Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility?

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Abstract. Bitcoin has grown in popularity and has now attracted the attention of individual and institutional investors. Accurate Bitcoin price direction forecasts are important for determining the trend in Bitcoin prices and asset allocation. This paper addresses several unanswered questions. How important are business cycle variables like interest rates, inflation, and market volatility for forecasting Bitcoin prices? Does the importance of these variables change across time? Are the most important macroeconomic variables for forecasting Bitcoin prices the same as those for gold prices? To answer these questions, we utilize tree-based machine learning classifiers, along with traditional logit econometric models. The analysis reveals several important findings. First, random forests predict Bitcoin and gold price directions with a higher degree of accuracy than logit models. Prediction accuracy for bagging and random forests is between 75% and 80% for a five-day prediction. For 10-day to 20-day forecasts bagging and random forests record accuracies greater than 85%. Second, technical indicators are the most important features for predicting Bitcoin and gold price direction, suggesting some degree of market inefficiency. Third, oil price volatility is important for predicting Bitcoin and gold prices indicating that Bitcoin is a substitute for gold in diversifying this type of volatility. By comparison, gold prices are more influenced by inflation than Bitcoin prices, indicating that gold can be used as a hedge or diversification asset against inflation.

Keywords: forecasting; machine learning; random forests; Bitcoin; gold; inflation

1. Introduction

Bitcoin is a decentralized digital currency that allows users to send and receive the currency on a peer-to peer Bitcoin network (Nakamoto, 2008) that uses blockchain technology (Kaur et al., 2020). The Bitcoin network dispenses with the need for financial intermediaries which can reduce transaction costs (Kayal & Rohilla, 2021). Bitcoin was initiated in 2009 as the world's first cryptocurrency. As an asset to invest in, Bitcoin was initially the domain of retail investors. Bitcoin has grown in popularity and has now attracted the attention of institutional investors. In the investment literature, Bitcoin is sometimes compared to gold because both assets have low correlation with other financial assets like stocks and bonds and therefore may be useful for portfolio diversification (Henriques & Sadorsky, 2018; Kyriazis, 2020). Much has been written about the benefits of using gold to hedge assets against inflation or economic uncertainty (Areal et al., 2015; Baur & Lucey, 2010; Baur & McDermott, 2010, 2016; Beckmann et al., 2015; Bekiros et al., 2017; Blose, 2010; Ciner et al., 2013; Hillier et al., 2006; Hoang et al., 2016; Hood & Malik, 2013; Iqbal, 2017; Junttila et al., 2018; O'Connor et al., 2015; Reboredo, 2013; Tronzano, 2021). Recent research has identified Bitcoin as useful for hedging financial assets (Dyhrberg, 2016; Hussain Shahzad et al., 2020; Selmi et al., 2018; Shahzad et al., 2019; Umar et al., 2021). The COVID-19 pandemic has brought new concerns about how to mitigate financial risk (Chevallier, 2020; Chiang, 2022; Yao et al., 2021). As the pandemic grinds on and supply chain and monetary policy factors push up inflation and interest rates, questions arise as to how important business cycle variables like economic policy uncertainty, market volatility, interest rates, and inflation are for forecasting Bitcoin prices. Forecasting Bitcoin prices are important for making well informed decision about the market trends of this asset.

While there is an existing literature on forecasting Bitcoin prices (Adcock & Gradojevic, 2019; Atsalakis et al., 2019; Chen et al., 2020; Hamayel & Owda, 2021; Jang & Lee, 2018; Jaquart et al., 2021; Kraaijeveld & De Smedt, 2020; Lahmiri & Bekiros, 2019; Mudassir et al., 2020; Nakano et al., 2018; Pabuçcu et al., 2020), there are several important gaps in the literature which lead to research questions. First, how important are macroeconomic variables like interest rates, inflation, and market volatility for forecasting Bitcoin prices? Interest rates, inflation, and market volatility are variables that characterize the business cycle and have important impacts on asset prices (Lee, 1992; Thorbecke, 1997). Most asset prices move pro-cyclical with the business cycle and increase during periods of low interest rates, stable inflation and low stock market volatility. Assets that move counter-cyclical may be useful for hedging and risk diversification. If Bitcoin prices are affected by business cycle conditions, then business cycle variables should be important predictors. Alternatively, if Bitcoin prices are not affected by business cycle conditions then business cycle variables should not be important predictors. Second, does the importance of these variables change across time? If variable importance changes across time, then models and predictions should be frequently updated otherwise prediction accuracy will decrease. Third, are the most important macroeconomic variables for forecasting Bitcoin prices the same as those for gold prices? Existing studies predict either Bitcoin prices or gold prices but do not consider gold and Bitcoin in the same study which leaves unanswered the question of how Bitcoin and gold price predictions compare over a common time period. If the most important macroeconomic variables for forecasting Bitcoin prices are the same as those for gold prices, then this offers support for Bitcoin providing similar portfolio diversification benefits as gold. In such cases, Bitcoin and gold are substitutes for one another. The objective of this paper is to provide answers for these research questions.

In answering the research questions described above, the following approach is used. First, this paper predicts Bitcoin and gold price direction. The choice to predict price direction rather than prices is based on research showing that asset price direction can be forecast with considerable accuracy (Ballings et al., 2015; Basak et al., 2019; Leung et al., 2000; Lohrmann & Luukka, 2019; Nyberg, 2011; Nyberg & Pönkä, 2016; Pönkä, 2016). Theoretical reasons for price direction predictability are rooted in behavioral finance (Christoffersen & Diebold, 2006; Gray & Vogel, 2016; Lo et al., 2000; Moskowitz et al., 2012). Behavioral finance is based on the limits to arbitrage and investor psychology. In many investing situations true arbitrage, where profits are earned with zero risk after costs, is not possible. Investor psychology recognizes that not all investors are rational all of the time and this can give rise to behavioral bias where market prices differ from fundamentals. Limits to arbitrage and behavioral bias lead to asset mispricing which can be detected in price direction. The importance of estimating price direction predictability can be motivated by the importance of market timing. Investors and fund managers are interested in the sign rather than the actual value when determining asset allocation (Pesaran & Timmermann, 2002).

Second, tree-based ensemble machine learning classifiers are used to predict Bitcoin and gold price direction. The decision to use tree-based ensemble machine learning methods is based on research showing that these methods have high accuracy when predicting stock price direction. For example, in predicting stock price direction for 5767 publicly listed European companies, Ballings et al. (2015) compare ensemble methods like random forest, AdaBoost, and Kernel Factory against single classifiers like neural networks, logistic regression, Support Vector Machines (SVMs) and K-nearest neighbor. They find that random forest is the top algorithm. Basak et al. (2019) use random forests to predict stock price direction for 10 companies many of which are technology or social media oriented (AAPL, AMZN, FB, MSFT, TWTR). Feature selection is based on technical indicators. They find that the predictive accuracy of random forests is higher than that of artificial neural networks, support vector machine, and logit models. Khan et al. (2020) use 12 machine learning methods (Naïve Bayes, multinomial Naïve Bayes, SVM, logistic regression, multilayer perception, K-nearest neighbor, CART, linear discriminant analysis, AdaBoost, gradient boosting, random forests, extremely randomized trees) applied to social media and financial data to predict stock prices (Karachi Stock Exchange, London Stock Exchange, New York Stock Exchange and 8 US technology companies). The random forests method is consistently ranked as one of the best methods.

Third, technical indicators and macroeconomic factors are used as features in predicting Bitcoin and gold prices. Technical indicators have proven useful for predicting Bitcoin prices (Adcock & Gradojevic, 2019; Jaquart et al., 2021; Mudassir et al., 2020; Pabuçcu et al., 2020). A set of macroeconomic variables consisting of economic policy uncertainty (EPU), interest rates, market volatility, and inflation has not been used to predict Bitcoin price direction. Notice that a common set of macroeconomic variables is used to predict both gold price direction and Bitcoin price direction and this facilitates a comparison to see which macroeconomic variables are important for price prediction. While existing research studies Bitcoin price forecasting or gold price forecasting, we are not aware of any study that conducts an analysis of price direction forecasting for both Bitcoin and gold using a common set of macroeconomic variables as features. A novel approach to our analysis is that variable importance is analyzed using time series cross-validation techniques which demonstrate how variable importance changes across time.

Fourth, price direction predictions are computed for a multistep forecast horizon of one day to twenty days. Five days corresponds to one week of trading days, 10 days corresponds to two weeks of trading days, and 20 days corresponds to approximately one month of trading days. A multistep forecast horizon facilitates a deeper analysis of how prediction accuracy and variable importance changes across the forecast horizon.

The analysis reported in this paper reveals several important findings. First, in predicting Bitcoin and gold price direction, random forests have higher predictive accuracy than logit models. This is not a new result but does confirm the findings from many previous studies. Second, technical indicators are the most important features for predicting Bitcoin and gold price direction. Third, the importance of macroeconomic variables in predicting Bitcoin and gold price direction is mixed. The oil volatility index is an important predictor for both Bitcoin and gold. Bitcoin can be used as a substitute for gold in diversifying this type of risk. Ten-year bond yields are more important for predicting Bitcoin while inflation is important for predicting gold price direction. Gold is more influenced by inflation than gold and this indicates that gold can be used as a hedge or diversification asset against inflation.

This paper is organized as follows. The next section, Section 2, presents the background literature on Bitcoin price forecasting. Section 3 describes the methods (logit regression, bagging, and random forests) used in the paper to forecast Bitcoin price direction. Section 4 provides a description of the Bitcoin price data and the features. Empirical results on forecast accuracy and feature importance are reported in Section 5. Section 6 discusses the results. Section 7 concludes the paper.

2. Background literature

There is a recent literature using machine learning models to predict Bitcoin prices. Jang and Lee (2018) use Bayesian ANNs to forecast daily Bitcoin prices. Blockchain information (trading volume, block size, transactions per block, hash rate, number of transactions, miner's revenue) and economic variables (stock prices of major exchanges, oil prices, VIX, gold prices) are used as features. The Bayesian ANN outperforms the benchmark linear regression model. Nakano et al. (2018) uses artificial networks to test trading strategies on high frequency Bitcoin price data. The data set consists of 15-minute intervals covering the period July 31, 2016 to January 24, 2018. Technical indicators are used as features. Bitcoin trading based on signals generated from the ANN can outperform a buy and hold strategy provided trading costs are not too high (5 basis points is set as a benchmark for trading costs). Adcock and Gradojevic (2019) use feedforward neural networks to predict bitcoin prices. They use daily data for the period April 22, 2011 to March 2, 2018 and the features include 50 day and 200 day moving averages, and the CBOE volatility index (VIX). Compared to other forecasting methods like random walk, ARIMAX, GARCH-M, and linear regression, the feedforward neural network produced the most accurate point and density forecasts. Bitcoin volume and the VIX were of little importance for forecasting Bitcoin prices. Atsalakis et al. (2019) use a hybrid Neuro-Fuzzy controller (PATSOS) to forecast the direction in the daily rate of change of Bitcoin prices. The data set covers the period September 13, 2011 to December 12, 2017. Lagged differences of the data are used as features. The PATSOS model outperform an ANN and generates profitable trading signals. Lahmiri and Bekiros (2019) use deep learning to forecast the daily price of Bitcoin, Digital Cash and Ripple. They find that that long-short term memory neural networks (LSTM) have higher predictive accuracy than the generalized regression neural network. They conclude that deep learning methods are computationally intensive but useful for modelling and forecasting the hidden nonlinear patterns in these cryptocurrencies. Chen et al. (2020) use several machine learning methods to forecast high frequency (5-minute intervals) Bitcoin prices. The features include bitcoin price characteristics, bitcoin marketing and trading characteristics, investor attention and media, and gold prices. The data covers the period July 17, 2017 to January 17, 2018. Machine models include SVM, RF, XGB, and LSTM. Statistical models include logit, LDA, QDA, and ARIMA. Analysis is conducted for daily Bitcoin prices and prices measured at 5-minute intervals. For daily prediction, statistical methods and machine learning achieve accuracy of 66% and 65% respectively which outperforms the benchmark methods. Kraaijeveld and De Smedt (2020) study the usefulness of Twitter sentiment for predicting the prices of Bitcoin, Ethereum, XRP, Bitcoin Cash, EOS, Litecoin, Cardano, Stellar, and TRON. Bivariate causality analysis is used to determine the impact of sentiment on cryptocurrencies prices. Twitter sentiment does have predictive power for the returns of Bitcoin, Bitcoin Cash, and Litecoin. Up to 14% of the tweets were posted by Bot accounts. Mudassir et al. (2020) use ANN, SSAN, SVM, and LSTM to predict Bitcoin prices and price direction. The daily data set covers the period April 1, 2013 to December 31, 2019 although analysis was conducted over several sub-periods. The feature set consists of technical indicators. Forecasts are constructed for one, seven, thirty, and ninety days. Overall, LSTM performed the best. Pabuccu et al. (2020) use Support Vector Machines (SVM), Artificial Neural Networks (ANN), the Naïve Bayes (NB), Random Forest (RF), and logit regression to predict Bitcoin prices. The data set covered the time period 2008 to October 2020. Analysis was conducted for both discrete (price direction) and continuous (price returns) data. Technical indicators were used as features. For classification, ANN has the highest predictive accuracy while NB has the lowest. For the continuous data, RF has the highest predictive accuracy and NB has the lowest. Jaquart et al. (2021) use machine learning (artificial neural networks, LSTM, gradient boosting, and random forests) to predict high frequency (one minute to 60 minutes) Bitcoin prices. The feature set includes technical indicators, block-chain indicators, sentiment indicators, and asset indicators (stock returns, VIX returns, gold returns). Technical indicators are the most important features. The high frequency data set covers the period March 4, 2019 to December 10, 2019. They find that a quantile based long-short trading strategy can generate monthly returns of up to 39%. However, once trading costs are included negative returns are realized which is consistent with the large number of trades made over short holding periods. Hamayel and Owda (2021) apply three machine learning methods (LSTM, bi-LSTM and gated recurrent unit (GRU)) to predict three types of cryptocurrencies – Bitcoin, Litecoin, and Ethereum. Their data consists of daily observations on open, high, low, and close prices (in USD) from January 1, 2018 to June 30, 2021. The GRU method outperformed other algorithms with lowest RMSE and MAPE, but it is not clear why. The RMSE is considerably smaller for Litecoin, followed by Ethereum and Bitcoin, but provides no explanation at all for any of the results.

Machine learning methods have been demonstrated to be effective in predicting gold prices. To forecast the change in weekly gold prices Parisi et al. (2008) use artificial neural networks (ANN). The explanatory variables include lagged gold price changes and lagged changes in the Dow Jones Index. Compared to recursive ward networks or feed forward networks rolling ward networks have better forecasting accuracy. Yazdani-Chamzini et al. (2012) forecast the monthly gold prices using ANN, adaptive neuro-fuzzy inference system (ANFIS), and ARIMA. They find that ANFIS outperforms the other models and the results are robust to different training and test sets. Mahato and Attar (2014) use ensemble methods to predict gold prices. Gold and silver price accuracy of 85% and 79%, respectively can be achieved using stacking and hybrid bagging. Pierdzioch et al. (2015) forecast monthly gold prices using regression boosting. They find that macroeconomic variables like inflation rates, exchange rates, stock market, and interest rates have predictive power. Trading rules generated from boosting do not beat a simple buy and hold strategy. Pierdzioch et al. (2016a) use quantile regression boosting to forecast gold prices. Trading rules generated from this approach can, in situations with low trading costs, and specific quantiles outperform a buy and hold strategy. Pierdzioch et al. (2016b) use a boosting regression to forecast gold price volatility. Compared to an autoregressive model, boosting provides better forecasts. Alameer et al. (2019) use a neural network whale optimization algorithm to forecast monthly prices of gold. This approach has better forecasting performance compared to several other machine learning methods (classic neural network, particle swarm neural network, and grey wolf optimization) and ARIMA models. Risse (2019) combines wavelets and support vector machine (SVM) to predict monthly gold prices. The feature space includes variables for interest rates, exchange rates, commodity prices, and stock prices. Wavelets are applied to each of these predictors in order to generate additional features for the SVM. The wavelet SVM produces more accurate gold price forecasts than other models like SVM, random forest, or boosting. Livieris et al. (2020) combine deep learning with long short-term memory (LSTM) to predict gold prices. Forecasting performance can be increased by adding LSTM layers to the deep learning process. Using random forests to predict the returns of gold, silver, platinum, and palladium Pierdzioch and Risse (2020) find that forecasts from multivariate models are more accurate than forecasts from univariate models. Plakandaras et al. (2021) combine ensemble empirical mode decomposition with SVM to predict monthly gold prices. Interest rates and asset prices are included as features. A two-step process is used where in the first step the data are filtered and then in the second step the filtered data are used in a SVM. Forecast accuracy is higher than that obtained from ordinary least squares or least absolute shrinkage. Sadorsky (2021) finds that tree-based classifiers like random forests produce higher accuracy than logit models for predicting gold and silver price direction. Technical indicators are used as features. Trading rules built from random forest predictions outperform a buy and hold strategy.

There are several takeaways from this literature on Bitcoin price forecasting. First, machine learning methods have higher prediction accuracy than parametric regression approaches. Second, while different authors use different data sets and different methods, technical indicators are probably the most important features in predicting Bitcoin prices. Third, there is no clear consensus on the impact of business cycle variables like interest rates, inflation, and market volatility for forecasting Bitcoin prices. Market volatility, as captured by the VIX, is included in studies by Jang and Lee (2018), Adcock and Gradojevic (2019) and Jaquart et al. (2021) but other important business cycle variables like interest rates and inflation appear to not have been studied. Consequently, the impact of business cycle conditions on Bitcoin price forecast is largely under studied. Notice also, that while some papers study the predictability of Bitcoin or gold no paper studies both assets at once. Consequently, the impact of business cycle conditions on Bitcoin price prediction and a comparison of these impacts on gold price forecasting leaves a void in the literature that this paper attempts to fill.

3. Methods

3.1. The models used in prediction Bitcoin and gold price direction

This section describes the models used for predicting the direction of Bitcoin and gold prices. Tree-based machine learning methods like random forests and bagging are collections or ensembles of decision trees. If the response variable is continuous the decision tree is referred to as a regression tree. If the response variable is categorical the decision tree is referred to as a classification tree. Tree-based methods partition the predictor space into a sequence of smaller non-overlapping regions. The sequential process of creating these non-overlapping regions can be described using a decision tree which is why these methods are referred to as tree-based methods. This section provides a short discussion on bagging, and random forests. A more complete and rigorous treatment of decision trees, bagging, and random forests can be found in James et al. (2013) and Hastie et al. (2009).

In a typical classification tree-based model, the data set is split randomly into a training data set and a testing data set. A tree is grown on the training data set using recursive binary splitting and a classification error rate along with either a Gini index or an entropy measure are used to determine the splitting rules. The classification error rate is the fraction of training observations in a region that do not belong to the most commonly occurring class. Every value of each predictor is examined as a possible split. Decision trees have high variance which means that small changes in the data can affect the outcome of the tree and its predictions. One way to achieve lower variance is to use bagging (bootstrap aggregation). With bagging, bootstrap replication is used to create many copies of the original training data set and a decision tree fit to each copy. The predictions from the test data are then averaged across many trees with the outcome being a low variance machine learning method.

Another way to reduce the variance is to use random forests which are an ensemble method that reduces variance by introducing decorrelation between the trees (Breiman, 2001). A large number of decision trees are built on bootstrapped training samples. Each time a split in a tree occurs a random sample of predictors is chosen from the full set of predictors. For a classification problem, the number of predictors chosen at random is calculated as the floor of the square root of the total number of predictors (James et al., 2013). Even though choosing predictors at random may seem unintuitive, averaging results from non-correlated trees is more effective for reducing variance than averaging trees that are highly correlated.

A logit model is used as a benchmark for comparison purposes. Price direction is classified as either up (price change from one period to the next is positive) or down (price change from one period to the next is non-positive). A multistep forecast horizon, denoted by $h = 1,2,3, \ldots ,20$, is used in order to see how forecast accuracy changes across the forecast horizon. A 5-day forecast corresponds to one week of trading data, a 10-day forecast corresponds to two weeks of trading data, and a 20-day forecast approximately matches the average number of trading days in a month. The features used in the analysis include widely used technical indicators like the relative strength indicator (RSI), stochastic oscillator (slow, fast), advance – decline line (ADX), moving average cross-over divergence (MACD), price rate of change (ROC), on balance volume (OBV), the 50-day moving average, 200-day moving average, money flow index (MFI), and Williams accumulation and distribution (WAD) and macroeconomic variables representing interest rates, economic policy uncertainty, market uncertainty, and inflation. Technical indicators have predictive power for predicting stock prices and are widely used in academics and practice (Bustos & Pomares-Quimbaya, 2020; Neely et al., 2014; Wang et al., 2020; Yin et al., 2017; Yin & Yang, 2016). Achelis (2013) explains the purpose and calculation of these technical indicators. In addition to the technical indicators, the feature set includes economic policy uncertainty and equity market uncertainty. The importance of these variables for forecasting Bitcoin prices are discussed in the data section.

The predictive accuracy of a logit model can be improved by using boosting (James et al., 2013). Boosting is implemented by using a sequential algorithm. In the first step, a logit model is fit to the data. In the second step, a logit model is fit to the residuals from the first step. This process of predicting residuals continues through several steps, or iterations, and the final model is obtained by summing the fits from each iteration. Boosting works by fitting successive models to the residuals of the previous model.

3.2. Setup of the models

This section of the paper describes the specifics of the machine learning models. The data set was randomly split so that 70% of the data was used for training the models and 30% used for testing the predictions. The logit model uses all the features in predicting Bitcoin price direction. The bagging decision tree model also uses all the features in predicting Bitcoin price direction. Random forests and tree bagging were estimated with 500 trees. The random forests were estimated with 500 trees and 4 (the floor of the square root of the number of features, 23) randomly chosen predictors at each split. RFs are not sensitive to the number of trees provided a large enough number of trees are chosen. A very large number of trees does not lead to overfitting, but a small number of trees results in high test error. A tuned random forests model is included where the number of randomly chosen predictors was determined by cross-validation (10 folds, repeated 10 times).

In addition to a logit model, a boosted logit model was also used in the analysis. A boosted logit model improves upon the logit model by using a sequential learning algorithm. The number of iterations was chosen using cross-validation (10 folds, repeated 10 times).

Forecasting accuracy is evaluated using several measures obtained from the confusion matrix. Prediction accuracy is the number of true positives and true negatives divided by the total number of predictions. This value ranges from zero to one hundred. The kappa statistic adjusts prediction accuracy by accounting for the possibility of a chance occurrence of a correct prediction. The kappa statistic provides a better indicator of accuracy then the standard accuracy measure listed above when the classification data is unbalanced. The positive predictive value measures the proportion of positive predictions that were correctly classified as positive (true positives divided by the sum of true positives and false positives). The negative predictive value measures the proportion of negative predictions that were correctly classified (true negatives divided by the sum of true negatives and false negatives).

All calculations were done in R (R Core Team, 2019) using the random forests machine learning package (Breiman et al., 2018), the generalized boosted models package (Greenwell et al., 2020), and the caret package (Kuhn et al., 2020). Computations were carried out on a Dell Latitude 5591 laptop with Intel Core i7-8850H CPU @ 2.60Hz. The estimation for Figures 1 – 6 took 12.6 minutes. The estimation for Figures 7a and 7b took 24.2 minutes. The estimation for Figures 8a and 8b took 22 minutes.

4. Materials

The data for this study consists of daily Bitcoin and gold prices and macroeconomic variables. Technical indicators have been shown to be important predictors of Bitcoin prices (Adcock & Gradojevic, 2019; Mudassir et al., 2020; Nakano et al., 2018; Pabuçcu et al., 2020) and gold prices (Sadorsky, 2021). Bitcoin and gold prices are used to calculate technical indicators like the relative strength indicator (RSI), stochastic oscillator (slow, fast), advance – decline line (ADX), moving average cross-over divergence (MACD), price rate of change (ROC), on balance volume, money flow index (MFI), Williams accumulation and distribution

(WAD), and the 50-day and 200-day moving averages. These technical indicators are used as features in the prediction models. Technical indicators were calculated using the default settings in the R package TTR (Ulrich, 2020).

Macroeconomic variables are included for economic policy uncertainty (EPU), interest rates, market volatility, and inflation. Market volatility as measured by the VIX has been used to predict Bitcoin prices (Adcock & Gradojevic, 2019; Jaquart et al., 2021). Interest rates and inflation are commonly used to predict gold prices (Pierdzioch et al., 2015; Plakandaras et al., 2021).

Economic policy uncertainty is measured using the US economic policy uncertainty index (Baker et al., 2016) and economic market uncertainty is measured using the economic market uncertainty index (EMU). Interest rates are measured using the yield on the US ten- year bond (Tenyrbond), three-month T-bill (ThreemTbill), and the spread (spread) between these variables. Equity and oil market uncertainty is measured using the VIX and the OVX respectively. The VIX is the CBOE volatility index that represents the US stock market expectations of volatility for the next 30 days. OVX is an estimate of the expected volatility over the next thirty days of the US crude oil prices. Variables are included for expected five-year inflation (Fiveyrinfexp) and break-even inflation (be_inflation). The equity market volatility infectious disease tracker (EMV_IDT) is included to account for the impact of the COVID-19 pandemic.

The Bitcoin and gold price data comes from Yahoo Finance and the other data comes from the St. Louis Federal Reserve. The data set covers the period September 17, 2014 (the earliest date for which Bitcoin price data are available from Yahoo Finance) to December 29, 2021. Recall that Bitcoin price data before September 2014 may be unreliable because on

February 24, 2014 Mt Gox (at the time the largest trader of Bitcoins) suspended all trading of Bitcoin due to a large theft of Bitcoins which had gone undetected for several years[1].

A plot of Bitcoin closing prices (BTC) shows a relatively flat pattern in the data from September 2014 to July 2016, followed by a sharp increase in prices from September 2017 to January 2018, another flat period from July 2018 to September 2020, and another sharp increase in prices from September 2020 to November 2021 (Figure 1a). The rise in Bitcoin prices between late 2017 and early 2018 was mostly driven by retail investors looking for an exciting new asset class outside of the mainstream global financial system to invest in. The rapid increase in Bitcoin prices since September 2020 has been the subject of much discussion. Possible reasons for this increase include, a large increase in institutional investors (in response to institutional investor acceptance of the importance of Bitcoin) and the possible use of Bitcoin as an inflation hedge in response to the fiscal stimulus provided by governments in response to the COVID-19 pandemic[2]. Gold prices (GLD) were fairly flat between 2014 and 2019, after which time they increased in response to the COVID-19 pandemic. The EPU, EMU and EMV_IDT show large increases around the time when COVID-19 was declared a pandemic by the World Health Organization in March of 2020 (Figure 1b). The values of these variables have trended downwards after the big increase in March of 2020, but the variability has not decreased to pre-COVID-19 levels.

[1] https://www.bloomberg.com/news/articles/2021-01-31/-trillion-dollar-mt-gox-demise-as-told-by-a-bitcoin-insider

[2] https://theconversation.com/bitcoin-why-the-price-has-exploded-and-where-it-goes-from-here-152765

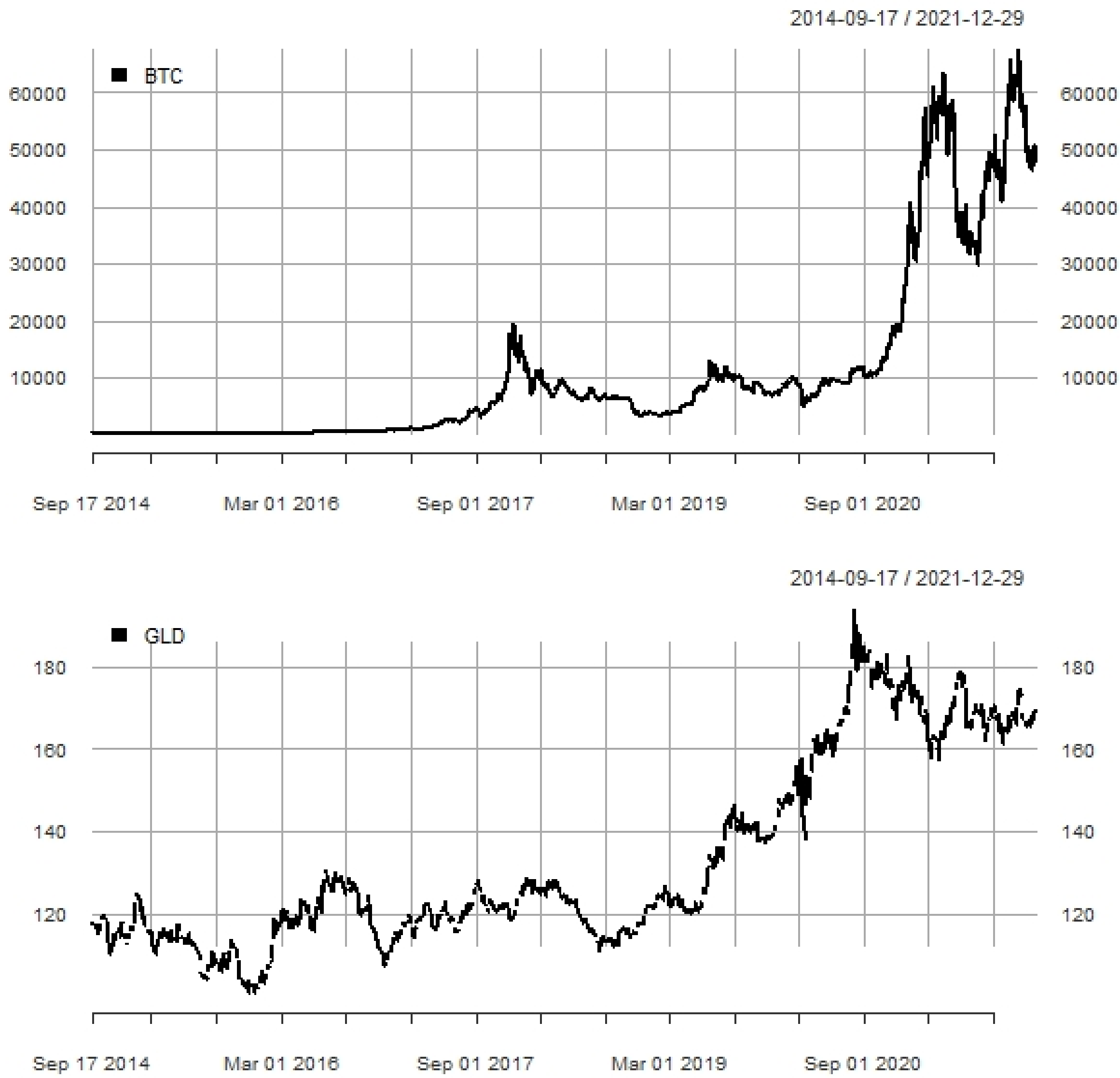


Figure 1a. Time series plots of bitcoin and gold prices.

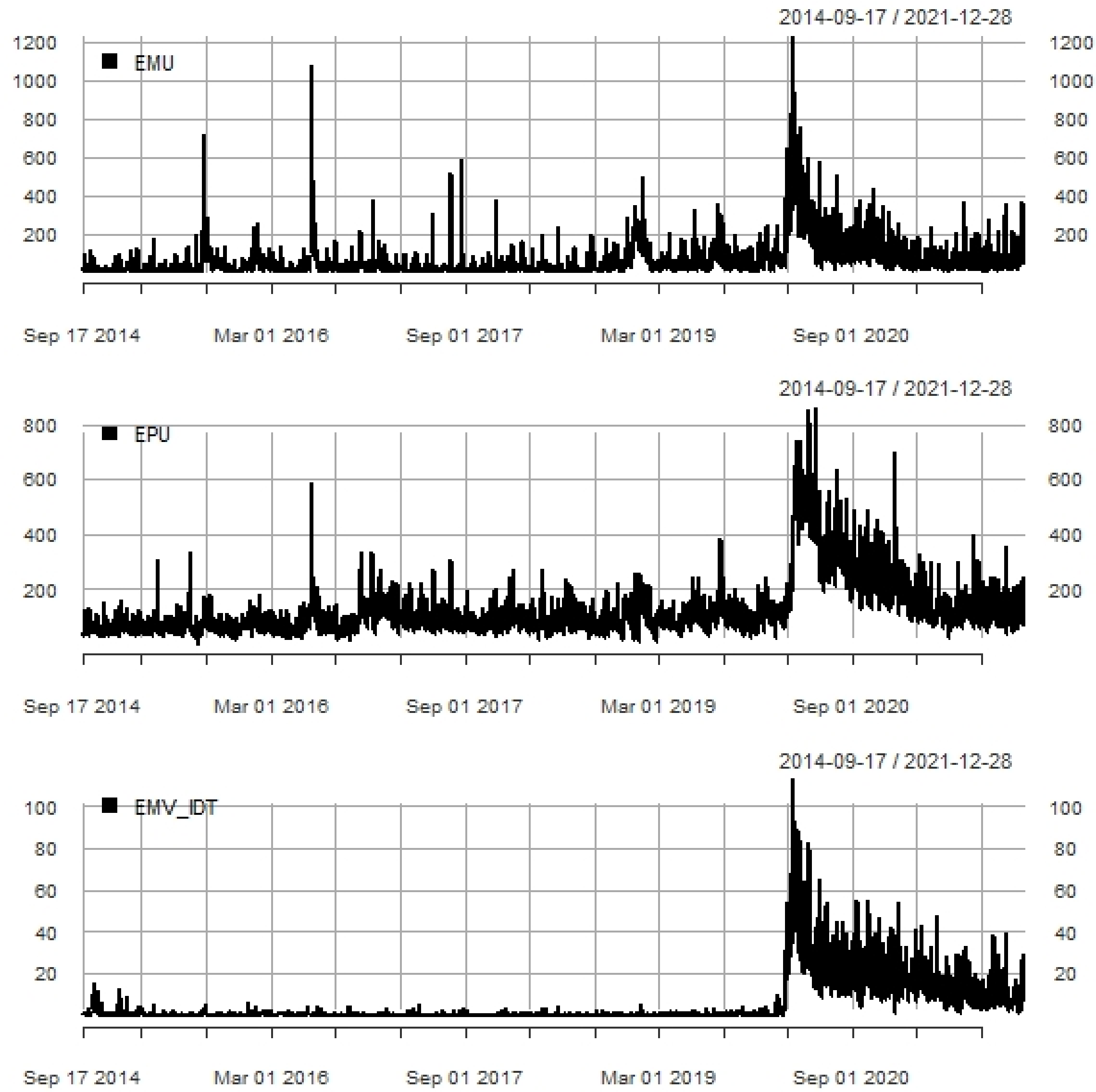


Figure 1b. Time series plots of EMU, EPU, and EMV_IDT.

Summary statistics are reported in Table 1 for Bitcoin and gold returns (calculated as $100*\ln(p_t/p_{t-1})$ where p is the closing price) and the level values of the market uncertainty, policy uncertainty, interest rate and inflation variables. Bitcoin (BTC) and gold (GLD) had positive mean values over the sample period but exhibited skewness and kurtosis which is characteristic of financial assets. According to the coefficient of variation, gold prices are more variable than

Bitcoin. EVM_IDT has more variation than either EPU or EMU. Non-normality in the data are apparent as for each variable as the median is different from the mean, skewness and kurtosis are pronounced, and the normality test rejects the null hypothesis of normality.

Table 1. Summary statistics

	median	mean	std.dev	coef.var	skewness	kurtosis	W	W(p)
BTC	0.200	0.178	3.927	22.127	-0.802	11.271	0.904	<0.001
GLD	0.050	0.023	0.884	39.324	-0.170	3.609	0.962	<0.001
EMU	33.000	67.513	96.613	1.431	3.984	25.481	0.611	<0.001
EPU	92.670	125.294	105.739	0.844	2.626	8.657	0.724	<0.001
Tenyrbond	2.070	1.971	0.645	0.327	-0.372	-0.479	0.970	<0.001
ThreemTbill	0.310	0.783	0.841	1.075	0.713	-1.073	0.811	<0.001
be_inflation	1.640	1.700	0.450	0.264	0.472	0.733	0.967	<0.001
spread	1.230	1.174	0.697	0.594	-0.246	-0.716	0.978	<0.001
EMV_IDT	0.540	5.345	10.885	2.037	3.249	14.614	0.557	<0.001
Fiveyrinfexp	1.990	1.957	0.239	0.122	-0.562	-0.079	0.972	<0.001
VIX	15.600	17.637	7.594	0.431	2.905	13.932	0.761	<0.001
OVX	36.100	40.376	20.722	0.513	4.972	36.774	0.584	<0.001

Data for the period September 18, 2014 to December 28, 2021. BTC and GLD measured in log returns and other variables measured in levels. W is the Wilcox test for normality and W(p) is the associated p value.

5. Results

Before getting to the main results on predicting Bitcoin price direction, it is useful to see how the random forests test error varies with the number of trees. Figure 2a (Bitcoin) and Figure 2b (gold) shows how the out-of-bag error, test error for the up classification and test error for the down classification varies with the number of trees. For both the 10-day and 20-day forecast horizons, the test error drops off quickly as the number of trees approach 100. After 100 trees the test error displays little variation. Random forests prediction precision is not affected by using too many trees but fewer trees can lead to imprecise forecasts. In this paper, random forests are estimated using 500 trees.

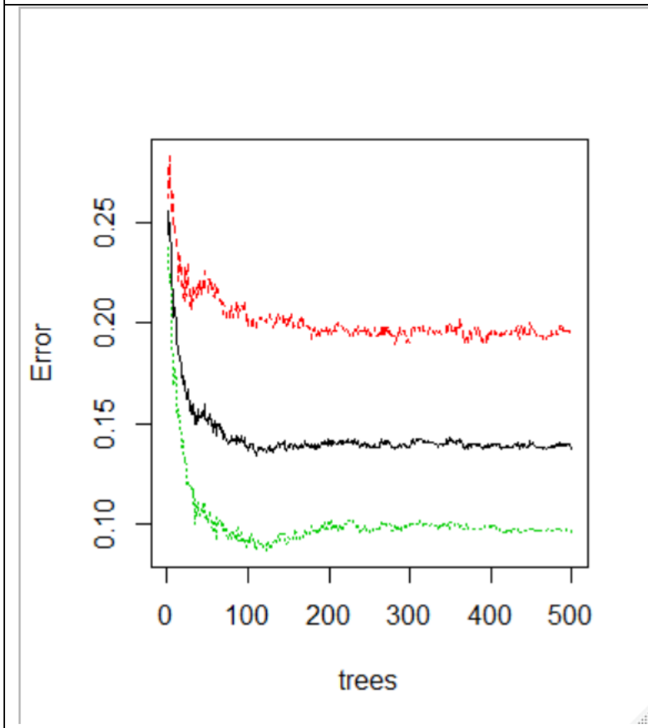
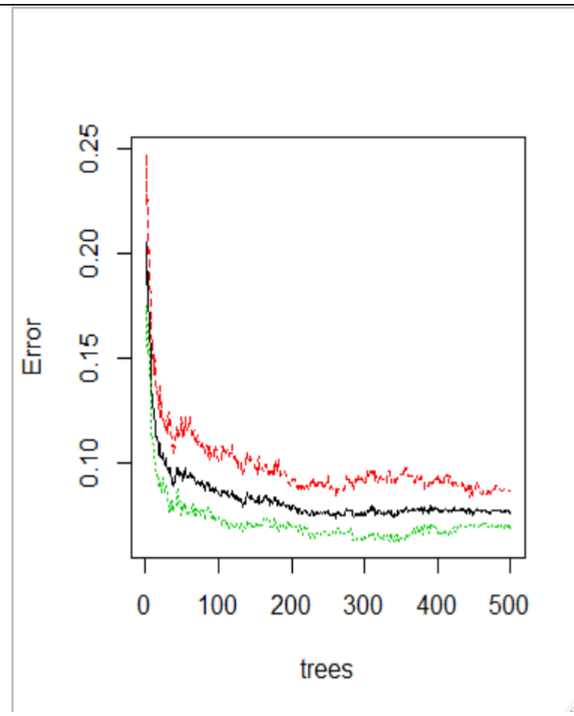
10-day forecast horizon	20-day forecast horizon
	

Figure 2a. Bitcoin random forest sensitivity to the number of trees. The plots show the test error vs the number of trees. OOB (Red), down classification (Black), up classification (Green).

10-day forecast horizon	20-day forecast horizon

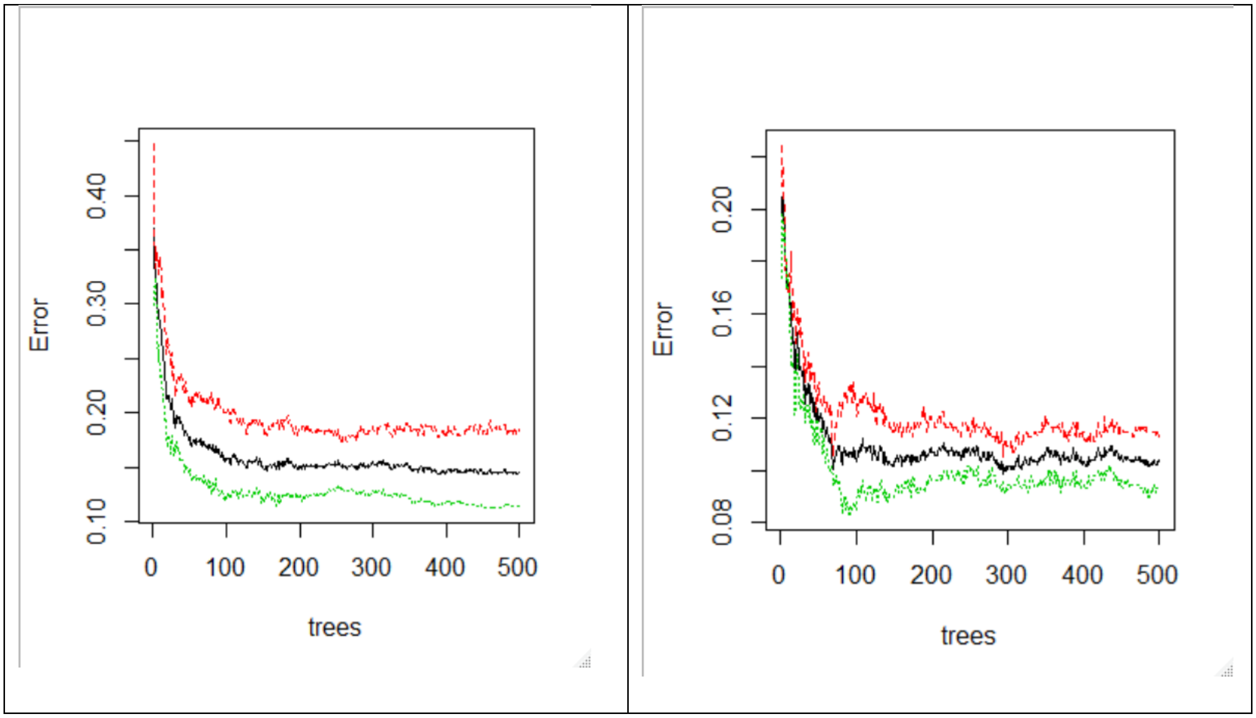


Figure 2b. Gold random forest sensitivity to the number of trees. The plots show the test error vs the number of trees. OOB (Red), down classification (Black), up classification (Green).

It is also useful to see which predictors are the most important when making predictions from the random forests model. The importance of each predictor was assessed using the mean decrease in accuracy. These accuracy measures are calculated from the out-of-bag (OOB) data. Results are presented for a 10-day and 20-day forecast horizon (Table 2). For Bitcoin, MA50, WAD, MACDSignal, ADX, OVX, VIX, and the Tenyrbond each rank in the top 10 for the 10-day and 20-day forecasts. For gold, MA50, MA200, WAD, OnBalanceVolume, MACDSignal, MACD, ThreemTbill, and be_inflation each rank in the top 10 for the 10-day and 20-day forecasts. Technical indicators like MA50, WAD, and MACDSignal are important predictors for each of Bitcoin and gold. The ten-year bond, VIX, and OVX are important macroeconomic variables for predicting Bitcoin direction. The three-month T-bill and break-even inflation are important macroeconomic variables for predicting gold price direction. Macroeconomic variables are important for predicting Bitcoin and gold price direction, but the importance of these variables depends upon whether Bitcoin or gold is being forecast. Variable importance will be further investigated later in the paper when the results from time series cross-validation are reported.

Table 2. The importance of predictors

	BTC		GLD	
	10-day	20-day	10-day	20-day
EMU	14.497	14.541	12.305	10.181
EPU	19.366	14.403	11.834	8.316
Tenyrbond	32.306	35.766	24.747	24.567
ThreemTbill	29.821	23.918	25.746	30.074
be_inflation	30.616	29.644	26.240	25.996
spread	30.780	30.249	22.742	23.332
EMV_IDT	16.342	15.761	14.338	12.559
Fiveyrinfexp	25.356	27.017	21.619	28.151
VIX	30.617	33.599	20.763	21.256
OVX	35.641	32.933	22.192	24.318
RSI	22.164	25.288	23.000	22.818
StoFASTK	17.486	19.101	14.037	15.062
StoFASTD	20.259	18.728	14.008	18.070
StoSLOWD	22.833	21.042	16.605	17.752
ADX	31.738	31.709	25.452	23.135
MACD	28.402	32.467	27.140	25.661
MACDSignal	35.186	37.889	26.070	25.243
PriceRateOfChange	25.136	28.092	22.872	20.332
OnBalanceVolume	27.907	27.484	30.482	35.859
MA200	30.419	36.339	31.307	37.198
MA50	35.857	37.279	34.523	39.798
MFI	25.211	22.465	24.240	21.853
WAD	34.523	31.979	30.534	31.745

Importance of predictors calculated from a random forests model. Values reported for a 10-day forecast and a 20-day forecast. Values are shown for the mean decrease in accuracy.

Turning now to the forecast accuracy of the models, Bitcoin price direction accuracy shows that random forests, tuned random forests, and tree bagging have higher accuracy than either logit or boosted logit (Figure 3). At 5 days, random forests, tuned random forests, and tree bagging reach an accuracy between 75% and 80%. After 15 days random forests record accuracy values greater than 90%. This is because since easy profits are quickly snatched by competitive traders over short horizons, risk-based asset predictability tends to be higher with forecast horizon (Israel et al., 2020). This is not surprising because "logistic regressions assume a particular relationship between the explanatory factors" (Joseph, 2019). For gold the results are similar in that random forests, tuned random forests, and tree bagging have higher accuracy than either logit or boosted logit.

One concern may be that since Bitcoin prices experienced wide variation in 2021, this may affect the prediction accuracy. To address this concern, a random forests model was estimated using data from September 17, 2014 to December 31, 2020. This sub-sample omits the most recent year where Bitcoin prices increased to $60,000, fell to $30,000, and then increased back to $60,000. Accuracy measures at 5, 10, 15, and 20 days were (0.7585, 0.7631), (0.8680, 0.8760), (0.9074, 0.9237), and (0.9194, 0.9316) respectively where the first number in parenthesis is the accuracy calculated using the full data set and the second number in parenthesis is the accuracy calculated using the sub-sample of data. For each forecast horizon, the accuracy measures for the full data set and the sub-sample are similar. This shows that the prediction accuracy of the random forests was not affected by the volatility that occurred in the year 2021.

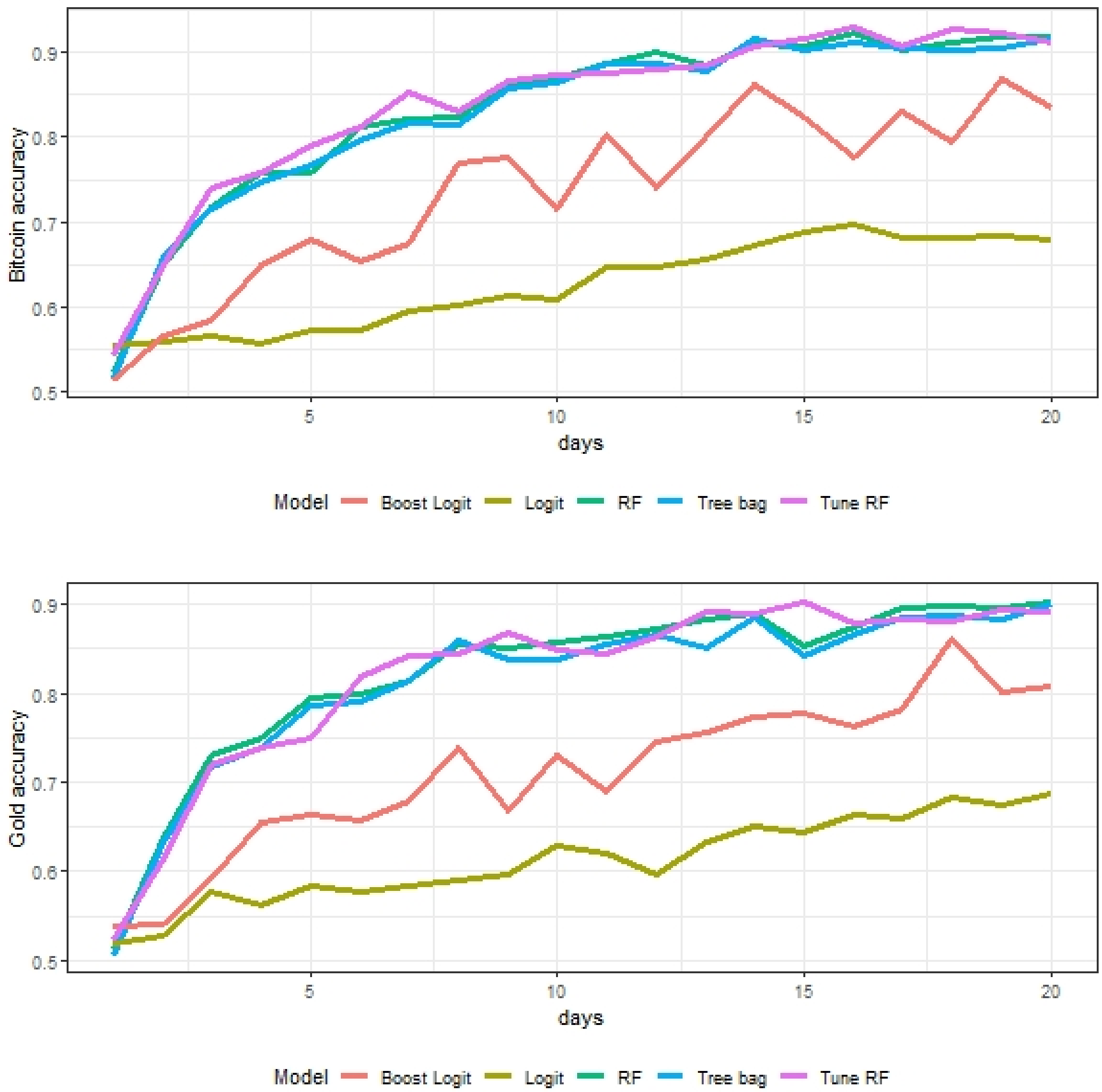
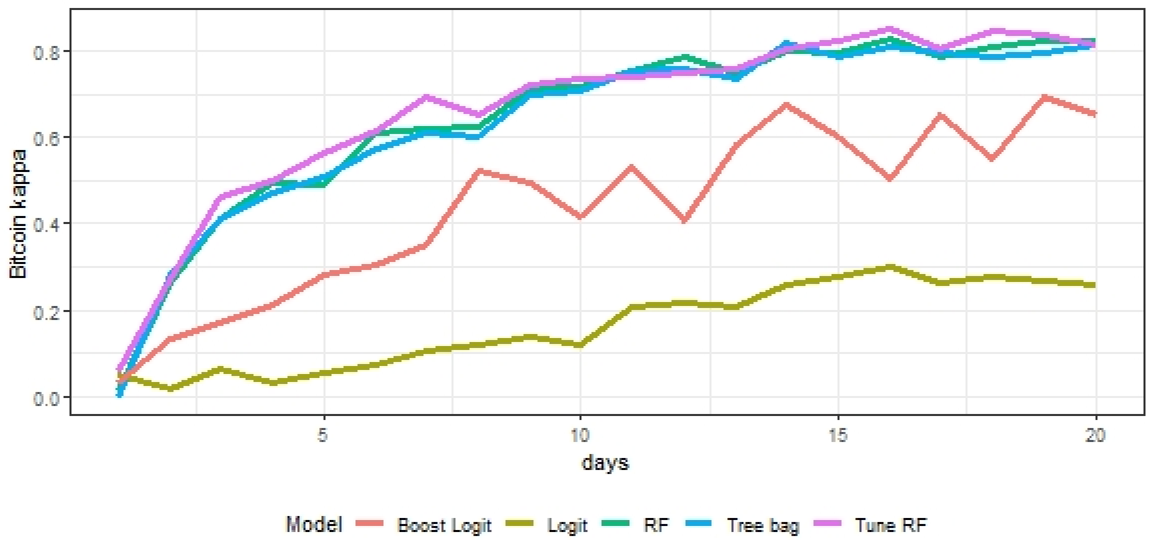


Figure 3. Bitcoin and gold price direction prediction accuracy.

The kappa statistic adjusts prediction accuracy by accounting for the possibility of a correct prediction just by chance. The pattern of kappa values (Figure 4) is similar to that of the prediction accuracy (Figure 3). Random forests and bagging have the highest kappa while logit and boosted logit have lower kappa values. This result holds for both Bitcoin and gold.



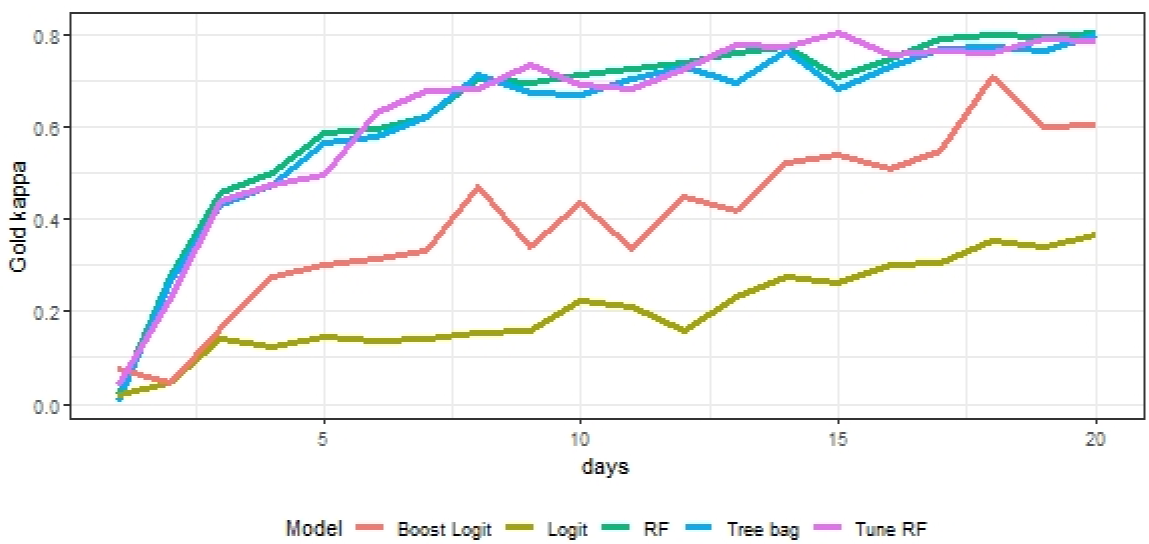


Figure 4. Bitcoin and gold price direction kappa.

It is also of interest to see how prediction accuracy varies by classification. In other words, do the models predict one type of classification better than the other? For each model the pattern of positive prediction accuracy is similar to that of negative prediction accuracy (Figures 5, 6). Prediction accuracy tends to be similar for each classification.

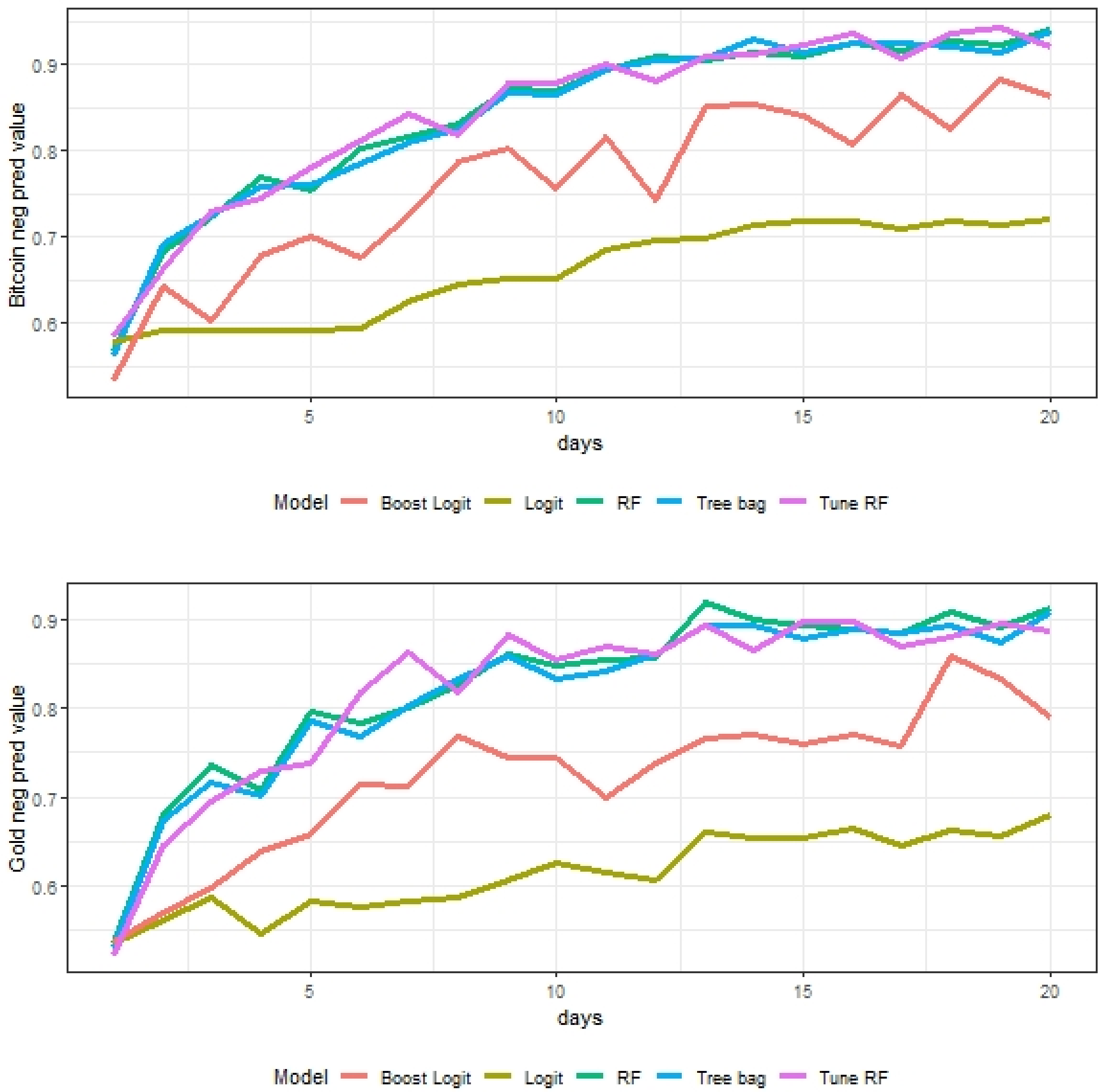
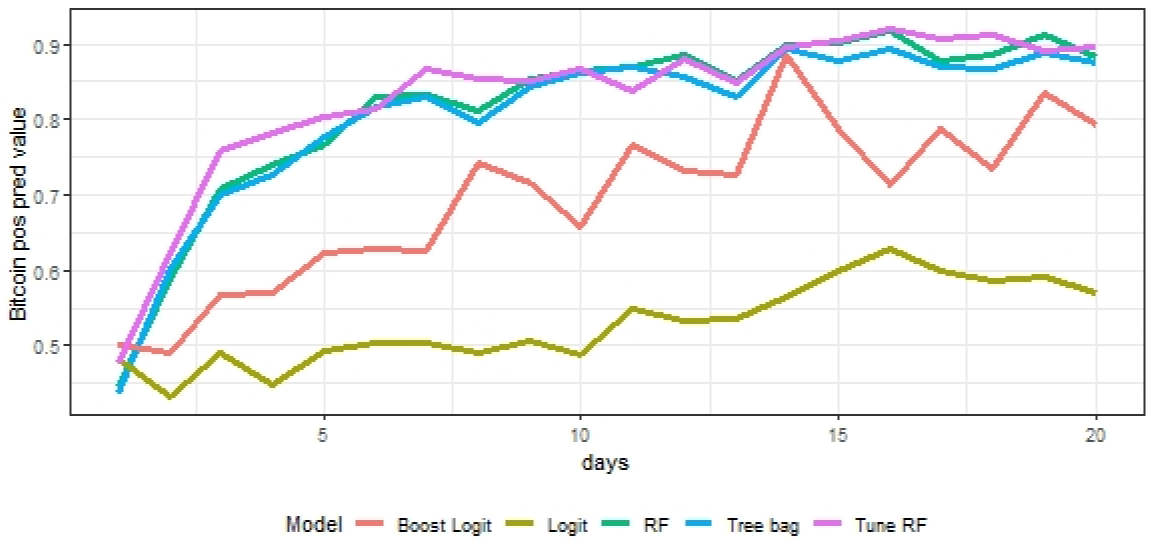


Figure 5. Bitcoin and gold price direction negative predictive value.



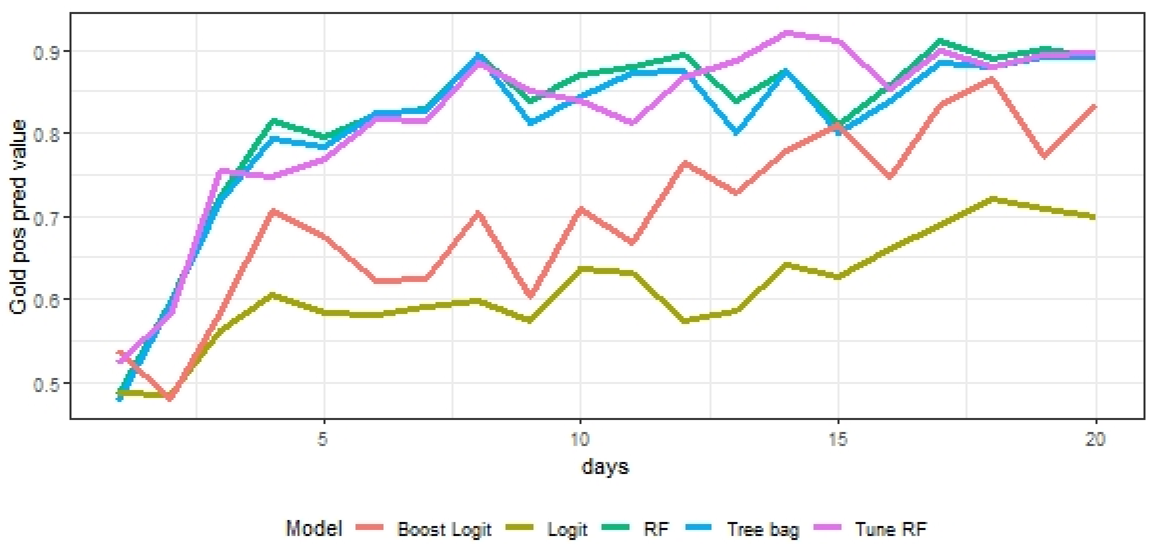


Figure 6. Bitcoin and gold price direction positive predictive value.

The prediction accuracy results presented so far have been based on randomly splitting the data set into a training data set and a test data set. When working with time series data this approach may not be accurate unless care is taken to preserve the time series features in the data. Bergmeir et al. (2018) investigate time series cross-validation and find that with autoregressive models *k*-fold cross validation is possible so long as the errors are uncorrelated. Since the models used in this paper are used to predict Bitcoin price direction (which is a classification variable rather than a continuous variable) and some of the features like the MA50 and MA200 embody important past information on stock prices, the residual serial correlation is alleviated.

In order to investigate further, random forests were used to generate Bitcoin and gold price direction forecasts using a rolling fixed window approach. The first 70% of the data are used as the initial training data set to generate forecasts from one period through to twenty periods. Then, one additional observation is added to the training data and the earliest observation is dropped and forecasts are recomputed. This fixed window training data (the training data set always includes 70% of the data) is rolled through the data until the end of the data is reached. This process is referred to as time-series cross-validation (tsCV) and is compared with the cross-validation (CV) approach used earlier in the paper which is obtained by randomly splitting the data set into a test set and a training set.

A comparison of random forest Bitcoin and gold price direction accuracy from CV and tsCV are shown in Table 3. For a 10-day forecast horizon, the prediction accuracy, kappa, negative predictive accuracy and positive predictive accuracy values from tsCV are high but less than the corresponding values from the CV approach. For the 20-day forecast horizon the accuracy and kappa values from the CV are greater than those from tsCV but the difference is not as large as in the case of the 10-day predictions. Similar to Bitcoin, for gold each accuracy measure tsCV values tend to be smaller than those for CV but overall, the tsCV and CV prediction accuracy is high.

Table 3. Comparing random forests prediction accuracy for Bitcoin and gold

	10-day	20-day	10-day	20-day
	CV	tsCV	CV	tsCV
		A. Bitcoin		
Accuracy	0.8680	0.8324	0.9193	0.8947

Kappa.	0.7154	0.6517	0.8248	0.7779
Pos pred value	0.8656	0.7748	0.8826	0.8472
Neg pred value	0.8693	0.8727	0.9402	0.9255
		B. Gold		
Accuracy	0.8583	0.8189	0.9023	0.8778
Kappa	0.7117	0.6309	0.8052	0.7549
Pos pred value	0.8713	0.8128	0.8913	0.8761
Neg pred value	0.8491	0.8233	0.9134	0.8794

Cross-validation (CV) and time-series cross-validation (tsCV) calculated from random forests. Values shown for a 10-day forecast horizon and a 20-day forecast horizon.

A tsCV approach provides an opportunity to see how variable importance changes through time. Figures 7a and 7b show variable importance calculated as mean decrease in accuracy along with a LOESS smoothed curve for the 20-day Bitcoin random forest forecast horizon. The importance of each predictor varies across time. The EPU, Tenyrbond, EMV_IDT, and OVX show noticeable increases across time. The be_inflation, VIX, and WAD show noticeable decreases in importance across time. Other variables show either little change in importance across time or exhibit strong nonlinear patterns (MA200). For gold, EPU, EMV_IDT, and WAD show strong increases in importance across time (Figures 8a, 8b). The three-month Treasury-bill and MA200 show strong decreases in importance across time. The variable importance of EMU, be_inflation, spread, and five-year inflation expectations show nonlinear patterns.

Descriptive statistics on the variable importance shows that for Bitcoin, MA50, MACDSignal, Tenyrbond, MA200, and WAD are the five most important features for forecasting 20-days ahead (Table 4). Technical indicators appear to be the most important features, which points to some degree of market inefficiency. For Bitcoin, the ten-year bond yield and OVX are the most important macroeconomic predictors. The ten-year bond and the OVX are also the most important macroeconomic predictors for the 10-day forecast horizon (Table 5).

The four most important features for gold at the 20-day and 10-day forecast horizon are MA200, MA50, OnbalanceVolume, and WAD (Tables 4 and 5). This shows that similar to Bitcoin, technical indicators are the most important features. At the 20-day forecast horizon, the most important macroeconomic variables are the three-month T-bill, OVX, and break-even inflation (Table 4). At the 10-day forecast horizon, the most important macroeconomic variables are break-even inflation and the OVX (Table 5).

Notice that OVX is an important macroeconomic variable for predicting both Bitcoin and gold price direction. The ten-year bond yield is important for predicting Bitcoin price direction and break-even inflation is important for gold price direction.

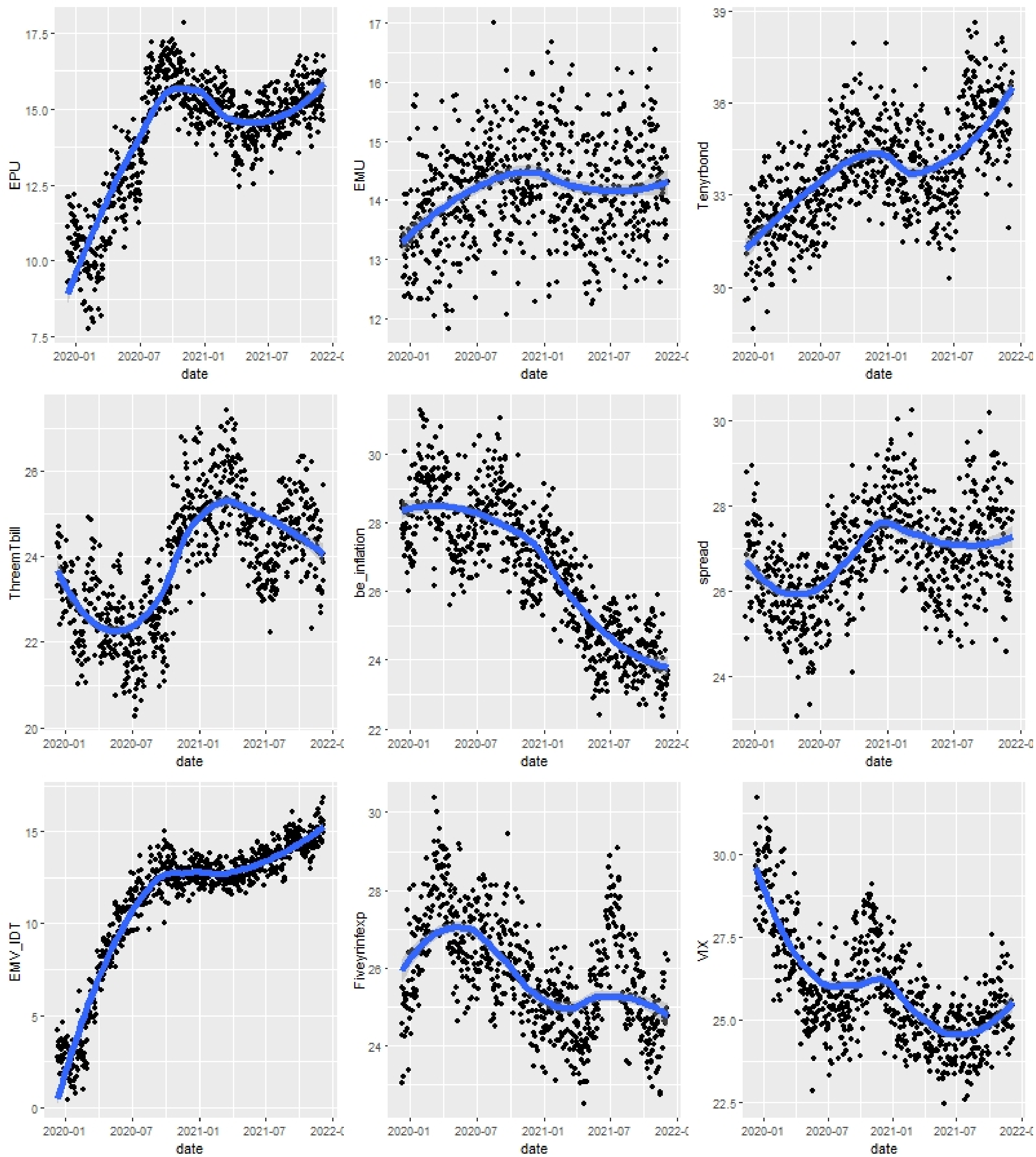


Figure 7a. Macroeconomic variable importance for predicting Bitcoin price direction (random forests 20-day forecast horizon).

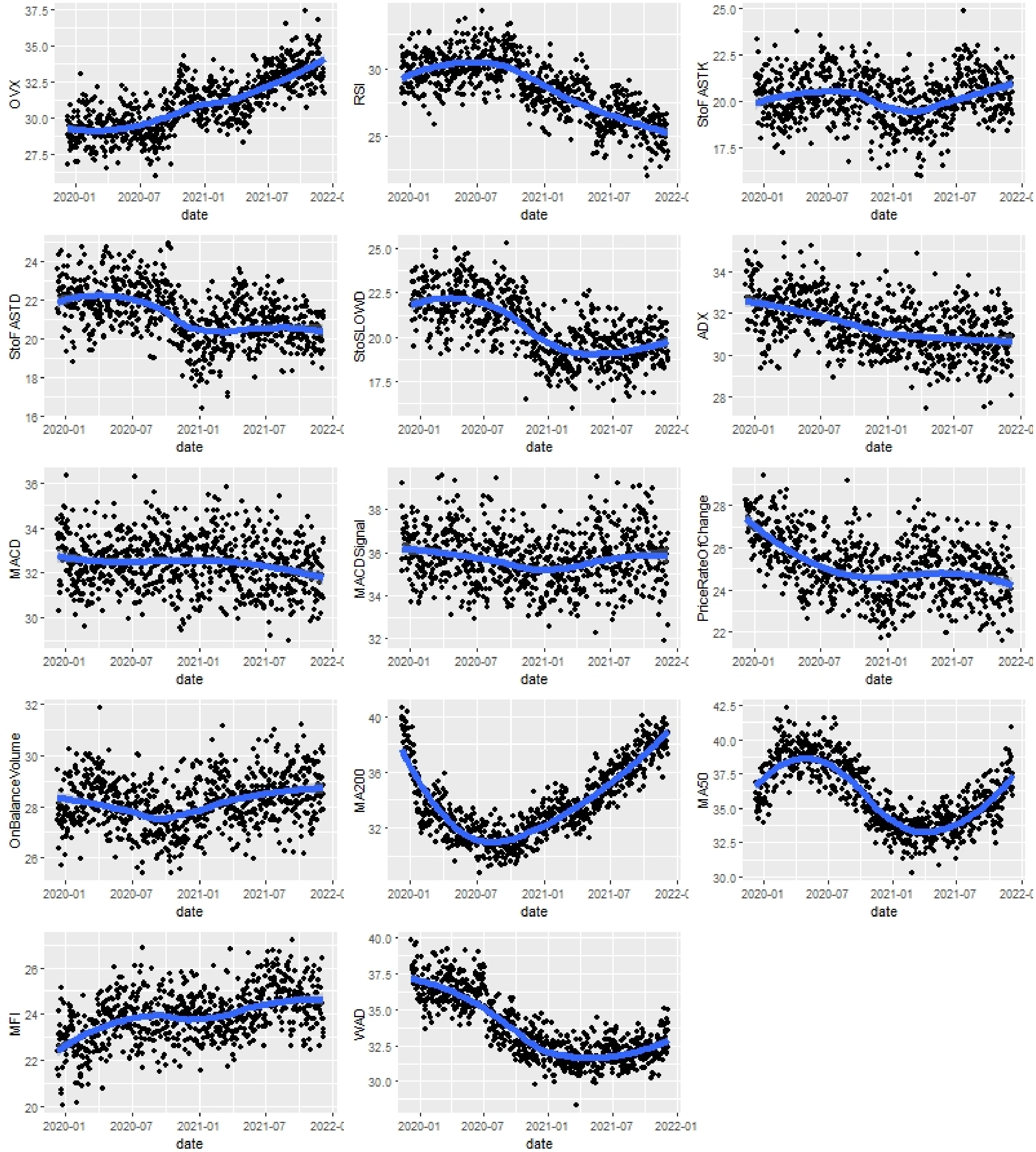


Figure 7b. Technical indicators variable importance for predicting Bitcoin price direction (random forests 20-day forecast horizon).

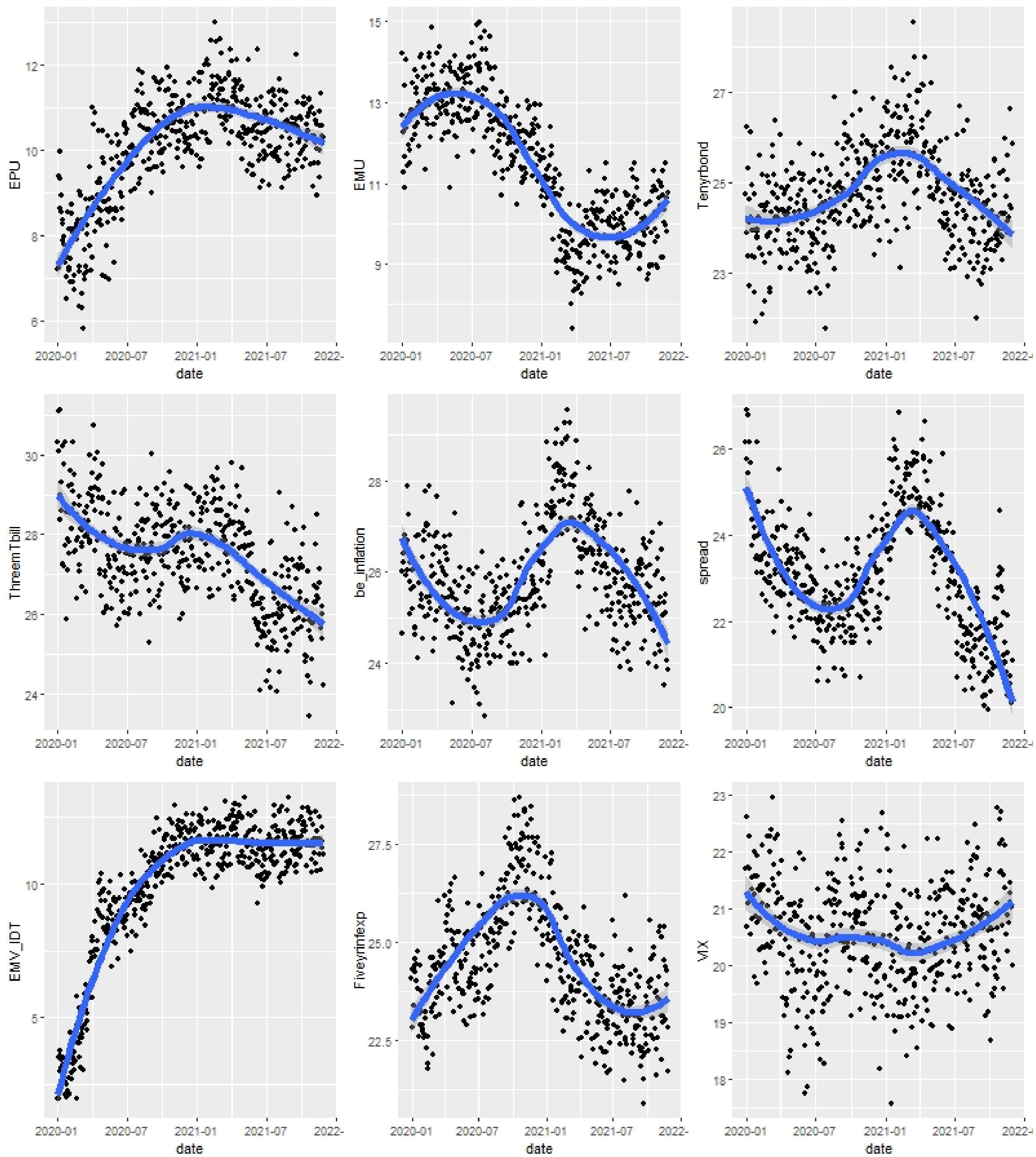


Figure 8a. Macroeconomic variable importance for predicting gold price direction (random forests 20-day forecast horizon).

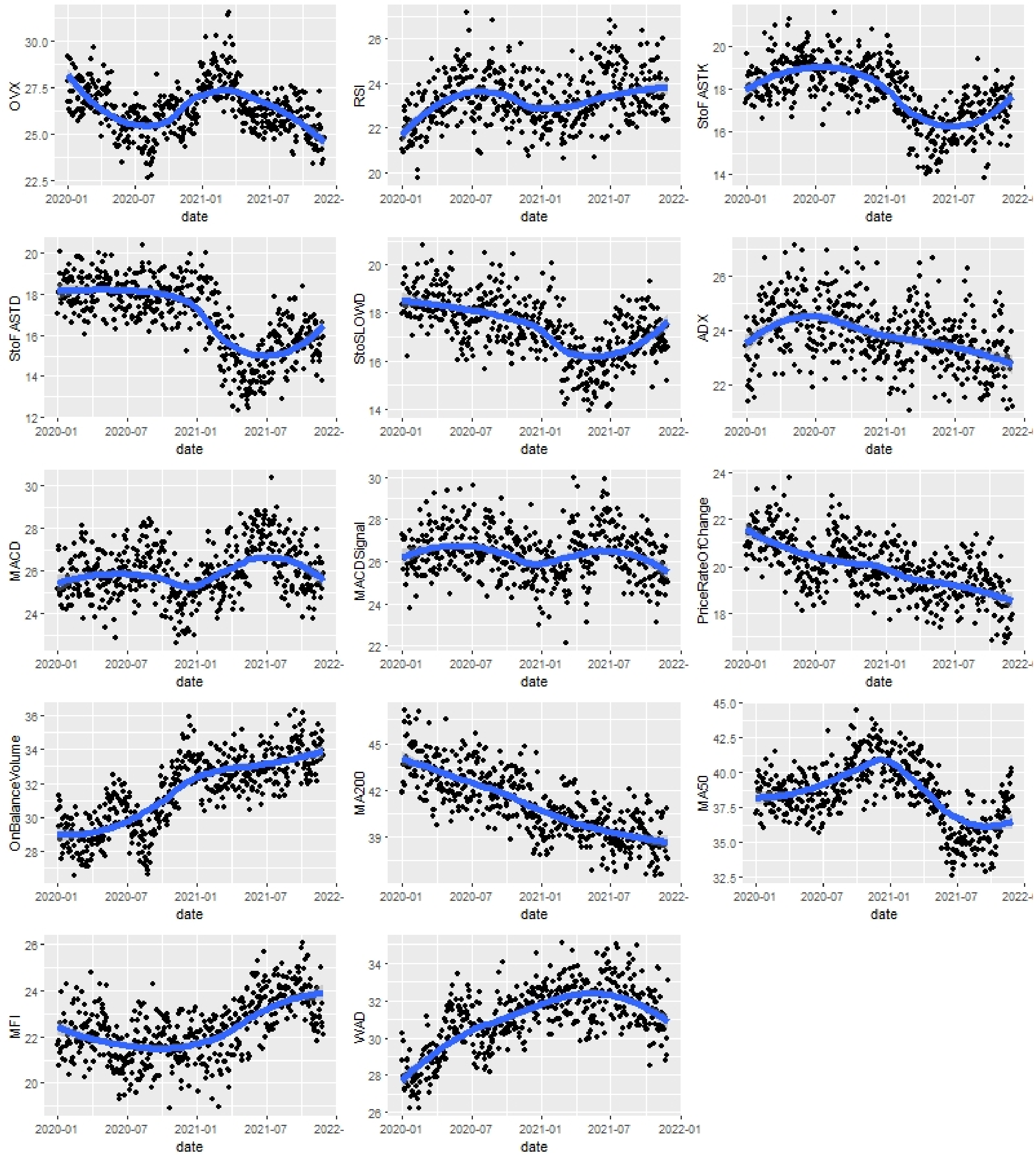


Figure 8b. Technical indicators variable importance for predicting gold price direction (random forests 20-day forecast horizon).

Table 4. Variable importance (mean decrease in accuracy) for 20-day price direction forecast.

	Bitcoin				Gold			
	mean	sd	cv	rank(mean)	mean	sd	cv	rank(mean)
EMU	14.142	0.864	0.061	21	11.429	1.632	0.143	21
EPU	14.041	2.045	0.146	22	10.098	1.264	0.125	22
Tenyrbond	33.808	1.695	0.050	3	24.721	1.067	0.043	10
ThreemTbill	23.832	1.437	0.060	17	27.447	1.266	0.046	5
be_inflation	26.636	2.014	0.076	12	25.845	1.184	0.046	9
Spread	26.784	1.159	0.043	11	23.062	1.421	0.062	14
EMV_IDT	11.157	3.683	0.330	23	9.964	2.666	0.268	23
Fiveyrinfexp	25.888	1.411	0.055	13	24.489	1.505	0.061	11
VIX	25.866	1.640	0.063	14	20.543	0.939	0.046	16
OVX	30.869	1.922	0.062	8	26.325	1.343	0.051	7
RSI	28.485	2.200	0.077	9	23.281	1.175	0.050	13
StoFASTK	20.179	1.319	0.065	20	17.771	1.476	0.083	18
StoFASTD	21.183	1.426	0.067	18	16.859	1.743	0.103	20
StoSLOWD	20.507	1.752	0.085	19	17.352	1.276	0.074	19
ADX	31.378	1.307	0.042	7	23.836	1.164	0.049	12
MACD	32.418	1.215	0.037	6	25.972	1.264	0.049	8
MACDSignal	35.695	1.294	0.036	2	26.403	1.189	0.045	6
PriceRateOfChange	25.104	1.426	0.057	15	19.897	1.212	0.061	17
OnBalanceVolume	28.166	1.030	0.037	10	31.509	2.125	0.067	3
MA200	33.730	2.593	0.077	4	41.056	2.139	0.052	1
MA50	35.955	2.371	0.066	1	38.384	2.288	0.060	2
MFI	23.919	1.134	0.047	16	22.347	1.316	0.059	15
WAD	33.583	2.219	0.066	5	31.057	1.712	0.055	4

Importance calculated using time series cross-validation from a random forests price direction prediction model. The mean (mean), standard deviation (sd), and coefficient of variation (cv) are reported.

Table 5. Variable importance (mean decrease in accuracy) for 10-day price direction forecast.

	Bitcoin				Gold			
	mean	sd	cv	rank(mean)	mean	sd	cv	rank(mean)
EMU	14.022	1.225	0.087	22	14.504	1.223	0.084	21
EPU	16.778	1.939	0.116	21	11.186	2.010	0.180	23
Tenyrbond	34.376	1.442	0.042	5	25.138	1.034	0.041	10
ThreemTbill	26.822	2.038	0.076	13	24.880	1.018	0.041	11
be_inflation	28.300	1.752	0.062	10	28.859	1.670	0.058	7
Spread	27.791	1.563	0.056	11	23.202	1.152	0.050	14
EMV_IDT	10.826	4.393	0.406	23	12.015	3.458	0.288	22

Fiveyrinfexp	26.387	3.002	0.114	15	24.197	1.235	0.051	12
VIX	27.487	1.047	0.038	12	22.309	1.061	0.048	15
OVX	31.278	1.917	0.061	8	26.076	1.355	0.052	9
RSI	24.518	1.324	0.054	16	24.149	1.152	0.048	13
StoFASTK	18.194	1.243	0.068	20	16.781	1.284	0.076	19
StoFASTD	20.835	1.301	0.062	19	15.861	1.131	0.071	20
StoSLOWD	21.579	1.083	0.050	18	16.874	0.907	0.054	18
ADX	33.280	1.828	0.055	6	28.964	1.665	0.057	6
MACD	31.917	2.252	0.071	7	26.723	1.250	0.047	8
MACDSignal	38.616	1.573	0.041	1	29.202	1.268	0.043	5
PriceRateOfChange	23.848	1.413	0.059	17	21.873	1.282	0.059	16
OnBalanceVolume	29.913	1.164	0.039	9	30.248	2.792	0.092	3
MA200	35.009	1.703	0.049	4	36.063	1.556	0.043	1
MA50	36.882	2.681	0.073	2	35.537	1.986	0.056	2
MFI	26.621	1.235	0.046	14	21.514	2.095	0.097	17
WAD	35.909	2.888	0.080	3	29.936	1.493	0.050	4

Importance calculated using time series cross-validation from a random forests price direction prediction model. The mean (mean), standard deviation (sd), and coefficient of variation (cv) are reported.

6. Discussion

The analysis from this research reveals several interesting results. First, random forests and tree bagging have higher Bitcoin price direction prediction accuracy than either logit or boosted logit. At 5 days, random forests, tuned random forests, and tree bagging reach an accuracy between 75% and 80%. After 15 days random forests record accuracy values greater than 90%. These results are important in showing that non-parametric machine learning methods have higher predictive accuracy than regression based methods. The strong predictive power of tree-based machine learning models indicate that investors and policymakers alike should consider taking advantages of these models. These results are not supportive of the efficient markets hypothesis which postulates that stock prices are best characterized as a random walk. The results for gold are similar in that random forests, tuned random forests, and tree bagging have higher accuracy than either logit or boosted logit.

Second, technical indicators are more important features for predicting Bitcoin price direction than macroeconomic variables. This is consistent with previous research that finds technical indicators are important predictors of Bitcoin prices (Adcock & Gradojevic, 2019; Jaquart et al., 2021; Mudassir et al., 2020; Pabuçcu et al., 2020).Among the features that are not technical indicators, the yield on the ten year bond and the OVX are particularly important. This is a new result. Low government bond yields are providing an incentive for investors to allocate some of their money to Bitcoin in the hopes of earning higher returns. The oil volatility index (OVX) is an important predictor because of the relationship between oil and the business cycle. The price of oil is set by demand and supply conditions in the oil market. Uncertainty about future oil prices, reflected in the oil volatility index, can be used to gauge business cycle conditions like economic expansions or contractions. Typically, oil price volatility is high before an economic contraction and low during periods of economic expansion. Oil price volatility has been identified as an important leading economic indicator (Chatziantoniou et al., 2021). Oil price volatility is an important predictor for both Bitcoin and gold. Inflation, on the other hand, is more important for predicting gold price direction than Bitcoin price direction. The declining importance of inflation in Bitcoin indicates that there is no particular reason to consider Bitcoin as an inflation hedge. In contrast, inflation's relationship with gold shows a more cyclical pattern. This means that for a risk-averse investor, holding some gold in her portfolio may still be a good idea. Interestingly, the pandemic-induced equity market volatility (EMV_IDT) index exerts an equal and increasing influence on Bitcoin and gold price direction. This suggests that at a time of heightened uncertainty, investors do not distinguish much between assets on the basis of fundamentals. Overall, the results suggest that compared to gold, Bitcoin's connectedness with macro markets has increased in recent years. Greater participation by professional and institutional traders including hedge funds might be behind the tightening link between Bitcoin and mainstream financial assets.

As a practical example of the usefulness of the results, a portfolio analysis was conducted. Bitcoin price direction predictions for a 20-day horizon were used to generate trading signals. If the predicted price direction was positive, invest in Bitcoin otherwise do no invest in Bitcoin. The rolling window approach described in the previous section was used in the estimation of trading signals. The annualized mean, standard deviation, and Sharpe ratio values from this portfolio were 120.79%, 44.19%, and 2.73 respectively. By comparison, a buy and hold portfolio results in annualized mean, standard deviation, and Sharpe ratio values of 71.60%, 65.14%, and 1.10 respectively. The portfolio constructed from the random forests price direction predictions is preferred over the buy and hold portfolio because it has higher risk adjusted returns.

7. Conclusions

Bitcoin has attracted a lot of attention from individual and institutional investors. Accurate Bitcoin price direction forecasts are important for determining the trend in Bitcoin prices and asset allocation. This paper uses tree-based machine learning methods like bagging and random forests to predict Bitcoin and gold price direction. The features include technical indicators and important business cycle variables like interest rates, inflation, and market volatility. Forecasts are computed for multi-step periods and variable importance is analyzed using time series cross-validation techniques. Time series cross-validation techniques are important for demonstrating how variable importance changes across time.

This paper started out by posing some important research questions. After careful analytical analysis answers to these questions can now be provided. With respect to the first question as to which macroeconomic variables are most important for forecasting Bitcoin prices, it turns out that of the macroeconomic variables considered (market volatility, interest rates, inflation) the most important macroeconomic variables are the yield on the US ten-year bond and the oil volatility index (OVX). The inflation rate is not a strong predictor of Bitcoin price direction which indicates that Bitcoin is not a very good hedging instrument for inflation. Notice that technical indicators like MA50, MA200, WAD, and MACDSignal are important predictors for both Bitcoin and gold price direction and the importance of these variables tends to be higher than that of the macroeconomic variables considered.

Regarding the question as to whether the importance of variables changes across time, it was found that variable importance does change across time but not enough to change the relative ranking of the variables. Technical indicators like MA50, MA200, WAD, and MACDSignal are the most important predictors for both Bitcoin and gold price direction irrespective of the time period. For Bitcoin, the ten-year bond yield and OVX are the most important macroeconomic variables while for gold inflation and OVX are the most important.

With regards to the question as to whether the most important macroeconomic variables for forecasting Bitcoin prices are the same as those for gold prices, the answer is mixed. The oil price volatility index is an important predictor for both Bitcoin price direction and gold price direction indicating that Bitcoin is a substitute for gold in diversifying this type of volatility. Ten-year bond yields are also important for predicting Bitcoin price direction. The 10-year US Treasury bond is often used to gauge investor confidence and is a proxy for other financial assets like mortgage rates. The importance of the 10-year bond yield in predicting Bitcoin prices indicates that Bitcoin is being viewed by investors as an investable asset but not necessarily as a hedge against inflation. By comparison gold prices are more influenced by inflation than Bitcoin indicating that gold can be used as a hedge or diversification asset against inflation.

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