T	0.00272345	0.003034605	0.000114011	0.000195169
USDCHF_1D	0.004245262	0.004650842	7.83E-05	7.07E-05
USDCHF_12H	0.00311891	0.003579296	0.000166707	0.000125155
USDCHF_6H	0.003770612	0.004197416	0.000319247	0.000328318
USDCHF_1H	0.002998889	0.003586926	3.24E-05	1.51E-05
USDCHF_30T	0.004242147	0.004884931	4.11E-05	2.78E-05
USDJPY_1D	0.003562141	0.003902761	6.31E-05	1.49E-05
USDJPY_12H	0.002570239	0.002607259	5.14E-05	1.89E-05
USDJPY_6H	0.003088803	0.003197659	3.60E-05	1.36E-05
USDJPY_1H	0.004036237	0.004127952	0.000159392	0.000210096
USDJPY_30T	0.002691402	0.003357787	3.13E-05	8.68E-06
Mean	0.003322399	0.00373807	9.22321E-05	7.08954E-05

Model with lowest MSE

Currency and Frequency	GRU Tanh Bidirectional	
	In Sample	Out of Sample
EURUSD_1D	7.40E-05	2.33E-05
EURUSD_12H	2.25E-05	9.35E-06
EURUSD_6H	4.31E-05	6.53E-05
EURUSD_1H	2.35E-05	1.19E-05
EURUSD_30T	2.58E-05	1.13E-05
GBPUSD_1D	3.29E-05	2.87E-05
GBPUSD_12H	3.29E-05	1.92E-05
GBPUSD_6H	0.00010088	9.68E-05
GBPUSD_1H	6.15E-05	3.69E-05
GBPUSD_30T	1.96E-05	1.29E-05
USDCHF_1D	5.57E-05	3.41E-05
USDCHF_12H	4.03E-05	1.16E-05
USDCHF_6H	4.04E-05	1.25E-05
USDCHF_1H	5.32E-05	5.85E-05
USDCHF_30T	3.86E-05	5.36E-05
USDJPY_1D	2.89E-05	8.95E-06
USDJPY_12H	6.68E-05	4.80E-05
USDJPY_6H	1.95E-05	8.50E-06
USDJPY_1H	3.87E-05	1.70E-05
USDJPY_30T	3.90E-05	1.97E-05
Mean	4.28895E-05	2.94094E-05

Recurrent neural network single frequency vs multifrequency

Currency and Frequency	single		multi	
	In Sample	Out of Sample	In Sample	Out of Sample
GRU Relu Bidirectional				
EURUSD_1D	0.003264418	0.002508793	0.001600192	0.00141451
EURUSD_12H	0.001804951	0.001976188	0.001315873	0.002558812
EURUSD_6H	0.003681875	0.002461885	0.005572165	0.004675283
EURUSD_1H	0.002070203	0.000625061	0.002809075	0.000842808
EURUSD_30T	0.002019272	0.001011214	0.007909591	0.003631255
GBPUSD_1D	0.003268477	0.001078161	0.007566556	0.001922606
GBPUSD_12H	0.004628441	0.00077614	0.002002741	0.000287993
GBPUSD_6H	0.003690071	0.000304833	0.004973769	0.000842679
GBPUSD_1H	0.003498528	0.000116116	0.002858165	0.000145563
GBPUSD_30T	0.002436929	0.000274796	0.01060341	0.000917182
USDCHF_1D	0.003381599	0.003802104	0.004018882	0.002693601
USDCHF_12H	0.005414608	0.006338591	0.004200715	0.004029691
USDCHF_6H	0.00229487	0.002524693	0.001252894	0.000885794
USDCHF_1H	0.00311218	0.003806221	0.00377987	0.005021711
USDCHF_30T	0.002605188	0.003176072	0.011548418	0.014116974
USDJPY_1D	0.003850373	0.002772214	0.003833288	0.003126358
USDJPY_12H	0.004921299	0.004387937	0.003415277	0.003284397
USDJPY_6H	0.003069344	0.00267188	0.006328044	0.007032551
USDJPY_1H	0.002900043	0.002304077	0.00301213	0.002265188
USDJPY_30T	0.00224058	0.001590825	0.01140475	0.010427575
Mean	0.003207662	0.00222539	0.00500029	0.003506127
GRU Relu forward				
EURUSD_1D	0.004515877	0.003002102	0.004905307	0.003372196
EURUSD_12H	0.003761206	0.003486629	0.006595444	0.005606485
EURUSD_6H	0.003921711	0.002497948	0.008169597	0.006435292
EURUSD_1H	0.004403116	0.003055279	0.003977727	0.001507072
EURUSD_30T	0.003890968	0.002241523	0.007350246	0.003578599
GBPUSD_1D	0.004125347	0.000723338	0.007110231	0.00164177
GBPUSD_12H	0.001596336	0.00035417	0.004951344	0.000993578
GBPUSD_6H	0.005500077	0.00064289	0.003443115	0.000304046
GBPUSD_1H	0.003083498	0.000604044	0.005017692	0.000312495
GBPUSD_30T	0.002898972	0.000148486	0.013053786	0.002405268
USDCHF_1D	0.009482416	0.011774896	0.003322871	0.001350411
USDCHF_12H	0.006215273	0.007890506	0.002446723	0.001716367
USDCHF_6H	0.003654939	0.004146543	0.00506943	0.006273679
USDCHF_1H	0.00258969	0.003090261	0.002720264	0.003457188
USDCHF_30T	0.002781555	0.003499343	0.010586558	0.013447225
USDJPY_1D	0.002742899	0.002404767	0.005166901	0.004357106
USDJPY_12H	0.002443389	0.002344669	0.003087702	0.002599103
USDJPY_6H	0.003449132	0.002884945	0.003969108	0.004816965
USDJPY_1H	0.003270028	0.003171229	0.003561468	0.002557045
USDJPY_30T	0.002303494	0.002172991	0.008715298	0.007954829

Mean	3.83E-03	3.01E-03	0.005661041	0.003734336
GRU Tanh Bidirectional				
EURUSD_1D	0.000550794	0.000538757	0.000806388	0.000650794
EURUSD_12H	0.002389571	0.002087286	0.000422621	0.000299481
EURUSD_6H	0.000154944	0.000102952	0.000377615	0.000151466
EURUSD_1H	0.000262996	3.08E-05	0.000318452	0.000259541
EURUSD_30T	8.90E-05	9.10E-05	0.000152552	9.68E-05
GBPUSD_1D	0.00040952	0.000186909	0.000619897	0.000518153
GBPUSD_12H	0.000425576	0.000104514	0.005478862	0.001164701
GBPUSD_6H	0.000133072	5.87E-05	0.000222009	0.000138404
GBPUSD_1H	2.74E-05	1.76E-05	0.000241073	0.000169746
GBPUSD_30T	0.000102446	1.08E-05	4.02E-05	1.65E-05
USDCHF_1D	0.001419555	0.001377875	0.003309961	0.002171862
USDCHF_12H	0.000235081	0.000122869	0.00149262	0.00076994
USDCHF_6H	0.000117892	6.00E-05	0.000625067	0.000269836
USDCHF_1H	4.53E-05	3.73E-05	0.000622972	0.000719392
USDCHF_30T	1.63E-05	6.90E-06	4.11E-05	4.15E-05
USDJPY_1D	0.00040242	0.000200462	0.001356887	0.000712293
USDJPY_12H	0.000251021	0.000202049	0.000524949	0.00024101
USDJPY_6H	0.000108625	6.03E-05	0.000367799	0.000208181
USDJPY_1H	4.01E-05	2.30E-05	0.000226138	0.000175771
USDJPY_30T	4.04E-05	8.09E-06	0.000250732	0.000255995
Mean	3.61E-04	2.66E-04	0.000874897	0.000451567
GRU Tanh forward				
EURUSD_1D	0.000547363	0.000294357	0.000779434	0.000498998
EURUSD_12H	0.00037586	0.000366956	0.000900803	0.000739943
EURUSD_6H	0.000156339	0.000169519	0.000304427	0.000168922
EURUSD_1H	8.26E-05	3.27E-05	5.80E-05	6.78E-05
EURUSD_30T	0.000133514	0.0001726	0.000544223	0.00015724
GBPUSD_1D	0.000863967	0.000231997	0.000946543	0.00105262
GBPUSD_12H	0.000832904	0.000274174	0.000387108	0.000217407
GBPUSD_6H	0.000289487	7.91E-05	0.000210813	0.000108503
GBPUSD_1H	4.71E-05	3.52E-05	6.71E-05	2.31E-05
GBPUSD_30T	8.15E-05	4.17E-05	0.000107711	7.67E-05
USDCHF_1D	0.001034684	0.000865974	0.002757218	0.001303155
USDCHF_12H	0.000294718	0.000144912	0.003139904	0.002862081
USDCHF_6H	0.000614527	0.000541701	0.000681481	0.00025657
USDCHF_1H	3.27E-05	2.31E-05	0.000233971	0.000176866
USDCHF_30T	1.69E-05	4.73E-06	4.96E-05	5.02E-05
USDJPY_1D	0.000566972	0.00020133	0.001257887	0.001158159
USDJPY_12H	0.000294898	0.000188022	0.002211989	0.001772744
USDJPY_6H	0.000182391	0.000170614	0.000255254	0.000101026
USDJPY_1H	0.000197502	9.20E-05	0.000101651	2.50E-05
USDJPY_30T	7.77E-05	3.91E-05	3.75E-05	3.69E-05
Mean	3.36E-04	1.98E-04	0.000751633	0.000542694

LSTM Relu Bidirectional				
EURUSD_1D	0.000646601	0.000477242	0.003282524	0.004266454
EURUSD_12H	0.001781473	0.002271858	0.000581833	0.000464477
EURUSD_6H	0.000484017	0.000572836	0.002801754	0.002336874
EURUSD_1H	0.001236252	0.000782335	0.002109197	0.001493156
EURUSD_30T	0.000651753	0.000410656	0.008684234	0.00489835
GBPUSD_1D	0.000899452	0.000476266	0.001208502	0.000589517
GBPUSD_12H	0.000584252	0.000189026	0.00299204	0.000497529
GBPUSD_6H	0.001402092	0.000108173	0.003755517	0.000627497
GBPUSD_1H	0.001538053	0.000120323	0.002576424	0.000185838
GBPUSD_30T	0.001448046	0.000179853	0.010552931	0.001112045
USDCHF_1D	0.001500302	0.000838828	0.003942629	0.002327312
USDCHF_12H	0.001532165	0.001369681	0.001422351	0.000614392
USDCHF_6H	0.0017615	0.00192644	0.004677046	0.005481635
USDCHF_1H	0.003380316	0.004217774	0.002225646	0.002765861
USDCHF_30T	0.00263084	0.00293319	0.01172267	0.014279066
USDJPY_1D	0.000767427	0.000329108	0.001809655	0.001249284
USDJPY_12H	0.001434876	0.001372796	0.000567307	0.000328786
USDJPY_6H	0.000896078	0.000700275	0.003817865	0.003804151
USDJPY_1H	0.00228328	0.00216007	0.003300674	0.00316756
USDJPY_30T	0.002166076	0.002411678	0.008832768	0.007614164
Mean	0.001451243	0.00119242	0.004043178	0.002905197
LSTM Relu forward				
EURUSD_1D	0.000956876	0.000701727	0.002001242	0.002526855
EURUSD_12H	0.002376047	0.002850674	0.001255424	0.001495186
EURUSD_6H	0.001537763	0.002085426	0.003059928	0.002443466
EURUSD_1H	0.002679884	0.001083536	0.002747494	0.001132335
EURUSD_30T	0.002620105	0.001305268	0.007836731	0.003807934
GBPUSD_1D	0.003149294	0.001065977	0.003045818	0.001106883
GBPUSD_12H	0.002440605	0.000622988	0.002869006	0.000436751
GBPUSD_6H	0.001911535	0.000276965	0.002398119	0.000354773
GBPUSD_1H	0.002309129	0.000156728	0.002530077	0.000524187
GBPUSD_30T	0.002320939	0.000288851	0.010909613	0.00135342
USDCHF_1D	0.005184083	0.006166027	0.003747551	0.00126575
USDCHF_12H	0.002781219	0.002570386	0.002749496	0.001831999
USDCHF_6H	0.002841884	0.003254781	0.001736477	0.001623693
USDCHF_1H	0.00214713	0.00261582	0.002660172	0.003065953
USDCHF_30T	0.002359283	0.002592896	0.012781013	0.015651133
USDJPY_1D	0.001821802	0.001161809	0.003915742	0.003173063
USDJPY_12H	0.001791801	0.0014219	0.002761174	0.002726422
USDJPY_6H	0.000809604	0.000592112	0.004630488	0.005103915
USDJPY_1H	0.001876947	0.001784609	0.003214747	0.002780813
USDJPY_30T	0.002118625	0.001985001	0.013963149	0.012238441
Mean	0.002301728	0.001729174	0.004540673	0.003232149

LSTM Tanh Bidirectional				
EURUSD_1D	0.000534389	0.000368498	0.001143026	0.000945469
EURUSD_12H	0.000314574	0.000174082	0.003292629	0.002335385
EURUSD_6H	0.000259049	0.000508039	0.000794375	0.000224627
EURUSD_1H	0.000101767	8.29E-05	0.000215043	5.11E-05
EURUSD_30T	0.000216816	0.000125221	0.002133258	0.000660647
GBPUSD_1D	0.00138551	0.000275364	0.001104585	0.001218729
GBPUSD_12H	0.000406774	0.000118637	0.001867613	0.000342936
GBPUSD_6H	0.000264347	6.48E-05	0.000174885	0.000118608
GBPUSD_1H	6.13E-05	3.45E-05	7.39E-05	9.56E-05
GBPUSD_30T	6.25E-05	4.72E-05	7.20E-05	1.74E-05
USDCHF_1D	0.00102671	0.000563364	0.003076095	0.001534717
USDCHF_12H	0.000289928	0.000105889	0.001338639	0.000594794
USDCHF_6H	0.000665103	0.000651929	0.000610207	0.000260116
USDCHF_1H	0.000108804	9.14E-05	0.000138868	7.89E-05
USDCHF_30T	1.38E-05	4.95E-06	4.34E-05	3.25E-05
USDJPY_1D	0.000626735	0.000486395	0.000911141	0.000334355
USDJPY_12H	0.000329364	0.000254369	0.000648458	0.000746725
USDJPY_6H	0.000146509	9.05E-05	0.001134261	0.000742271
USDJPY_1H	2.49E-05	1.12E-05	4.90E-05	2.17E-05
USDJPY_30T	9.92E-05	9.09E-06	4.06E-05	1.69E-05
Mean	0.000346904	0.000203416	0.000943099	0.000518672

LSTM Tanh forward				
EURUSD_1D	0.000741205	0.000512807	0.001034733	0.001049399
EURUSD_12H	0.000345858	0.000367943	0.000639042	0.001011705
EURUSD_6H	0.000283605	0.000114141	0.000488054	0.00016185
EURUSD_1H	7.07E-05	2.23E-05	0.000186525	0.000453624
EURUSD_30T	0.000270454	0.000301993	0.000106624	0.000116367
GBPUSD_1D	0.000873749	0.000429257	0.000876884	0.000825538
GBPUSD_12H	0.000516829	0.000141321	0.001490421	0.00035002
GBPUSD_6H	0.000127112	6.52E-05	0.000208925	0.000121069
GBPUSD_1H	9.95E-05	9.19E-05	0.000129024	7.15E-05
GBPUSD_30T	2.72E-05	7.53E-05	5.84E-05	2.22E-05
USDCHF_1D	0.000826196	0.000277496	0.002828265	0.00129066
USDCHF_12H	0.001229451	0.001052051	0.001424879	0.000555466
USDCHF_6H	0.000182393	0.00010063	0.005040801	0.00612983
USDCHF_1H	0.000159003	0.000160018	0.000204839	0.000198912
USDCHF_30T	5.61E-05	6.92E-05	0.000417516	0.000445191
USDJPY_1D	0.001275144	0.00089141	0.001064862	0.000925865
USDJPY_12H	0.000923487	0.001247426	0.000656764	0.000316547
USDJPY_6H	0.000215203	0.000118273	0.000317779	0.000156973
USDJPY_1H	0.00014967	8.11E-05	3.99E-05	1.79E-05
USDJPY_30T	3.52E-05	1.54E-05	0.000212989	0.000133231
Mean	0.000420407	0.000306762	0.000871359	0.000717691

AEMA-RNN single frequency vs multifrequency

Currency and Frequency	single		multi	
	In Sample	Out of Sample	In Sample	Out of Sample
GRU Relu Bidirectional				
EURUSD_1D	0.000443229	0.000248624	0.003429689	0.003547061
EURUSD_12H	0.000246072	0.000207135	0.003287497	0.003457673
EURUSD_6H	9.82E-05	8.61E-05	0.003722039	4.08E-03
EURUSD_1H	0.001422648	0.001465934	0.00335705	0.00348906
EURUSD_30T	0.000212351	0.000385776	0.002307877	0.00249447
GBPUSD_1D	0.000455889	0.000191745	0.003350562	0.003568077
GBPUSD_12H	0.000185123	0.00010604	0.002336133	2.57E-03
GBPUSD_6H	8.01E-05	9.80E-05	3.46E-03	3.49E-03
GBPUSD_1H	0.001315384	0.000239831	0.003489793	3.64E-03
GBPUSD_30T	0.002286183	0.000567917	0.003141476	0.003037168
USDCHF_1D	0.000214338	6.21E-05	0.003097447	3.38E-03
USDCHF_12H	0.000127273	4.34E-05	0.002881237	2.82E-03
USDCHF_6H	5.37E-05	1.96E-05	3.28E-03	3.42E-03
USDCHF_1H	0.000611334	0.000678887	0.003463471	0.003653681
USDCHF_30T	0.001831243	0.001667874	0.003104656	0.003248023
USDJPY_1D	0.000622524	0.000235766	0.002507904	0.002555229
USDJPY_12H	0.000561153	0.000109292	0.003536348	0.003956326
USDJPY_6H	0.000145129	0.000110513	0.003215027	0.003236342
USDJPY_1H	0.002438919	0.003875681	0.003287777	0.003354308
USDJPY_30T	0.002069871	0.00283074	0.003296164	0.003734429
Mean	0.000771031	0.000661549	0.003177778	0.003336481
GRU Relu forward				
EURUSD_1D	0.000478781	0.000325808	0.003472925	0.003885241
EURUSD_12H	0.000299871	0.000111475	0.003353193	0.003510472
EURUSD_6H	3.11E-04	5.64E-04	0.003431621	3.44E-03
EURUSD_1H	0.001307133	0.001379669	0.003524869	0.003599522
EURUSD_30T	0.000821247	0.000545807	0.002784439	0.003083456
GBPUSD_1D	0.000564528	0.00024966	0.003650885	0.00383935
GBPUSD_12H	0.000242298	0.000121673	0.003122506	4.79E-03
GBPUSD_6H	2.25E-04	1.03E-04	4.33E-03	4.72E-03
GBPUSD_1H	6.68587E-05	0.000297834	0.002639441	3.12E-03
GBPUSD_30T	0.002804412	0.000812502	0.00337372	0.003714608
USDCHF_1D	0.000241978	7.86E-05	0.002248421	2.66E-03
USDCHF_12H	0.000130659	3.93E-05	0.003677499	3.78E-03
USDCHF_6H	6.89E-05	3.33E-05	3.81E-03	4.44E-03
USDCHF_1H	1.35391E-05	4.8413E-06	0.003038703	0.003231939
USDCHF_30T	0.001499633	0.001870315	0.002966368	0.003224442
USDJPY_1D	0.000532539	0.000234369	0.002775881	0.002652472
USDJPY_12H	0.000594708	0.000113337	0.002782407	0.003016595
USDJPY_6H	0.000816494	0.000147291	0.003803581	0.003891136
USDJPY_1H	0.002497351	0.00413478	0.00309443	0.003340031
USDJPY_30T	0.003598446	0.004151132	0.004189656	0.004571453

Mean	**0.000855766**	**0.000765944**	**0.003303126**	**0.003626251**
GRU Tanh Bidirectional				
EURUSD_1D	**0.000817883**	**0.000613922**	**7.40023E-05**	**2.32894E-05**
EURUSD_12H	**0.000799897**	**0.000807952**	**2.24999E-05**	**9.35139E-06**
EURUSD_6H	**6.14E-04**	**3.46E-04**	**4.30507E-05**	**6.53E-05**
EURUSD_1H	**1.62025E-05**	**7.35916E-06**	**2.35035E-05**	**1.19071E-05**
EURUSD_30T	**5.96473E-06**	**6.10171E-06**	**2.58168E-05**	**1.13381E-05**
GBPUSD_1D	**0.000753472**	**0.000868242**	**3.28545E-05**	**2.86702E-05**
GBPUSD_12H	**0.000655454**	**0.00095846**	**3.2947E-05**	**1.92E-05**
GBPUSD_6H	**6.89E-04**	**7.34E-04**	**1.01E-04**	**9.68E-05**
GBPUSD_1H	**1.40918E-05**	**2.02938E-05**	**6.15475E-05**	**3.69E-05**
GBPUSD_30T	**8.76448E-06**	**1.38679E-05**	**1.96347E-05**	**1.29145E-05**
USDCHF_1D	**0.000320668**	**1.19E-04**	**5.56519E-05**	**3.41E-05**
USDCHF_12H	**0.000187766**	**7.94E-05**	**4.02598E-05**	**1.16E-05**
USDCHF_6H	**5.61E-05**	**2.41E-05**	**4.04E-05**	**1.25E-05**
USDCHF_1H	**1.02644E-05**	**4.9056E-06**	**5.31597E-05**	**5.85053E-05**
USDCHF_30T	**8.54269E-06**	**1.9787E-06**	**3.85803E-05**	**5.36023E-05**
USDJPY_1D	**0.000596614**	**0.000236436**	**2.88762E-05**	**8.95289E-06**
USDJPY_12H	**0.000503548**	**0.000307388**	**6.68357E-05**	**4.79812E-05**
USDJPY_6H	**0.000452433**	**0.000145749**	**1.95264E-05**	**8.49935E-06**
USDJPY_1H	**1.68939E-05**	**7.71428E-06**	**3.87414E-05**	**1.70213E-05**
USDJPY_30T	**8.95691E-06**	**4.13637E-06**	**3.90356E-05**	**1.97307E-05**
Mean	**0.000326801**	**0.000265346**	**4.28895E-05**	**2.94094E-05**
GRU Tanh forward				
EURUSD_1D	**0.000825085**	**0.000425665**	**9.52573E-05**	**0.000112663**
EURUSD_12H	**0.000809513**	**0.000703693**	**5.24859E-05**	**3.28694E-05**
EURUSD_6H	**6.85E-04**	**5.28E-04**	**3.97725E-05**	**1.52E-05**
EURUSD_1H	**1.9086E-05**	**3.22617E-05**	**2.64354E-05**	**1.82489E-05**
EURUSD_30T	**1.2301E-05**	**5.02138E-06**	**5.72595E-05**	**1.35267E-05**
GBPUSD_1D	**0.000759216**	**0.001430547**	**2.84215E-05**	**8.55859E-06**
GBPUSD_12H	**0.000685633**	**0.001484101**	**0.000144393**	**9.04E-05**
GBPUSD_6H	**5.93E-04**	**1.10E-03**	**7.40E-05**	**1.35E-05**
GBPUSD_1H	**3.24528E-05**	**3.96889E-05**	**5.08551E-05**	**2.57E-05**
GBPUSD_30T	**8.6649E-06**	**4.32029E-06**	**9.38828E-05**	**8.30836E-05**
USDCHF_1D	**0.000306888**	**1.15E-04**	**6.75612E-05**	**3.86E-05**
USDCHF_12H	**0.000205567**	**7.13E-05**	**0.000156448**	**1.25E-04**
USDCHF_6H	**1.03E-04**	**4.42E-05**	**7.12E-05**	**3.75E-05**
USDCHF_1H	**1.11013E-05**	**4.64768E-06**	**5.8667E-05**	**1.93031E-05**
USDCHF_30T	**1.3905E-05**	**9.19175E-06**	**6.79553E-05**	**4.30244E-05**
USDJPY_1D	**0.000627763**	**0.000466593**	**6.72987E-05**	**4.32659E-05**
USDJPY_12H	**0.00053215**	**0.000169876**	**2.78209E-05**	**1.24688E-05**
USDJPY_6H	**0.000463676**	**0.000412657**	**0.000222682**	**0.000167206**
USDJPY_1H	**2.45675E-05**	**1.57034E-05**	**0.000160916**	**7.08561E-05**
USDJPY_30T	**9.05783E-06**	**4.44978E-06**	**2.44496E-05**	**1.172E-05**
Mean	**0.000336399**	**0.000353389**	**7.93886E-05**	**4.91148E-05**

LSTM Relu Bidirectional				
EURUSD_1D	0.000359513	0.000222005	0.000718228	0.000560193
EURUSD_12H	0.000209114	0.000238781	0.001446392	0.001445735
EURUSD_6H	1.30E-04	9.80E-05	0.001682895	1.88E-03
EURUSD_1H	0.000686673	0.000697724	0.001171081	0.000381129
EURUSD_30T	0.001430812	0.001593241	0.002293806	0.000798304
GBPUSD_1D	0.000678704	0.000999973	0.001045356	0.000715109
GBPUSD_12H	0.000233745	6.32114E-05	0.001549193	3.19E-04
GBPUSD_6H	8.30E-05	5.71E-05	3.83E-03	6.55E-04
GBPUSD_1H	0.000607485	4.18337E-05	0.001687875	2.48E-04
GBPUSD_30T	0.001903209	0.0003751	0.003066537	0.000565708
USDCHF_1D	0.000226745	7.22E-05	0.003204526	1.58E-03
USDCHF_12H	0.000136928	3.92E-05	0.001357506	8.06E-04
USDCHF_6H	5.78E-05	2.40E-05	1.95E-03	2.31E-03
USDCHF_1H	0.00025325	0.000266383	0.003035085	0.0040915
USDCHF_30T	0.001340398	0.001507544	0.003423641	0.003930676
USDJPY_1D	0.000442852	0.000150672	0.001141303	0.00064809
USDJPY_12H	0.000247441	0.000100865	0.001890518	0.003042937
USDJPY_6H	0.000214591	0.000175966	0.001848987	0.002493375
USDJPY_1H	0.002436554	0.003920583	0.001617525	0.002109557
USDJPY_30T	0.00273299	0.004034094	0.002774728	0.00287565
Mean	0.000720595	0.000733927	0.002036476	0.001572709
LSTM Relu forward				
EURUSD_1D	0.000423136	0.000112108	0.003503378	0.00440255
EURUSD_12H	2.53E-04	8.13E-05	0.002733758	3.16E-03
EURUSD_6H	0.000398169	0.000375336	0.003379449	0.003780143
EURUSD_1H	0.001151242	0.001100398	0.003436007	0.003905063
EURUSD_30T	0.002061276	0.003077799	0.002961357	0.003324533
GBPUSD_1D	0.000656902	0.000922847	0.003005217	3.21E-03
GBPUSD_12H	4.52E-04	3.36E-04	4.10E-03	4.54E-03
GBPUSD_6H	0.000185239	9.92862E-05	0.003248394	3.83E-03
GBPUSD_1H	0.001920513	0.000373246	0.003029602	0.003485614
GBPUSD_30T	0.003358092	9.27E-04	0.00272345	3.03E-03
USDCHF_1D	0.000284187	1.12E-04	0.004245262	4.65E-03
USDCHF_12H	1.43E-04	4.54E-05	3.12E-03	3.58E-03
USDCHF_6H	7.61413E-05	2.16566E-05	0.003770612	0.004197416
USDCHF_1H	0.000304521	0.000349454	0.002998889	0.003586926
USDCHF_30T	0.00141902	0.001642298	0.004242147	0.004884931
USDJPY_1D	0.000773043	0.000290484	0.003562141	0.003902761
USDJPY_12H	0.000460177	0.000157911	0.002570239	0.002607259
USDJPY_6H	0.00034687	0.000203352	0.003088803	0.003197659
USDJPY_1H	0.00258046	0.00402606	0.004036237	0.004127952
USDJPY_30T	0.001765896	0.002346142	0.002691402	0.003357787
Mean	0.000950635	0.000829964	0.003322399	0.00373807

LSTM Tanh Bidirectional				
EURUSD_1D	0.000883073	0.000751868	9.76026E-05	3.42387E-05
EURUSD_12H	7.75E-04	4.15E-04	4.5345E-05	5.92E-05
EURUSD_6H	0.000128633	0.000131254	3.99602E-05	2.64383E-05
EURUSD_1H	1.61315E-05	3.35139E-05	0.000206435	0.000224514
EURUSD_30T	6.7174E-06	5.26913E-06	2.85491E-05	9.75326E-06
GBPUSD_1D	0.000762349	0.001442196	2.35371E-05	9.51E-06
GBPUSD_12H	6.68E-04	8.30E-04	4.36E-05	4.26E-05
GBPUSD_6H	0.000112767	7.66441E-05	2.70065E-05	8.97E-06
GBPUSD_1H	1.42706E-05	1.6364E-05	6.76444E-05	4.1396E-05
GBPUSD_30T	7.53079E-06	5.22E-06	8.01834E-05	9.04E-05
USDCHF_1D	0.000263464	8.90E-05	7.87487E-05	6.32E-05
USDCHF_12H	1.65E-04	6.45E-05	3.13E-05	1.21E-05
USDCHF_6H	8.23448E-05	2.46476E-05	2.99793E-05	1.42072E-05
USDCHF_1H	1.81946E-05	1.24335E-05	0.000134096	7.91921E-05
USDCHF_30T	1.25902E-05	5.74303E-06	2.94664E-05	9.29399E-06
USDJPY_1D	0.000613552	0.000320303	2.50733E-05	1.25109E-05
USDJPY_12H	0.000523591	0.000153092	3.59076E-05	2.81426E-05
USDJPY_6H	0.000135167	4.84964E-05	2.90574E-05	9.04505E-06
USDJPY_1H	1.98276E-05	6.12584E-06	2.84742E-05	8.44162E-06
USDJPY_30T	1.11556E-05	1.1947E-05	0.000323364	0.000472566
Mean	0.00026095	0.000222159	7.0268E-05	6.27853E-05
LSTM Tanh forward				
EURUSD_1D	0.000921075	0.000500184	0.000170002	6.75405E-05
EURUSD_12H	8.39E-04	5.46E-04	0.000144563	9.29E-05
EURUSD_6H	0.0001392	8.31529E-05	4.83746E-05	1.31789E-05
EURUSD_1H	1.64012E-05	1.40897E-05	0.00011886	6.31449E-05
EURUSD_30T	1.34702E-05	4.64395E-05	4.22528E-05	3.4194E-05
GBPUSD_1D	0.000803939	0.001190406	3.65077E-05	1.63E-05
GBPUSD_12H	6.91E-04	1.41E-03	1.01E-04	6.13E-05
GBPUSD_6H	0.000109265	4.10747E-05	3.10505E-05	8.69E-06
GBPUSD_1H	2.08546E-05	6.93828E-06	5.93255E-05	3.22901E-05
GBPUSD_30T	1.21474E-05	1.33E-05	0.000114011	1.95E-04
USDCHF_1D	0.000238018	7.79E-05	7.83403E-05	7.07E-05
USDCHF_12H	1.73E-04	5.09E-05	1.67E-04	1.25E-04
USDCHF_6H	7.96192E-05	2.98344E-05	0.000319247	0.000328318
USDCHF_1H	1.11076E-05	4.27527E-06	3.24118E-05	1.5117E-05
USDCHF_30T	2.02237E-05	7.89123E-06	4.10646E-05	2.78186E-05
USDJPY_1D	0.000642689	0.000229469	6.30572E-05	1.4927E-05
USDJPY_12H	0.00053522	0.00021895	5.14192E-05	1.88671E-05
USDJPY_6H	0.000173661	8.40341E-05	3.59803E-05	1.36237E-05
USDJPY_1H	1.5461E-05	5.22589E-06	0.000159392	0.000210096
USDJPY_30T	1.0288E-05	9.67407E-06	3.12606E-05	8.67627E-06
Mean	0.000273248	0.0002283	9.22321E-05	7.08954E-05

RNN VS ARMA-RNN Single Frequency

Currency and Frequency	RNN		RNN-ARMA	
	In Sample	Out of Sample	In Sample	Out of Sample
GRU Relu Bidirectional				
EURUSD_1D	0.003264418	0.002508793	0.000443229	0.000248624
EURUSD_12H	0.001804951	0.001976188	0.000246072	0.000207135
EURUSD_6H	3.68E-03	2.46E-03	9.81976E-05	8.61E-05
EURUSD_1H	0.002070203	0.000625061	0.001422648	0.001465934
EURUSD_30T	0.002019272	0.001011214	0.000212351	0.000385776
GBPUSD_1D	0.003268477	0.001078161	0.000455889	0.000191745
GBPUSD_12H	0.004628441	0.00077614	0.000185123	1.06E-04
GBPUSD_6H	3.69E-03	3.05E-04	8.01E-05	9.80E-05
GBPUSD_1H	0.003498528	0.000116116	0.001315384	2.40E-04
GBPUSD_30T	0.002436929	0.000274796	0.002286183	0.000567917
USDCHF_1D	0.003381599	3.80E-03	0.000214338	6.21E-05
USDCHF_12H	0.005414608	6.34E-03	0.000127273	4.34E-05
USDCHF_6H	2.29E-03	2.52E-03	5.37E-05	1.96E-05
USDCHF_1H	0.00311218	0.003806221	0.000611334	0.000678887
USDCHF_30T	0.002605188	0.003176072	0.001831243	0.001667874
USDJPY_1D	0.003850373	0.002772214	0.000622524	0.000235766
USDJPY_12H	0.004921299	0.004387937	0.000561153	0.000109292
USDJPY_6H	0.003069344	0.00267188	0.000145129	0.000110513
USDJPY_1H	0.002900043	0.002304077	0.002438919	0.003875681
USDJPY_30T	0.00224058	0.001590825	0.002069871	0.00283074
Mean	0.003207662	0.00222539	0.000771031	0.000661549
GRU Relu forward				
EURUSD_1D	0.004515877	0.003002102	0.000478781	0.000325808
EURUSD_12H	0.003761206	0.003486629	0.000299871	0.000111475
EURUSD_6H	3.92E-03	2.50E-03	0.000311012	5.64E-04
EURUSD_1H	0.004403116	0.003055279	0.001307133	0.001379669
EURUSD_30T	0.003890968	0.002241523	0.000821247	0.000545807
GBPUSD_1D	0.004125347	0.000723338	0.000564528	0.00024966
GBPUSD_12H	0.001596336	0.00035417	0.000242298	1.22E-04
GBPUSD_6H	5.50E-03	6.43E-04	2.25E-04	1.03E-04
GBPUSD_1H	0.003083498	0.000604044	6.68587E-05	2.98E-04
GBPUSD_30T	0.002898972	0.000148486	0.002804412	0.000812502
USDCHF_1D	0.009482416	1.18E-02	0.000241978	7.86E-05
USDCHF_12H	0.006215273	7.89E-03	0.000130659	3.93E-05
USDCHF_6H	3.65E-03	4.15E-03	6.89E-05	3.33E-05
USDCHF_1H	0.00258969	0.003090261	1.35391E-05	4.8413E-06
USDCHF_30T	0.002781555	0.003499343	0.001499633	0.001870315
USDJPY_1D	0.002742899	0.002404767	0.000532539	0.000234369
USDJPY_12H	0.002443389	0.002344669	0.000594708	0.000113337
USDJPY_6H	0.003449132	0.002884945	0.000816494	0.000147291
USDJPY_1H	0.003270028	0.003171229	0.002497351	0.00413478
USDJPY_30T	0.002303494	0.002172991	0.003598446	0.004151132

Mean	0.003831496	0.003006828	0.000855766	0.000765944
GRU Tanh Bidirectional				
EURUSD_1D	0.000550794	0.000538757	0.000817883	0.000613922
EURUSD_12H	0.002389571	0.002087286	0.000799897	0.000807952
EURUSD_6H	1.55E-04	1.03E-04	0.000613668	3.46E-04
EURUSD_1H	0.000262996	3.0793E-05	1.62025E-05	7.35916E-06
EURUSD_30T	8.90448E-05	9.09626E-05	5.96473E-06	6.10171E-06
GBPUSD_1D	0.00040952	0.000186909	0.000753472	0.000868242
GBPUSD_12H	0.000425576	0.000104514	0.000655454	9.58E-04
GBPUSD_6H	1.33E-04	5.87E-05	6.89E-04	7.34E-04
GBPUSD_1H	2.73753E-05	1.76291E-05	1.40918E-05	2.03E-05
GBPUSD_30T	0.000102446	1.08221E-05	8.76448E-06	1.38679E-05
USDCHF_1D	0.001419555	1.38E-03	0.000320668	1.19E-04
USDCHF_12H	0.000235081	1.23E-04	0.000187766	7.94E-05
USDCHF_6H	1.18E-04	6.00E-05	5.61E-05	2.41E-05
USDCHF_1H	4.53476E-05	3.73461E-05	1.02644E-05	4.9056E-06
USDCHF_30T	1.63055E-05	6.90432E-06	8.54269E-06	1.9787E-06
USDJPY_1D	0.00040242	0.000200462	0.000596614	0.000236436
USDJPY_12H	0.000251021	0.000202049	0.000503548	0.000307388
USDJPY_6H	0.000108625	6.03387E-05	0.000452433	0.000145749
USDJPY_1H	4.00549E-05	2.29787E-05	1.68939E-05	7.71428E-06
USDJPY_30T	4.04063E-05	8.09388E-06	8.95691E-06	4.13637E-06
Mean	0.000361102	0.000266408	0.000326801	0.000265346
GRU Tanh forward				
EURUSD_1D	0.000547363	0.000294357	0.000825085	0.000425665
EURUSD_12H	0.00037586	0.000366956	0.000809513	0.000703693
EURUSD_6H	1.56E-04	1.70E-04	0.00068517	5.28E-04
EURUSD_1H	8.26314E-05	3.27372E-05	1.9086E-05	3.22617E-05
EURUSD_30T	0.000133514	0.0001726	1.2301E-05	5.02138E-06
GBPUSD_1D	0.000863967	0.000231997	0.000759216	0.001430547
GBPUSD_12H	0.000832904	0.000274174	0.000685633	1.48E-03
GBPUSD_6H	2.89E-04	7.91E-05	5.93E-04	1.10E-03
GBPUSD_1H	4.70524E-05	3.52311E-05	3.24528E-05	3.97E-05
GBPUSD_30T	8.14908E-05	4.17311E-05	8.6649E-06	4.32029E-06
USDCHF_1D	0.001034684	8.66E-04	0.000306888	1.15E-04
USDCHF_12H	0.000294718	1.45E-04	0.000205567	7.13E-05
USDCHF_6H	6.15E-04	5.42E-04	1.03E-04	4.42E-05
USDCHF_1H	3.27385E-05	2.31331E-05	1.11013E-05	4.64768E-06
USDCHF_30T	1.69339E-05	4.72775E-06	1.3905E-05	9.19175E-06
USDJPY_1D	0.000566972	0.00020133	0.000627763	0.000466593
USDJPY_12H	0.000294898	0.000188022	0.00053215	0.000169876
USDJPY_6H	0.000182391	0.000170614	0.000463676	0.000412657
USDJPY_1H	0.000197502	9.19914E-05	2.45675E-05	1.57034E-05
USDJPY_30T	7.76997E-05	3.90597E-05	9.05783E-06	4.44978E-06
Mean	0.000336184	0.000198495	0.000336399	0.000353389

LSTM Relu Bidirectional				
EURUSD_1D	0.000646601	0.000477242	0.000359513	0.000222005
EURUSD_12H	0.001781473	0.002271858	0.000209114	0.000238781
EURUSD_6H	4.84E-04	5.73E-04	0.00013009	9.80E-05
EURUSD_1H	0.001236252	0.000782335	0.000686673	0.000697724
EURUSD_30T	0.000651753	0.000410656	0.001430812	0.001593241
GBPUSD_1D	0.000899452	0.000476266	0.000678704	0.000999973
GBPUSD_12H	0.000584252	0.000189026	0.000233745	6.32E-05
GBPUSD_6H	1.40E-03	1.08E-04	8.30E-05	5.71E-05
GBPUSD_1H	0.001538053	0.000120323	0.000607485	4.18E-05
GBPUSD_30T	0.001448046	0.000179853	0.001903209	0.0003751
USDCHF_1D	0.001500302	8.39E-04	0.000226745	7.22E-05
USDCHF_12H	0.001532165	1.37E-03	0.000136928	3.92E-05
USDCHF_6H	1.76E-03	1.93E-03	5.78E-05	2.40E-05
USDCHF_1H	0.003380316	0.004217774	0.00025325	0.000266383
USDCHF_30T	0.00263084	0.00293319	0.001340398	0.001507544
USDJPY_1D	0.000767427	0.000329108	0.000442852	0.000150672
USDJPY_12H	0.001434876	0.001372796	0.000247441	0.000100865
USDJPY_6H	0.000896078	0.000700275	0.000214591	0.000175966
USDJPY_1H	0.00228328	0.00216007	0.002436554	0.003920583
USDJPY_30T	0.002166076	0.002411678	0.00273299	0.004034094
Mean	0.001451243	0.00119242	0.000720595	0.000733927
LSTM Relu forward				
EURUSD_1D	0.000956876	0.000701727	0.000423136	0.000112108
EURUSD_12H	2.38E-03	2.85E-03	0.000252757	8.13E-05
EURUSD_6H	0.001537763	0.002085426	0.000398169	0.000375336
EURUSD_1H	0.002679884	0.001083536	0.001151242	0.001100398
EURUSD_30T	0.002620105	0.001305268	0.002061276	0.003077799
GBPUSD_1D	0.003149294	0.001065977	0.000656902	9.23E-04
GBPUSD_12H	2.44E-03	6.23E-04	4.52E-04	3.36E-04
GBPUSD_6H	0.001911535	0.000276965	0.000185239	9.93E-05
GBPUSD_1H	0.002309129	0.000156728	0.001920513	0.000373246
GBPUSD_30T	0.002320939	2.89E-04	0.003358092	9.27E-04
USDCHF_1D	0.005184083	6.17E-03	0.000284187	1.12E-04
USDCHF_12H	2.78E-03	2.57E-03	1.43E-04	4.54E-05
USDCHF_6H	0.002841884	0.003254781	7.61413E-05	2.16566E-05
USDCHF_1H	0.00214713	0.00261582	0.000304521	0.000349454
USDCHF_30T	0.002359283	0.002592896	0.00141902	0.001642298
USDJPY_1D	0.001821802	0.001161809	0.000773043	0.000290484
USDJPY_12H	0.001791801	0.0014219	0.000460177	0.000157911
USDJPY_6H	0.000809604	0.000592112	0.00034687	0.000203352
USDJPY_1H	0.001876947	0.001784609	0.00258046	0.00402606
USDJPY_30T	0.002118625	0.001985001	0.001765896	0.002346142
Mean	0.002301728	0.001729174	0.000950635	0.000829964

LSTM Tanh Bidirectional				
EURUSD_1D	0.000534389	0.000368498	0.000883073	0.000751868
EURUSD_12H	3.15E-04	1.74E-04	0.000774773	4.15E-04
EURUSD_6H	0.000259049	0.000508039	0.000128633	0.000131254
EURUSD_1H	0.000101767	8.2938E-05	1.61315E-05	3.35139E-05
EURUSD_30T	0.000216816	0.000125221	6.7174E-06	5.26913E-06
GBPUSD_1D	0.00138551	0.000275364	0.000762349	1.44E-03
GBPUSD_12H	4.07E-04	1.19E-04	6.68E-04	8.30E-04
GBPUSD_6H	0.000264347	6.47637E-05	0.000112767	7.66E-05
GBPUSD_1H	6.13139E-05	3.44806E-05	1.42706E-05	1.6364E-05
GBPUSD_30T	6.25001E-05	4.72E-05	7.53079E-06	5.22E-06
USDCHF_1D	0.00102671	5.63E-04	0.000263464	8.90E-05
USDCHF_12H	2.90E-04	1.06E-04	1.65E-04	6.45E-05
USDCHF_6H	0.000665103	0.000651929	8.23448E-05	2.46476E-05
USDCHF_1H	0.000108804	9.14051E-05	1.81946E-05	1.24335E-05
USDCHF_30T	1.37775E-05	4.9502E-06	1.25902E-05	5.74303E-06
USDJPY_1D	0.000626735	0.000486395	0.000613552	0.000320303
USDJPY_12H	0.000329364	0.000254369	0.000523591	0.000153092
USDJPY_6H	0.000146509	9.04961E-05	0.000135167	4.84964E-05
USDJPY_1H	2.49025E-05	1.11884E-05	1.98276E-05	6.12584E-06
USDJPY_30T	9.92157E-05	9.08674E-06	1.11556E-05	1.1947E-05
Mean	0.000346904	0.000203416	0.00026095	0.000222159
LSTM Tanh forward				
EURUSD_1D	0.000741205	0.000512807	0.000921075	0.000500184
EURUSD_12H	3.46E-04	3.68E-04	0.000838533	5.46E-04
EURUSD_6H	0.000283605	0.000114141	0.0001392	8.31529E-05
EURUSD_1H	7.07338E-05	2.22789E-05	1.64012E-05	1.40897E-05
EURUSD_30T	0.000270454	0.000301993	1.34702E-05	4.64395E-05
GBPUSD_1D	0.000873749	0.000429257	0.000803939	1.19E-03
GBPUSD_12H	5.17E-04	1.41E-04	6.91E-04	1.41E-03
GBPUSD_6H	0.000127112	6.52116E-05	0.000109265	4.11E-05
GBPUSD_1H	9.95217E-05	9.18987E-05	2.08546E-05	6.93828E-06
GBPUSD_30T	2.72305E-05	7.53E-05	1.21474E-05	1.33E-05
USDCHF_1D	0.000826196	2.77E-04	0.000238018	7.79E-05
USDCHF_12H	1.23E-03	1.05E-03	1.73E-04	5.09E-05
USDCHF_6H	0.000182393	0.00010063	7.96192E-05	2.98344E-05
USDCHF_1H	0.000159003	0.000160018	1.11076E-05	4.27527E-06
USDCHF_30T	5.61232E-05	6.92379E-05	2.02237E-05	7.89123E-06
USDJPY_1D	0.001275144	0.00089141	0.000642689	0.000229469
USDJPY_12H	0.000923487	0.001247426	0.00053522	0.00021895
USDJPY_6H	0.000215203	0.000118273	0.000173661	8.40341E-05
USDJPY_1H	0.00014967	8.11119E-05	1.5461E-05	5.22589E-06
USDJPY_30T	3.51631E-05	1.53992E-05	1.0288E-05	9.67407E-06
Mean	0.000420407	0.000306762	0.000273248	0.0002283

RNN VS ARMA-RNN Multifrequency

Currency and Frequency	RNN-ARMA		RNN	
	In Sample	Out of Sample	In Sample	Out of Sample
GRU Relu Bidirectional				
EURUSD_1D	0.003429689	0.003547061	0.001600192	0.00141451
EURUSD_12H	0.003287497	0.003457673	0.001315873	0.002558812
EURUSD_6H	3.72E-03	4.08E-03	0.005572165	4.68E-03
EURUSD_1H	0.00335705	0.00348906	0.002809075	0.000842808
EURUSD_30T	0.002307877	0.00249447	0.007909591	0.003631255
GBPUSD_1D	0.003350562	0.003568077	0.007566556	0.001922606
GBPUSD_12H	0.002336133	0.002572818	0.002002741	2.88E-04
GBPUSD_6H	3.46E-03	3.49E-03	4.97E-03	8.43E-04
GBPUSD_1H	0.003489793	0.003642495	0.002858165	1.46E-04
GBPUSD_30T	0.003141476	0.003037168	0.01060341	0.000917182
USDCHF_1D	0.003097447	3.38E-03	0.004018882	2.69E-03
USDCHF_12H	0.002881237	2.82E-03	0.004200715	4.03E-03
USDCHF_6H	3.28E-03	3.42E-03	1.25E-03	8.86E-04
USDCHF_1H	0.003463471	0.003653681	0.00377987	0.005021711
USDCHF_30T	0.003104656	0.003248023	0.011548418	0.014116974
USDJPY_1D	0.002507904	0.002555229	0.003833288	0.003126358
USDJPY_12H	0.003536348	0.003956326	0.003415277	0.003284397
USDJPY_6H	0.003215027	0.003236342	0.006328044	0.007032551
USDJPY_1H	0.003287777	0.003354308	0.00301213	0.002265188
USDJPY_30T	0.003296164	0.003734429	0.01140475	0.010427575
Mean	0.003177778	0.003336481	0.00500029	0.003506127
GRU Relu forward				
EURUSD_1D	0.003472925	0.003885241	0.004905307	0.003372196
EURUSD_12H	0.003353193	0.003510472	0.006595444	0.005606485
EURUSD_6H	3.43E-03	3.44E-03	0.008169597	6.44E-03
EURUSD_1H	0.003524869	0.003599522	0.003977727	0.001507072
EURUSD_30T	0.002784439	0.003083456	0.007350246	0.003578599
GBPUSD_1D	0.003650885	0.00383935	0.007110231	0.00164177
GBPUSD_12H	0.003122506	0.004794059	0.004951344	9.94E-04
GBPUSD_6H	4.33E-03	4.72E-03	3.44E-03	3.04E-04
GBPUSD_1H	0.002639441	0.0031225	0.005017692	3.12E-04
GBPUSD_30T	0.00337372	0.003714608	0.013053786	0.002405268
USDCHF_1D	0.002248421	2.66E-03	0.003322871	1.35E-03
USDCHF_12H	0.003677499	3.78E-03	0.002446723	1.72E-03
USDCHF_6H	3.81E-03	4.44E-03	5.07E-03	6.27E-03
USDCHF_1H	0.003038703	0.003231939	0.002720264	0.003457188
USDCHF_30T	0.002966368	0.003224442	0.010586558	0.013447225
USDJPY_1D	0.002775881	0.002652472	0.005166901	0.004357106
USDJPY_12H	0.002782407	0.003016595	0.003087702	0.002599103
USDJPY_6H	0.003803581	0.003891136	0.003969108	0.004816965
USDJPY_1H	0.00309443	0.003340031	0.003561468	0.002557045
USDJPY_30T	0.004189656	0.004571453	0.008715298	0.007954829

Mean	0.003303126	0.003626251	0.005661041	0.003734336
GRU Tanh Bidirectional				
EURUSD_1D	7.40023E-05	2.32894E-05	0.000806388	0.000650794
EURUSD_12H	2.24999E-05	9.35139E-06	0.000422621	0.000299481
EURUSD_6H	4.31E-05	6.53E-05	0.000377615	1.51E-04
EURUSD_1H	2.35035E-05	1.19071E-05	0.000318452	0.000259541
EURUSD_30T	2.58168E-05	1.13381E-05	0.000152552	9.68159E-05
GBPUSD_1D	3.28545E-05	2.86702E-05	0.000619897	0.000518153
GBPUSD_12H	3.2947E-05	1.9246E-05	0.005478862	1.16E-03
GBPUSD_6H	1.01E-04	9.68E-05	2.22E-04	1.38E-04
GBPUSD_1H	6.15475E-05	3.69361E-05	0.000241073	1.70E-04
GBPUSD_30T	1.96347E-05	1.29145E-05	4.02096E-05	1.64931E-05
USDCHF_1D	5.56519E-05	3.41E-05	0.003309961	2.17E-03
USDCHF_12H	4.02598E-05	1.16E-05	0.00149262	7.70E-04
USDCHF_6H	4.04E-05	1.25E-05	6.25E-04	2.70E-04
USDCHF_1H	5.31597E-05	5.85053E-05	0.000622972	0.000719392
USDCHF_30T	3.85803E-05	5.36023E-05	4.11397E-05	4.14724E-05
USDJPY_1D	2.88762E-05	8.95289E-06	0.001356887	0.000712293
USDJPY_12H	6.68357E-05	4.79812E-05	0.000524949	0.00024101
USDJPY_6H	1.95264E-05	8.49935E-06	0.000367799	0.000208181
USDJPY_1H	3.87414E-05	1.70213E-05	0.000226138	0.000175771
USDJPY_30T	3.90356E-05	1.97307E-05	0.000250732	0.000255995
Mean	4.28895E-05	2.94094E-05	0.000874897	0.000451567
GRU Tanh forward				
EURUSD_1D	9.52573E-05	0.000112663	0.000779434	0.000498998
EURUSD_12H	5.24859E-05	3.28694E-05	0.000900803	0.000739943
EURUSD_6H	3.98E-05	1.52E-05	0.000304427	1.69E-04
EURUSD_1H	2.64354E-05	1.82489E-05	5.80367E-05	6.77597E-05
EURUSD_30T	5.72595E-05	1.35267E-05	0.000544223	0.00015724
GBPUSD_1D	2.84215E-05	8.55859E-06	0.000946543	0.00105262
GBPUSD_12H	0.000144393	9.03984E-05	0.000387108	2.17E-04
GBPUSD_6H	7.40E-05	1.35E-05	2.11E-04	1.09E-04
GBPUSD_1H	5.08551E-05	2.56713E-05	6.71052E-05	2.31E-05
GBPUSD_30T	9.38828E-05	8.30836E-05	0.000107711	7.67386E-05
USDCHF_1D	6.75612E-05	3.86E-05	0.002757218	1.30E-03
USDCHF_12H	0.000156448	1.25E-04	0.003139904	2.86E-03
USDCHF_6H	7.12E-05	3.75E-05	6.81E-04	2.57E-04
USDCHF_1H	5.8667E-05	1.93031E-05	0.000233971	0.000176866
USDCHF_30T	6.79553E-05	4.30244E-05	4.95584E-05	5.02027E-05
USDJPY_1D	6.72987E-05	4.32659E-05	0.001257887	0.001158159
USDJPY_12H	2.78209E-05	1.24688E-05	0.002211989	0.001772744
USDJPY_6H	0.000222682	0.000167206	0.000255254	0.000101026
USDJPY_1H	0.000160916	7.08561E-05	0.000101651	2.49695E-05
USDJPY_30T	2.44496E-05	1.172E-05	3.75444E-05	3.6878E-05
Mean	7.93886E-05	4.91148E-05	0.000751633	0.000542694

LSTM Relu Bidirectional				
EURUSD_1D	0.000718228	0.000560193	0.003282524	0.004266454
EURUSD_12H	0.001446392	0.001445735	0.000581833	0.000464477
EURUSD_6H	1.68E-03	1.88E-03	0.002801754	2.34E-03
EURUSD_1H	0.001171081	0.000381129	0.002109197	0.001493156
EURUSD_30T	0.002293806	0.000798304	0.008684234	0.00489835
GBPUSD_1D	0.001045356	0.000715109	0.001208502	0.000589517
GBPUSD_12H	0.001549193	0.000319063	0.00299204	4.98E-04
GBPUSD_6H	3.83E-03	6.55E-04	3.76E-03	6.27E-04
GBPUSD_1H	0.001687875	0.000248019	0.002576424	1.86E-04
GBPUSD_30T	0.003066537	0.000565708	0.010552931	0.001112045
USDCHF_1D	0.003204526	1.58E-03	0.003942629	2.33E-03
USDCHF_12H	0.001357506	8.06E-04	0.001422351	6.14E-04
USDCHF_6H	1.95E-03	2.31E-03	4.68E-03	5.48E-03
USDCHF_1H	0.003035085	0.0040915	0.002225646	0.002765861
USDCHF_30T	0.003423641	0.003930676	0.01172267	0.014279066
USDJPY_1D	0.001141303	0.00064809	0.001809655	0.001249284
USDJPY_12H	0.001890518	0.003042937	0.000567307	0.000328786
USDJPY_6H	0.001848987	0.002493375	0.003817865	0.003804151
USDJPY_1H	0.001617525	0.002109557	0.003300674	0.00316756
USDJPY_30T	0.002774728	0.00287565	0.008832768	0.007614164
Mean	0.002036476	0.001572709	0.004043178	0.002905197
LSTM Relu forward				
EURUSD_1D	0.003503378	0.00440255	0.002001242	0.002526855
EURUSD_12H	2.73E-03	3.16E-03	0.001255424	1.50E-03
EURUSD_6H	0.003379449	0.003780143	0.003059928	0.002443466
EURUSD_1H	0.003436007	0.003905063	0.002747494	0.001132335
EURUSD_30T	0.002961357	0.003324533	0.007836731	0.003807934
GBPUSD_1D	0.003005217	0.003208342	0.003045818	1.11E-03
GBPUSD_12H	4.10E-03	4.54E-03	2.87E-03	4.37E-04
GBPUSD_6H	0.003248394	0.003825904	0.002398119	3.55E-04
GBPUSD_1H	0.003029602	0.003485614	0.002530077	0.000524187
GBPUSD_30T	0.00272345	3.03E-03	0.010909613	1.35E-03
USDCHF_1D	0.004245262	4.65E-03	0.003747551	1.27E-03
USDCHF_12H	3.12E-03	3.58E-03	2.75E-03	1.83E-03
USDCHF_6H	0.003770612	0.004197416	0.001736477	0.001623693
USDCHF_1H	0.002998889	0.003586926	0.002660172	0.003065953
USDCHF_30T	0.004242147	0.004884931	0.012781013	0.015651133
USDJPY_1D	0.003562141	0.003902761	0.003915742	0.003173063
USDJPY_12H	0.002570239	0.002607259	0.002761174	0.002726422
USDJPY_6H	0.003088803	0.003197659	0.004630488	0.005103915
USDJPY_1H	0.004036237	0.004127952	0.003214747	0.002780813
USDJPY_30T	0.002691402	0.003357787	0.013963149	0.012238441
Mean	0.003322399	0.00373807	0.004540673	0.003232149

LSTM Tanh Bidirectional				
EURUSD_1D	9.76026E-05	3.42387E-05	0.001143026	0.000945469
EURUSD_12H	4.53E-05	5.92E-05	0.003292629	2.34E-03
EURUSD_6H	3.99602E-05	2.64383E-05	0.000794375	0.000224627
EURUSD_1H	0.000206435	0.000224514	0.000215043	5.11252E-05
EURUSD_30T	2.85491E-05	9.75326E-06	0.002133258	0.000660647
GBPUSD_1D	2.35371E-05	9.51394E-06	0.001104585	1.22E-03
GBPUSD_12H	4.36E-05	4.26E-05	1.87E-03	3.43E-04
GBPUSD_6H	2.70065E-05	8.97005E-06	0.000174885	1.19E-04
GBPUSD_1H	6.76444E-05	4.1396E-05	7.39337E-05	9.55957E-05
GBPUSD_30T	8.01834E-05	9.04E-05	7.19733E-05	1.74E-05
USDCHF_1D	7.87487E-05	6.32E-05	0.003076095	1.53E-03
USDCHF_12H	3.13E-05	1.21E-05	1.34E-03	5.95E-04
USDCHF_6H	2.99793E-05	1.42072E-05	0.000610207	0.000260116
USDCHF_1H	0.000134096	7.91921E-05	0.000138868	7.88816E-05
USDCHF_30T	2.94664E-05	9.29399E-06	4.34221E-05	3.24662E-05
USDJPY_1D	2.50733E-05	1.25109E-05	0.000911141	0.000334355
USDJPY_12H	3.59076E-05	2.81426E-05	0.000648458	0.000746725
USDJPY_6H	2.90574E-05	9.04505E-06	0.001134261	0.000742271
USDJPY_1H	2.84742E-05	8.44162E-06	4.90076E-05	2.17232E-05
USDJPY_30T	0.000323364	0.000472566	4.05625E-05	1.68632E-05
Mean	7.0268E-05	6.27853E-05	0.000943099	0.000518672
LSTM Tanh forward				
EURUSD_1D	0.000170002	6.75405E-05	0.001034733	0.001049399
EURUSD_12H	1.45E-04	9.29E-05	0.000639042	1.01E-03
EURUSD_6H	4.83746E-05	1.31789E-05	0.000488054	0.00016185
EURUSD_1H	0.00011886	6.31449E-05	0.000186525	0.000453624
EURUSD_30T	4.22528E-05	3.4194E-05	0.000106624	0.000116367
GBPUSD_1D	3.65077E-05	1.62504E-05	0.000876884	8.26E-04
GBPUSD_12H	1.01E-04	6.13E-05	1.49E-03	3.50E-04
GBPUSD_6H	3.10505E-05	8.68811E-06	0.000208925	1.21E-04
GBPUSD_1H	5.93255E-05	3.22901E-05	0.000129024	7.14711E-05
GBPUSD_30T	0.000114011	1.95E-04	5.84094E-05	2.22E-05
USDCHF_1D	7.83403E-05	7.07E-05	0.002828265	1.29E-03
USDCHF_12H	1.67E-04	1.25E-04	1.42E-03	5.55E-04
USDCHF_6H	0.000319247	0.000328318	0.005040801	0.00612983
USDCHF_1H	3.24118E-05	1.5117E-05	0.000204839	0.000198912
USDCHF_30T	4.10646E-05	2.78186E-05	0.000417516	0.000445191
USDJPY_1D	6.30572E-05	1.4927E-05	0.001064862	0.000925865
USDJPY_12H	5.14192E-05	1.88671E-05	0.000656764	0.000316547
USDJPY_6H	3.59803E-05	1.36237E-05	0.000317779	0.000156973
USDJPY_1H	0.000159392	0.000210096	3.98517E-05	1.78567E-05
USDJPY_30T	3.12606E-05	8.67627E-06	0.000212989	0.000133231
Mean	9.22321E-05	7.08954E-05	0.000871359	0.000717691