Assessing the impact of monetary and fiscal policy on stock markets using machine learning: A US Study

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Abstract

Monetary and fiscal policy have considerable influence on stock market performance in the United States of America (USA). It is estimated that 10% to 15% of the $814 billion dollars dispersed as economic impact payments (stimulus cheques) following the passing of the CARES and Consolidated Appropriations Acts, were invested in the stock market. This coincided with the S&P 500 recovering from its lowest point during the pandemic on the 20th of March 2020 and rebounding to grow by 100% over the next year to a record high. This study investigates the impact of monetary and fiscal policy on stock market performance using machine learning models. Long Short-Term Memory (LSTM) Networks, Autoregressive Integrated Moving Average (ARIMA), Structural Vector Autoregression (SVAR), Linear Regression, and Random Forest are the chosen models to implement this research. Similar studies have only employed SVAR models to analyse this topic but have not employed machine learning (ML) models, unlike this study. In the intervening years since the most recent studies, events such as COVID-19, central bank policies like quantitative easing and technological innovations in finance have impacted stock market performance. This research finds that ML models such as ARIMA and LSTM offer better predictive capabilities and capture insights not obtained in SVAR models. However, SVAR identifies relationships that are not captured in the ML models mentioned above and should be employed alongside these models when researching economic policy and stock market performance. The results show that monetary policy affects stock market performance and has a strong positive correlation with the S&P 500. Fiscal policy has less of an impact than monetary policy when analysed in isolation. However, both monetary and fiscal policy combined are shown to have a positive correlation with the S&P 500. This research offers valuable knowledge for policymakers, traders, and quantitative analysts looking to analyse the impact of economic policy on stock market performance and suitable models for this exercise.

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1. Introduction

While a relatively small proportion of families living in the USA are invested directly in individual stocks at 14%, 52% of families are invested in stocks indirectly in some form, such as 401(k) retirement accounts (Parker and Fry, 2020). Responding to the COVID-19 pandemic, Central Banks, including the Federal Reserve of the United States (The Fed), have changed monetary policy, intending to reduce the impact on the economy resulting from the pandemic to fulfil its critical goals of price stability, maximum employment, and stable long-term interest rates. This research investigates the effects of monetary and fiscal policy on stock market performance in the United States of America (USA), with the S&P 500 as the proxy stock market index. This research provides additional insight on the impact of economic policy which is beneficial to governments, central banks, and institutional and retail investors. The findings show a strong positive correlation and between monetary policy and stock market performance, while fiscal policy plays less of a factor.

The Fed attempts to achieve these targets while navigating the impacts of the pandemic with increased money supply, quantitative easing and lowering of interest rates. At the start of 2020, The Feds balance was roughly the same level as five years previous but has since increased by another $4.5 trillion to $8.8 billion as of February 2021 (Selgin, 2021). Interest rates have reduced to 0.25% since the pandemic's start and did not change until March 2022, with a 0.25% increase to 0.5% (FRED, 2022a). While long-term economic outcomes resulting from COVID-19 are not clearly understood, stock markets have recorded volatile movements since the beginning of the pandemic. The S&P 500 listed at an all-time high in February 2020 but lost more than 33% of its value within 30 days including a 12% single-day drop in March 2020 (Heyden and Heyden, 2021). Since March 2020, markets have rebounded, with the S&P 500 reaching record highs in January 2022.

Both monetary and fiscal policy's influence on stock market performance is assessed in this research, as their interaction plays a fundamental role in the economy and should not be analysed solely (Chatziantoniou et al., 2012). Not only is it necessary to understand monetary and fiscal policy's relationship with stock market performance due to the number of citizens with a stake in financial markets, but it is also essential to understand the connection between economic policy, stock markets, and the economy, to get an understanding of the macroeconomy. In the business cycle context, monetary and fiscal policy is essential in stabilising inflation and output gaps Prukumpai and Sethapramote (2019), which makes it crucial to understand the policy's impact as governments and central banks respond to COVID-19 (Wei and Han, 2021). The findings in this research also allow for comparison with literature that examined the same subject but in different countries, including China and Romania (Lei Hu, 2018; Caraiani and Călin, 2020).

Combining state-of-the-art data analysis with economic theory provides new knowledge of how economic policy and stock markets interrelate. This research compares the efficacy of Machine Learning (ML) models to conventional time series analysis. Execution of ML models and time series data analysis allows for examination of how monetary and fiscal policy affect stock markets. Comparable literature that examines monetary and fiscal policy impact on stock markets uses Structural Vector Autoregression (SVAR) as the optimal conventional model for this subject (e.g. Caraiani and Călin, 2020; Chatziantoniou et al., 2012). Using additional Machine Learning models such as Long Short-Term Memory (LSTM) and Autoregressive Integrated Moving Average (ARIMA) allows for the comparison of advanced ML models with SVAR. ML models such as ARIMA and LSTM capture correlations under certain conditions that SVAR does not. This research provides additional insight, which is useful for stock market traders, governments, central banks, and the public.

The inclusion of up-to-date data allows for further understanding of the topic, as the most recent literature that examined US data in this context was in 2012, especially considering the economic policy changes in response to the COVID-19 pandemic. The dataset is processed through ML models such as ARIMA and LSTM. While previous literature on the subject uses quarterly data, the inclusion of weekly and monthly data allows for comparison to the findings from the SVAR model performed on the quarterly dataset. The SVAR quarterly model acts as the control to analyse the findings of the ML models. The results allow for the evaluation of each model and data frequency in the context of the relationship between monetary and fiscal policy and stock market performance. The findings show that ARIMA, LSTM, and Linear Regression provide additional insight not captured in the SVAR model and show a strong correlation between monetary policy and the macroeconomy both together and in isolation, with stock market performance. Identified also, are stronger correlations when analysing monthly data, while weekly data does not provide additional information as many of the included variables are not available weekly, and data interpolation is relied upon to fill in the gaps.

2. Literature Review

ML is the process of building and refining an analytical model that can learn from specific training data relating to the topic in question and improve its accuracy by adding more data (Janiesch et al., 2021). In the context of this research, ML algorithms are used to analyse the relationship between monetary, fiscal, macroeconomic, and stock market performance. ML models such as LSTM and ARIMA are state-of-the-art methodologies for analysing time series data such as stock market performance, making these models suitable for this research topic (Gonçalves et al., 2019). ML is a subset of Artificial Intelligence (AI) that uses data and algorithms to find patterns and improve its accuracy through multiple iterations and the addition of problem-specific data. The term 'Machine Learning' is originally coined in Arthur Samuels's seminal paper on using a computer to beat a human at the game of checkers (Samuel and Gabel, 1959). AI's big breakthrough occurred with the publication "Computing Machinery and Intelligence" and the Turing Test (Turing, 1950). Marvin Minsky's and John McCarthy's Dartmouth Workshop of 1956 is accepted as the birth of AI. A boom in funding and research led to optimism in 1965, with HA Simon declaring that "machines will be capable, within twenty years of doing any work a man can do" (Kober and Peters, 2014).

Prior to strides made in AI during the twentieth century, more historic developments date back to the eighth and ninth centuries when Muḥammad ibn Mūsā al-Khwārizmī created algebra and introduced the concept of algorithms (Nabirahni et al., 2019). Gottfried Wilhelm Leibniz made relatively massive contributions to calculus and is credited with formulating modern binary systems (Lande, 2014). He also contributed to linear systems by arranging coefficients of linear equations into an array, now known as Gaussian Elimination, after Carl Friedrich Gauss, who later worked on this method. Gaussian Elimination is used to solve the system of linear equations, which is a fundamental concept in ML algorithms today and is a critical component of this research. Boole introduced the concept of Boolean algebra, detailed in "An Investigation of the Laws of Thought" (Boole, 1854), which provides a more comprehensive explanation of the computer architecture concepts today on which ML models are executed. These concepts have the potential to be used in financial and economic research and analysis but have not been feasible up until recent years, with TensorFlow, Google's open-source AI library used in this research, originally released in 2015.

In 2011, IBM Watson appeared on the game show Jeopardy!, defeating top human contestants and attracting increased attention to AI, showcasing the technology's ability. This breakthrough opened the door for the use of AI in finance and economics with access to greater quantities of data and Moore's Law allowing for exponentially faster data processing used to apply AI algorithms that have existed historically but have not been feasible up until recent years for financial research. Enhanced memory and processing power allow AI algorithms to come to fruition, with Deep Learning (a variation of ML) providing improved flexibility when analysing larger nonlinear datasets requiring less human interaction (Chatzis et al., 2018). LSTMs are a form of deep learning, a machine learning concept based on artificial neural networks used in this research (Janiesch et al., 2021).

ML has applications in Commerce, Marketing, Education, Science, Retail, and Lifestyle. Specific examples of these are the creation of autonomous vehicles, spam filters for emails, and cancer cell detection (Kourou et al., 2021). More specifically, ML is increasingly used in economics and stock market analysis with the advent of algorithm trading (Yadav, 2015). As the most recent study of US data was in 2012, this up-to-date research examines if the findings from previous research are similar or if factors such as algorithmic trading has impacted the relationship between stock market performance and economic policy. The availability of ML algorithms such as ARIMA and LSTM, which were not as prevalent when the most recent research was carried out on this topic, provides a unique analysis of this topic in this research.

2.1 Overview of theoretical background

2.1.1 Fiscal Policy

Fiscal policy is the use of government spending and taxation to influence the economy by determining the sources of income and how to best spend them in order to optimise the economic performance of the state according to its economic programs (Mohammad et al., 2019). The objective of fiscal policy from a governmental perspective is to create strong and sustainable economic growth and to reduce poverty over the long term. Fiscal policy determines how much income citizens retain after-tax, impacting the economy, while it also plays a critical role in determining the size of government expenditure as taxes are used to pay for public services and public debt servicing. These factors impact stock market performance as the level of retained earnings for citizens impacts consumer sentiment and ultimately revenue streams for publicly traded companies.

During the 2007-2008 global economic crisis, the role and objectives of fiscal policy gained prominence when governments intervened to mitigate the impact of the crisis and stimulate the economy. The US government passed acts such as the Economic Stimulus Act of 2008 and the American Recovery and Reinvestment Act of 2009 with the goal of kick-starting the economy and preventing a deepening recession. The importance of fiscal policy as a tool to influence the economy has waxed and waned with a laissez-faire and limited government approach prevailing prior to the 1930s. In response to the stock market crash and the Great Depression of the 1920s, policymakers pushed for governments to play a more proactive role in the economy to boost the economy and prevent the long-term effects of financial crises and unemployment with the "New Deal" economic programs between 1933 and 1939. In the latter part of the twentieth century, the idea of small government prevailed and the role of government in markets reduced with open markets determining the allocation of goods and services. However, when the 2007-2008 global financial crisis threatened worldwide recession, the role of expansionary fiscal policy returned to prevalence with an increased role of government intervention in markets (Horton and El-Ganainy, 2009).

In response to the recession caused by the COVID-19 pandemic, the US government passed three specific bills aimed to stimulate the economy and offset the impact resulting from the pandemic. It is estimated that 10% to 15% of the $814 billion dollars dispersed as economic impact payments (stimulus checks) following the passing of the CARES and Consolidated Appropriations Acts, were invested in the stock market (Greenwood et al, 2022). This coincided with the S&P 500 recovering from its lowest point during the pandemic on 20th of March 2020, to reaching record highs by the end of 2020 and continuing the trend until the end of 2022.

2.1.2 Monetary Policy

There are two instruments that government organisations in a market economy can use to influence the economic activity, one of them being monetary policy, and the other being fiscal policy. The goal of these organisations is to keep prices stable, maintain low levels of unemployment, and increase the aggregate output of the economy (Friedman 2000). Central banks execute monetary policy on behalf of the government, which in the case of the US is the Fed. In most financial systems, banks are mandated by law hold claims against the Central Bank to produce deposits and make loans (Friedman, 2001). Central banks also hold claims against itself enabling it to have influence over the money and credit in the economic system. The supply of money for everyday transactions has been a standard function of governments for centuries, which originally took the form of gold (Fioretos and Heldt, 2019)

Until the establishment of the Bretton Woods systems in 1944, the US dollar was convertible to gold, meaning the Fed was limited in terms of the money supply due to the gold standard, where the dollar had a value directly linked to gold. With the removal of the gold standard, the dollar became a Fiat currency as a physical commodity did not back it. Fiat currencies provide central banks such as The Fed with greater control over the economy as they control money printing, but this can create the risk of hyperinflation, which is a rapid, excessive, and out-of-control price increase. Inflation will be represented in this study, providing insight into the correlation between monetary policy and stock market performance (Woodford, 2011).

2.1.3 Economics and Machine Learning

Economics helps us to better understand society, although more work needs to be done to better understand the interrelation between economics and culture, as most of this research falls on deaf ears among mainstream economists, even though real-world cases show the critical role of this interrelation (Azis, 2019). This paper provides an understanding of the relationship between markets and economic policy and lays a foundation for further study on this relationship. AI is used to analyse and predict stock markets as well as the impact of economic policy. Algorithmic trading, or High-Frequency Trading (HFT), is commonplace in trading and accounts for around 70% of equity trading in the United States (Yadav, 2015). ML is used in economic research, on subjects such as nowcasting the US GDP growth using tree-based models (Gogas and Papadimitriou, 2021). Soybilgen and Yazgan (2021) forecasting the GDP growth of Japan using Random Forest and Gradient Boosting, and Yoon (2021) using a GARCH model to identify the determinants of the Bitcoin price are other examples of ML been used in economic and financial literature (Chen et al. 2021).

Chatziantoniou (2012) and Lei Hu (2018) are identified as benchmarks for analysing the impact of monetary and fiscal policy on stock markets, with the latter based on the former. These papers use a Vector Auto Regression (VAR) model, which is considered state of the art for time series data analysis. Numerous papers focus on using Machine and Deep Learning algorithms, for example, Fischer and Krauss (2018), which use LSTM networks. LSTMs are a form of deep learning and a state-of-the-art sequence learning technique, although they "are less commonly applied to financial time series predictions, yet inherently suitable for this domain" (Fischer and Krauss, 2018). When evaluating the performance of stock markets over some time, time series methods are the most appropriate analysis techniques. Parmezan et al., (2019) investigate the best ML methods for time series analysis and identify Artificial Neural Networks (ANN), Support Vector Machine (SVM), and Nearest Neighbours as suitable time series analysis methodologies. Changes in Monetary policy, such as Central Bank announcements on interest changes, can impact stock markets as macroeconomics can inform market participants to move price valuations upwards and downwards (Lyócsa et al., 2019).

3. Data Description

The data is analysed from 1970 (Q2) to 2022 (Q1) on a weekly, monthly, and quarterly basis (Table 1). Quarterly is the highest frequency that provides meaningful results when including the fiscal policy variable (Chatziantoniou, et al., 2012). SVAR analysis allows for comparison to previous literature, which also analyses quarterly data using the SVAR model which is discussed in Section 4, and shows if there are changes to the relationship between variables following the publication of previous literature on the subject.

Table 1: The date intervals at which each variable is reported

Variables	**Quarterly**	**Monthly**	**Weekly**
M2	Yes	Yes	Yes
FEDFUNDS	Yes	Yes	Yes
IGREA	Yes	Yes	No
GDP	Yes	No	No
CPI	Yes	Yes	No
GOV	Yes	No	No
S&P 500	Yes	Yes	Yes

As seen in Table 1, GDP and Government Expenditure are only reported quarterly, while IGREA and CPI are reported quarterly and monthly. M2, FEDFUNDS and S&P 500 are reported on a quarterly, monthly, and weekly basis. The missing data are imputed using the linear method as this reflected the most accurate data during the data preparation phase.

Government Expenditure (GOV) represents the fiscal policy, while M2SL represents the variable for money supply and accounts for monetary policy. FEDFUNDS is the interest rate variable, which also accounts for monetary policy. The independent variables (representing the macroeconomy) examined are the Index of Global Real Economic Activity (IGREA), Gross Domestic Product (GDP), and the Consumer Price Index (CPI) as independent variables. The dependent variable is the S&P 500, a US stock market index based on the market capitalisations of the 500 largest companies with common stock listings on the NYSE or NASDAQ (Vortelinos et al., 2018).

Taxation is a frequently used proxy for fiscal policy; however, it requires modelling the simultaneous correlation between taxes and economic activity. Therefore, as a novel approach, Government Expenditure will be used instead of taxation as a proxy for fiscal policy. As well as not requiring simultaneous correlation modelling, this economic dynamics adjustment is more sensitive to government expenditure (Afonso and Sousa, 2011). Therefore, the Government Expenditure metric is suitable to capture fiscal policy without assumptions and overly intricate data wrangling, which may not produce an accurate reflection of the fiscal policy at the period represented. Government Expenditure is be represented in billions of dollars at each time interval and seasonally adjusted.

M2SL is used as money supply for monthly and quarterly analysis, and WM2NS is used for the weekly analysis as M2SL is not reported on a weekly basis. M2 comprises of the components of M1 which are liquid deposits consisting of Other Checkable Deposits (OCDs) and savings deposits including money market deposit accounts, plus time deposits less than $100,000 and retail MMF's minuses Keogh and IRA balances at depository institutions, and MMF's (before May 2020). The frequency of M2SL reporting is monthly, and the unit of measurement is billions of dollars, which is seasonally adjusted. WM2NS is reported weekly, and the unit of measurement is billions of dollars, which is not seasonally adjusted.

Prior literature on this subject used the 3-month interbank rate as the benchmark for the interest variable but these studies investigate different states such as Germany, United Kingdom, Romania and China (Chatziantoniou et al., 2012; Boiciuc, 2015; Lei Hu, 2018). FEDFUNDS is used in this research as it is a more direct monetary policy measure, and the frequency of reporting is daily and not seasonally adjusted. The unit metric is expressed in percentages and calculated as a volume-weighted median of overnight federal funds transactions. Although the banks set this variable, it is based on the Federal Funds Rate (FEDFUNDS), set by the Federal Open Market Committee (FOMC) of the US Federal Reserve, which meets eight times yearly to set the FEDFUNDS rate.

IGREA is an index designed to measure trends in global economic activity by evaluating global commodity markets proposed in Kilian (2009). IGREA is expressed in percentage deviations from trends based on global bulk dry cargo freight rates and is employed as a substitute for the quantity of shipping in global industrial commodity markets (Kilian and Zhou, 2018; FRED, 2022b). Advantages of using this index over alternative measures of economic activity such as GDP include giving proper weight to emerging economies, responding instantly to shifts in aggregate demand for industrial commodities and capturing the amplitude of fluctuations in industrial production faster than GDP (Kilian and Zhou, 2018).

GDP and CPI are included in the model to incorporate the impulse mechanisms of the underlying forces of monetary and fiscal policy. The macroeconomic variables also provide additional information on factors impacting stock market prices and the impact of economic policy on inflation and GDP. The SVAR model, discussed in detail below, examines the correlation between all variables, including these macroeconomic variables. CPI is utilised as a measure of inflation, as it correlates with different prices, such as import prices, producer prices, and industrial production (Ali Naqvi, Sulaiman Bagaba and Ramzani, 2018). Consumer Price Index for All Urban Consumers (CPIAUCSL) is the proxy for inflation. CPIAUCSL measures the average monthly change in the price for goods and services paid by urban consumers between any two time periods. CPIAUCSL represents an index format reported monthly and is seasonally adjusted. GDP is reported quarterly in the form of billions of dollars and is seasonally adjusted. All variables included in this research are summarised in Table 2.

Table 2: Description of the included variables

Variables	Description
M2	M2 includes the components of M1 plus “near money” comprising of money market accounts, plus time deposits less than $100,000 and retail MMF’s minuses Keogh and IRA balances.
FEDFUNDS	The Target Interest rate set by the FOMC, the Federal Reserve, which commercial banks lend and borrow to each other overnight.
IGREA	Index obtained from global bulk dry cargo shipping rates that aims to act as a proxy for the volume of shipping in global commodity markets (FRED, 2022b).
GDP	The overall market value of goods and services produced within a region or country.
CPI	An index measuring the price of a weighted average market basket of consumer goods and services purchased by households
GOV	Total expenditure by a government on goods and services, including administration, income transfers and public investment
S&P 500	A free-float weighted stock market index comprising 500 largest companies listed on US stock market exchanges

The data for M2, FEDFUNDS, IGREA, GDP, CPI, and GOV is sourced from the US Bureau of Economic Analysis and retrieved from the Federal Reserve Bank of St. Louis (FRED). The S&P 500 (the stock market index of choice) data is sourced from investing.com, as this source provides prices that match the time intervals for which the independent variables are captured. It also provides the data in a useable format and a more extended time range than other sources analysed. Data from investing.com are also cross-referenced with the S&P 500 from the official NASDAQ website to validate the accuracy of the data. These sources include the opening price for the period, in excel/CSV format, and at no cost. The investing.com data are available on a daily and monthly sequence with the daily data used for the weekly analysis and the monthly data used for the monthly and quarterly analysis. The selected observation date is the beginning of each period (i.e. weekly, monthly, quarterly) for the independent variables representing monetary, fiscal, and macroeconomic data. This strategy provides the most accurate data from reputable and official sources while requiring the least amount of data wrangling.

4. Methodological approach and variables included

4.1 Methodology

The data (Table 2) are analysed quarterly, monthly, and weekly as this enables the exploitation of advanced ML models (Table 3), which provide more insight than traditional statistical models when used on more granular data. However, there is a trade-off when fiscal is factored in, as US government expenditure is reported quarterly only. GDP is also not captured on a more granular level as GDP statistics are only published quarterly from US government sources such as FRED.

Table 3: Description of models used

Methods	Description
SVAR	Vector autoregression (VAR) is a stochastic model employed to capture the contemporaneous (occurring at the same time) interactions between multiple variables, with SVAR being an extended to focus on the role of shocks in the dynamics of the model.
LSTM	Long Short-Term Memory (LSTM) networks are recurrent neural network capable of processing entire sequences and use feedback connections to identify order dependence.
ARIMA (ARIMAX)	Autoregressive Integrated Moving Average (ARIMA) It is a generalisation of the simpler Autoregressive Moving Average and adds the notion of integration. A standard notation is used for ARIMA(p,d,q). ARIMAX is extended to have a dependant variable that can be viewed as a multiple regression model.
Linear Regression	linear regression is a linear approach for modelling the relationship between a scalar response and one or more dependent and independent variables.
Random Forest	Random forest is an ensemble learning method for classification, regression based on the concept of multiple decision trees

SVAR is used to explore the connections between the variables in question and examine how monetary and fiscal policies correlate to the stock market Index. This methodology is used to examine the effects of monetary and fiscal policy on stock market performance (Lei Hu, 2018; Chatziantoniou et al., 2012), as outlined in Section 2. Sims (1980) recommends a VAR model, which provides an equation on the lagged values of each variable, explaining how the model develops. However, there are limitations to this as it does not provide the current correlation between variables, which is why the SVAR model is used in this study. Another key aim of this research is to compare the performance of AI and ML algorithms with traditional statistical models used in economic literature, such as the VAR and SVAR models. LSTMs networks are used on this dataset, which is a state-of-the-art sequence learning model used in previous literature for financial market predictions (e.g. Fischer and Krauss, 2018).

Training and testing of data

Data are split into two tranches, training (80%), and test (20%), using the data outlined in the data description allowing for testing the model's accuracy on in and out of sample data to get an optimal bias-variance trade-off. This methodology provides insights to answer the research questions outlined and compare the performance of the SVAR model vs Machine Learning algorithms.

SVAR Model

The relationship between the stock market (SP500) and the proxy variables for fiscal policy (GOV), Monetary Policy (M2 & FEDFUNDS), and the macroeconomy (IGREA, GDP, CPI) are expressed as follows using the SVAR model with where Yt = (GDP, CPI, GOV, M2, FEDFUNDS, SP500) a 6 x 1-order vector.

$$\Gamma_0 Y_t = \delta + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \cdots + \Gamma_p Y_{t-p} + u_t$$

P denotes the lag order, Γ denotes the 6 x 6 -order matrix, Γ and others represent the 6 x 6-order lag relation matrix, and $\mathrm{U_I}$ represents a 6 x 1-order structural stochastic disturbance term vector. If Γ_0 is defined and reversible, multiply the two sides of Equation (1) by Γ_0^{-1} simultaneously to obtain the corresponding reduced VAR form:

$$Y_t = \mathrm{c} + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + \epsilon_t$$

By enforcing constraints on Γ_0, structural disturbances can be identified. Seen below is the equation depicting study of the correlations between all variables in the model.

$$\begin{bmatrix} \epsilon_{1,t}^{is} \\ \epsilon_{1,t}^{ps} \\ \epsilon_{1,t}^{gs} \\ \epsilon_{1,t}^{mss} \\ \epsilon_{1,t}^{irs} \\ \epsilon_{1,t}^{sms} \end{bmatrix} = \begin{bmatrix} a(1) & 0 & 0 & 0 & 0 & 0 \\ a(2) & a(3) & 0 & 0 & 0 & 0 \\ a(4) & a(5) & a(6) & 0 & 0 & 0 \\ a(7) & a(8) & a(9) & a(10) & 0 & 0 \\ a(11) & a(12) & a(13) & a(14) & a(15) & 0 \\ a(16) & a(17) & a(18) & a(19) & a(20) & a(21) \end{bmatrix} x \begin{bmatrix} \epsilon_{1,t}^{GDP} \\ \epsilon_{1,t}^{CPI} \\ \epsilon_{1,t}^{GOV} \\ \epsilon_{1,t}^{M1} \\ \epsilon_{1,t}^{FED} \\ \epsilon_{1,t}^{SP500} \end{bmatrix}$$

For this Equation, *is* denotes revenue shocks, *ps* denotes price shocks, *gs* denotes government expenditure shocks, *mss* denotes money supply shocks, *irs* denotes interest rate shocks, and *sms* represents stock market shocks (Chatziantoniou et al., 2012; Boiciuc, 2015; Lei Hu, 2018).

LSTMs

LSTM networks are one of the most sophisticated models used for sequence learning and include time series prediction, speech recognition, and handwriting recognition (Hochreiter and Schmidhuber, 1997; Graves et al., 2009; Alex Graves, 2013; Schmidhuber, 2015). LSTMs comprise an input layer, one or multiple hidden layers, and an output layer. They are constructed to learn long-term dependencies and are determined to be a suitable model for analysing financial and economic (Fischer and Krauss, 2018). The equations for the forward pass of an LSTM cell with a forget gate are:

$$f_t = \sigma_g\left(W_f x_t + U_f h_t - 1 + b_f\right)$$
$$i_t = \sigma_g(W_i x_t + U_i h_t - 1 + b_i)$$
$$o_t = \sigma_g(W_o x_t + U_o h_t - 1 + b_o)$$
$$\widetilde{c_t} = \sigma_g(W_o x_t + U_o h_t - 1 + b_o)$$
$$c_t = f_t\ o\ c_t - 1 + i_t o\ \tilde{c}_t$$
$$h_t = o_h\ o\ \sigma_h\ (c_t)$$

where the initial values are $c_O = 0$ and $h_O = 0$, and 0 denotes the element-wise product.

$x_t \in R^d$: Input vector to the LSTM unit

$x_t \in (0,1)^h$: forget gate's activation vector

$i_t \in (0,1)^h$: input/update gate's activation vector

$o_t \in (0,1)^h$: output gate's activation vector

$h_t \in (-1,1)^h$: hidden state vector, also known as the output vector of the LSTM unit

$\widetilde{c_t} \in (-1,1)^h$: cell input activation vector

$c_t \in R^h$: cell state vector

W ∈ $\mathrm{R}^{\mathrm{hxd}}$, U ∈ R^{hxh} and $b \in R^h$ weight matrices and bias vector parameters which need to be learned during training where the superscripts d and h refer to the number of input features and several hidden units, respectively.

ARIMA

ARIMA is a time series model used for forecasting stationary time series data that uses time series data to predict future trends and better understand the dataset's characteristics. A statistical model is autoregressive if it predicts future values based on past values. For example, ARIMA might be used to predict a stock's future prices based on its past performance. In recent literature, such models have been used to predict future statistics such as COVID-19 cases based on preliminary data. The model is expressed as ARIMA (p, D, q), where the parameters p, D and q denote the structure of the forecasting model, which is a combination of auto-regression AR (p), moving average MA (q) and differencing degree D (Fan et al., 2021). The ARIMA model is described as follows:

$$\left(1-\sum_{i=1}^{p}\phi\mathrm{i}\,L^{i}\right)(1-L)^{D}X_{t}=\left(1-\sum_{i=1}^{p}\theta\mathrm{i}\,L^{i}\right)$$

In this study, ARIMAX, the version of ARIMA used for multivariate time series analysis, will be referred to as ARIMAX from here on.

Linear Regression

Linear regression models the relationship between the dependent and independent variables. In this research, a Multiple Linear Regression (MLR) is used as there is multiple independent variables. The shortcomings of linear regression are that it sometimes only explores a relationship between the mean of the input variables and output variables. Just as the mean is not a full description of a single variable, linear regression does not provide a clear understanding of variable relationships. Therefore, an analysis of the various factors is done using a MLR model, with the dependent (target) variable being influenced by many independent variables (Rath et al., 2020).

$$y=\beta_0+\beta_1X_1+\cdots+\beta_nX_n+\epsilon$$

y is the prediction of the dependent variable.

β0 indicates the point where the line intersects the Y-axis.

β1X1 is the regression coefficient (B1) of the first independent variable. (X1)

βnXn is the regression coefficient of the last independent variable. ϵ → Refers to the error term.

Random Forest

The first algorithm for random forest was suggested by Ho (1995) and later expanded by Breiman (2001), is composed of many deep yet decorrelated decision trees built on different bootstrap samples of the training data. Two fundamental techniques are used in the random forest algorithm random feature selection to decorrelate the trees and bagging, to build them on different bootstrap samples. When using the Random Forest Algorithm to solve regression problems, the mean squared error (MSE) is used to determine how data branches from each node.

$$\mathrm{MSE} = \frac{1}{N} + \Sigma_{\mathrm{i=1}}^{\mathrm{N}} (\mathrm{fi} - \mathrm{yi})^2$$

N = the number of data points

fi is the value returned by the model

yi is the actual value for data point *i*

This formula calculates the distance of each node from the predicted actual value, helping to decide which branch is the better decision for your forest. Here, *yi* is the value of the data point you are testing at a certain node, and fi is the value returned by the decision tree.

4.2 Variables Included

As detailed on a more granular level in Section 3, the variables included are M2, FEDFUNDS, GOV, IGREA, GDP, CPI, and the S&P 500. M2 and FEDFUNDS represent monetary policy, while GOV represents fiscal policy. IGREA is included to represent the demand variation in the commodity market while also covering inherited international inflation. GDP is included to represent economic activity, and CPI is the metric for inflation. The S&P 500 (SP500) represent stock market performance and is the dependent variable. Table 4 demonstrates the variables included and their characteristics. The table outlines the number of observations for each variable before imputation, the unit of measurement, what policy it is acting as a proxy for and the source used to obtain the data. These variables are selected based on previous literature (Chatziantoniou et al., 2012; Boiciuc, 2015; Lei Hu, 2018).

Table 4: Number of observations and characteristics of each variable

Data Set	Variable Type	Variables	Proxy for	Unit	Source	Quarterly Observations (Q-n)	Monthly Observations (M-n)	Weekly Observations (W-n)
M2	Independent	Money Supply	Monetary	Dollars (Billions)	St Louis Fed (FRED)	208	624	2158
FEDFUNDS	Independent	Interest Rate	Monetary	Percentage	St Louis Fed (FRED)	208	624	2158
GOV	Independent	Government Expenditure	Fiscal	Dollars (Billions)	St Louis Fed (FRED)	208	208	208
IGREA	Independent	Commodity Demand Variation	Macro Economy	Index	St Louis Fed (FRED)	208	624	624
GDP	Independent	Economic Activity	Macro Economy	Dollars (Billions)	St Louis Fed (FRED)	208	208	208
CPI	Independent	Inflation	Macro Economy	Percentage	St Louis Fed (FRED)	208	624	624
Total Observations	N/A	N/A	N/A	N/A	N/A	1248	2912	5980
SP500	Dependent	Stock Index	Stock Market	Index	investing .com	208	620	1987
Total Observations + SP500	N/A	Total + SP500	N/A	N/A	N/A	1456	3532	7967

5. Results

SVAR (VAR) Results

It is observed that the SVAR model performs best on quarterly data in terms of forecasting with an MSE of 165234.12, MAE of 406.49, RMSE of 456.88, and an R2 Score of 0.73 when all variables are included. However, SVAR provides metrics that are not captured by the alternative ML models, as it measures the impulse responses to structural shocks and as seen in Fig 1. which shows that there are negligible responses to structural shocks between the variables including the monetary and fiscal variables contrary to what is observed in Bjørnland and Leitemo (2009) and Chatziantoniou et al. (2012) which is further discussed in Section 6. Discussion.

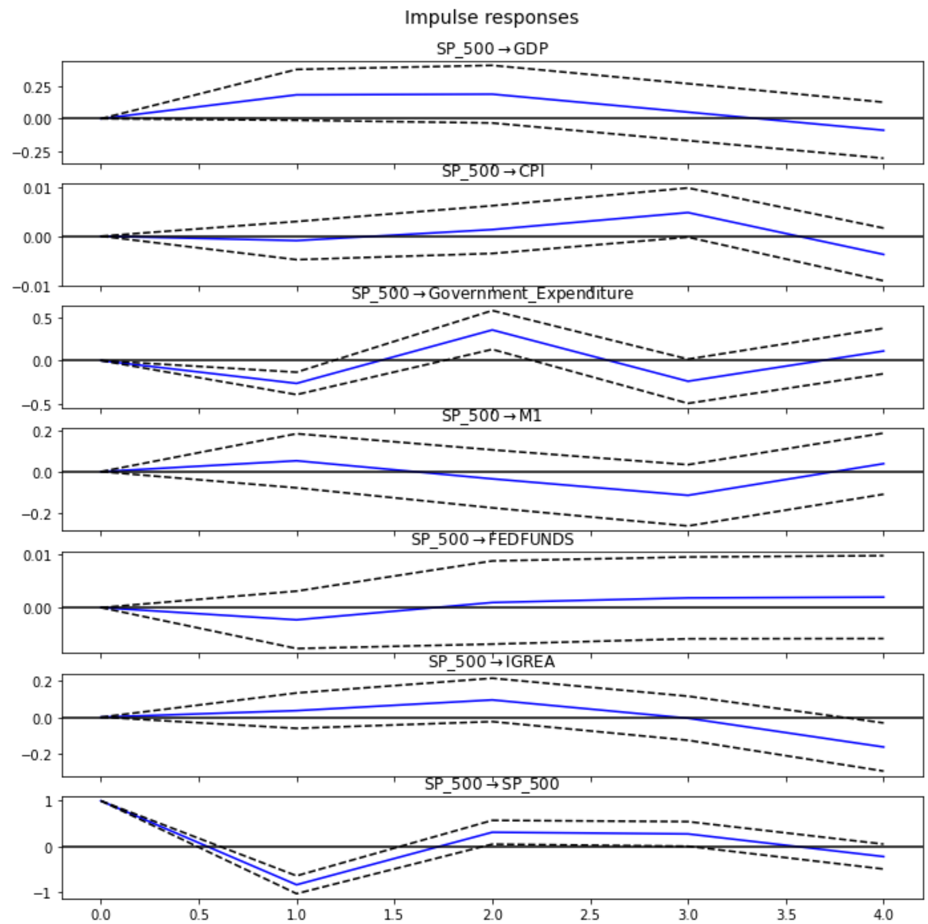

Figure 1: SVAR - Quarterly - All Variables

Like the quarterly data, there is a limited response to structural shocks in the weekly data; however, there is some impact between the variables identified. S&P 500 responds positively to GDP and CPI but negatively to government expenditure, as seen in Fig 2. This shows a greater relationship between macroeconomic variables and the S&P 500 than fiscal and monetary policy and the S&P 500.

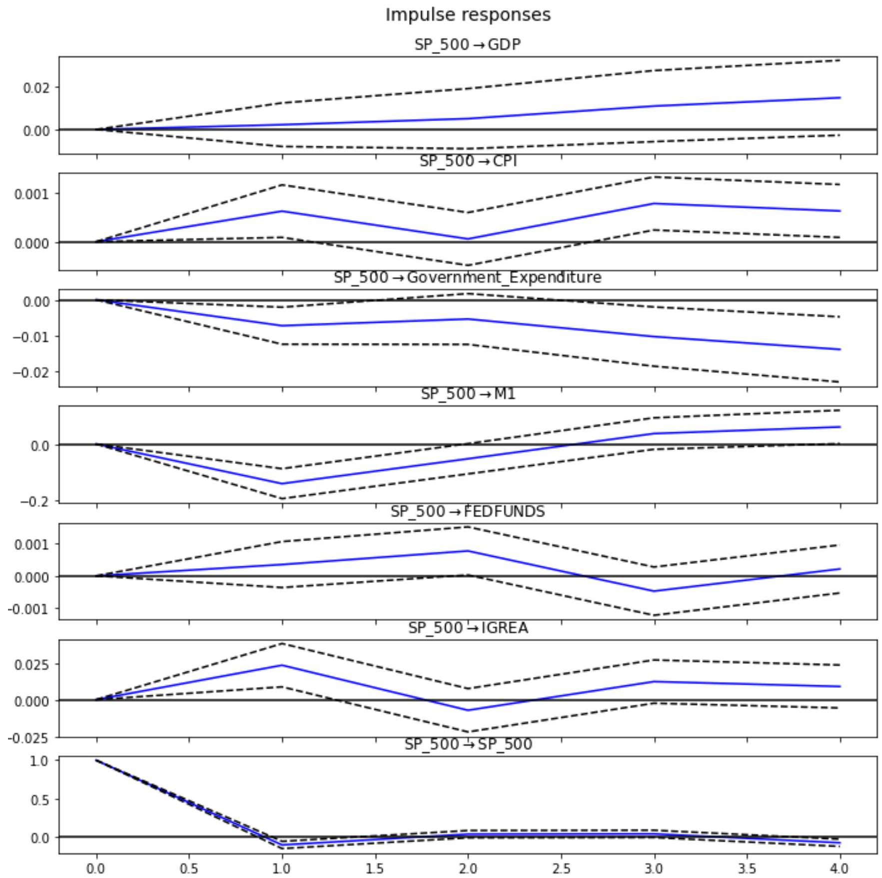

Figure 2: SVAR – Weekly – All Variables

LSTM Results

The monthly monetary model returns an MSE of 0.21, MAE of 0.46, RMSE of 0.37, and an R2 Score of 0.39, showing that close to half of the S&P 500 data points are explainable from monetary variables, which is depicted in Fig 3. The monthly, monetary plus fiscal model returns an MSE of 0.27, MAE of 0.52, RMSE of 0.41, and an R2 Score of 0.24, showing a relationship between the variables that is less than monetary on its own, as shown in Fig 4. Negative R2 scores are returned when including fiscal and macroeconomic variables solely and when all variables are included across any of the time intervals analysed.

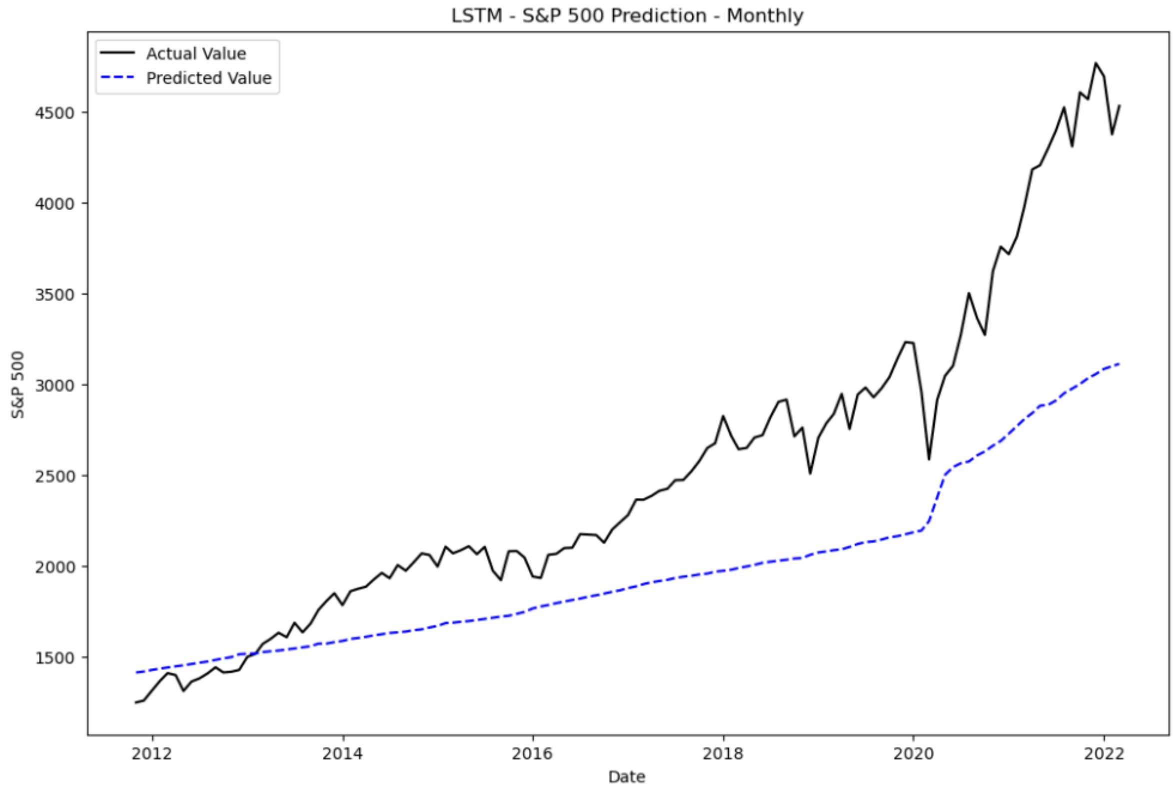

Figure 3: LSTM – Monthly – Monetary Variables

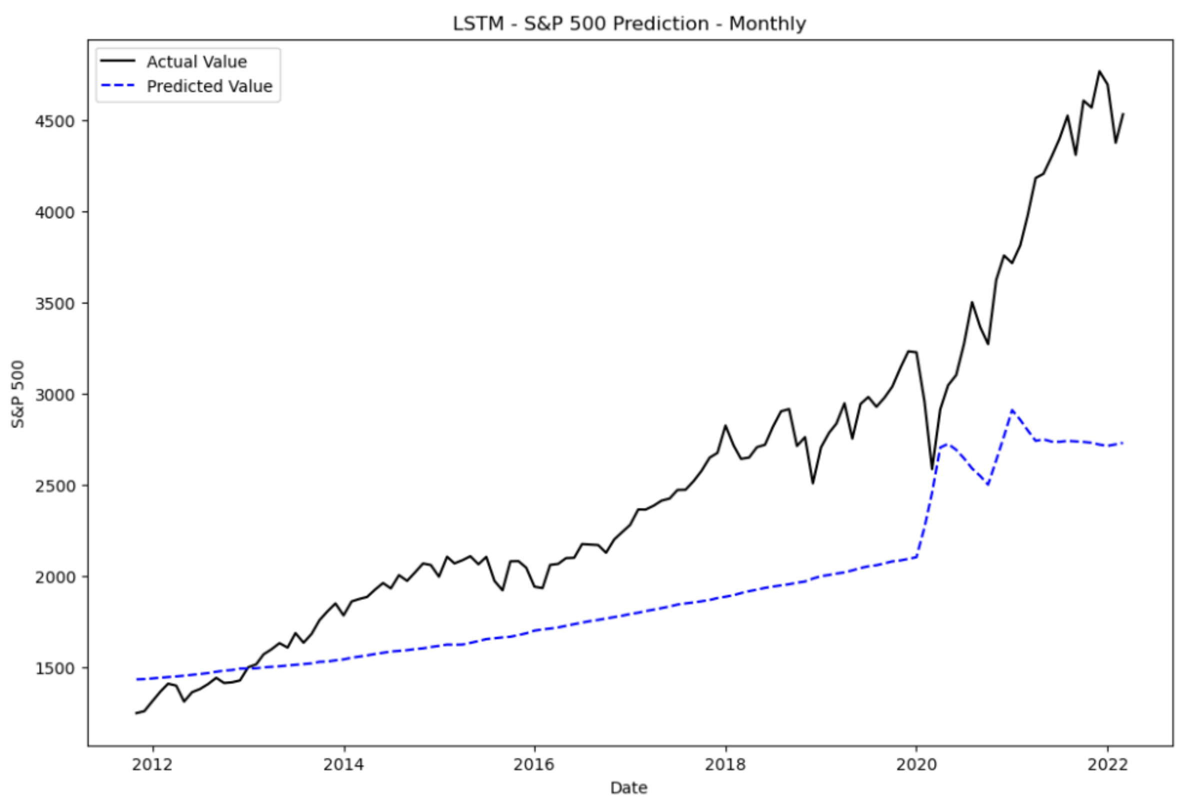

Figure 4: LSTM – Monthly – Monetary and Fiscal Variables

ARIMA (ARIMAX) Results

ARIMAX returns a positive R2 score for monetary and macroeconomic data analysed on quarterly, as seen in Tables 5 and 6. Monetary data produces an R2 Score of 0.75 for quarterly intervals, while monthly intervals also return an R2 score of 0.75, which show a strong correlation between the independent and dependent variables. As seen below in Fig 5 (the quarterly analysis of monetary variables), and Fig 6 (the monthly analysis of monetary variables), there is a visual correlation between the predicted and actual values for the S&P 500. For the monthly (Fig 7) analysis of the macroeconomic data, it is observed that there is a visual correlation. However, there is a widening gap between the predicted and actual values post early 2020 explaining the R2 scores for this model, which is 0.66 for the monthly macroeconomic model. Apart from the aforementioned models, the only other model to produce a positive R2 score is the weekly monetary and fiscal model at 0.20, depicted in Fig 8. Like the macroeconomic models, there is a strong correlation until the stock market dip in early 2020 and more volatile predictions thereafter.

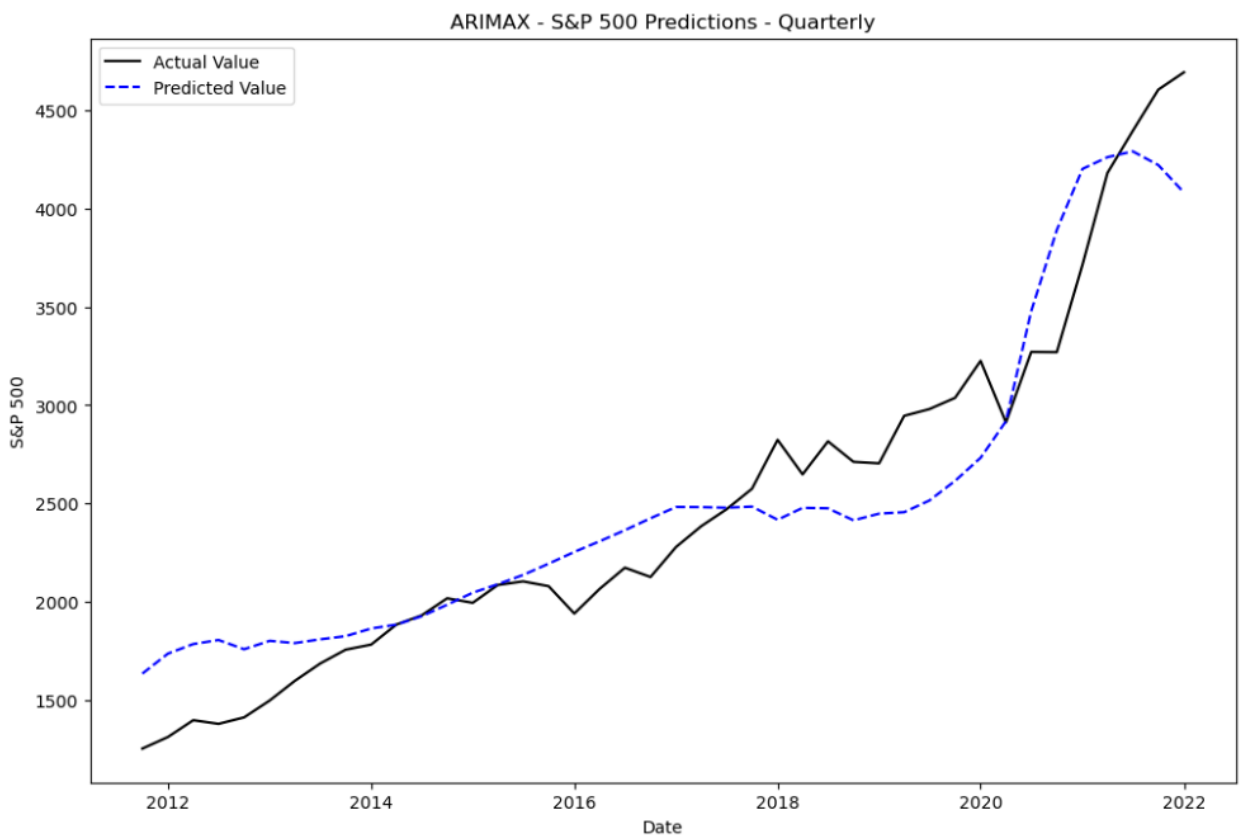

Figure 5: ARIMAX - Quarterly – Monetary Variables

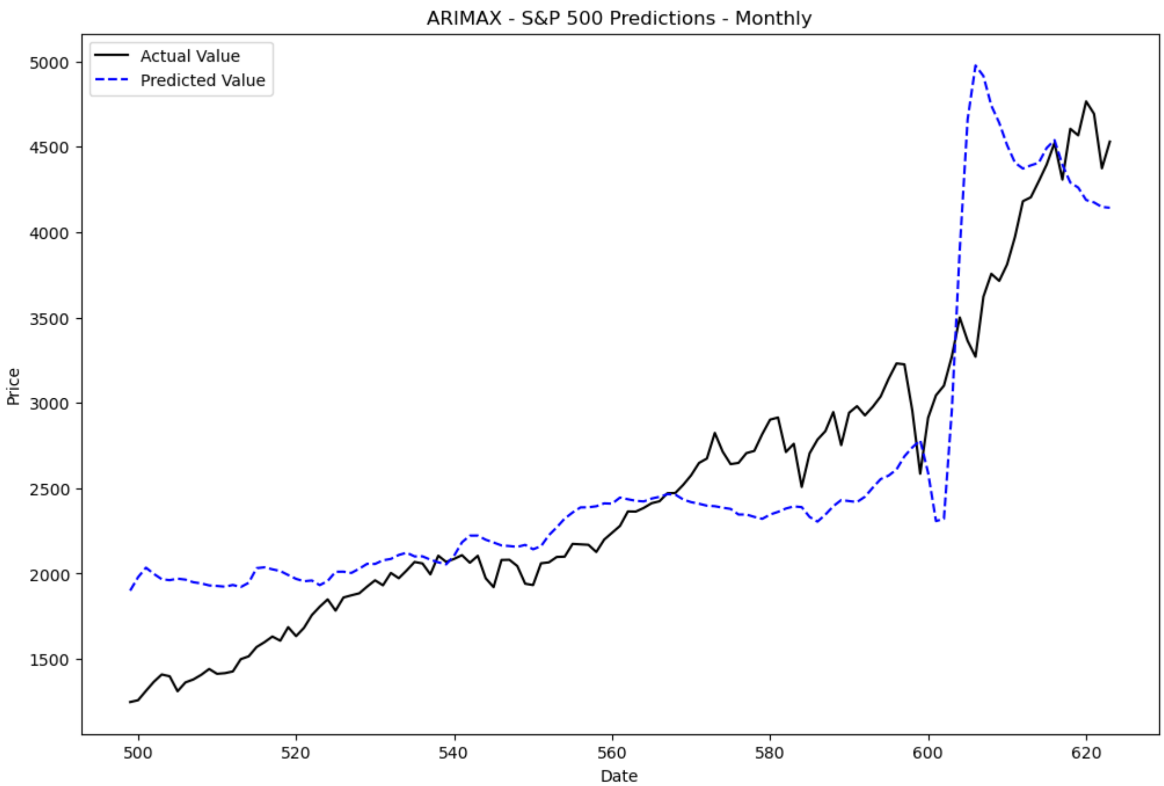

Figure 6: ARIMAX - Monthly – Monetary Variables

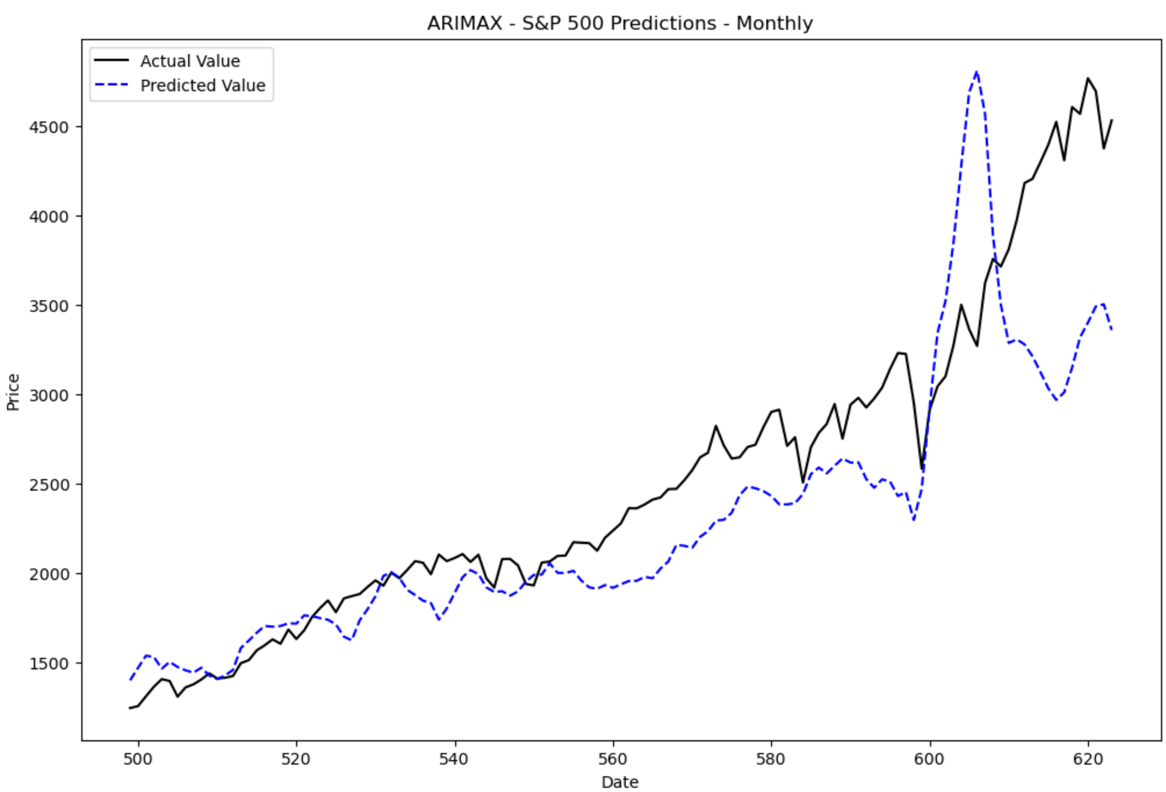

Figure 7: ARIMAX - Monthly – Macroeconomic Variables

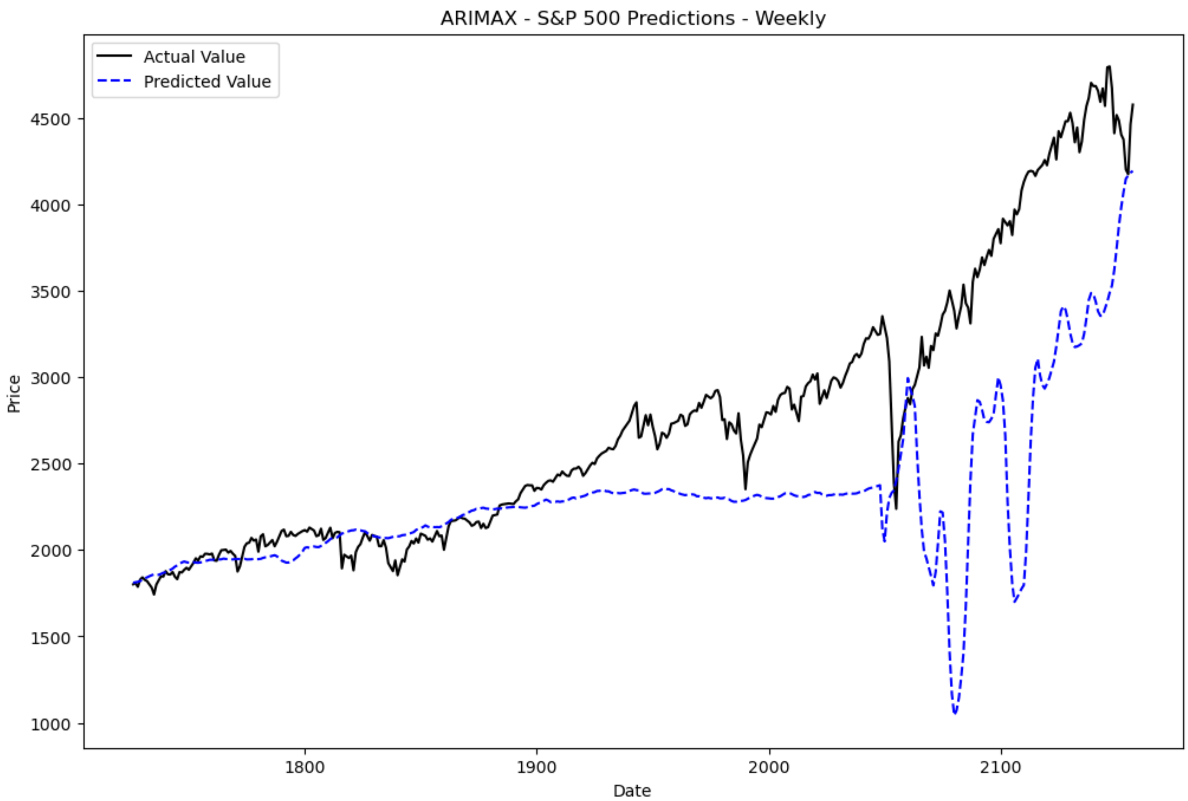

Figure 8: ARIMAX - Weekly – Monetary and Fiscal Variables

Linear Regression Results

Linear Regression returns varied results across the various combinations of models, time intervals and data analysed, as seen in Tables 5, 6, and 7. The combinations which produce the best efficacy and are quarterly and monthly time intervals, including only monetary values (M2 and FEDFUNDS). The quarterly analysis returns an MSE of 0.05, MAE of 0.22, RMSE of 0.17, and an R2 Score of 0.86, while the monthly analysis produces an MSE of 0.05, MAE of 0.23, RMSE of 0.17, and an R2 Score of 0.85. When the results are graphed, there is a visual correlation between the independent monetary variables and the dependent variable (S&P 500), as seen below in Fig 9 (quarterly results) and Fig 10 (monthly results).

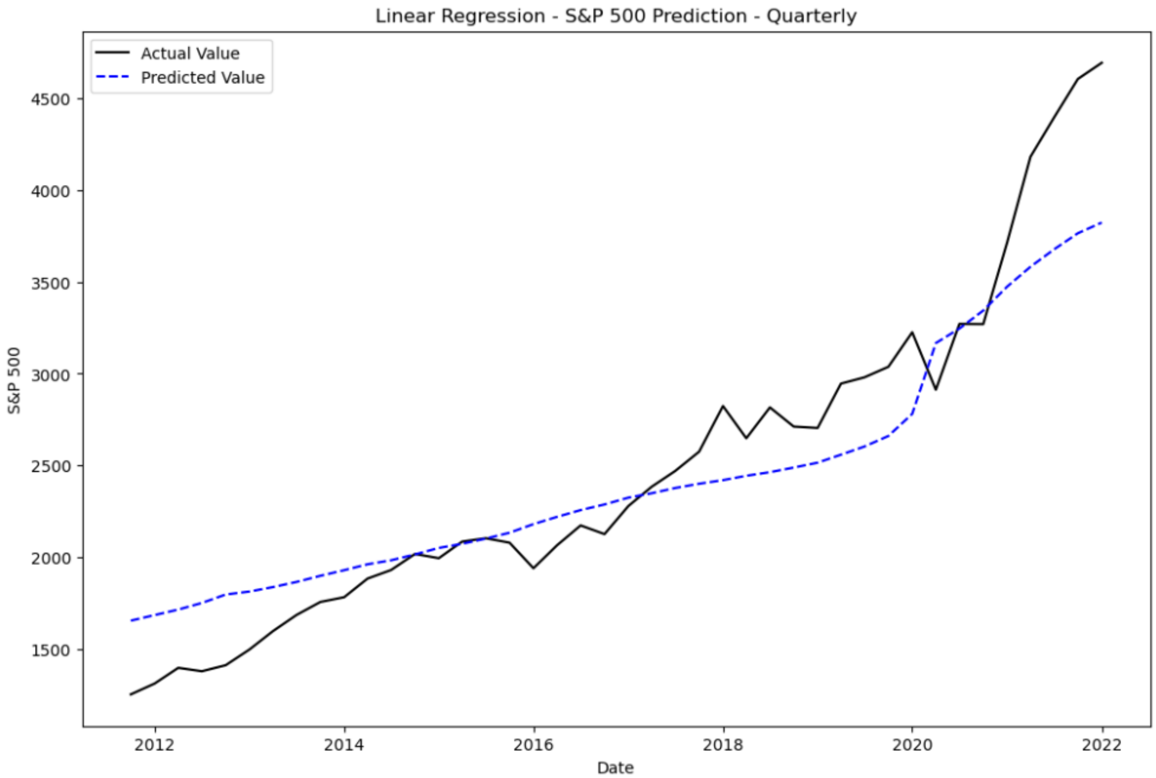

Figure 9: Linear Regression - Quarterly – Monetary Variables

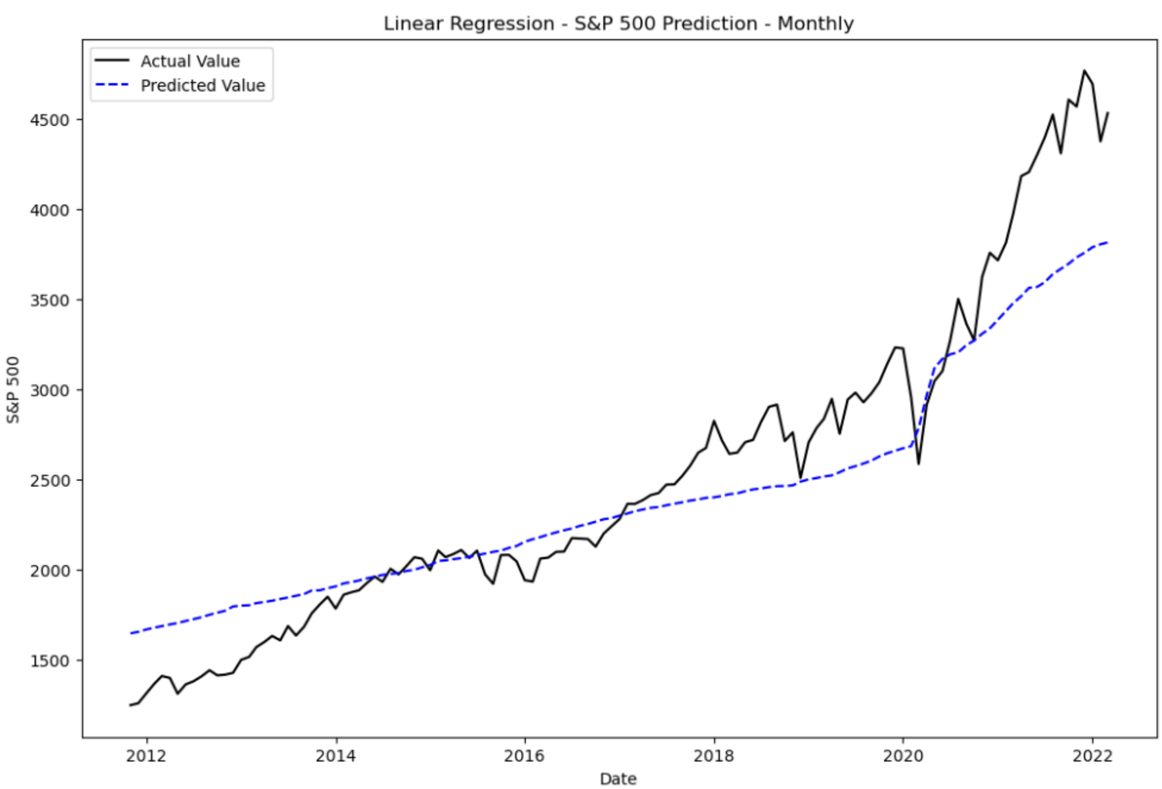

Figure 7: Linear Regression - Monthly – Monetary Variables

The weekly analysis of the monetary variables shows a correlation between the dependent and independent variables even though they return results with less efficacy than the quarterly and monthly models. As seen in Fig 11, there is a visual correlation, and the model produces the following results an MSE of 0.08, MAE of 0.29, RMSE of 0.22, and an R2 Score of 0.61. In terms of the other combinations, they produce a negative R2 score except for macroeconomic data analysed on quarterly and monthly data with an R2 score of 0.20 (Fig 12) and 0.14 (Fig 13), respectively. In contrast, the monetary and fiscal data combination analysed on quarterly returns an R2 score of 0.30 as seen in Fig 14, which returns an MSE of 0.25, MAE of 0.50, and RMSE of 0.38. This shows a relationship between independent and dependent variables for 30% of the data points.

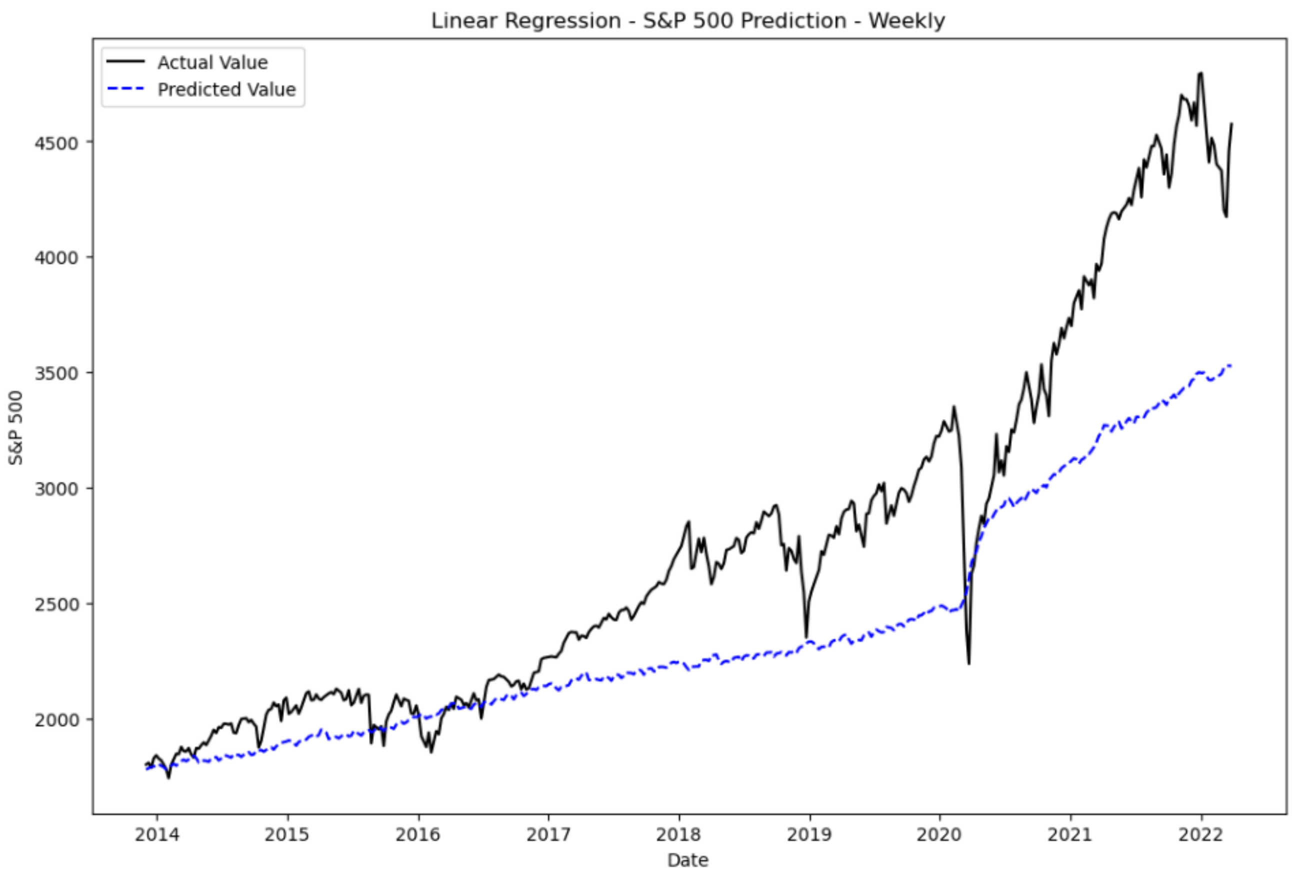

Figure 8: Linear Regression - Weekly – Monetary Variables

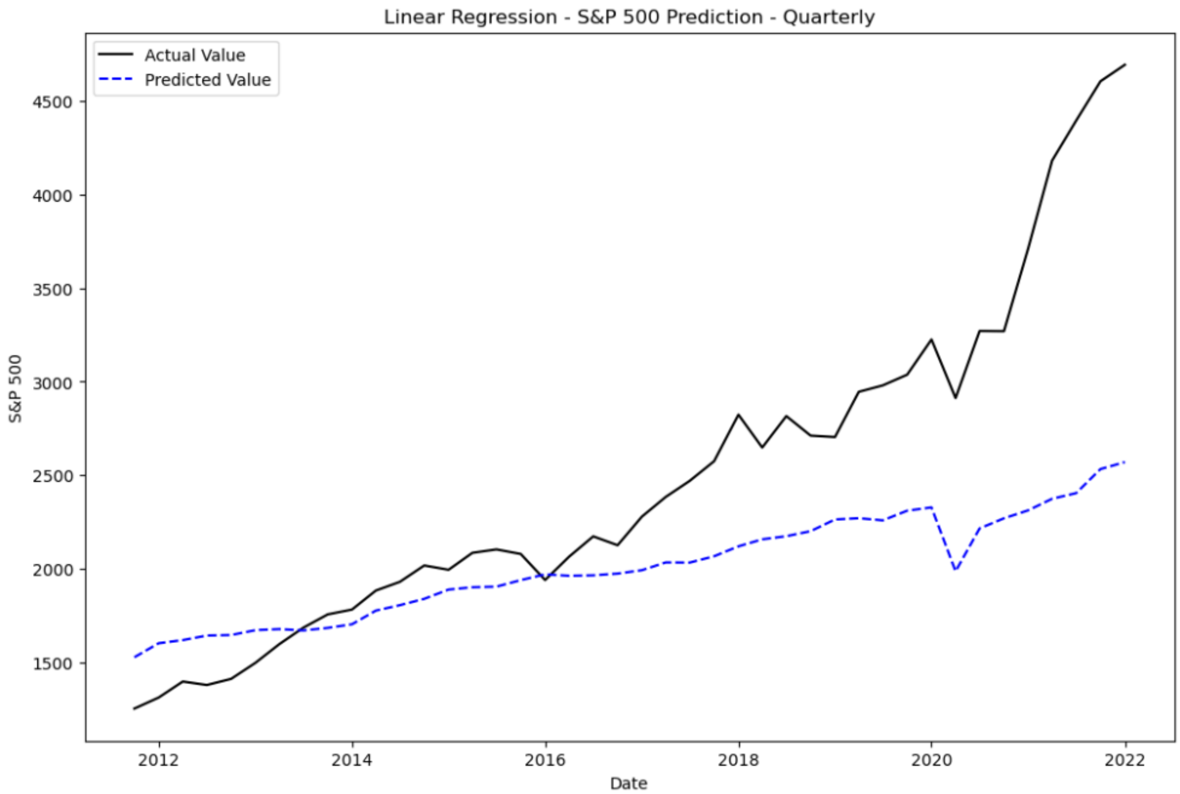

Figure 9: Linear Regression - Quarterly – Macroeconomic Variables

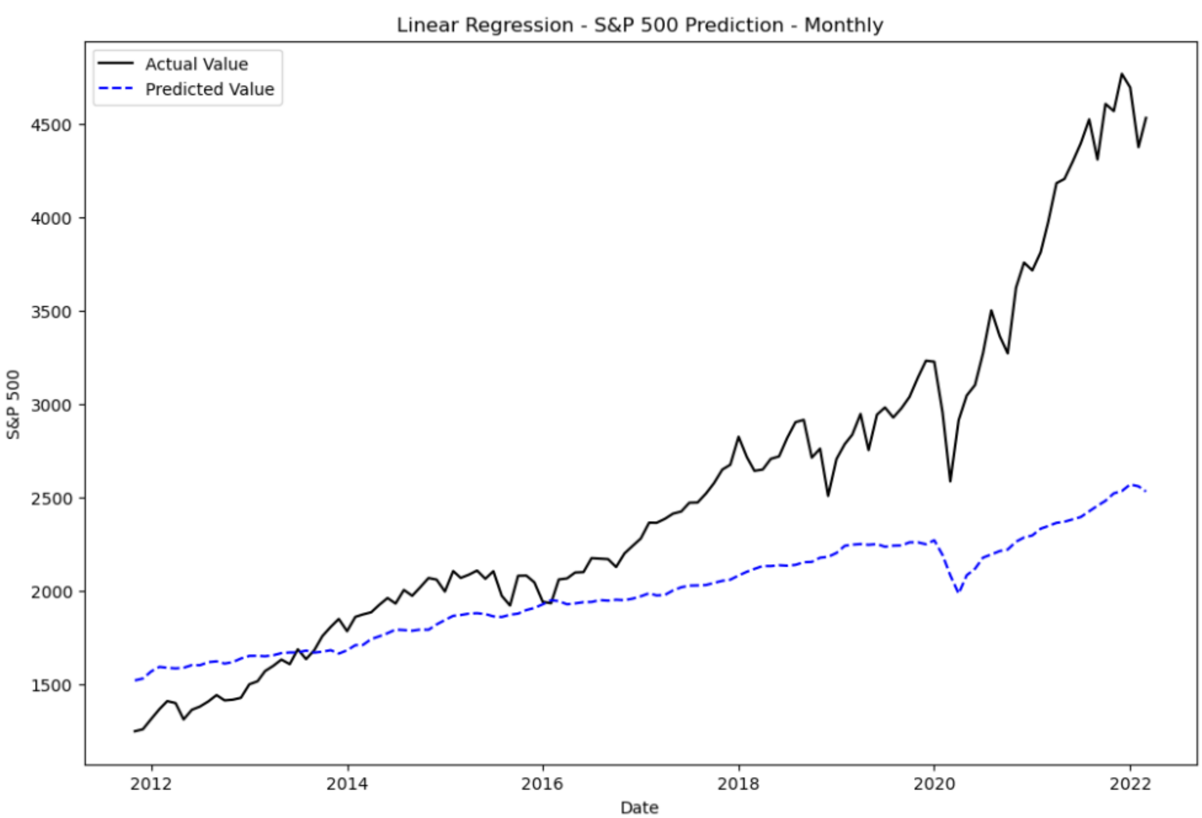

Figure 10: Linear Regression - Monthly – Macroeconomic Variables

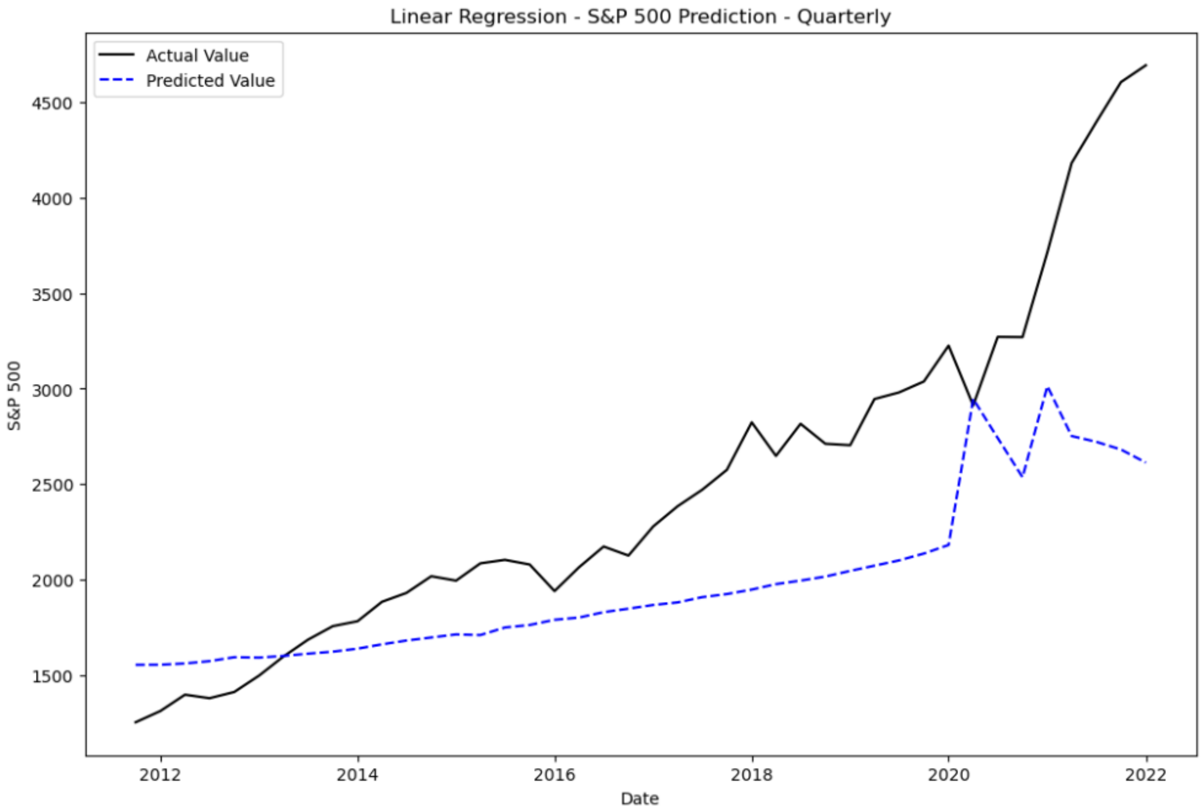

Figure 14: Linear Regression - Quarterly – Monetary and Fiscal Variables

Random Forest Results

Random Forest produces the results with the least efficacy of all models across all three time periods analysed and does not show any correlation between the dependent and independent variables. The combination that produces the results with the best efficacy, as seen in Table 7, is the weekly time interval on only the macro-economic variables with an MSE of 0.53, MAE of 0.73, RMSE of 0.56, and an R2 Score of -1.48. As seen in Fig 15 the predicted values do not show any relationship between the actual and predicted values meaning the model still has poor efficacy.

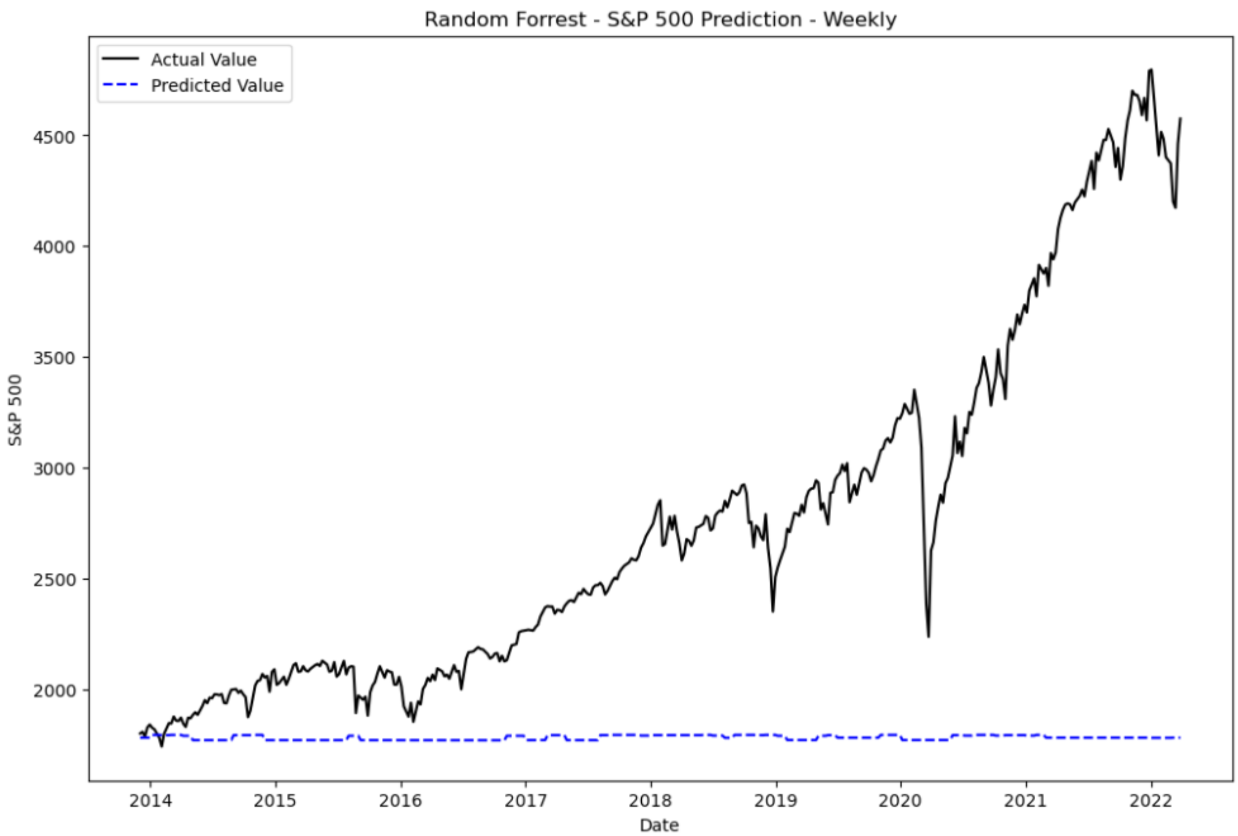

Figure 11: Random Forest - Weekly – Macroeconomic Variables

The metrics used to compare each model are Mean Squared Average (MSE), Mean Average Error (MAE), Root Mean Square Error (RMSE), and R-squared (R2) Score.

Table 5: Performance of each model quarterly

Methodology		**Variables Included**							**Results**			
Methods	**Data Included**	**M2**	**FEDFUNDS**	**GOV**	**IGREA**	**GDP**	**CPI**	**SP500**	**MSE**	**MAE**	**RMSE**	**R2 Score**
SVAR	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	165234.12	406.49	456.88	0.73
LSTM	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	0.46	0.68	0.56	-0.28
LSTM	Monetary	Yes	Yes	No	No	No	No	Yes	0.31	0.55	0.44	0.15
LSTM	Fiscal	No	No	Yes	No	No	No	Yes	0.67	0.82	0.67	-0.87
LSTM	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	0.32	0.56	0.45	0.11
LSTM	Macro	No	No	No	Yes	Yes	Yes	Yes	0.75	0.87	0.73	-1.11
ARIMAX	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	1.60	1.26	1.01	-23.23
ARIMAX	Monetary	Yes	Yes	No	No	No	No	Yes	0.01	0.09	0.07	0.88
ARIMAX	Fiscal	No	No	Yes	No	No	No	Yes	0.36	0.60	0.36	-4.43
ARIMAX	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	1.81	1.34	0.90	-26.46
ARIMAX	Macro	No	No	No	Yes	Yes	Yes	Yes	0.09	0.30	0.24	-0.32
Linear Regression	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	1.27	1.13	0.76	-2.54
Linear Regression	Monetary	Yes	Yes	No	No	No	No	Yes	0.05	0.22	0.17	0.86
Linear Regression	Fiscal	No	No	Yes	No	No	No	Yes	0.40	0.63	0.48	-0.11
Linear Regression	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	0.25	0.50	0.38	0.30
Linear Regression	Macro	No	No	No	Yes	Yes	Yes	Yes	0.29	0.53	0.37	0.20
Random Forest	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	1.01	1.00	0.81	-1.82
Random Forest	Monetary	Yes	Yes	No	No	No	No	Yes	1.01	1.00	0.81	-1.82
Random Forest	Fiscal	No	No	Yes	No	No	No	Yes	0.99	0.99	0.81	-1.76
Random Forest	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	1.00	1.00	0.81	-1.79
Random Forest	Macro	No	No	No	Yes	Yes	Yes	Yes	1.03	1.01	0.82	-1.88

Table 6: Performance of each model monthly

Methodology		Variables Included							Results			
Methods	**Data Included**	**M2**	**FEDFUNDS**	**GOV**	**IGREA**	**GDP**	**CPI**	**SP500**	**MSE**	**MAE**	**RMSE**	**R2 Score**
SVAR	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	594529.67	771.06	978.7645	-9.53
LSTM	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	0.43	0.66	0.53	-0.22
LSTM	Monetary	Yes	Yes	No	No	No	No	Yes	0.21	0.46	0.37	0.39
LSTM	Fiscal	No	No	Yes	No	No	No	Yes	0.36	0.60	0.47	-0.02
LSTM	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	0.27	0.52	0.41	0.24
LSTM	Macro	No	No	No	Yes	Yes	Yes	Yes	0.70	0.83	0.69	-0.97
ARIMAX	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	0.77	0.88	0.53	-11.27
ARIMAX	Monetary	Yes	Yes	No	No	No	No	Yes	0.02	0.12	0.10	0.75
ARIMAX	Fiscal	No	No	Yes	No	No	No	Yes	0.97	0.98	0.47	-14.39
ARIMAX	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	1.53	1.24	0.68	-23.29
ARIMAX	Macro	No	No	No	Yes	Yes	Yes	Yes	0.02	0.15	0.10	0.66
Linear Regression	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	1.28	1.13	0.79	-2.64
Linear Regression	Monetary	Yes	Yes	No	No	No	No	Yes	0.05	0.23	0.17	0.85
Linear Regression	Fiscal	No	No	Yes	No	No	No	Yes	0.41	0.64	0.50	-0.17
Linear Regression	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	0.44	0.66	0.52	-0.24
Linear Regression	Macro	No	No	No	Yes	Yes	Yes	Yes	0.30	0.55	0.39	0.14
Random Forest	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	1.05	1.03	0.83	-1.98
Random Forest	Monetary	Yes	Yes	No	No	No	No	Yes	1.11	1.05	0.87	-2.14
Random Forest	Fiscal	No	No	Yes	No	No	No	Yes	0.97	0.98	0.80	-1.74
Random Forest	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	1.04	1.02	0.84	-1.96
Random Forest	Macro	No	No	No	Yes	Yes	Yes	Yes	1.11	1.05	0.87	-2.13

Table 7: Performance of each model on a weekly basis

Methodology		Variables Included							Results			
Methods	**Data Included**	**M2**	**FEDFUNDS**	**GOV**	**IGREA**	**GDP**	**CPI**	**SP500**	**MSE**	**MAE**	**RMSE**	**R2 Score**
SVAR	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	810525924.85	28469.74	38399.03	-1.10
LSTM	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	0.30	0.55	0.47	-0.39
LSTM	Monetary	Yes	Yes	No	No	No	No	Yes	0.14	0.37	0.31	0.35
LSTM	Fiscal	No	No	Yes	No	No	No	Yes	0.31	0.56	0.47	-0.47
LSTM	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	0.23	0.48	0.41	-0.09
LSTM	Macro	No	No	No	Yes	Yes	Yes	Yes	0.43	0.66	0.56	-1.04
ARIMAX	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	0.15	0.38	0.24	-1.24
ARIMAX	Monetary	Yes	Yes	No	No	No	No	Yes	0.17	0.41	0.32	-1.58
ARIMAX	Fiscal	No	No	Yes	No	No	No	Yes	0.18	0.42	0.32	-1.69
ARIMAX	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	0.05	0.23	0.15	0.20
ARIMAX	Macro	No	No	No	Yes	Yes	Yes	Yes	0.12	0.35	0.27	-0.83
Linear Regression	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	0.73	0.85	0.59	-2.42
Linear Regression	Monetary	Yes	Yes	No	No	No	No	Yes	0.08	0.29	0.22	0.61
Linear Regression	Fiscal	No	No	Yes	No	No	No	Yes	0.37	0.61	0.51	-0.74
Linear Regression	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	0.32	0.57	0.48	-0.51
Linear Regression	Macro	No	No	No	Yes	Yes	Yes	Yes	0.39	0.63	0.51	-0.85
Random Forest	All	Yes	Yes	Yes	Yes	Yes	Yes	Yes	0.55	0.74	0.58	-1.57
Random Forest	Monetary	Yes	Yes	No	No	No	No	Yes	0.59	0.77	0.62	-1.77
Random Forest	Fiscal	No	No	Yes	No	No	No	Yes	0.91	0.95	0.83	-3.24
Random Forest	Monetary & Fiscal	Yes	Yes	Yes	No	No	No	Yes	0.56	0.75	0.60	-1.64
Random Forest	Macro	No	No	No	Yes	Yes	Yes	Yes	0.53	0.73	0.56	-1.48

6. Discussion

6.1 Impact of monetary & fiscal policy on the S&P 500

The results from LSTM, ARIMAX, and Linear regression support the theory that there is a correlation between monetary policy and the S&P 500, but there is little evidence of a correlation between fiscal policy and the S&P 500 index when analysed in isolation. When combined monetary and fiscal policy data is analysed, as recommended in Chatziantoniou et al. (2012), there is a correlation with the S&P 500. This supports the findings from Bjørnland and Leitemo (2009) and Chatziantoniou et al. (2012). However, these papers rely on the SVAR model for their findings, while the SVAR model in this study does not find the same results which are discussed in Section 6.2. As observed in Tables 5, 6, and 7, there is a correlation between monetary variables (M2 and FEDFUNDS) and the S&P 500 across all three time frequencies (quarterly, monthly, and weekly) using linear regression, and LSTM models. ARIMAX produces positive correlations between monetary variables and the S&P 500 on a quarterly and monthly basis but not weekly.

Despite the fiscal policy variable (GOV) not showing efficacy across any of the models or data frequencies when analysed solely, positive correlations are identified with the S&P 500 when combined with the monetary policy variables in some instances. For example, when using the ARIMAX model on weekly data, a positive R2 score is returned of 0.20, while all other variable combinations return a negative R2 score for this model. This finding is also in line with Bjørnland and Leitemo (2009) and Chatziantoniou et al. (2012), who find a relationship with the S&P 500 when monetary variables are combined with the fiscal variable. There is also a positive R2 score of 0.11 when running the LSTM model for monetary and fiscal quarterly data, although this is likely driven mainly by the monetary variables, which return an R2 score of 0.15 when processed solely using LSTM.

There is a positive R2 score when processing the macroeconomic variables solely vs the S&P 500 using ARIMAX and linear regression on quarterly and monthly data. The results show that monetary policy impacts stock market performance in a US context while fiscal policy has limited influence when analysed in isolation. The results also show that macroeconomic data impacts stock market performance, especially when combined with monetary data but not to the same degree that monetary policy impacts the S&P 500.

6.2 Model Comparison

As detailed in Section 5, the SVAR model does not produce the same findings as prior literature with the most recent analysis published in 2012. This can be explained by adding the tranche of data in the intervening years to the time of writing (2022) plus the addition of data dating back to 1970, with comparable literature only using data from 1991. The prevalence of algorithmic trading, as discussed in Yadav (2015), and the use of quantitative easing as an additional tool by the Federal Reserve Corbet et al. (2019) are also potential reasons data from 2021 to 2022 might not follow the same pattern as (Chatziantoniou et al., 2012). Given that these factors flatten the impact of monetary policy shocks on the S&P 500, the use of additional machine learning offers alternative methods to assess the impact of monetary and fiscal policy on the stock market performance.

As discussed in Section 6.1, it is identified using multiple models that monetary policy does have a relationship with the S&P 500. Given factors such as algorithmic trading and quantitative easing, models such as ARIMAX and LSTM offer alternatives to SVAR and can identify relationships between data variables that SVAR cannot. Advances in machine learning, as discussed in Section 2, make machine learning models more accessible and feasible to implement with the advent of Amazon Web Services, Google TensorFlow, and Keras. TensorFlow, for example, was first released in 2015, post the most recent publication of SVAR analysis on US data in 2012.

Linear regression and ARIMAX provides the greatest efficacy when assessing monetary policy solely vs the S&P 500, while LSTM also shows a strong correlation between monetary data and the S&P 500. These models are frequently used for financial and time series predictions, and the findings in this research show the efficacy of these models on financial data. LSTMs are found to outperform models, including Random Forest in Fischer and Krauss (2018), and it is also identified in Parmezan et al. (2019) that SARIMA, the seasonal version of ARIMA (ARIMAX), is state of the art in time series prediction.

The only model to perform poorly on the data over all time frequencies analysed is Random Forest, which performs worse on error metrics compared to the other ML models and produces all negative R2 scores meaning that it is not a good fit for the data in question. While Fischer and Krauss (2018) report that LSTM outperforms Random Forest, it still produces positive results for Random Forest. Taking this into account, the model may suit certain financial data, but for this study, the data does not suit the model and offers no beneficial insight. Of the models in this research, three observe similar results showing a relationship between monetary data and the S&P 500, meaning that the Random Forest study does not disprove that monetary policy impacts stock market performance in a US context.

6.3 Time Frequency Comparison

As stated in Section 3 , Chatziantoniou et al. (2012) use quarterly data because the fiscal policy proxy (Government Expenditure) is only reported every quarter, but in order to optimise the benefit of the included ML models such as LSTM, and ARIMAX, higher frequency data (monthly and weekly) are analysed. Discussed in Section 3 are the frequencies at which each variable is reported and the imputation method for missing variables. When comparing the results detailed in Tables 5, 6, and 7, in Section 5, seven models return a positive R2 score for quarterly data and six for monthly data, and four models return a positive R2 score for weekly data.

For quarterly data, the best performing model for linear regression is monetary data with an 0.86 R2 score, while there are also positive R2 scores returned for monetary plus fiscal data combined at 0.30 and macroeconomic variables at a 0.20 R2 score. There are also positive R2 scores identified for monetary (0.88) and macroeconomic data (0.32) using ARIMAX, while LSTM reports a negligible R2 score of 0.15. Taking all this into account, linear regression and ARIMAX provide the most insight as they specifically identify monetary and macroeconomic variables as having the strongest relationship with the S&P 500.

Monthly data provides two positive R2 scores for LSTM for monetary and monetary plus fiscal combined at 0.39 and 0.24, respectively. ARIMAX and linear regression confer as they both identify positive R2 scores for monetary and macroeconomic variables, with ARIMAX monetary returning an R2 of 0.88 and Linear monetary returning an R2 score of 0.86, while ARIMAX performs better on macroeconomic data at 0.66 vs 0.14. Like the quarterly analysis, ARIMAX and linear regression show efficacy for monetary and macroeconomic data correlating with the S&P 500. Unlike the quarterly study, LSTM shows efficacy for monetary variables when analysed solely and combined with fiscal data. ARIMAX returns two positive R2 scores using monthly data, while linear regression returns a score of 0.88 for the monetary variable. Weekly data returns the lowest efficacy across all three time frequencies, with ARIMAX and linear regression not returning similar results to quarterly and monthly data, especially regarding macroeconomic data, which reports no positive R2 score.

Based on these results, quarterly data reports the strongest correlation supporting the theory that monetary policy influences stock market performance, followed closely by monthly and weekly data in a distant third. Monthly and quarterly data reports are the best fit for these models, with weekly data not providing additional insight. This could be because only the macroeconomic variables are reported weekly, and FEDFUNDS is driven by the Fed's target interest rate announced only eight times per year (FRED, 2022a). These findings offer knowledge that is beneficial for policymakers as they need to factor into account the impact on financial markets considering the number of citizens at 52% who have a stake in the stock market. It is also beneficial to traders and quantitative analysts who must assess the impact of monetary and fiscal policy they on markets they are invested in.

6.4 Limitations of Study

While several models return results supporting the theory that monetary and fiscal policy have a relationship with stock market performance, there are also several combinations that return negative results particularly with the ARIMAX model that need to be considered as seen in Table 6. For example, when all variables are analysed monthly, an R2 score of -11.27 is returned as depicted in Appendix 11.1.1. An R2 score of -14.39 is also returned when we monetary and fiscal policy combined is analysed on monthly data which are depicted in Appendix 11.1.2. There is also an R2 score of -23.29 is also observed for monetary and fiscal policy with monthly data which are depicted in Appendix 11.1.3.

It appears that fiscal policy variable is the key component which is causing these extreme outliers results as there is also similar results in Table 5 for models that contain the fiscal data. As seen in the Fig 17, 18, and 19 in 11.1 Additional Figures, the predicted and actual values appear to have a relationship up until 2020 where there is step decline in the predicted variable with all three models eventually predicting negative values for the S&P 500 up to minus 10,000 in the case of monetary and fiscal variables combined. These limitations show that multiple models should be employed when analysing economic data as certain models may produce extreme contradictory findings.

7. Conclusion

US Monetary policy purports to have a strong correlation with the S&P 500 based on the findings in this research, which is in line with the conclusion of Bjørnland and Leitemo, (2009) and Chatziantoniou et al. (2012). However, the findings in these papers are based solely on SVAR, while the findings in this current research are based on Linear Regression, LSTM, and ARIMAX. Factors influencing the different results for SVAR are potentially due to influences such as quantitative easing and the prevalence of algorithmic trading in the additional data included in the intervening years.

The inclusion of additional data and lower data frequencies data to optimise the benefit of ML models, which typically perform better with the inclusion of more data points, make ARIMAX and LSTM suitable models for this research and offer better predictive capabilities than SVAR. While ML models show efficacy on economic and financial data in this context, it is recommended that SVAR should be used as well as ML models when analysing economic data as it allows comparison to similar research, which determines SVAR to be the optimal model for analysing economic policy vs stock market performance. SVAR also captures information such as structural shocks that ARIMAX and LSTM do not.

Quarterly data reports the strongest correlation between monetary policy and the S&P 500, while monthly data also shows strong efficacy also. Weekly data does not offer additional information due to variables IGREA, GDP, CPI, and GOV not being reported at this frequency. Quarterly data performs the best for the same reasons that weekly data does not, as the previously mentioned variables are not reported as a higher frequency meaning. The same reasons are provided in previous literature which only analyse quarterly data

(Bjørnland and Leitemo, 2009; Chatziantoniou, et al., 2012). This research comes to same conclusion but strong efficacy is returned for monthly data meaning that it is also a data frequency that is a good fit for this research

While monetary data reports a strong relationship with stock market performance, fiscal and monetary data combined also show a correlation with the S&P 500. Although not a key aim of this research, macroeconomic data is found to have a relationship with the S&P 500 and should be analysed in future research in more depth. ML models such as ARIMAX and LSTM are suitable for analysing the relationship between economic policy and stock market performance. Data reported monthly are also an appropriate frequency for analysing economic policy based on the findings in this research, but quarterly data still provides the best efficacy.

The findings in this research offer knowledge that is beneficial for economic and financial analysts who are analysing the effects of monetary and fiscal policy on the stock market. This also offers insight for governmental organisations and central banks who are analysing the implications of economic policy on financial markets, especially considering the number of citizens that have a stake in stock markets. This research also is beneficial to public and who want to educate themselves on this subject due to the number of people invested in the financial products such as 401(k) and other retirement accounts as previously mentioned.

9. Abbreviations

The Fed - Federal Reserve of the United States

USA/US – United States of America

AI - Artificial Intelligence

ML – Machine Learning

LSTM – Long Short-Term Memory

ARIMA – Autoregressive Integrated Moving Average

SVAR – Structural Vector Autoregression

VAR – Vector Autoregression

MLR - Multiple Linear Regression

IGREA - Global Real Economic Activity

GDP - Gross Domestic Product

GOV – Government Expenditure

CPI - Consumer Price Index

OCDs - Other Checkable Deposits

FOMC - Federal Open Market Committee

CPIAUCSL - Consumer Price Index for All Urban Consumers

FRED - Federal Reserve Bank of St. Louis

IS - Revenue Shocks

PS - Price Shocks

GS - Government Expenditure

MSS - Money Supply Shocks

IRS - Interest Rate Shocks

MSE - Mean Squared Average

MAE - Mean Average Error

RMSE - Root Mean Square Error

R2 Score - R-squared Score

10. Bibliography

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