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Algorithmic Trading

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Abstract

The motivation for this research comes from the increasing significance of algorithmic trading in financial markets. The study aims to assess the predictive capabilities of different machine learning models and their applicability to various asset classes.The research involves data collection and preprocessing, followed by the implementation of Support Vector Regression, Random Forest, and Neural Network models. The models are trained on historical data and evaluated using metrics such as the mean-squared error, Sharpe Ratio, Hit-Rate and a Buy&Hold strategy to benchmark their performance. The results indicate that all models achieve good predictive accuracy and robustness across various asset classes. The use of a bigger number of lags and training years generally improve the performance of the models. Surprisingly, the models did not achieve the best results with the lags provided by the auto correlation function. However, the RF model quickly overfits with Hit Rates around 90% on the training data, requiring fine-tuning to achieve comparable results. In conclusion, this thesis demonstrates the potential of machine learning models in enhancing algorithmic trading strategies across various asset classes. The study's findings reveal that SVR, RF and NN models achieve good predictive accuracy and robustness, outperforming the Buy&Hold strategy under certain conditions.

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Chapter 2

Introduction

In their introduction, Prasad and Seetharaman [1] outline the transformative impact of digital technology on stock trading, moving from in-person transactions within designated spaces or over the phone to the utilization of computers and specialized platforms by investors. Digital tools have improved this shift, which has enabled analysts to generate forecasts, significantly aiding investors in making informed decisions on buying or selling stocks.

Additionally, as information technology advanced and computing skills improved, traders started to leverage computer programming to automate their trading strategies. This automation enabled them to profit from short-lived trading signals, a practice known as algorithmic trading. In this approach, trades are executed automatically by a computer script.

Tracking stock prices accurately is challenging due to their unpredictable nature and frequent pattern changes, rendering current strategies quickly outdated. Consequently, there's a continuous demand for research in the trading domain to capitalize on stock market opportunities. Recently, researchers in computer science and mathematics have turned their attention to artificial intelligence (AI) for generating trading signals. AI, a complex and in-demand skill set, is rapidly evolving and becoming extensively used in financial markets and big data analytics. Technically, AI encompasses machine learning (ML), with ML including deep learning (DL) as a subset. It's crucial to explore the role of machine learning within the stock market context to understand its impact on generating trading signals.

2.1 Initial situation

The advent of algorithmic trading, henceforth referred to as Algo-Trading, has revolutionized the landscape of financial markets. By leveraging complex algorithms, Algo-Trading automates decision-making processes, utilizing real-time market data analysis to optimize investment decisions and eliminate the influence of human emotions. A striking illustration of its dominance is seen in the Forex market, where, as reported by Kissell [2], approximately 92% of trades in 2019 were executed via trading algorithms, highlighting the critical role algorithmic strategies play in modern trading environments.

Despite the growing prominence of Algo-Trading, there exists a significant gap in research, particularly concerning the assessment of the effectiveness of Machine Learning based trading strategies, such as Random Forest (RF), Support Vector Machine

(SVM), and Neural Network (NN), as compared to traditional investment strategies like the Buy&Hold approach. This gap underscores the imperative for a comprehensive evaluation of these innovative trading methodologies to discern their efficacy and potential advantages over conventional strategies, while also addressing the reproducibility issue prevalent in many studies, where the lack of shared seeds, hyperparameters, and detailed implementation steps undermines the ability to verify and build upon research findings. Additionally, the issue of reproducibility poses a significant challenge within ML-based trading strategies. Many ML models, including those mentioned, always initiate their learning process from randomly generated starting points. This randomness leads to variations in model performance, even when the same algorithm is applied to identical data under seemingly the same conditions. Such variability complicates the assessment of the 'model effectiveness', as replicating results exactly can be difficult, if not impossible, without stringent control over the initialization and training processes. Addressing this reproducibility challenge is crucial for advancing the credibility and reliability of ML-based trading strategies.

Publicly available reproducible research on this subject is sparse, owing to market efficiency concerns. Nevertheless, we aim to examine this area, seeking to bridge the knowledge gap and put the spotlight on the utility and performance of ML-based algorithmic trading strategies.

2.2 Research Question

This study focuses on evaluating the effectiveness of trading strategies based on ML compared to the traditional Buy&Hold strategy. It explores whether using advanced algorithms for trading can offer a competitive edge in improving investment returns. Acknowledging the intricate and multifaceted nature of financial markets is essential, especially considering that most financial data does not adhere to independent and identically distributed characteristics. This context underscores the importance of evaluating how ML strategies compare with the established Buy&Hold method.

The research breaks down into two main areas for detailed examination:

Performance Evaluation:
This part investigates whether ML algorithms can outperform the Buy&Hold strategy in financial terms. It includes a quantitative comparison of the returns each approach generates over time and under various market conditions. Rather than just seeking a yes-or-no answer, this section aims to identify which particular ML models offer superior performance. This comprehensive analysis is not only crucial for identifying which ML models outperform the Buy&Hold strategy, but also essential for building investor trust. Investors are often wary of "black-box" models. Therefore, providing clear explanations of how these algorithms work can enhance their credibility and adoption in the financial sector. With the help of Linear Parameter Data (LPD), as introduced by Wildi [3], such strategies can be made transparent. This paper will not go into further detail on the LPD implementation and meaning.

Risk and Limitations Assessment:
This section focuses on the risks and possible drawbacks of using ML for trading. ML algorithms rely on complex data patterns and predictions, which may not always foresee market volatility or rare, significant events. This investigation looks into the stability and reliability of ML strategies and their potential weaknesses, including

the risk of overfitting, and how well these algorithms adapt to new information. Furthermore, making sure the investors understand the risks involved in trusting the predictions blindly is a bad idea.

By addressing these areas, the study aims to provide a thorough evaluation of ML-based trading strategies compared to the Buy&Hold method. It is important to note that much of current trading still relies on linear models due to their transparency and ease of explainability. The results are intended to enrich discussions on incorporating machine learning into financial trading, potentially offering insights into their applicability and benefits over traditional methods.

2.3 Research Objectives

The goals of this thesis are:

1. Evaluate the performance of ML-based trading strategies against the traditional Buy&Hold approach.

2. Identify and understand the risks and limitations of applying ML in trading strategies.

3. Create a reproducible framework for prediction of financial time-series.

Through a combination of literature review, data analysis and modeling of chosen assets e.g commodities, stocks, cryptocurrencies, this thesis aims to provide a detailed examination of ML-based trading strategies within the financial sector, while also ensuring that the results can be reproduced and understood.

We choose these objectives due to our interest in combining ML methods and financial time-series and to expand on available literature in this area. The goal of this project is to create an explainable and reproducible framework to use and expand upon and create predictions for varying financial time-series.

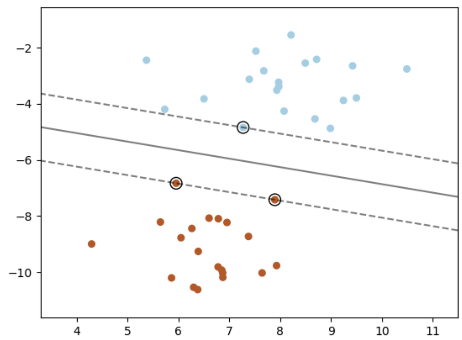
Chapter 3

Theoretical Foundation

In our thesis, we have adopted an analytical approach utilizing Python as a programming language. This strategic choice stems from the unique strengths and specialized tools that Python offers. From the extensive machine learning libraries, such as scikit-learn [4]. Our selection of models for data processing and analysis leverages open-source solutions, prioritizing transparency, reproducibility. The forthcoming sections will detail the specific models and analytical techniques employed. They range from Support Vector Machines, Random Forests and Neural Networks.

3.1 SVM

The theoretical foundation of Support Vector Machines (SVMs), as detailed in the work by Cortes and Vapnik [5], presents a overview of a learning machine designed for two-group classification problems. SVM conceptually maps input vectors non-linearly to a very high-dimensional feature space, where a linear hyperplane is constructed. This unique approach enables the SVM to exhibit high generalization ability, even in cases where the training data cannot be separated without errors.



A support vector machine creates a hyperplane in a space of high dimensions. This technique is applied for various purposes including classification and regression. Essentially, the most effective separation between classes is accomplished by the hyperplane that maintains the greatest distance from the nearest training data points across all classes, known as the functional margin. Generally, a wider margin correlates with a reduced error rate in the model's predictions. The accompanying figure

?? illustrates the decision-making process for a problem where the classes can be separated linearly, highlighting three specific samples located on the margin boundaries, which are called support vectors.

3.1.1 SVR

As Smola and Schölkopf [6] pointed out, Support Vector Regression (SVR) builds upon the theoretical foundation of SVMs by extending the principles of margin optimization from classification to regression tasks. The primary goal in SVR is not just to fit a model that predicts targets accurately but to do so with a specified precision, controlled by the parameter epsilon ϵ . SVR is introduced as an extension of SVMs for function estimation, focusing on finding a function that deviates from the actual observed targets by a margin not greater than ϵ for all training data points, while also being as flat as possible. This concept of "flatness" translates to finding a model with a small norm, which in the context of SVR means minimizing the coefficients of the model in the feature space. The notion of ϵ-sensitive loss is central to SVR, where errors are tolerated as long as they are within the ϵ margin, see Figure 3.1, beyond which they are penalized linearly. This approach to loss known as the ϵ-insensitive loss function, encourages models that fit the data within a specified precision without overfitting.

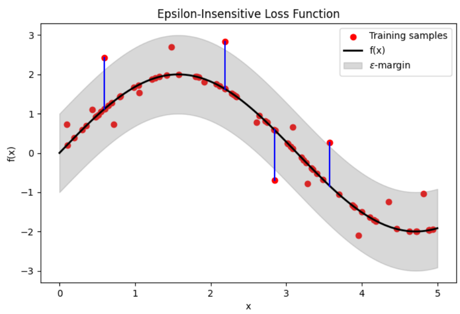


FIGURE 3.1: ϵ-insensitive loss function in SVR, showing the tolerated deviations within the ϵ margin (gray area) and linear penalties for outliers (blue lines).

In summary, SVR extends the SVM framework from classification to regression, emphasizing the creation of models that generalize well by maintaining a balance between model complexity and fitting precision. Through the use of kernels, SVR tackles nonlinear relationships effectively, and its formulation as a convex optimization problem ensures that the solutions are optimal and unique.

3.1.2 Hyperparameters

The performance and effectiveness of SVM and SVR models are significantly influenced by their hyperparameters. Selecting the appropriate hyperparameters is crucial for optimizing the model's ability to generalize well to unseen data. Key hyperparameters for a SVR include:

- **Kernel Type:** The choice of kernel (e.g., linear, polynomial, radial basis function, sigmoid) determines the transformation of the input data into a higher-dimensional space. The kernel type affects the model's capacity to handle nonlinear relationships between features and the target variable.

- **C (Regularization parameter):** Controls the trade-off between achieving a low error on the training data and minimizing the norm of the coefficients. A larger C value may lead to a more complex model by allowing fewer errors, whereas a smaller C encourages a simpler model with a larger margin.
- **Epsilon (ϵ):** Relevant in SVR, it defines the epsilon-tube within which no penalty is associated in the training loss function with points predicted within a distance ϵ from the actual value.

3.1.3 Limitations

While SVMs offer powerful modeling capabilities, they are not without limitations:

- **Scalability:** SVMs tend to be computationally intensive, especially with large datasets, due to the quadratic complexity in the number of samples. This can make the training time impractically long for large-scale problems.
- **Kernel Selection:** The performance of SVMs is heavily dependent on the choice of the kernel. Selecting the appropriate kernel and tuning its parameters can be non-trivial and requires extensive experimentation, which is not further inspected in this work, as we focus on reproduciblity.
- **Interpretability:** SVM models, especially with non-linear kernels, can be difficult to interpret compared to more straightforward models such as linear regression. This can be a shortcoming in applications where understanding the model's decision-making process is important. By limiting the SVM to a 2D space, the workings can be properly explained.
- **Sensitivity to Feature Scaling:** SVMs are sensitive to the scale of the input features. Hence, proper preprocessing of the data, including normalization, is essential for the model to perform optimally.

Despite these inadequacies, SVMs remain popular choices due to their robustness and effectiveness in many classification and regression tasks, particularly when the data has a clear margin of separation or when dealing with high-dimensional spaces.

3.2 Decision Tree

The conceptual underpinnings of Decision Trees, as initially formulated in the works by Breiman et al. [7], lay the groundwork for an intuitively accessible approach to classification and regression tasks. At their core, Decision Trees are non-parametric models, which iteratively partition the feature space into a hierarchy of simpler regions. By employing a top-down, greedy approach known as recursive binary splitting, shown in Figure 3.2. These models assist the identification of variable thresholds that return the most effective split in terms of some impurity criterion, like Gini impurity or entropy for classification tasks. In regression tasks this is typically the reduction of the variance.

A Decision Tree can be visualized as a flowchart-like structure where each internal node represents a "check" on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label or a continuous outcome. The paths from root to leaf encapsulate classification rules or regression predictions that can be easily interpreted. This intrinsic interpretability is a significant advantage of Decision Trees, often making them a preferred choice in domains where understanding the decision-making process is as crucial as predictive accuracy as it is in the financial sector.

In practice, Decision Trees delineate a decision boundary by dividing the feature space into regions with homogeneous labels or close response values. Despite their simplicity, these boundaries are capable of modeling complex non-linear interactions through the aggregation of several decision splits. The decision tree depicted in Figure 3.2 offers a snapshot of such a model. It demonstrates a two-level hierarchical division using lagged log-returns from Bitcoin as input features. At the first node, the model queries Lag 6, followed by a further query on Lag 4, to categorize data points. This process encapsulates the tree's predictive logic based on the provided training data characteristics. However, decision trees can grow to be overly intricate, risking overfitting to the training dataset. Thus, tree pruning techniques are essential to simplify the model, enhancing its ability to generalize to unseen data. In the previously mentioned figure, the pruned tree illustrates a streamlined decision-making process with a focus on two critical lags, which helps to avoid potential overfitting.

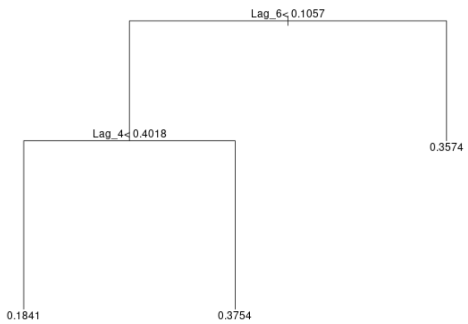


FIGURE 3.2: Pruned Decision Tree using Lag 6 and Lag 4 to predict Bitcoins closing price, highlighting model simplicity and focus to prevent overfitting.

3.2.1 Random Forest

Building upon the foundation laid by Decision Trees, the Random Forest algorithm incorporate the simplicity of Decision Trees with ensemble learning's[1] robustness. Initially introduced by Breiman [9], Random Forest constructs a multitude of decision trees at training time and outputs the mode of the classes in classification tasks or mean prediction in regressions of the individual trees. Random Forest effectively addresses the tendency of Decision Trees to overfit the training data by introducing randomness in two ways: each tree is built from a random sample of the data, and a subset of features is randomly selected at each split point within a tree.

This ensemble method enhances predictive performance by capitalizing on the strength of multiple learners while mitigating their individual weaknesses. In a Random Forest, each tree operates as an independent predictor, with their collective decisions leading

[1] "Ensemble learning combines multiple learners to improve predictive performance" [8]

to a single, more accurate and generalized result. The randomness injected into the model building phase ensures that the trees are decorrelated, thereby reducing the variance without substantially increasing bias, a concept known as the bias-variance tradeoff.

The Random Forest algorithm is particularly adept at handling high-dimensional datasets and can maintain accuracy even when a large proportion of the data is noisy. Its ability to run in parallel makes it computationally efficient, and it retains the interpretability feature of Decision Trees to some extent through variable importance measures. However, the ensemble nature of the model does lead to a reduction in the interpretability compared to a single Decision Tree. Despite this, Random Forests have proven to be a versatile and powerful predictive modeling technique widely used across various domains like Finance, Healthcare, E-Commerce and others.

3.2.2 Hyperparameters

The efficacy and performance of Random Forest models are deeply influenced by their hyperparameters. Careful tuning of these hyperparameters is key to enhancing the model's prediction accuracy and its ability to generalize effectively to unseen data. Due to the reproducibility focus we won't tune any of our models to not falsify the results on the testset, since it's what we would optimize for. Principal hyperparameters for a Random Forest include:

- **Number of Trees:** Refers to the number of trees in the forest. Increasing the number of trees generally improves model performance and makes the predictions more stable, but it also makes the computation more expensive in terms of time and resources.

- **Maximum Depth:** The maximum depth of each tree. Deeper trees can model more complex patterns by creating more splits, but they also increase the risk of overfitting. Not setting this parameter allows the trees to expand until all leaves are pure or contain less than the minimum samples required to split further.

- **Minimum Samples Split:** The minimum number of samples required to split an internal node. Higher values prevent the creation of nodes that contain too few samples, potentially reducing overfitting but could also prevent the model from learning complex patterns.

- **Minimum Samples:** The minimum number of samples required to be at a leaf node. Setting this higher forces more conservative learning patterns, also affecting the model's ability to capture intricate patterns.

- **Bootstrap:** Whether bootstrap samples are used when building trees. If False, the whole dataset is used to build each tree. Enabling bootstrap sampling helps in adding randomness to the model, potentially improving accuracy through reducing variance.

3.2.3 Limitations

The Random Forest algorithm, while versatile and powerful, is not without its weaknesses. Understanding these constraints is essential for effectively applying the model to real-world problems. Key limitations include:

- **Model Complexity and Interpretability:** Although Random Forest maintains some level of interpretability through feature importance scores, the ensemble nature of the model significantly reduces its overall interpretability compared to a single Decision Tree. The complexity of having multiple trees makes it challenging to provide a clear and straightforward explanation of how specific predictions are made.

- **Overfitting with Noisy Data:** Despite being more resistant to overfitting compared to individual decision trees, Random Forest models can still overfit particularly noisy datasets. The randomness introduced in the model can sometimes lead to a reduction in the bias at the expense of increasing the variance, especially if the noise level in the data is high.

- **Predictions Beyond Training Data:** Random Forest models, by their nature, cannot extrapolate predictions beyond the range observed in the training data. This restriction stems from the fact that predictions are made based on the aggregation of outputs from trees that rely on the training data feature space.

Despite these boundaries, Random Forest remains a highly effective tool for many predictive tasks across various fields. Awareness and careful management of its limitations allow practitioners to leverage the algorithm's strengths, such as handling imbalanced datasets, providing feature importance insights, and maintaining robustness to outliers.

3.3 Neural Network

The foundational principles of Neural Networks derive inspiration from the biological neural networks that constitute animal brains, an analogy that underpins their design and operation. This conceptual framework was progressively refined through seminal research, notably by pioneers such as McCulloch and Pitts [10], who introduced the first mathematical model of a neural network. If we define $z_t := b + w_1 x_{1t} + w_2 x_{2t} + \ldots + w_N x_{Nt}$, the formula for the simple activation function is given in 3.1. Which results in two states, the neuron 'fires' or it is 'resting' in dependency on $z_t > (\leq) 0$

$$f(z_t) = \begin{cases} 1, & \text{if } z_t > 0 \\ 0, & \text{otherwise} \end{cases} \tag{3.1}$$

Neural Networks are structured as a collection of nodes, or neurons, arranged in layers: an input layer that receives the data, one or more hidden layers that perform computations, and an output layer that delivers the prediction or classification.

Neural Networks are inherently parametric models, characterized by their ability to learn complex and non-linear relationships between inputs and outputs through a process known as training. Training involves adjusting the weights and biases, which are illustrated in 3.3, of the network based on the differences between the actual and predicted outputs, typically using a method called backpropagation. This method calculates the gradient of the loss function with respect to each weight and bias, iteratively improving the model through gradient descent or variants thereof as stated by Prince [11].

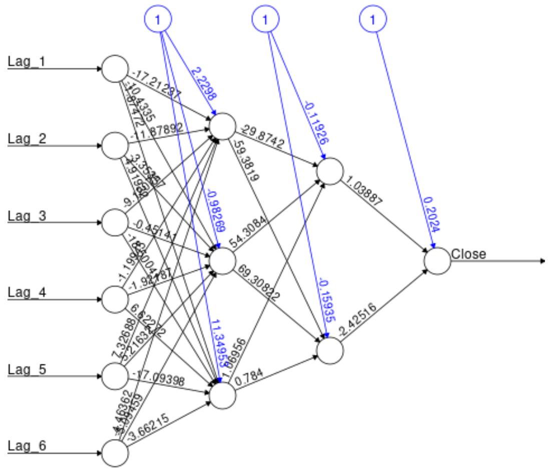


FIGURE 3.3: Feedforward Neural Network architecture employed to predict Bitcoins closing price. The network comprises an input layer with features, two hidden layers for feature transformation, and an output layer for the final prediction.

The architecture of a Neural Network resembles a dense mesh, where each neuron in one layer is connected to every neuron in the subsequent layer, facilitating a rich, layered complexity of learned representations. These connections, or weights, are the heart of the network's learning capability, enabling the model to capture both simple and intricate patterns within the data.

According to Schmidhuber [12] Neural Networks are especially potent in tasks that involve high-dimensional data, such as image recognition, natural language processing, and time series analysis. Their ability to automatically and adaptively learn spatial hierarchies of features, a process analog to feature engineering in traditional machine learning, sets them apart as a powerful tool in the machine learning arsenal.

However, the strength of Neural Networks also brings forth challenges, including the risk of overfitting to training data, especially when the network architecture is overly complex relative to the simplicity of the task or the amount of available data. To mitigate overfitting, various regularization techniques, such as dropout, presented by Srivastava et al. [13] and early stopping presented by Prechelt [14], are employed. Additionally, training Neural Networks can be computationally intensive, requiring sophisticated hardware like GPUs for efficient computation.

Despite these challenges, the versatility and efficacy of Neural Networks have been demonstrated across a wide range of applications, making them a cornerstone of contemporary machine learning and artificial intelligence research. Their ongoing development and application continue to push the boundaries of what is computationally achievable, reflecting the dynamic interplay between theoretical insights and practical advancements in the field [12].

3.3.1 Hyperparameters

Neural Network performance and generalization largely depend on the defined hyperparameters. Key hyperparameters include:

- **Learning Rate:** Determines the step size at each iteration while moving toward a minimum of the loss function. Too large of a learning rate can cause overshooting, while the learning rate being too small leads to slow convergence.
- **Number of Epochs:** Represents the number of times the learning algorithm will work through the entire training dataset. More epochs can improve learning until a point of overfitting.
- **Batch Size:** The number of training examples utilized in one iteration. A smaller batch size often provides a regularizing effect and lowers generalization error.
- **Number of Layers and Neuron Count:** Depth and width of the network, affecting its ability to represent complex functions. Requires careful balancing to match the problem's complexity. If there are too many Neurons and Layers, the training data gets memorized, causing overfitting. The Neural Network does not generalize in this case.
- **Activation Functions:** Non-linear functions like ReLU or Sigmoid that determine the output of a node given an input or set of inputs. The type of function chosen decides how the model treats outputs - in the case of ReLU, the model sets anything below zero to zero.

Selecting the appropriate hyperparameters for Neural Networks is essential to construct a resilient model capable of accurate predictions while maintaining a balance between bias and variance [15].

3.3.2 Limitations

Despite their adaptability, Neural Networks have their flaws including the following:

- **Random Initialization:** Numerical optimizations have to start at randomly initialized points, and due to the nature of numerical operations can end in different minima, accordingly.
- **Data Dependency:** They tend to require large amounts of data to perform optimally, which can be a constraint in data-scarce scenarios.
- **Transparency:** Often criticized as black boxes, they provide limited insight into how they derive their predictions.
- **Computation Cost:** NNs necessitate significant computational resources, particularly during training with deep architectures.
- **Overfitting Risk:** They are prone to overfitting, although this can be mitigated with previously mentioned regularization techniques.

Understanding these deficiencies is vital for effective Neural Network application in machine learning tasks.

Chapter 4

Data

The foundation of any empirical analysis lies in the quality and relevance of the data it utilizes. In the realm of financial markets, the rapid evolution of assets, coupled with the advent of new technologies, has broadened the spectrum of investment opportunities. This diversity necessitates a comprehensive dataset that not only spans traditional assets like stocks and precious metals, but also includes modern financial investment opportunities such as cryptocurrencies. The data chapter of this research document outlines the precise process undertaken to gather the historical time series data of a selected group of assets. These assets have been chosen to represent a cross-section of the financial market, highlighting the contrast and comparison across different asset classes and the potential for technological advancements in trading strategies. By leveraging the yfinance Python library, we have sourced historical data from Yahoo Finance, a reputable global provider of financial information. This chapter details our systematic approach to data acquisition and the specific features of the collected data.

4.1 Data Source

In this research, we acquired historical time series data for a diverse portfolio of assets utilizing yfinance. Yfinance is a tool designed to download historical market data from Yahoo Finance, which offers comprehensive global stock market quotes. The selection of these assets was based on their significance and varied nature, encompassing cryptocurrency, technology stock, and a precious metal, to provide a broad perspective on different market conditions and investment possibilities.

We used yfinance, which is publicly available and well-documented in its GitHub repository, to retrieve exactly a decade of daily market data. This library provides a convenient interface with Yahoo Finance's API, allowing us to efficiently import financial data into the Python environment.

The downloaded datasets include the following features: Date, Open, High, Low, Close, Volume, Dividends, and Stock Splits. Our analysis primarily focuses on the Date and Close features, as these are most relevant to assessing price trends and investment returns and thus making them the focus of our data acquisition. Further details of the datasets are presented in Table 4.1. Following the acquisition, the datasets were stored in .csv files, ensuring they were easily accessible for subsequent processing and analysis.

By using yfinance and Yahoo Finance as the backbone for our data collection, we

Asset	Data Frequency	From	To	Observations	Currency
MSFT	daily (weekdays)	2014-04-28	2024-04-24	2518	USD
XAU	daily (weekdays)	2014-04-28	2024-04-26	2518	USD
BTC	daily (with weekends)	2014-09-17	2024-04-26	3463	USD

TABLE 4.1: Data Specifications for the examined assets

Date	Open	High	Low	Close	Volume	Dividends	Stock Splits
2014-03-10	32.17	32.18	31.94	32.02	19006600	0.0	0.0
2014-03-11	32.07	32.37	31.94	32.20	25216400	0.0	0.0
2014-03-12	32.01	32.54	32.00	32.41	30494100	0.0	0.0

TABLE 4.2: Daily trading information of MSFT including opening, highest, lowest, and closing prices, alongside trading volume, dividends issued, and stock splits, the prices are rounded to two decimals and the date feature was adjusted to have a compact table

secured a reliable and reproducible dataset that is vital for the integrity of our time series analysis. This approach ensured that our research was grounded on a robust set of historical data, encompassing various market conditions and asset classes. We decided to look into three different asset classes particularly equities, commodities and alternatives. This decision was made to capture the breadth of the market and account for possible differences between these asset classes.

4.2 Data Structure

This section delineates the underlying data structure employed throughout the current research, as depicted in Figure A.1. In pursuit of maintaining clarity and facilitating reproducibility, the data structure has been designed to be as straightforward and transparent as possible.

4.3 Data Features

Each assets daily performance is encapsulated through Open, High, Low, and Close prices, alongside Volume, Dividends, and Stock Split data. For this study we are going to concentrate ourselves only on the daily Closing Price. Due to the fact that we make our predictions solely based on the close. The other features are not the focus of this study, they are still important for understanding the asset's performance and may be used in future analyses. Therefore, the features are listed for completion purposes. A preview of the data can be observed in Table 4.2.

4.3.1 Date

The assets under consideration exhibit divergent timestamps, attributable to the geographical locations of their listings. Specifically, MSFT and XAU are traded in New York on the NASDAQ and COMEX, respectively, with a standard timestamp of UTC 05:00:00, adjusting to UTC 04:00:00 during daylight saving time. In contrast, Bitcoin, which is traded on a continuous 24/7 basis, have its closing prices uniformly recorded at UTC 00:00:00, irrespective of daylight saving adjustments. Given that our models do not account for the variations in closing times due to geographical listings and daylight saving time adjustments. This paragraphs purpose is solely to ensure transparency.

Given the reliance on daily data for the scope of this research, the specific timestamps, while indicative of the assets standardized recording conventions, become secondary to our analytical objectives. This methodology is underpinned by the rationale that the most salient information for our study is captured in the closing prices [16], which are aggregated on a daily basis. These daily closing prices are instrumental in representing the day-to-day fluctuations and overarching trends of the assets under investigation. Consequently, for the purposes of this analysis, the exact timing of data capture within each 24-hour cycle is rendered non-essential. Our focus is squarely on the closing prices, as they encapsulate the market sentiments and movements we aim to analyze. In comparison, the opening price is more of an indicator of how the day will proceed.

4.3.2 Prices

Open

The price at which an asset starts trading upon the market's opening on any given day, setting the initial market sentiment.

High

The highest price point reached by the asset during the trading day. This represents the maximum price that buyers were willing to pay for the asset on the given day.

Low

The lowest price at which the asset traded during the trading day. This represents the minimum price that sellers were willing to sell the asset for on that particular day. The low price point indicates the lowest valuation the market placed on the asset within the trading period.

Close

The closing price refers to the final price at which an asset is traded during its respective trading session. For equities such as MSFT or commodities like XAU this figure represents the last transaction price before the market closes. In the realm of cryptocurrencies, which operate in a market devoid of closing hours, the closing price is conventionally recorded at UTC 00:00:00, marking the end of one trading day and the beginning of the next.

4.3.3 Volume

The volume of trades executed during the day offers insights into the intensity of market activity. High volumes can indicate strong interest in the asset, while low volumes may suggest a lack of engagement, affecting the assets liquidity and volatility.

4.3.4 Dividends

Dividend data, while indicative of a company's profitability and its distribution policy, can influence the stock's valuation on and around the ex-dividend date.

4.3.5 Stock Split

Stock split information can be important for historical data accuracy. Splits can significantly change the stock price and volume.

Chapter 5

Methods

This project embarked on a comprehensive methodology, starting with a literature review and the current state of affairs in time series prediction and ending with a quantitative analysis of various financial time series. The literature review aimed to discover the current state of research, while providing an informed information base for the empirical investigation. The subsequent quantitative evaluation leveraged advanced statistical and machine learning techniques to analyze the data, the specifics of which are demonstrated in this section and visually summarized in Figure 5.1. The datasets employed in this analysis are detailed in Chapter 4.

FIGURE 5.1: Overview of the process pipeline

5.1 Tools

The preprocessing and analysis of data were predominantly conducted using Python, leveraging Pandas for data wrangling and Matplotlib for data visualization. Pandas provided a robust framework for reading, cleaning, and structuring data, while Matplotlib facilitated the initial exploration of the data through visual means. Furthermore, statistical analysis and model development were supported by NumPy, Statsmodels and Scikit-learn, with the first aiding in numerical operations, the second in statistical tests and the third in applying machine learning algorithms. To save and keep track of the different models we used joblib. In the last step of the process we wrote the results into a json file.

5.2 Data Preprocessing

Data preprocessing forms the base pillar of our analytical approach, ensuring the integrity and usability of the financial time series data for subsequent analysis. This phase encompasses various steps for preparing the raw data, so that the modeling delivers comprehensive results.

5.2.1 Reading and Cleaning Data

The initial step involved reading the financial data, which was stored in CSV format within a designated directory detailed in A.1. This process was automated to iterate over the dataset, identifying the file corresponding to the specific asset. The data was loaded into a Pandas DataFrame, with the 'Date' column converted to datetime format and set as the index, ensuring a temporal order essential for time series analysis.

5.2.2 Visualization for Initial Analysis

To gain insights into the data, visualizations of the closing prices, alongside their logarithmic transformations and differences, the so called log-returns are done. They can be calculated as follows $X_t = diff(log(X_t))$. Log-returns highlight the variability in price changes over time. Additionally the logarithmic transformed volume is displayed to assess trading activity intensity. This exploratory step is illustrated in Figure 5.2, facilitated an intuitive understanding of the assets price movements and volatility over time.

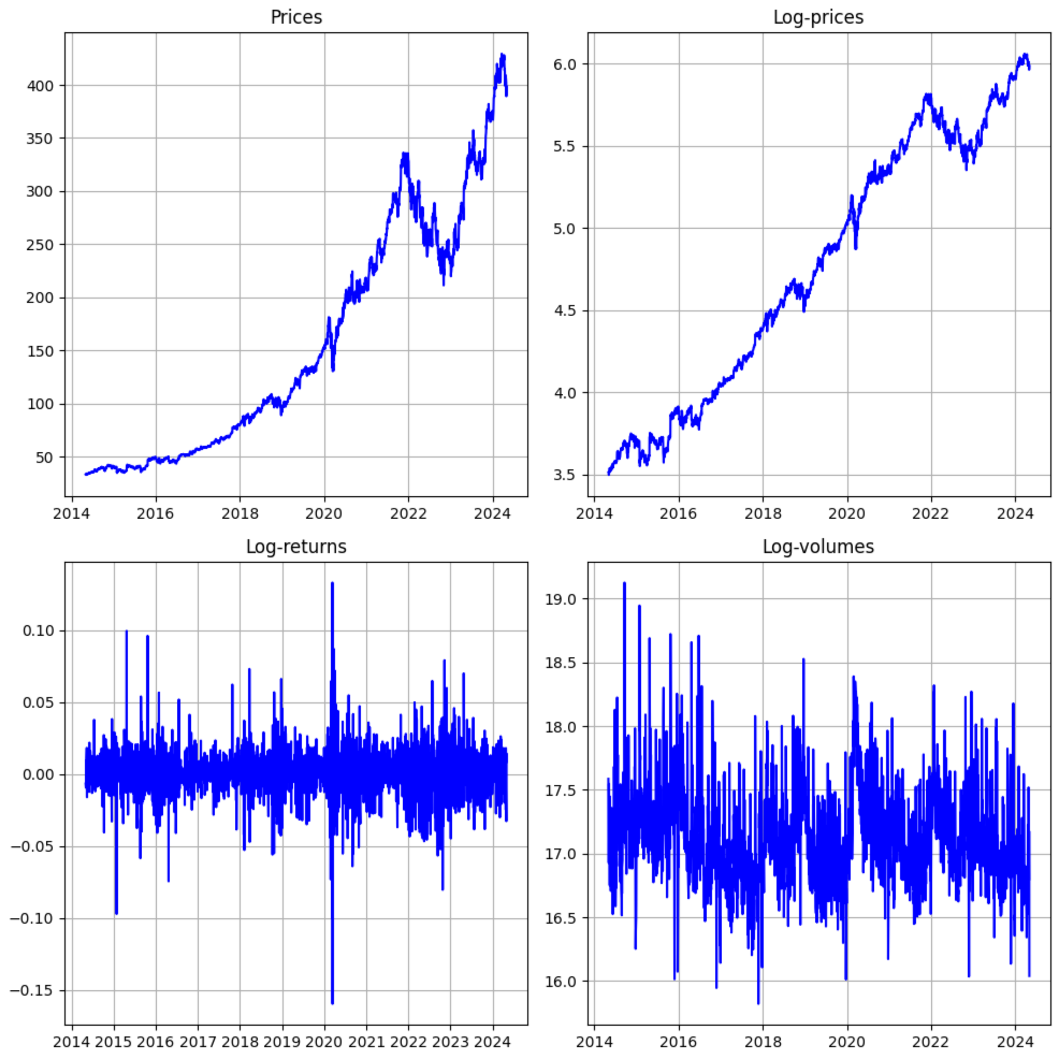


FIGURE 5.2: Four-panel visualization of MSFT Prices, Log-prices, Log-returns and Log-volumes.

5.2.3 Auto correlation Function

The auto correlation function (acf) at lag k measures the correlation between values in a time series separated by k periods. Mathematically, it is defined as the correlation

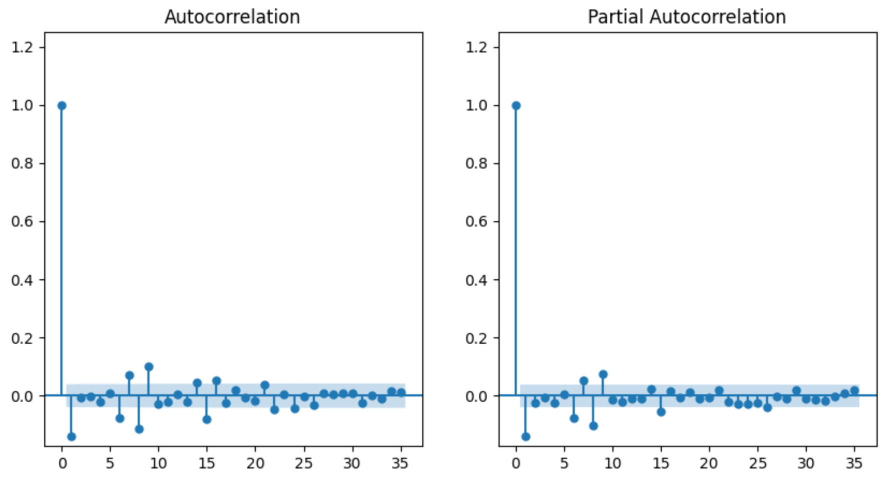


FIGURE 5.3: ACF and PACF of MSFT, the significant lags in the ACF are 1,6,7,8,9,14,15,16,22 and 24 suggesting that there are pattern in the data at these intervals. In order to keep the model as simple as possible a parsimonious approach has been taken.

between x_t and $x_{t \pm k}$, where x_t is the value of the time series at time t and $x_{t \pm k}$ is the value of the time series at time $t \pm k$. The acf is a tool for identifying the dependency structure within time series data and is useful in the context of time series forecasting, where it can help in determining the appropriate number of lags to use in our model configurations.

In our analysis, we computed the acf for the logarithmic returns of the closing prices. The acf was plotted alongside the partial auto correlation function to provide a view on the auto regressive, as well as the moving average dependencies. In the Figure 5.3 we used $\frac{1}{\sqrt{n}}$ to compute the standard error for the acf which is part of the statmodels toolbox, enabling the identification of significant lags. If the acf value at a particular lag exceeded the 95% confidence interval bounds, the lag was considered significant. In order to determine the number of lagged input features for the model, we used the first significant value of the acf when the model was set on auto, rather than a fixed given lag.

5.2.4 Feature Engineering

A crucial component of the preprocessing pipeline was the creation of lagged features, intended to capture temporal dependencies in the price movements. By generating lags of the log-differenced closing prices, the analysis aimed to utilize past values as predictors for future price trends, a common practice in time series forecasting. The creation of lags is in the auto lag dependent on the outcome of the acf analysis mentioned in 5.2.3. If none of the lags were significant then we have used only one lag. For the assets traded on weekdays only, we use the following lags: [1,5,10,15,20, auto], where auto is the lag number which the ACF plot has deemed relevant to the problem. We chose these lags because they correspond to the weekly movements in the asset prices. For example, a lag of 5 corresponds to the price movement from the previous week, while a lag of 10 corresponds to the price movement from two weeks ago.
For the assets traded on weekends as well, namely bitcoin, the following lags are used:

[1,7,14,21,28, auto], where auto is again the number which the acf plot has deemed relevant to the problem. This decision origins from the urge in finding out if there is an improvement of our predictions if we feed our models more or less data compared with only the relevant data according to the acf.

Date	Lag_0	Lag_1	Lag_2	Lag_3	Lag_4	Lag_5	Lag_6
2024-01-01	0.044022	0.002565	0.001365	-0.012474	-0.018938	0.021462	-0.025374
2024-01-02	0.017743	0.044022	0.002565	0.001365	-0.012474	-0.018938	0.021462
2024-01-03	-0.048065	0.017743	0.044022	0.002565	0.001365	-0.012474	-0.018938

Table 5.1: Lagged values of the log-returns for BTC. Each row represents a different day and shows the created features.

5.3 Data Splitting

For the purpose of training and evaluating the predictive models, the dataset was split into training and test subsets. This division was based on specific years, with asset data from certain years being allocated to the training set and others to the test set, allowing an out-of-sample assessment of the predictive capabilities of the models. In the table A.1 we used the entire dataset and made the splits accordingly to make a profound analysis of Bitcoin over the years. For the other assets we choose to make the splits in line with the table 5.2. We used in the initial splits a year of training data to predict the subsequent year. In a later stage we moved two respectively to three years of training to predict the consecutive year. Our decision to contain only the recent past instead of using the full dataset comes from the fact, that in time series prediction the recent past carries the most valuable information about the near future according to the naive method [16]. Additionally, we acknowledge that the 2020s have been marked with events that have a high impact on the market, such as the COVID-19 pandemic, the war in Ukraine, and more recently the invasion of Gaza.

Split No.	Training Set	Test Set
1	2019	2020
2	2020	2021
3	2021	2022
4	2022	2023
5	2023	2024
6	2018, 2019	2020
7	2019, 2020	2021
8	2020, 2021	2022
9	2021, 2022	2023
10	2022, 2023	2024
11	2017, 2018, 2019	2020
12	2018, 2019, 2020	2021
13	2019, 2020, 2021	2022
14	2020, 2021, 2022	2023
15	2021, 2022, 2023	2024

Table 5.2: Overall Training and Test Set Splits

5.4 Data Scaling

Initially, we considered standardizing the scale of the data features to improve model performance, MinMax scaling: $x_{\text{scaled}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$ This normalization process adjusts the feature values to a scale between 0 and 1 without distorting differences in value range. However, after careful consideration, we decided not to use MinMax scaling for our time series prediction task.

The reasons for avoiding MinMax scaling are potential problems with data leakages. In our case using MinMax scaling inadvertently encode future information, which caused the model have access to information that it should not have while training. To prevent this data leakage, we decided to use no further scaling for our data as they are log-returns. However, this decision restricts the usage of certain activation functions for the NNs, such as logit, which cannot fit negative data. As a result, ReLU was used to circumvent this restriction in the case of NN.

5.5 Model Initialization

To address the issue of numerical optimization in NNs, SVR, and RF, one common approach is to set seeds and use their initialization of the model. This helps to avoid getting stuck in local minima during the optimization process. In our study, we created a hundred random initiated models for each model composition and algorithm to ensure that we were not biased towards a particular set of initialization. This allowed us to explore the space of possible solutions more thoroughly and increase the likelihood of finding a global minimum. Additionally, averaging the predictions of the hundred models could help to reduce the variance and improve the robustness of the results across all algorithms.

5.6 Evaluation

5.6.1 Benchmark

To ensure a fair comparison of our models across different assets, we've established a Buy&Hold benchmark. This benchmark is based on the straightforward investment strategy of purchasing an asset at a designated starting point (A) and selling it at a specific endpoint (B), typically from the start to the end of a calendar year. This approach provides us with a simple but challenging benchmark, against which the performance of our models can be evaluated.

5.6.2 Sharpe Ratio

The Sharpe Ratio [17] is a metric conceived within Markowitz's mean-variance framework, serving as a simplified measure for investment performance by combining risk and return into a single figure. This ratio is particularly effective when comparing multiple investments, as it evaluates the excess return per unit of risk. The calculation subtracts the risk-free rate from the expected asset return and divides it by the assets standard deviation outlined in the formula 5.1.

$$\text{Sharpe Ratio} = \frac{r_p - r_{rf}}{\sigma} \tag{5.1}$$

It's important to note that while the Sharpe Ratio can be a powerful tool for comparison, it has limitations. It does not account for the skewness and kurtosis of the return distribution.

In our scenario, assuming a risk-free rate of zero can streamline the comparison process across various strategies by focusing solely on the generated excess returns shown in formula 5.2. We are aware that this does not reflect the actual investment environment.

$$\text{adapted Sharpe Ratio} = \frac{r_p}{\sigma} \tag{5.2}$$

5.6.3 Hit-Rate

This section details how the Hit-Rate is used to evaluate the performance of predictions in financial time series. An important consideration is the specific financial metric being predicted. For instance, consider predicting a assets closing price over a period of five days. A favorable outcome is defined as the predicted direction of price change matches the actual direction, meaning the values in the "True" and "Predicted" columns are the same. In Table 5.3 we present an example.

Date	True	Predicted
2021-01-01	1.0	1.0
2021-01-02	1.0	1.0
2021-01-03	1.0	1.0
2021-01-04	-1.0	1.0
2021-01-05	1.0	-1.0

TABLE 5.3: The signum of the log-returns represent the actual direction and the predicted direction the asset BTC will take. The first three correspond to one another, while the last two predict a wrong direction of the asset direction.

Inserting these results into the formula, we calculate the hit ratio as follows:

$$\text{Hit Ratio} = \left(\frac{\text{Number of favourable outcomes}}{\text{Total outcomes considered}}\right) \times 100\% \tag{5.3}$$

From the data provided, the favourable outcomes occur in the first three rows, where the "Predicted" equals the "True", resulting in three favorable outcomes. Using the following formula, the Hit-Rate is calculated as:

$$\text{Hit-Rate} = \left(\frac{3}{5}\right) \times 100\% = 60\% \tag{5.4}$$

Here, the numerator 3 represents the three days where the assets price direction was predicted correct, each counting as one favorable outcome. The total percentage, 60%, represents the hit ratio for this prediction over the five days. When defining a hit ratio in financial forecasting, one must specify a limit to the possible favorable outcomes, which in this example is the trading period of five days. For our research we decided to annualize the rate so it is comparable to the annualized Sharpe value.

The Hit-Rate thus provides a measure of the predictive accuracy over the specified period.

Chapter 6

Results

6.1 SVR

All our SVR models use the same hyperparameters to do the predictions, regardless of asset. This allows us to create a valid comparison between the assets and the effectiveness of the SVR - without skewing the results to optimize for the test sets by fine tuning the model. We run each model with 100 different seeds, ranging from 1 to 100. Following parameters are used for each prediction:

Parameter	value
C	1.0
dual	warn
epsilon	0.0
fit_intercept	True
intercept_scaling	1.0
loss	epsilon insensitive
max_iter	1000
random_state	seed used
tolerance	0.0001

Table 6.1: SVR Parameters

The hyperparameters in Table 6.1 were selected based on the default values provided by the scikit-learn package. This choice was made to ensure that the results are reproducible and that we not falsify the results towards benefiting the test performance. Using above parameters, following results for the different assets were achieved:

6.1.1 Bitcoin

Bitcoin from 2014 to 2024

Notable years are the year 2017, where the Bitcoin massively increased in value, and we expect the Buy&Hold to be consistently better than any model is able to predict. Another period with the same trend is the end of the year 2020, as well as the beginning of 2021, continuing the trend of the previous year.
We also expect our model to be able to beat the Buy&Hold approach in the year 2018, due to the Benchmark effectively causing a loss over the span of the year. The end of the year 2021 and the year 2022 should permit our model to beat the benchmark

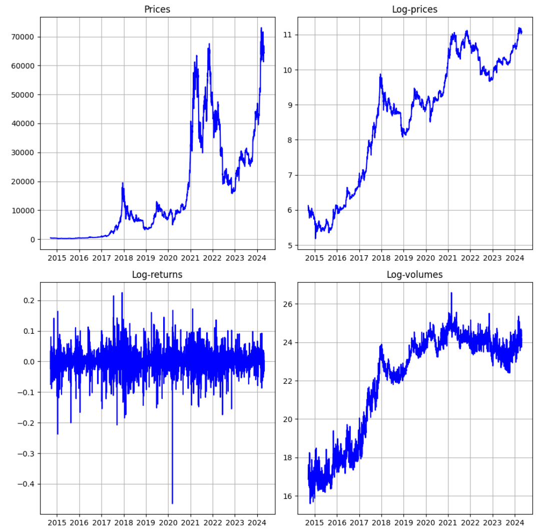


FIGURE 6.1: Bitcoin from 2014 to 2024

by a sizable margin, since the value of Bitcoin consistently fell in this time period, recovering in the years 2023 onwards.

ACF

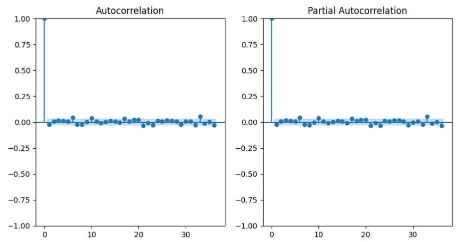


FIGURE 6.2: ACF and PACF of the time series Bitcoin

The Figure 6.2 shows the auto-correlation and partial auto-correlation of Bitcoin. This plot was made using all ten years of the downloaded Bitcoin dataset. There is an outlier at Lag six for the Auto correlation. It stands to reason that, if the model is allowed the information of six lags, that it would perform better than with just one lag. We aim to discover if this approach has validity and do an extensive analysis over the different years and their combinations, as mentioned in Table A.1.

6.1.2 Bitcoin Model Evaluation 2017

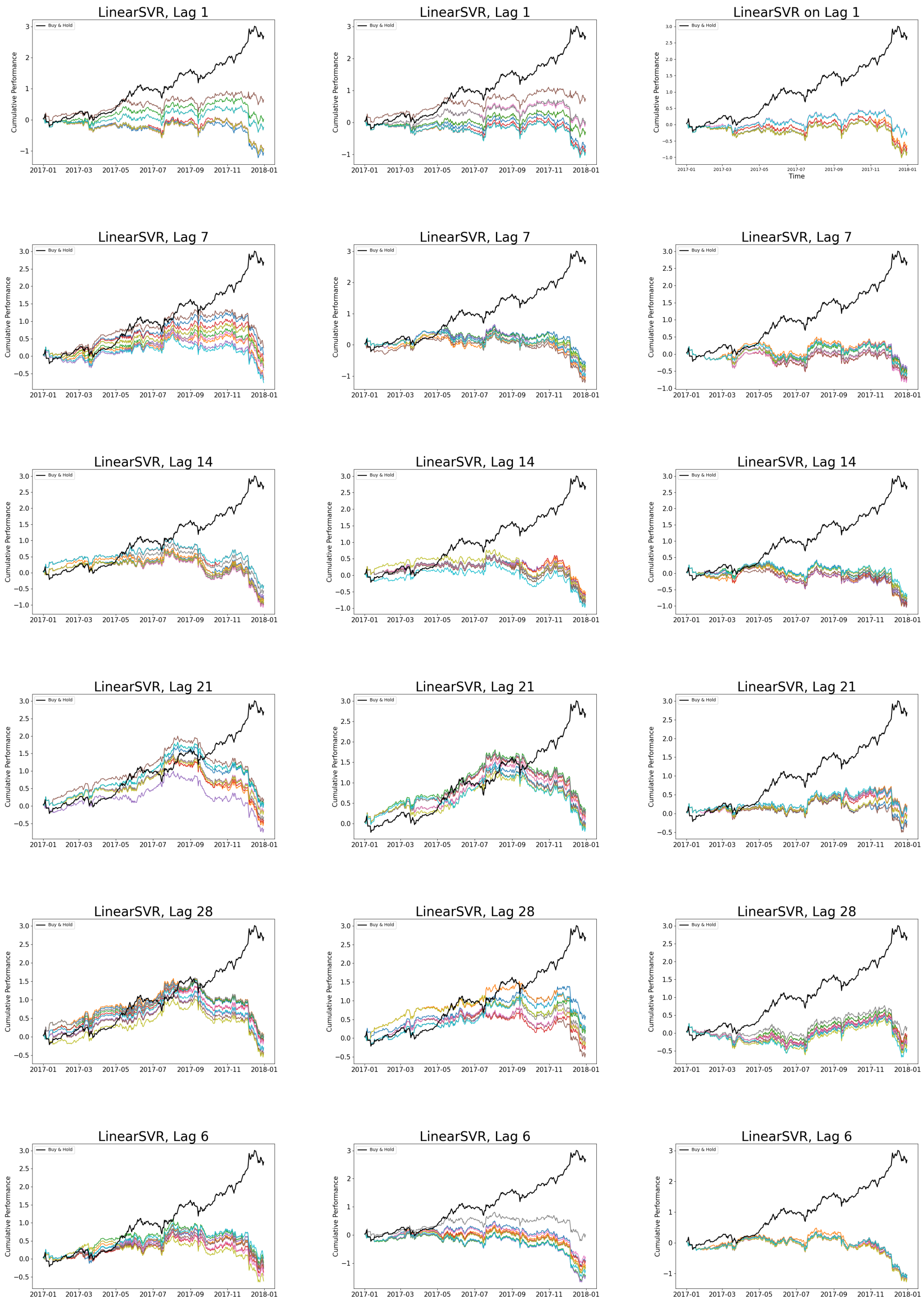
In this section, we use the year 2017 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 models are represented in this section - chosen based on the train MSE performance. We selected the ten best models based on their train MSE performance as it is a common metric for evaluating the accuracy of a regression model. Additionally, the train MSE provides a good indication of how well the model is fitting the training data, which is an important first step in model selection.

However, we acknowledge that alternative metrics such as the Hit-Rate or the Sharpe ratio could also be used for model selection, especially in the context of financial applications where risk-adjusted performance is important.

Regarding the expectation of the best in-sample MSE models to perform well out-of-sample, we recognize that this is not always the case and that overfitting can occur.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.



(A) Training 2014, 2015, 2016 and Test 2017 (B) Training 2015, 2016 and Test 2017 (C) Training 2016 and Test 2017

FIGURE 6.3: Performances in comparison with benchmark for the year 2017 on different lags
each row consists of a different number of lags

The Figure 6.3 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The most notable difference and improvement happens in the jump between Lag 1 and Lag 7. This performance improvement was expected and can be explained due to the ACF with a significance of 6 - which is represented in the last row.
The amount of years present for the training years has a heavy impact on performance

- with the best Performances being achieved by the models with the largest training dataset. This is consistent over all the different tested Lags, providing a clear benefit to the prediction of 2017.
Another consistent trend noticeable in the Performance plots is a clear decrease in performance once July of 2017 is reached - where the model is unable to predict the massive performance increase of the benchmark Buy & Hold.

The Figure 6.3 shows that there is general improvement for the SVM when providing a longer time frame to train on, up to a certain point. This performance can be attributed due to the model being able to infer this positive movement from the training data. What the model is not able to grasp is the continued increase during the year, and is thus unable to capitalize further on the continued return for Bitcoin in the year 2017. This can be explained due to there not being this stark of an increase in the years 2014-2016.

Performance Metrics

In this section, the MSE and the Hitratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.3 corresponds to a table.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2014-2017	1	0.56766	0.47671	-1.11307	1.00872E-3	2.49323E-3
2014-2017	7	0.57298	0.53425	0.04658	9.78587E-4	2.53352E-3
2014-2017	14	0.59124	0.51507	-0.819408	9.71723E-4	2.57846E-3
2014-2017	21	0.59018	0.53151	0.04815	9.68543E-4	2.57516E-3
2014-2017	28	0.57921	0.53425	-0.005055	**9.60412E-4**	2.60447E-3
2014-2017	auto	0.56386	0.51507	-0.205029	9.73888E-4	2.51304E-3
2015-2017	1	0.56361	0.48493	-0.766952	9.97499E-4	2.49564E-3
2015-2017	7	0.56772	0.49589	-0.578067	9.87049E-4	2.56568E-3
2015-2017	14	0.58413	0.50411	-0.815696	9.78374E-4	2.60270E-3
2015-2017	21	0.60739	0.53425	0.034669	9.78438E-4	2.58141E-3
2015-2017	28	0.60739	0.54247	0.613579	**9.66108E-4**	2.60283E-3
2015-2017	auto	0.56224	0.48493	-0.939861	9.83424E-4	2.55197E-3
2016-2017	1	0.60656	0.48493	-0.882748	6.47377E-4	2.54657E-3
2016-2017	7	0.58197	0.51781	-0.434144	6.24922E-4	2.61669E-3
2016-2017	14	0.61475	0.52055	-0.900578	6.27390E-4	2.61478E-3
2016-2017	21	0.62568	0.53973	-0.208272	6.20803E-4	2.61146E-3
2016-2017	28	0.62568	0.51781	-0.294429	**6.17817E-4**	2.60955E-3
2016-2017	auto	0.60383	0.49041	-1.19223	6.32546E-4	2.58507E-3

TABLE 6.2: Best Model for predicting the Year 2017

The Best Model was chosen based on the Train MSE. Based on the training data, a model using the years 2014-2017 would benefit the most when used in combination with Lag 28, with the lowest MSE on the training dataset. Using the ACF as a baseline, for Bitcoin this corresponds to a Lag = 6, would result in an increase of Train MSE of 0.13476E-4, and a decrease in Hit-Rate Train of 0.01918. The increase in performance is small, but the model has a lot more data to reference on each individual time step.
Using the above information provided by Table 6.2, the chosen Model uses Lag 28.

This would result in a Hitratio on the test dataset of 53.425% and a Sharpe Ratio of -0.005055 in the year 2017.
In comparison, choosing the Lag recommended by the ACF would reduce our Sharpe to -0.205029 and the Hitratio to 51.507%. In both cases, the model produced losses, as evident in the first column of Figure 6.3. A performance increase can be observed when there is more information available in the form of a higher Lag. In the training years 2015-2017, the model best approximating the training data is again Lag 28, with a similar performance difference to the next best, being Lag 21.
When choosing the model with Lag 28, a Hitratio of 60.739% is achieved in the training dataset, as well as the best Hitratio and Sharpe for the Test set, respectively. This performance is not beaten by another configuration. This model is represented, along with 9 other models, in the second column of Figure 6.3. Due to the similarity between the best ten models, a random effect can be excluded. Again, Lag 28 outperforms the other configurations even with a reduced dataset. only using 2016 to train.
While it provides the lowest MSE Train of all models, with 6.17817E-4, it is deficient in achieving a better result when looking at the test set. This is further reinforced in the third column of Figure 6.3, where the models are unable to properly predict the movement of the data.

Without further information, the best model chosen through the train MSE alone is the model using Lag 28 and only 2016 as training year and hints towards a possible overfitting. However, as shown in Figure 6.3, this approach is flawed. Instead, the best proposal includes the year 2015 as well, resulting in much better performance and Sharpe on the test set, compared to other tested combinations.

Figure 6.3 corresponds to these models, and shows the best 10 in comparison.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables B.1-B.18.

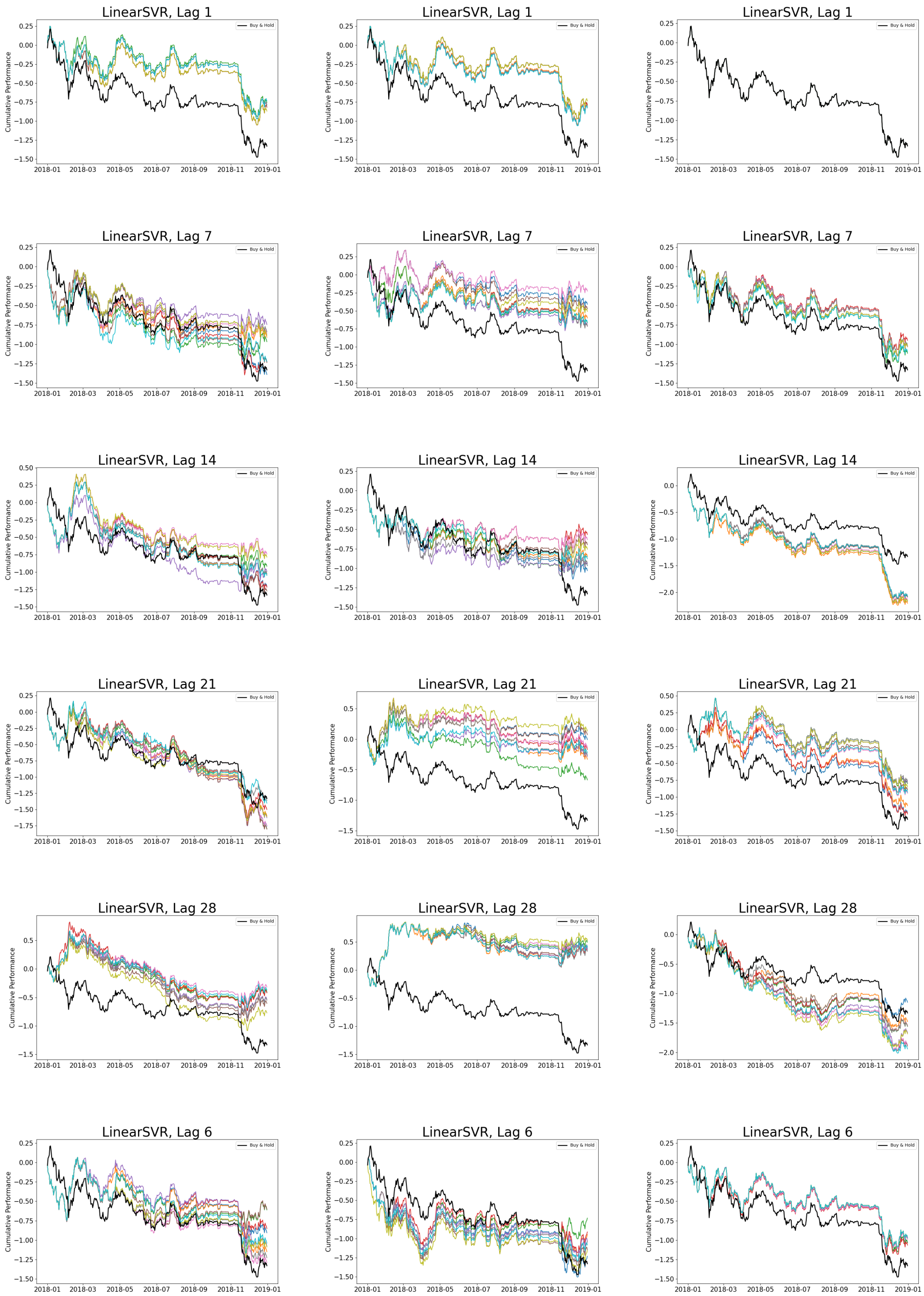
The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2017 can be found in Table B.19

6.1.3 Bitcoin Model Evaluation 2018

In this section, we use the year 2018 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 Models are represented in this section - chosen based on MSE on the train.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.



(A) Training 2015, 2016, 2017 and Test 2018 (B) Training 2016, 2017 and Test 2018 (C) Training 2017 and Test 2018

FIGURE 6.4: Performances in comparison with benchmark for the year 2018 on different lags
Each row consists of a different number of lags

The Figure 6.4 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The most notable difference and improvement happens in the jump between Lag 1 and Lag 7. This performance improvement was expected and can be explained due to the ACF, with a significance of 6 - which is represented in the last row.
The amount of years present for the training years has a heavy impact on performance

- with the general rule of more data improving the model performance.

The Figure 6.3 shows that there is a general improvement for the SVM when providing a longer time frame to train. This performance can be attributed due to the return massively increasing in that year specifically, as indicated by a cumulative performance of almost three by the end of 2017, with almost no loss in value of the Asset.

Performance Metrics

In this section, the MSE and the Hit ratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.4 corresponds to a table. The best model of all these configurations is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2015-2018	1	0.57482	0.51233	-0.960315	1.48195E-3	1.88490E-3
2015-2018	7	0.58303	0.49589	-1.695792	1.47858E-3	1.90795E-3
2015-2018	14	0.60036	0.50959	-1.468239	1.47506E-3	1.91374E-3
2015-2018	21	0.60219	0.49863	-2.148138	1.47135E-3	1.90946E-3
2015-2018	28	0.59672	0.51233	-0.500631	**1.46368E-3**	1.90059E-3
2015-2018	auto	0.57391	0.51781	-1.102213	1.47060E-3	1.89127E-3
2016-2018	1	0.59918	0.51233	-0.960315	1.54651E-3	1.90912E-3
2016-2018	7	0.59918	0.52877	-0.497507	1.55276E-3	1.90961E-3
2016-2018	14	0.60876	0.51781	-1.255623	1.56043E-3	1.94202E-3
2016-2018	21	0.61149	0.51781	-0.010895	1.54272E-3	1.89755E-3
2016-2018	28	0.61149	0.53151	0.469175	**1.53537E-3**	1.90774E-3
2016-2018	auto	0.59234	0.50411	-1.503453	1.55238E-3	1.90426E-3
2017-2018	1	0.6137	0.50959	-1.62335	2.42503E-3	1.96462E-3
2017-2018	7	0.63288	0.50685	-1.258795	2.43025E-3	1.99041E-3
2017-2018	14	0.63836	0.47123	-2.662364	2.43405E-3	2.04499E-3
2017-2018	21	0.63836	0.48493	-1.50484	2.41634E-3	1.99938E-3
2017-2018	28	0.6274	0.50137	-1.400095	**2.38711E-3**	1.98980E-3
2017-2018	auto	0.63288	0.50685	-1.258795	2.43272E-3	1.99069E-3

TABLE 6.3: Best Model for predicting the Year 2018

Just like in Table 6.2, the lowest MSE train is provided by the Models using Lag 28, as shown in 6.3. This was consistent across all three year combinations.
When choosing the best model, the lowest MSE of all three is chosen - in this case, the model using three years(2015-2017) as training, together with 28 Lags.
In Figure 6.4, the Model is able to beat the benchmark on the Test set, while avoiding major losses, such as the heavy losses in February and May 2018. However, the chosen model continually loses on Performance due to poorly chosen trades.

If we were to take in the information we received on model performance of the previous year, as shown in Figure 6.3 and in Table 6.2. The best model-choice when using previously acquired knowledge, is to use the model with two years(2016-2017) as training, together with 28 Lags. When using this prior knowledge, the benchmark is outperformed heavily. The model is able to avoid a loss of 1.5 in cumulative Performance and instead is able to make a profit of 0.5 during this year.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables C.1-C.18.

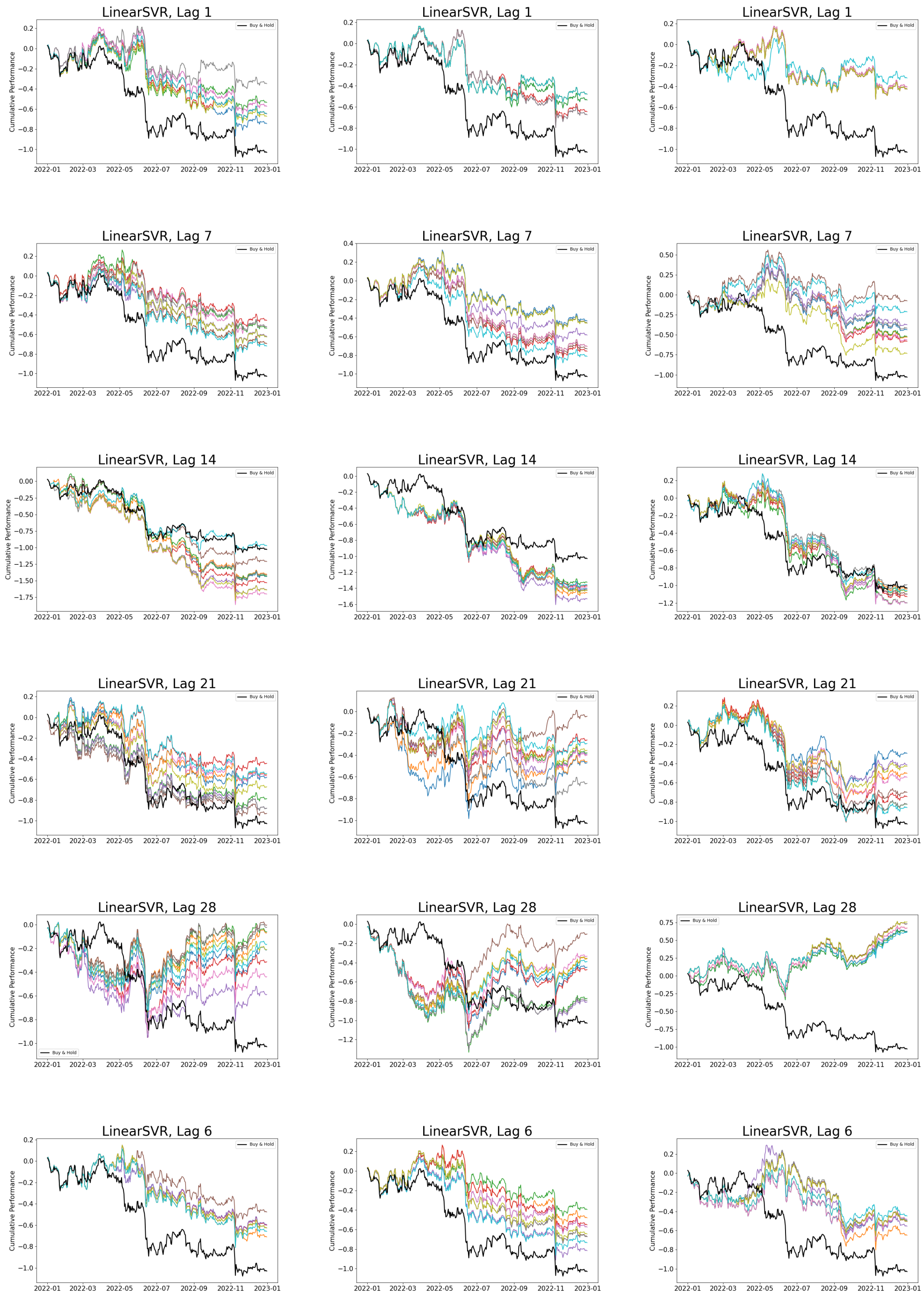
The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2018 can be found in Table C.19

6.1.4 Bitcoin Model Evaluation 2022

In this section, we use the year 2022 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.



(A) Training 2019, 2020, 2021 and Test 2022 (B) Training 2020, 2021 and Test 2022 (C) Training 2021 and Test 2022

FIGURE 6.5: Performances in comparison with benchmark for the year 2022 on different lags
Each row consists of a different number of lags

In Figure 6.5, there is a lot of uncertainty present between the 10 best models and consequently their performance. In the year 2022, Bitcoin lost a lot of value as an asset, only recovering 2023 and beyond. We expected our models to be able to beat the Buy&Hold approach. While this was the case with certain models, the performance and thus the predictions provided by our models varies a lot, and does not inspire confidence in being able to accurately predict the asset movement.

A big surprise was the consistently good performance of the Model using only 2021 as training. It is one of few models able to accurately predict the movement of Bitcoin in 2022 and capitalize on it.
A possible explanation for this performance is only the inclusion of a comparatively neutral asset performance in the year 2021. Due to this, the model was able to better approximate the movement of Bitcoin in the following year.

Performance Metrics

In this section, the MSE and the Hit ratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.5 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2019-2022	1	0.53558	0.46849	-1.156003	1.52949E-3	1.16414E-3
2019-2022	7	0.53102	0.47671	-0.972067	1.52797E-3	1.16516E-3
2019-2022	14	0.55109	0.46027	-2.248817	1.52321E-3	1.17437E-3
2019-2022	21	0.56478	0.48767	-0.904304	1.51402E-3	1.17361E-3
2019-2022	28	0.56752	0.50959	-0.327341	**1.50259E-3**	1.17184E-3
2019-2022	auto	0.53011	0.47671	-0.925364	1.52757E-3	1.16402E-3
2020-2022	1	0.53899	0.47397	-0.829877	1.67084E-3	1.16711E-3
2020-2022	7	0.54446	0.49315	-0.66969	1.66464E-3	1.16822E-3
2020-2022	14	0.56224	0.45479	-2.195653	1.66153E-3	1.18611E-3
2020-2022	21	0.58276	0.52877	-0.731133	1.64623E-3	1.16954E-3
2020-2022	28	0.58824	0.49041	-0.695431	**1.63595E-3**	1.17787E-3
2020-2022	auto	0.53899	0.48493	-0.891342	1.66510E-3	1.17191E-3
2021-2022	1	0.52329	0.48219	-0.657048	1.75796E-3	1.14962E-3
2021-2022	7	0.54521	0.49041	-0.676895	1.74485E-3	1.17422E-3
2021-2022	14	0.5863	0.46849	-1.864607	1.76684E-3	1.18628E-3
2021-2022	21	0.59452	0.49041	-0.456662	1.72605E-3	1.19501E-3
2021-2022	28	0.6137	0.48493	0.973491	**1.71392E-3**	1.20426E-3
2021-2022	auto	0.54521	0.45753	-0.769227	1.74014E-3	1.17173E-3

TABLE 6.4: Best Model for predicting the Year 2022

When using the MSE train, the best model uses the years 2019, 2020 and 2021 to train, including a Lag of 28. Using these metrics, a negative Sharpe Ratio of -0.327341 is achieved. This Sharpe Ratio is relatively consistent throughout our model configurations - except the model only utilizing the year 2021 with a Lag of 28.
This performance is surprising, due to no other model coming close to this performance. However, due to the nature of the preceding crisis years, this model configuration should be taken into consideration if this pattern persists.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables D.1-D.18.

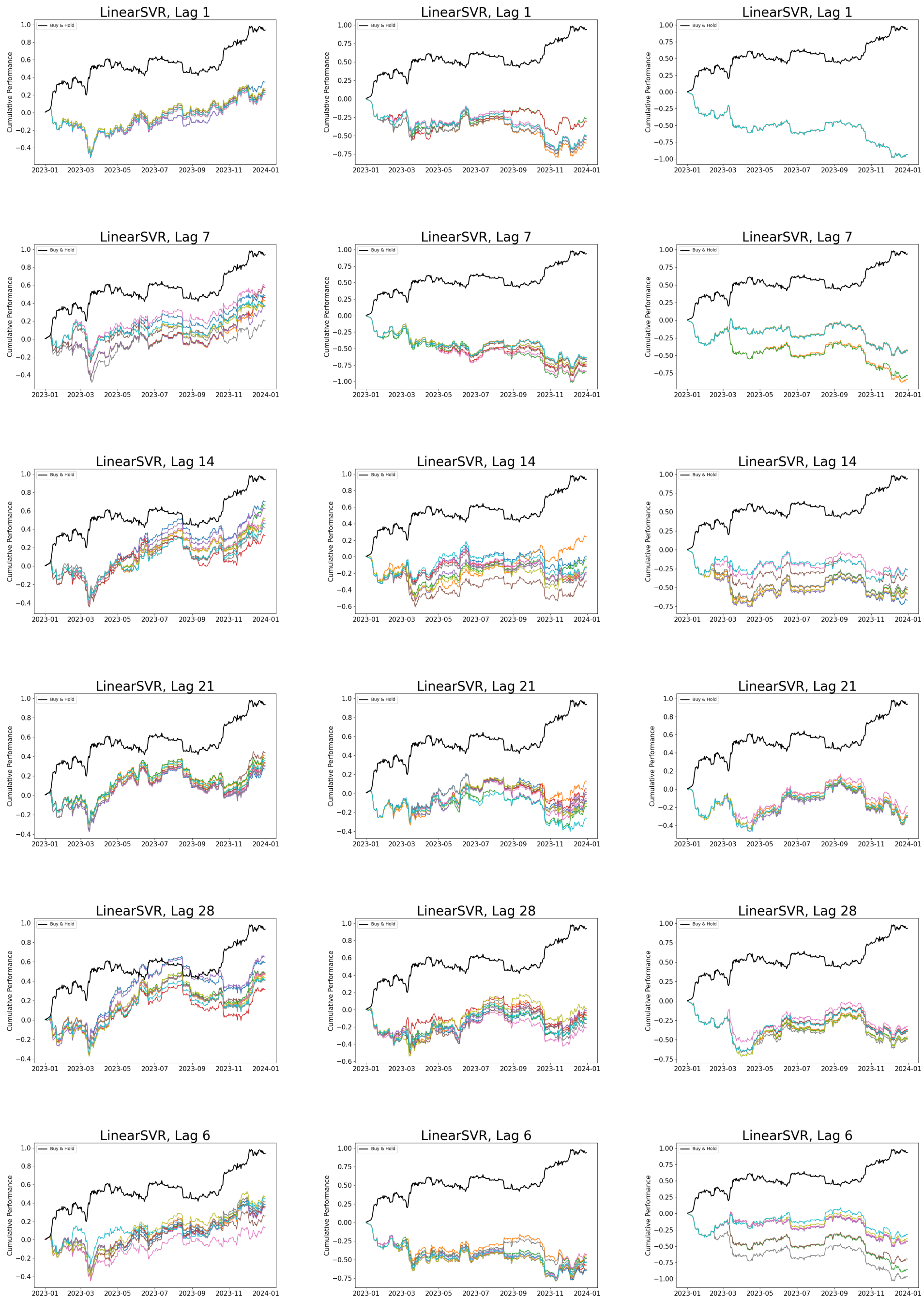
The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2022 can be found in Table D.19

6.1.5 Bitcoin Model Evaluation 2023

In the year 2023, Bitcoin recovers its value, almost doubling, from 20'000 to 40'000 USD. This increase is completely different from the previous years, and accordingly we expect our models to perform worse than Buy&Hold and in general make avoidable losses. In this section, we use the year 2023 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.
Our model was not able to beat the benchmark Buy&Hold, but some models still manage to create a Benefit for the investor.
The models using 2020, 2021 and 2022, with Lag 28 as training data manage to outperform all other models. This hints towards 2020 being an important year for these predictions. When looking at the movement present in Figure 6.2, the upwards movement is similar to the one present in 2023. While no decisions can be made upon this, there is clear incentive in considering this particular year range when trading Bitcoin.



(A) Training 2020, 2021, 2022 and Test 2023 (B) Training 2021, 2022 and Test 2023 (C) Training 2022 and Test 2023

FIGURE 6.6: Performances in comparison with benchmark for the year 2023 on different lags
Each row consists of a different number of lags

The Figure 6.6 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The Figure 6.6 shows that none of our models were able to beat the Buy&Hold benchmark at the end of the year. There was a brief period, where the model using Lag 28, with training years 2020-2022 was able to outperform this benchmark. Due to the temporary nature and not all models present achieving this, we assume chance was the cause of this performance. This result was expected, due to the steady increase in value of the asset in the year 2023, seen in Figure 6.1. In general, the models not using 2020 as training are unable to properly predict the development Bitcoin will go through. This is due to the asset decrease in the two preceding years - making the models expect that the asset will continue decreasing in value and making choices with this in mind. This can be explained through the removal of the increase of that year, depriving the model information that would allow such a prediction.

Performance Metrics

In this section, the MSE and the Hit ratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.6 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2020-2023	1	0.52555	0.54795	0.801247	1.49836E-3	5.18833E-4
2020-2023	7	0.53193	0.53699	1.123091	1.49939E-3	5.18747E-4
2020-2023	14	0.54471	0.56986	1.613486	1.49112E-3	5.15689E-4
2020-2023	21	0.56387	0.56712	0.620037	1.48608E-3	5.22908E-4
2020-2023	28	0.57117	0.5589	1.363742	**1.47812E-3**	5.19874E-4
2020-2023	auto	0.5365	0.55342	0.886554	1.50167E-3	5.21042E-4
2021-2023	1	0.53562	0.53425	-1.279332	1.44812E-3	5.27379E-4
2021-2023	7	0.52877	0.53151	-1.532401	1.44885E-3	5.32718E-4
2021-2023	14	0.53973	0.53699	0.014461	1.44784E-3	5.27966E-4
2021-2023	21	0.56301	0.55068	-0.202414	1.42614E-3	5.27652E-4
2021-2023	28	0.56712	0.53425	-0.266977	**1.41667E-3**	5.30669E-4
2021-2023	auto	0.52192	0.52329	-1.49178	1.45009E-3	5.30486E-4
2022-2023	1	0.53425	0.50137	-2.166654	1.12661E-3	5.39928E-4
2022-2023	7	0.57534	0.50959	-0.979588	1.13025E-3	5.60375E-4
2022-2023	14	0.58904	0.50685	-1.535895	1.11394E-3	5.62399E-4
2022-2023	21	0.58082	0.50685	-0.716931	1.10294E-3	5.47985E-4
2022-2023	28	0.59178	0.50411	-1.066225	**1.10087E-3**	5.72479E-4
2022-2023	auto	0.57534	0.50959	-0.979588	1.13031E-3	5.60308E-4

Table 6.5: Best Model for predicting the Year 2023

The model chosen based on the lowest MSE train is the model that only uses 2022 as training. However, even fielding the lowest MSE train, it is not a good choice and it's movements cause an active loss, represented by the Sharpe value of -1.066225.

Further, our analysis so far has shown that more training data provides a better result in general. This is true in this case as well, with the model performance increasing, the more data is provided. When using this information, the benchmark is not beaten, however the models still manage to make profit during 2023.

The most notable difference, as already stated, is the removal of the year 2020 in the training dataset. Removing it makes the models unable to account for this increase in value.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables E.1-E.18.

The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2023 can be found in Table E.19

6.1.6 Gold

Gold from 2014 to 2024

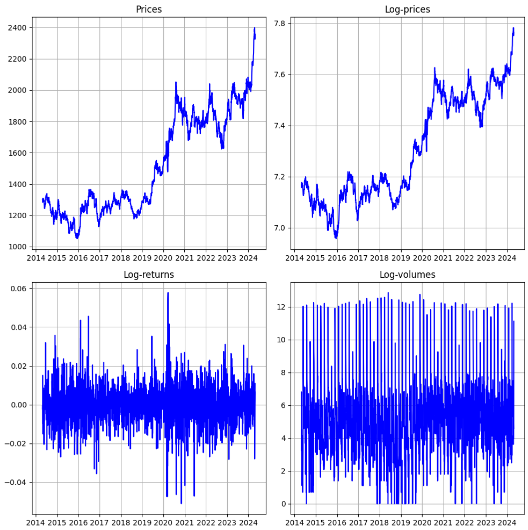


FIGURE 6.7: Gold prices (top-left panel), log prices (top-right panel), log returns (bottom-left panel) and log volumes (bottom-right panel) from 2014 to 2024

Figure 6.7 shows the prices, log prices, log returns and log volumes from which we draw our observations. Significant years for gold prices from 2014 to 2024 include 2019 and 2020, where gold saw a substantial surge in value, largely driven by economic uncertainties and the onset of the COVID-19 pandemic. During these years, the Buy&Hold strategy would likely outperform any predictive model due to the consistent upward trend in prices. Another important period is 2021 to 2023, where gold prices corrected and stabilized after reaching record highs. Here, our model could potentially beat the Buy&Hold approach by capitalizing on short-term fluctuations and mitigating losses. Finally, the end of 2024 shows a recovery in gold prices, with renewed growth driven by inflation concerns and economic volatility, making the Buy&Hold strategy again favorable.

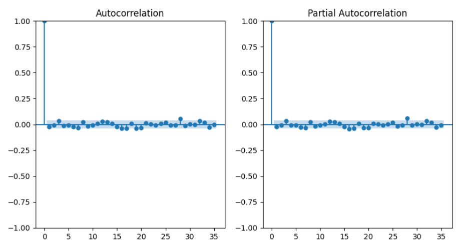


FIGURE 6.8: ACF and PACF of the time series Gold

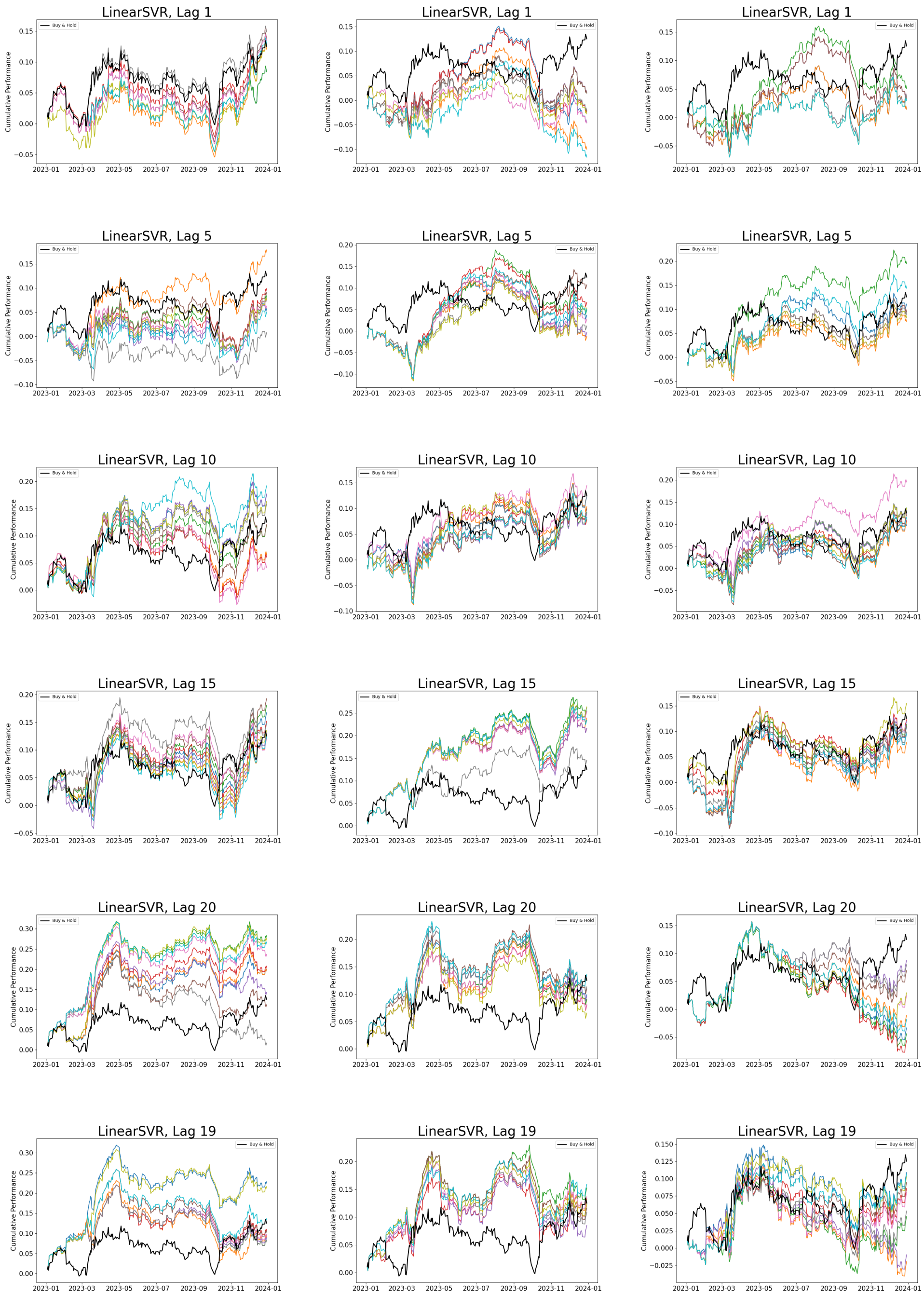
In Figure 6.8 the auto-correlation and partial auto-correlation of Gold can be observed. This plot was made using all available data. The first significant Lag is Lag 19. It stands to reason that, if the model is allowed the information of 19 lags, that it would perform better than with less lags. We aim to discover if this approach has validity and do an analysis for the year 2023 with different training combinations, as mentioned in Table 5.2.

6.1.7 Gold Model Evaluation 2023

In this section, we use the year 2023 as test year, while altering the Lags and the training years and comparing the performance metrics of the different models. The ten best Models for each Lag are presented in this section - based on their MSE on the train.

Performance Evaluation

As decision metric for the model selection the train MSE was crucial. The performances of the ten lowest values are then used to create a prediction and are compared with the benchmark. The Figure 6.9 showcases the performance of the models over different training splits and all available lags.



(A) Training 2020, 2021, 2022 and Test 2023 (B) Training 2021, 2022 and Test 2023 (C) Training 2022 and Test 2023

FIGURE 6.9: Performances in comparison with benchmark for the year 2023 on different lags
each row consists of a different number of lags

The most remarkable improvement happens between Lag 15 and Lag 20 in the first column, as well as between Lag 10 and 15 in the second column of Figure 6.9.This performance boost from Lag 15 to 20 was expected due to the ACF, with a significance of 19 - which is represented in the last row. In contrast the one from Lag 10 to 15 is unexpected.

The amount of training years has an impact on the performance, similarly the amount of lags - models with more than one year and more than 10 lags as training data perform in general better. These models are mostly outperforming the benchmark. Another trend noticeable in the Performance plots is that most models can follow and occasionally compete with the benchmark.

Overall the Figure 6.9 illustrates that there is a general improvement for the SVM when providing a longer time frame and more lags to train. This might be due to the price volatility in the test year 2023 and the previous training years. In conclusion the SVM can profit from longer training periods as well as from more data.

Performance Metrics

As previously introduced in 6.1.3 this section presents the MSE and Hitratio compactly. We explicitly decided against referring each individual table to focus on the relevant findings, but post them in the Appendix F.1-F.18 for completeness. The very best out of the ten, selected through the train MSE, are shown. Each plot in Figure 6.9 is represented with its best performing model as a table row in 6.6.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2020-2023	1	0.54233	0.51793	0.637068	1.22104E-4	6.88721E-5
2020-2023	5	0.53307	0.5259	0.43371	1.21771E-4	6.92854E-5
2020-2023	10	0.53836	0.54183	1.337242	1.20728E-4	6.86011E-5
2020-2023	15	0.54365	0.55378	1.272785	1.20222E-4	6.79373E-5
2020-2023	20	0.56481	0.54582	1.52394	**1.19248E-4**	6.75710E-5
2020-2023	auto	0.56481	0.53386	1.739542	1.19299E-4	6.75456E-5
2021-2023	1	0.5328	0.48207	-0.345404	9.17534E-5	6.92497E-5
2021-2023	5	0.52485	0.50199	0.280359	9.13258E-5	6.89965E-5
2021-2023	10	0.54871	0.53386	0.93319	9.08196E-5	6.81656E-5
2021-2023	15	0.53082	0.55378	2.003289	9.09098E-5	6.74756E-5
2021-2023	20	0.54871	0.52191	0.750957	9.01498E-5	6.70587E-5
2021-2023	auto	0.56262	0.55378	1.011934	**9.00185E-5**	6.69690E-5
2022-2023	1	0.52988	0.46614	0.109332	9.45339E-5	6.92725E-5
2022-2023	5	0.50996	0.48606	0.838639	9.40107E-5	6.94497E-5
2022-2023	10	0.56972	0.49004	0.728877	9.22267E-5	6.90083E-5
2022-2023	15	0.58167	0.48207	0.823346	9.11701E-5	6.95169E-5
2022-2023	20	0.61753	0.48207	-0.255076	9.09176E-5	6.97051E-5
2022-2023	auto	0.57769	0.48606	0.827848	**9.01398E-5**	6.93518E-5

TABLE 6.6: Best Model for predicting the Year 2023

In Table 6.6, the lowest train MSE is provided by the models using Lag 20 or auto lag, which is 19 in this case.
When choosing the best model, according to the lowest train MSE of all - here, the model using two years (2021-2023) as training, together with 19 Lags. Nonetheless this model has also the lowest test MSE and a solid sharpe ratio in the test. Further the model has an impressive Hit-Rate on the train and test data.
In Figure 6.9, the model is able to beat the benchmark on the test set, while capitalizing on the strong volatility in the early beginning of 2023.

A possible improvement could be achieved by averaging the models to have a smoother overall performance and not relying on one model. If we would follow this paradigm we would end up with result presented in 6.10. The Figure shows that the final performance is the same as the benchmark, due to bad trading decisions at the end of the year. Although the model was capable of being throughout the year better than the benchmark.

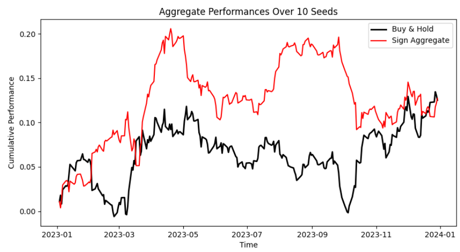


FIGURE 6.10: Aggregated model based on auto Lag and training data from 2021-2022

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables F.1-F.18.

The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2023 can be found in Table F.19

6.1.8 MSFT

MSFT from 2014 to 2024

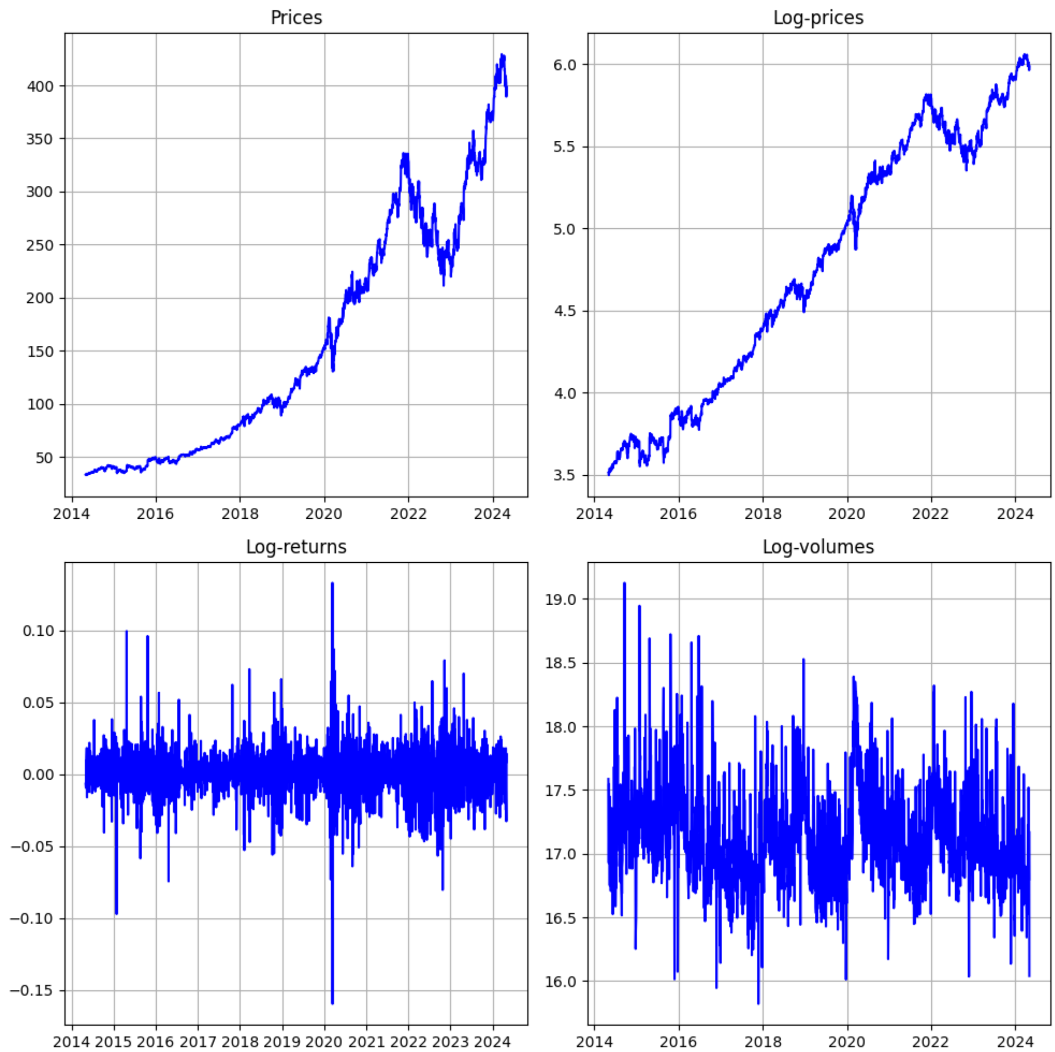


FIGURE 6.11: MSFT - prices (top-left panel), log prices (top-right panel), log returns (bottom-left panel) and log volumes (bottom-right panel) from 2014 to 2024

Figure 6.11 shows the prices, log prices, log returns and log volumes from which we conclude our observations. Significant years for MSFT prices from 2014 to 2024 include 2014 to 2022, where MSFT saw a steady rise in value, with a significant drawback in 2020 due to COVID-19. Most likely during these years, the Buy&Hold strategy would outperform any predictive model due to the consistent upward trend in prices. Another important period is between 2022 and 2024, where the asset prices decline after reaching a high and surge thereafter to a new high. In such an environment, our model might beat the Buy&Hold approach.

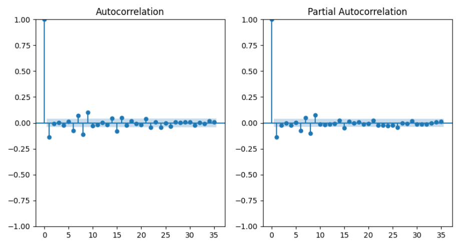


FIGURE 6.12: ACF and PACF of the time series MSFT

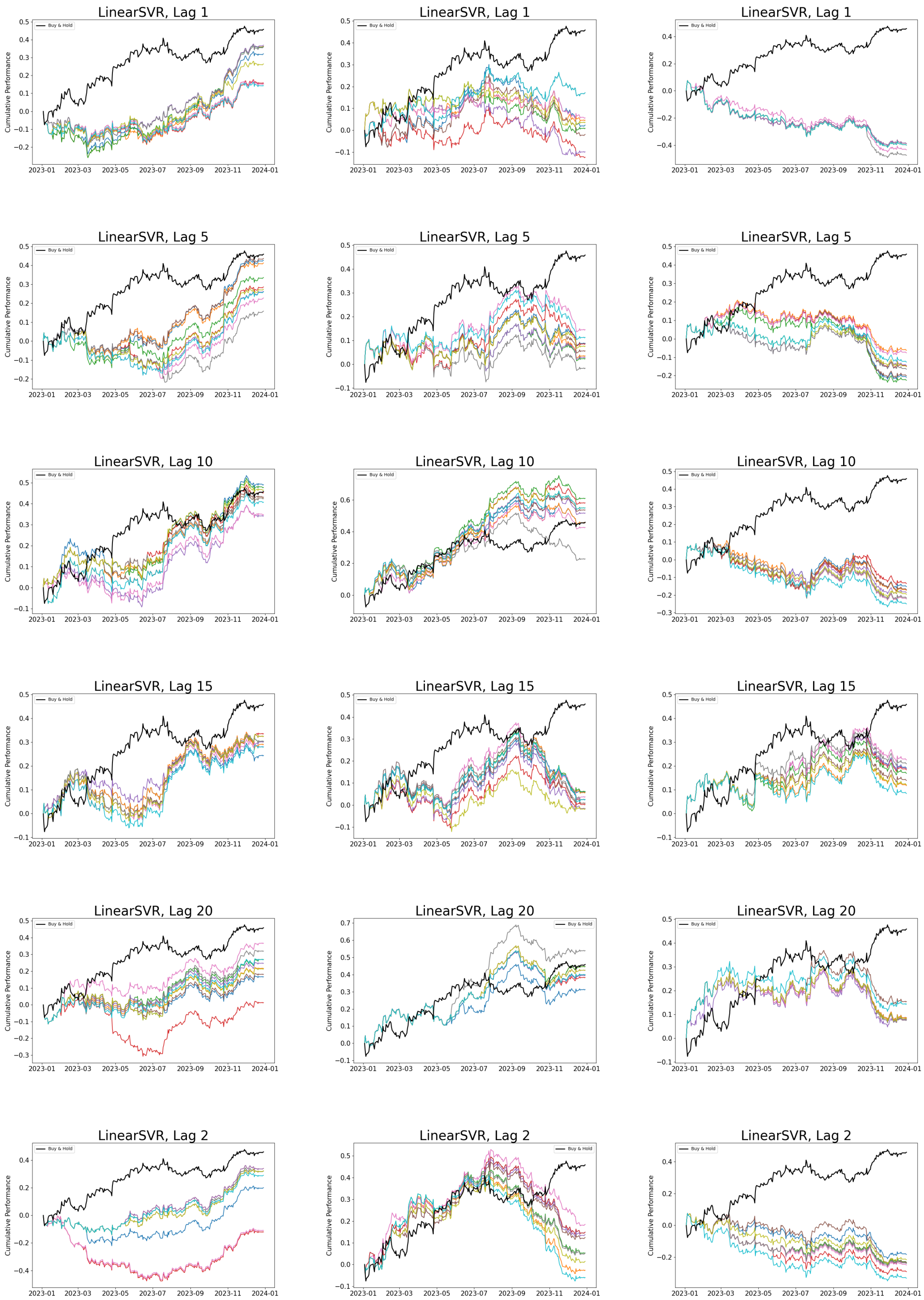
In Figure 6.12 the auto-correlation and partial auto-correlation of MSFT can be examined. This plot was made using all available data. The first significant Lag is 2. It stands to reason that, if the model is allowed the information of 2 lags, that it would perform as good as it would with more lags. Lets dive deeper to see if such a frugal model performs better than one with more data available. We aim to discover if this approach has validity and do an analysis for the year 2023 with different training combinations, mentioned in Table 5.2.

6.1.9 MSFT Model Evaluation 2023

In this section, we use the year 2023 as test year, while altering the Lags and the training years and comparing the performance and the metrics of the different models. The ten best Models for each Lag are presented in this section - based on their MSE on the train.

Performance Evaluation

As before, the train MSE is the decisive metric for the model selection. The performances of the ten lowest values are then used to create a prediction and are compared with the benchmark. The Figure 6.13 showcases the performance of the models over different training splits and all available lags.



(A) Training 2020, 2021, 2022 and Test 2023 (B) Training 2021, 2022 and Test 2023 (C) Training 2022 and Test 2023

FIGURE 6.13: Performances in comparison with benchmark for the year 2023 on different lags using MSFT data each row consists of a different number of lags

From Figure 6.13 we derive that the proposed model from the acf with Lag 2 is in terms of performance not better than the other models. Interestingly if we look at the models with Lag 10 they perform better than the ones provided by the acf. Nevertheless the acf shows that there are more significant lags till Lag 20 in Figure 5.3. This leads us to the assumption that for the equity MSFT it can be helpful to include all significant lags and not just the first.

Models in the third column that are trained with one year show poor performance. Globally speaking none of the models is consistently capable of outrunning the equities benchmark.

The models from the first column, with three training years, are able to prevent the end of the year loss, that most other models with more than 10 lags have.

The amount of training years has a feasible impact on the performance, similarly the amount of lags - models with more than one year and between 5 and 10 lags as training data perform broadly better.

Finally the Figure 6.13 illustrates that there is a general improvement in the SVM when providing a longer time frame than a year and all significant lags to train.

Performance Metrics

This section presents the MSE and Hitratio of the best models. To emphasize on the relevant findings we post all results in the Appendix G.1-G.18. The very best out of the ten, selected through the train MSE, are shown. Each plot in Figure 6.13 is represented with its best performing model as a table row in 6.7.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2020-2023	1	0.53175	0.524	1.289398	4.60859E-4	2.50890E-4
2020-2023	5	0.51323	0.548	1.714516	4.59970E-4	2.54377E-4
2020-2023	10	0.53042	0.528	1.978698	**4.41596E-4**	2.48243E-4
2020-2023	15	0.54365	0.516	0.977513	4.46356E-4	2.52808E-4
2020-2023	20	0.54497	0.508	0.667529	4.48126E-4	2.53401E-4
2020-2023	auto	0.50397	0.52	0.799559	4.60657E-4	2.54851E-4
2021-2023	1	0.50298	0.5	0.093265	3.37009E-4	2.49158E-4
2021-2023	5	0.53479	0.552	0.352627	3.32929E-4	2.47522E-4
2021-2023	10	0.53082	0.568	1.833599	**3.30198E-4**	2.46239E-4
2021-2023	15	0.55268	0.512	0.237149	3.34167E-4	2.51907E-4
2021-2023	20	0.53479	0.552	1.253074	3.33126E-4	2.46108E-4
2021-2023	auto	0.50497	0.532	0.595482	3.36744E-4	2.47528E-4
2022-2023	1	0.54582	0.452	-1.562388	4.94812E-4	2.57044E-4
2022-2023	5	0.54183	0.5	-0.834831	4.89161E-4	2.56542E-4
2022-2023	10	0.56175	0.484	-0.607898	4.81616E-4	2.61536E-4
2022-2023	15	0.57371	0.504	0.764516	**4.72098E-4**	2.60276E-4
2022-2023	20	0.58566	0.5	0.348047	4.79886E-4	2.70407E-4
2022-2023	auto	0.52988	0.48	-0.72843	4.91486E-4	2.52231E-4

TABLE 6.7: Best Model for predicting the Year 2023

In Table 6.7, the lowest train MSE is provided by the models using Lag 10 or 15.
When choosing the best model, according to the lowest train MSE of all - here, the model using two years (2021-2023) as training, together with 10 Lags. This model has also has the second lowest test MSE and a Sharpe ratio of 1.83 in the test. Further the model has an impressive Hit-Rate of 0.568 on the test data.
In Figure **??**, the model is able to compete with the benchmark on the test set and finally exceed it around the last quarter of the year.

6.1.10 Random Walk

In this section we want to present how our model performs on a generated random walk for the year 2024. The model uses the auto Lag based on the standard procedure we followed throughout the thesis and is than trained on three years of random walk. What we expect is that the model cannot learn to predict the random walk and generate a profit. For this purpose we illustrate in the Figure 6.14 how a hundred random initiate models would perform.

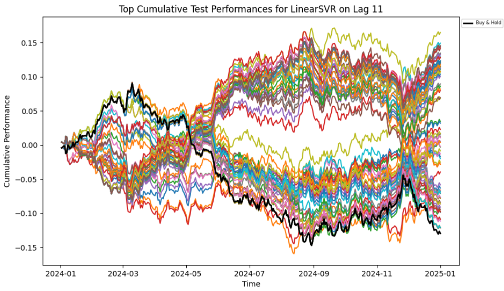


FIGURE 6.14: Random Walk prediction with 100 random seeds and auto lag.

As expected, the models cannot predict the random walk and therefore form a distribution around zero. Vividly represented with the hundred models in the Figure. This leads us to the assumption that our SVM model is trustworthy, as it behaves as expected, unable to predict the Random Walk with any consistency.

6.2 Random Forest

All our Random Forest models use the same hyperparameters to do the predictions, regardless of asset. This allows us to create a valid comparison between the assets and the effectiveness of the Random Forest (RF) - without skewing the results to optimize for the test sets by fine tuning the model. We run each model with 100 different seeds, ranging from 1 to 100. Following parameters are used for each prediction:

Parameter	value
bootstrap	True
ccp_alpha	0.0
criterion	squared_error
max_depth	2
max_features	1.0
max_leaf_nodes	None
max_samples	None
min_impurity_decrease	0.0
min_samples_leaf	1
min_samples_split	2
min_weight_fraction_leaf	0.0
monotonic_cst	None
n_estimators	500
n_jobs	None
oob_score	False
random_state	None
verbose	0
warm_start	False

TABLE 6.8: RF Parameters

The hyperparameters in Table 6.8 were selected based on the default values provided by the scikit-learn package in everything except the n_estimators and max_depth, in which we chose the values recommended in Lecture [18], with 2 and 500 respectively. This choice was made to ensure that the results are reproducible and that we not falsify the results towards benefiting the test performance.

Using above parameters, following results for the different assets were achieved:

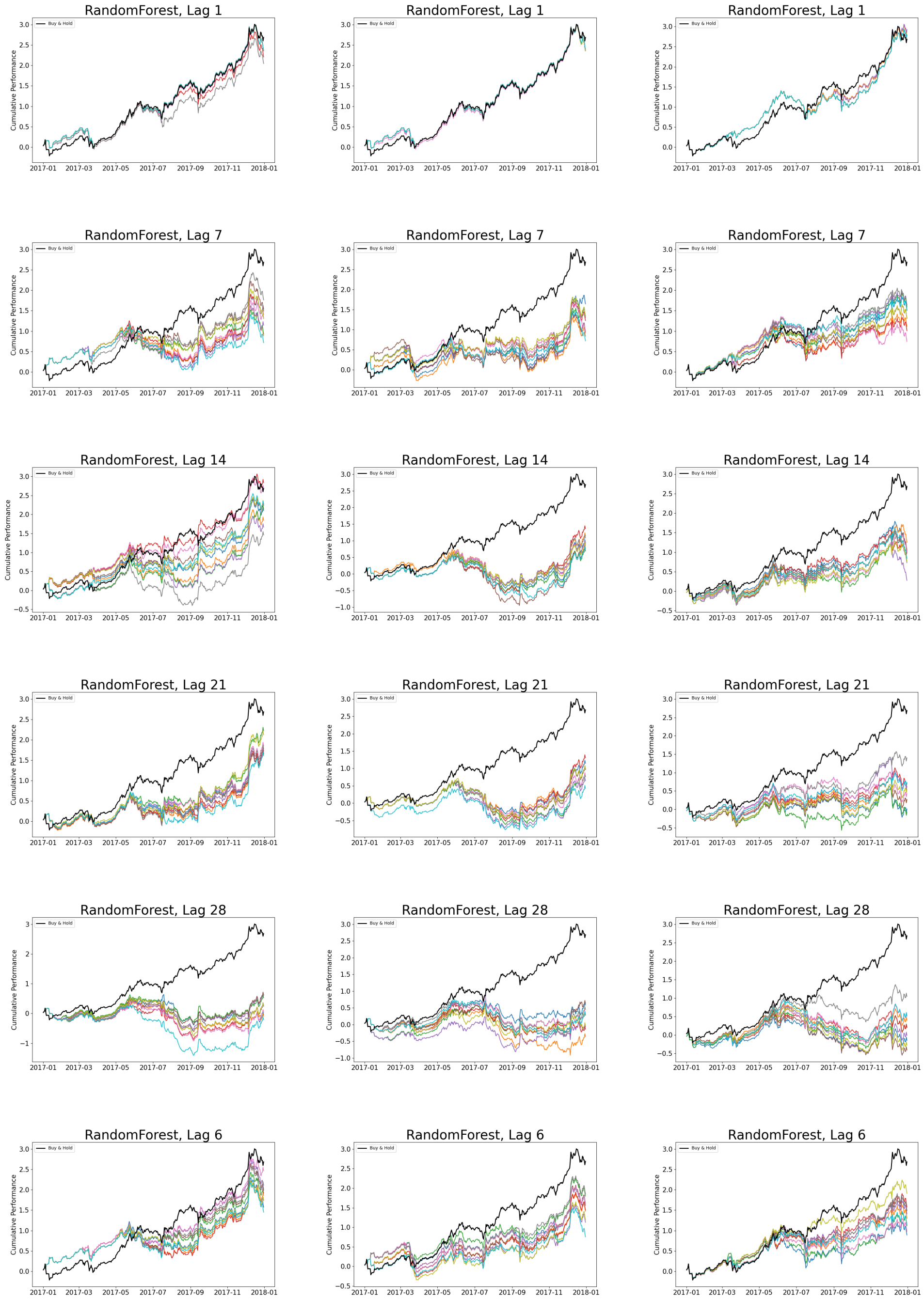
6.2.1 Bitcoin Model Evaluation 2017

In this section, we use the year 2017 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 Models are represented in this section - chosen based on MSE on the train.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.
Our model was not able to beat the benchmark Buy&Hold, but some models still manage to create a Benefit for the investor.

In the year 2017, the value of Bitcoin rose steadily. Due to this, the Buy&Hold approach is the most beneficial, over all the different combinations.



(A) Training 2014, 2015, 2016 and Test 2017 (B) Training 2015, 2016 and Test 2017 (C) Training 2016 and Test 2017

FIGURE 6.15: Performances in comparison with benchmark for the year 2017 on different lags
Each row consists of a different number of lags

The Figure 6.15 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The Figure 6.15 shows that none of our models were able to beat the Buy&Hold benchmark at the end of the year.

This result was expected, due to the steady increase in value of the asset in the year 2017, seen in Figure 6.1.

Performance Metrics

In this section, the MSE and the Hitratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.6 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2014-2017	1	0.54012	0.6	2.496862	9.19136E-4	2.45148E-3
2014-2017	7	0.57419	0.56986	1.62289	8.91508E-4	2.46689E-3
2014-2017	14	0.57056	0.5863	2.220976	8.81059E-4	2.47481E-3
2014-2017	21	0.55706	0.56712	1.744477	8.70360E-4	2.47820E-3
2014-2017	28	0.57797	0.52603	-0.047502	**8.65271E-4**	2.50015E-3
2014-2017	auto	0.5759	0.57808	1.657537	8.90450E-4	2.47033E-3
2015-2017	1	0.54993	0.6	2.496862	8.96987E-4	2.45844E-3
2015-2017	7	0.57729	0.57808	1.734	8.82530E-4	2.46272E-3
2015-2017	14	0.56498	0.54795	0.989481	8.58986E-4	2.47656E-3
2015-2017	21	0.56635	0.55068	1.206944	8.60101E-4	2.47166E-3
2015-2017	28	0.57866	0.53151	0.610094	**8.56029E-4**	2.50103E-3
2015-2017	auto	0.57729	0.57534	1.648338	8.82936E-4	2.46324E-3
2016-2017	1	0.5847	0.60274	2.971037	5.66444E-4	2.48298E-3
2016-2017	7	0.5929	0.59452	1.585973	5.51336E-4	2.54289E-3
2016-2017	14	0.5929	0.5863	1.081931	5.21058E-4	2.63684E-3
2016-2017	21	0.59016	0.5589	0.010523	5.15340E-4	2.61889E-3
2016-2017	28	0.59016	0.55342	-0.153543	**5.07801E-4**	2.63124E-3
2016-2017	auto	0.58743	0.57534	0.936494	5.51354E-4	2.53884E-3

Table 6.9: Best Model for predicting the Year 2017

The model chosen based on the lowest MSE train is the model that only uses 2016 as training. However, even fielding the lowest MSE train, it is not a good choice and it's movements cause a risk/reward imbalance, represented by the Sharpe value of -1.116491.

Further, our analysis so far, for other models, has shown that more training data provides a better result for Bitcoin. This is true in this case as well, with the model performance increasing, the more data is provided. When considering that more data provides a better image of the time series, the Sharpe values increases. When using the train years [2014,2015 and 2016] to -0.805617 and for [2015,2016] to -0.083182 , respectively.

Similar to the finding in the SVR model, the performance increases when using more lags. When looking at Figure 6.2, there is no direct correlation between the two years.

The currently most important year for a good prediction for the year 2017 is the inclusion of year 2015 in the training dataset.

There is a noticeable difference in spread for the models, when compared to Figure 6.3, increasing uncertainty and decreasing trust in the prediction provided by the Random Forest architecture.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables N.1-N.18.

The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2017 can be found in Table N.19.

Noticeable is the lack of correlation between train and test MSE - when compared to the SVR on the same dataset, seen in Table B.19. This difference between correlation is especially noticeable when using [2016] to train - where the SVR reaches up to 0.94483 correlation, while the best correlation for RF only reaches -0.690197.
Considering this, RF is not a reliable approach for the year 2017.

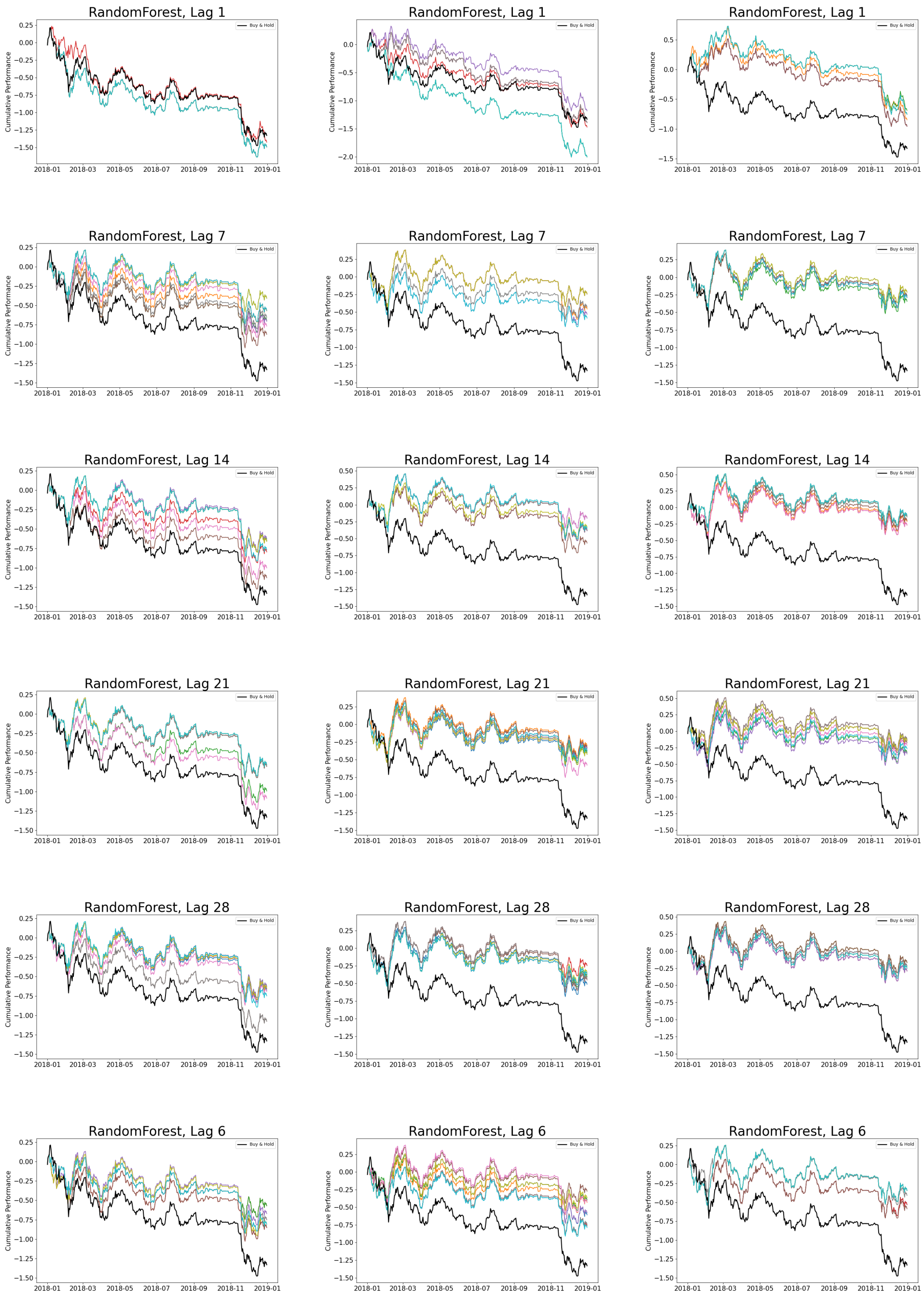
Further, due to the large hitratio in the training dataset and a comparatively low hit ratio for the test dataset, there is overfitting happening. Limiting the Random Forest network could improve the performance, but is not further investigated in the scope of this work to avoid Bias.

6.2.2 Bitcoin Model Evaluation 2018

In this section, we use the year 2018 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 Models are represented in this section - chosen based on MSE on the train.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the lowest values are then used to create a prediction and plotted against the Buy&Hold benchmark.
Our model is able to beat the benchmark Buy&Hold and creates a significant benefit when compared to the Buy&Hold approach.
From the start of 2018 to the end of 2018, Bitcoin lost value. Due to this, we expect our model to be able to outperform the benchmark Buy&Hold.



(A) Training 2015, 2016, 2017 and Test 2018

(B) Training 2016, 2017 and Test 2018

(C) Training 2017 and Test 2018

FIGURE 6.16: Performances in comparison with benchmark for the year 2018 on different lags
Each row consists of a different number of lags

The Figure 6.16 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The Figure 6.16 shows that most of our models were able to beat the Buy&Hold benchmark at the end of the year.

This result was expected, due to the loss in value of the asset in the year 2018, seen in Figure 6.1.

Performance Metrics

In this section, the MSE and the Hitratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.6 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2015-2018	1	0.56843	0.50959	-1.825405	1.38082E-3	1.98215E-3
2015-2018	7	0.57391	0.52603	-0.496278	1.36434E-3	1.88916E-3
2015-2018	14	0.57938	0.51781	-0.789956	**1.35866E-3**	1.88895E-3
2015-2018	21	0.57847	0.51507	-0.822238	1.35904E-3	1.89352E-3
2015-2018	28	0.57847	0.51507	-0.822238	1.36037E-3	1.89020E-3
2015-2018	auto	0.57391	0.52329	-0.693909	1.36449E-3	1.89307E-3
2016-2018	1	0.59644	0.47397	-2.452551	1.43931E-3	1.93255E-3
2016-2018	7	0.60192	0.52603	-0.296544	1.39980E-3	1.87410E-3
2016-2018	14	0.60602	0.52603	-0.241495	1.39311E-3	1.87704E-3
2016-2018	21	0.60739	0.51781	-0.511263	1.38437E-3	1.89557E-3
2016-2018	28	0.60602	0.52055	-0.622124	**1.38324E-3**	1.89312E-3
2016-2018	auto	0.60876	0.51507	-0.739878	1.39934E-3	1.87728E-3
2017-2018	1	0.6274	0.49041	-1.164585	2.20097E-3	1.97017E-3
2017-2018	7	0.63288	0.52877	-0.325132	2.11304E-3	1.90752E-3
2017-2018	14	0.63014	0.53151	-0.149091	2.09925E-3	1.89892E-3
2017-2018	21	0.63288	0.53151	-0.174958	2.08489E-3	1.92198E-3
2017-2018	28	0.63562	0.52877	-0.268889	**2.07159E-3**	1.93844E-3
2017-2018	auto	0.63014	0.52329	-0.646668	2.12069E-3	1.89994E-3

TABLE 6.10: Best Model for predicting the Year 2018

The model chosen based on the lowest MSE train is the model that uses the years [2015, 2016, 2017] as training.

Further, our analysis so far, for other models, has shown that more training data provides a better result for Bitcoin. While this was true when using the SVR and when predicting the year 2017 using RF, this is not the case when predicting the year 2018. In this specific case, the performance does not improve when including more lags, unlike the finding in SVR Section 6.1. When looking at Figure 6.2, the movement of 2018 can roughly be seen mirrored in 2015 - with a steady decline of asset value.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables O.1-O.18.

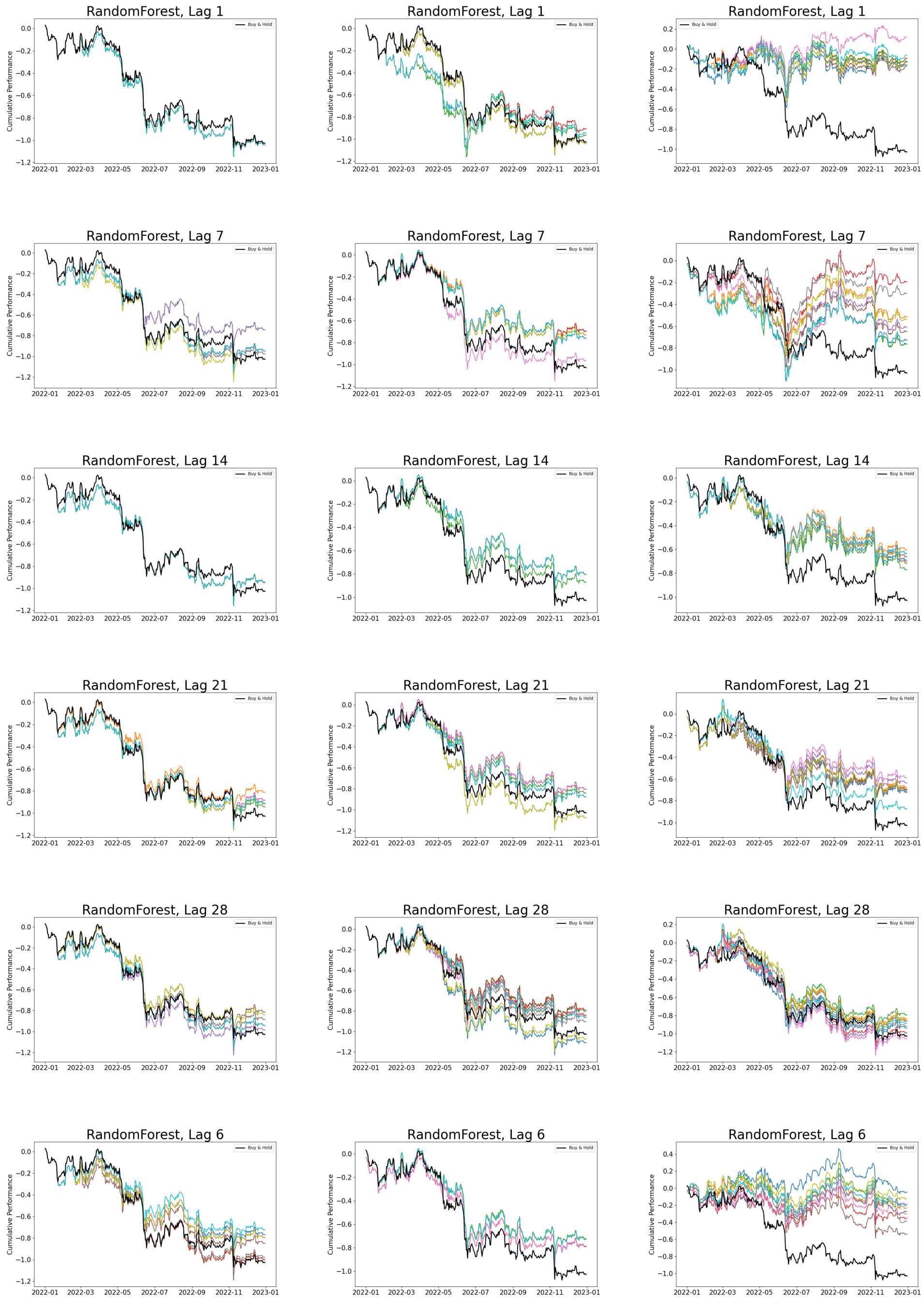
The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2018 can be found in Table O.19.

6.2.3 Bitcoin Model Evaluation 2022

In this section, we use the year 2022 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 Models are represented in this section - chosen based on MSE on the train.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.
Our model is able to beat the benchmark Buy&Hold and creates a significant benefit when compared to the Buy&Hold approach.
From the start of 2022 to the end of 2022, Bitcoin lost value after an initial uptick. Due to this, we expect our model to be able to outperform the benchmark Buy&Hold.



(A) Training 2019, 2020, 2021 and Test 2022 (B) Training 2020, 2021 and Test 2022 (C) Training 2021 and Test 2022

FIGURE 6.17: Performances in comparison with benchmark for the year 2022 on different lags
Each row consists of a different number of lags

The Figure 6.17 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The Figure 6.17 shows that most of our models were able to beat the Buy&Hold benchmark at the end of the year.

This result was expected, due to the loss in value of the asset in the year 2018, seen in Figure 6.1.

Performance Metrics

In this section, the MSE and the Hitratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.17 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2019-2022	1	0.54106	0.46575	-1.624646	1.48645E-3	1.15821E-3
2019-2022	7	0.53923	0.45479	-1.477272	1.33786E-3	1.16483E-3
2019-2022	14	0.54288	0.45753	-1.472763	1.33790E-3	1.16804E-3
2019-2022	21	0.54562	0.46027	-1.419327	1.33822E-3	1.16595E-3
2019-2022	28	0.54653	0.45753	-1.46944	**1.33790E-3**	1.17374E-3
2019-2022	auto	0.5438	0.45479	-1.198119	1.32984E-3	1.17946E-3
2020-2022	1	0.5472	0.46575	-1.624646	1.61369E-3	1.15563E-3
2020-2022	7	0.54993	0.45753	-1.086619	1.36940E-3	1.21464E-3
2020-2022	14	0.5513	0.45205	-1.254133	1.36506E-3	1.22106E-3
2020-2022	21	0.5554	0.45205	-1.254133	1.36235E-3	1.21756E-3
2020-2022	28	0.55267	0.44658	-1.733308	**1.35204E-3**	1.23020E-3
2020-2022	auto	0.54856	0.45479	-1.137617	1.36848E-3	1.23203E-3
2021-2022	1	0.6137	0.49863	-0.248663	1.65320E-3	1.14029E-3
2021-2022	7	0.62192	0.46027	-1.188249	1.57191E-3	1.17067E-3
2021-2022	14	0.55342	0.45753	-1.077759	1.53003E-3	1.18573E-3
2021-2022	21	0.5589	0.46301	-1.126992	1.52290E-3	1.16291E-3
2021-2022	28	0.58356	0.43836	-1.463382	1**.51583E-3**	1.16806E-3
2021-2022	auto	0.61918	0.47123	-0.071396	1.57071E-3	1.16139E-3

Table 6.11: Best Model for predicting the Year 2022

The model chosen based on the lowest MSE train is the model that uses the years [2019, 2020, 2021] as training.

Most models present end up losing money - as does the benchmark. The chosen model, without considering past interactions with the Asset, results in a Sharpe of -1.047841, while the benchmark ends up around the same Sharpe value, indicating too much risk for the provided reward for 2022.

No model configuration inspires confidence in performing well during 2022. However, most models provide a dampening of the loss during this year, allowing them to beat the benchmark Buy&Hold.

This is not the case for our chosen model, which performs in the same manner as the benchmark.

In this specific case, the performance does not improve when including more lags, unlike the finding in SVR Section 6.1. The model lacks information to predict the year 2022 properly, due to the reversal of direction. During 2022, the model has negative returns, which did not happen in any of the available train years.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables P.1-P.18.

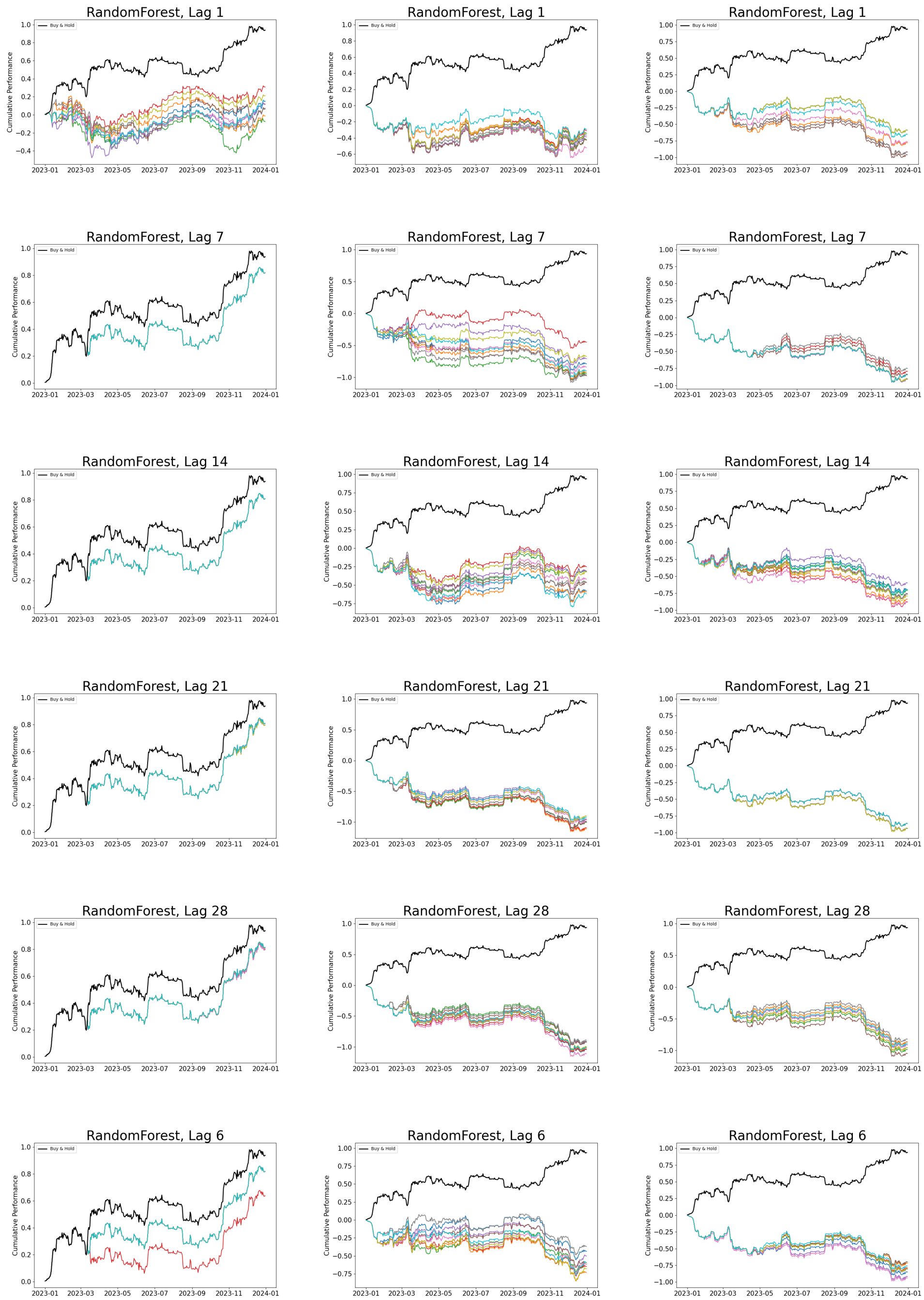
The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in the test year 2018 can be found in Table P.19.

6.2.4 Bitcoin Model Evaluation 2023

In this section, we use the year 2023 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 Models are represented in this section - chosen based on MSE on the train.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.
From start to the end of 2023, the asset gained value. We expect our model to not be able to beat Buy&Hold.



(A) Training 2020, 2021, 2022 and Test 2023 (B) Training 2021, 2022 and Test 2023 (C) Training 2022 and Test 2023

FIGURE 6.18: Performances in comparison with benchmark for the year 2023 on different lags
Each row consists of a different number of lags

The Figure 6.18 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. Further, it shows that the models were unable to beat the Buy&Hold benchmark at the end of the year.

This result was expected, due to the gain in value of the asset in the year 2023, seen in Figure 6.1.

Performance Metrics

In this section, the MSE and the Hit ratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.18 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2020-2023	1	0.55839	0.54247	0.271531	1.46412E-3	5.14069E-4
2020-2023	7	0.52007	0.50137	1.888714	1.32899E-3	5.16862E-4
2020-2023	14	0.52646	0.49863	1.866433	1.32743E-3	5.16288E-4
2020-2023	21	0.52646	0.49589	1.838701	1.32079E-3	5.16017E-4
2020-2023	28	0.53102	0.50137	1.877861	1.31079E-3	5.17026E-4
2020-2023	auto	0.51734	0.50137	1.888714	1.33005E-3	5.17357E-4
2021-2023	1	0.56575	0.53425	-0.784964	1.38963E-3	5.22741E-4
2021-2023	7	0.58356	0.49589	-1.813016	1.36769E-3	5.24936E-4
2021-2023	14	0.59178	0.52329	-1.328316	1.35001E-3	5.26255E-4
2021-2023	21	0.55753	0.49315	-2.311925	1.33913E-3	5.28709E-4
2021-2023	28	0.55479	0.49315	-2.417834	1.33074E-3	5.30982E-4
2021-2023	auto	0.59041	0.51781	-1.005181	1.36867E-3	5.27260E-4
2022-2023	1	0.5589	0.50137	-2.123771	1.03727E-3	5.37814E-4
2022-2023	7	0.56164	0.50411	-2.099321	1.00727E-3	5.54087E-4
2022-2023	14	0.59726	0.52329	-1.602202	9.84225E-4	5.50516E-4
2022-2023	21	0.57534	0.50411	-1.994182	9.77617E-4	5.50629E-4
2022-2023	28	0.57808	0.50685	-2.007552	9.59275E-4	5.51285E-4
2022-2023	auto	0.56164	0.49863	-1.961963	1.01576E-3	5.49484E-4

Table 6.12: Best Model for predicting the Year 2023

The model chosen based on the lowest MSE train is the model that uses the year 2022 as training.

Many models have a negative Sharpe value, without considering past interactions with the Asset, results in a Sharpe of -1.915925, meaning inadequate risk for the provided return.

Further, no model configuration inspires confidence in performing well during 2023. Most models never manage to beat the Buy&Hold approach, only sometimes due to luck are they able to be better than Buy&Hold. These models lose this gain quickly during the rest of the year, as can be seen in Figure 6.18, with Lag auto.

In this specific case, the performance does not significantly or consistently improve when including more lags, unlike the finding in SVR Section 6.1.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables Q.1-Q.18.

The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2018 can be found in Table Q.19.

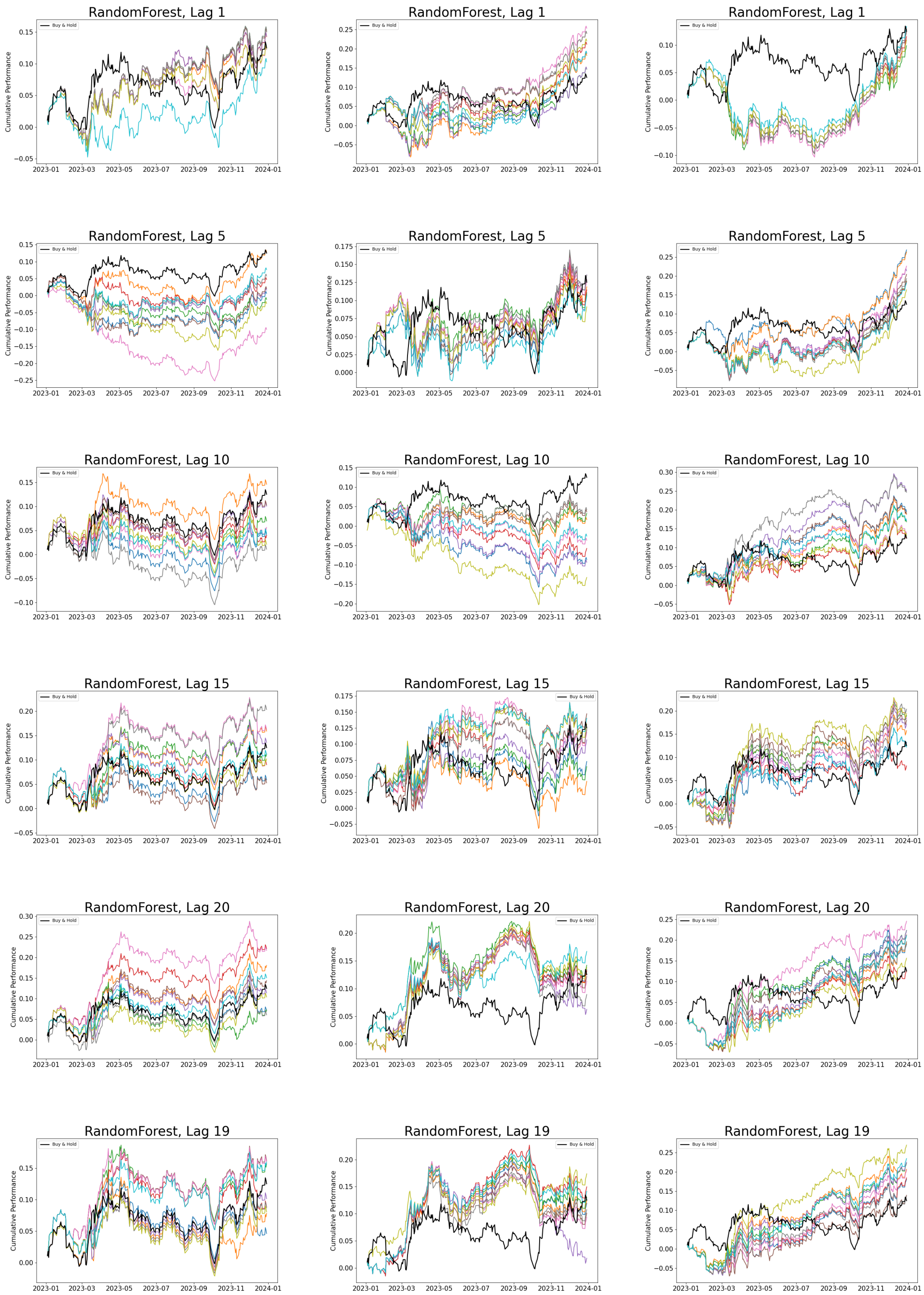
6.2.5 Gold

Gold Model Evaluation 2023

In this section, we use the year 2023 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 Models are represented in this section - chosen based on MSE on the train.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.
From the start of 2023 to the end of 2023, the asset had volatile phases and gained value. We expect our model to be able to beat Buy&Hold approach.



(A) Training 2020, 2021, 2022 and Test 2023 (B) Training 2021, 2022 and Test 2023 (C) Training 2022 and Test 2023

FIGURE 6.19: Performances in comparison with benchmark for the year 2023 on different lags using Gold data each row consists of a different number of lags

The Figure 6.19 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The Figure 6.19 shows that some of our models are able to beat the Buy&Hold benchmark at the end of the year.

This result was expected, due to the volatility of the asset in the year 2023, seen in Figure 6.7 in the bottom-left panel.

The proposed model from the acf, bottom row in Figure 6.19 does not lead to a significant performance increase. For gold it appears that less training data and less lags have a positive influence on the RF performance , while more training data and more available lags have not such an impact.

Performance Metrics

In this section, the MSE and the Hit ratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.19 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2020-2023	1	0.56085	0.52191	1.141643	1.16170E-4	6.87957E-5
2020-2023	5	0.55952	0.46215	0.046971	1.14234E-4	6.91794E-5
2020-2023	10	0.58333	0.50199	0.302506	1.12046E-4	6.88579E-5
2020-2023	15	0.58862	0.49402	0.448793	1.11945E-4	6.89370E-5
2020-2023	20	0.59921	0.51394	0.537645	**1.11382E-4**	6.89008E-5
2020-2023	auto	0.59788	0.50996	0.350069	1.11398E-4	6.89106E-5
2021-2023	1	0.55666	0.52988	1.433017	8.68138E-5	6.85765E-5
2021-2023	5	0.60437	0.54582	0.820131	8.51529E-5	7.25207E-5
2021-2023	10	0.66004	0.51394	-0.656915	8.45425E-5	7.22810E-5
2021-2023	15	0.66004	0.5498	0.55267	8.43622E-5	7.09655E-5
2021-2023	20	0.666	0.5259	1.021837	**8.32843E-5**	7.10404E-5
2021-2023	auto	0.67197	0.5259	0.906165	8.33411E-5	7.14495E-5
2022-2023	1	0.58566	0.54582	0.948131	8.45620E-5	6.95251E-5
2022-2023	5	0.67729	0.55777	2.056779	8.28715E-5	6.78935E-5
2022-2023	10	0.72112	0.55777	1.490271	8.05784E-5	6.89170E-5
2022-2023	15	0.72908	0.52191	1.006211	8.01917E-5	6.87837E-5
2022-2023	20	0.7012	0.52988	1.44778	**7.85867E-5**	6.87683E-5
2022-2023	auto	0.71315	0.5259	1.378139	7.86186E-5	6.91203E-5

TABLE 6.13: Best Model for predicting the Year 2023

The model chosen based on the lowest MSE train is the model that uses the years 2021-2022 as training.

A few models have a negative Sharpe value. The chosen model, without considering past interactions with the commodity, results in a Sharpe of 0.06812, meaning inadequate risk for the provided return.

There are model configuration that inspire confidence in performing well during 2023. Although, most models don't manage to beat the Buy&Hold approach, some do, due to the right decisions they are able to be better than Buy&Hold. These models are keeping the gains during the rest of the year, as it can be seen in Figure 6.19, with Lag 2.

In this specific case, the performance does not consistently improve when including more lags, unlike the finding in SVR Section 6.1. Another finding is that the RF models have an extremely high Hit-Rate on the training data, this could be a possible sign of overfitting. And the models seemingly perform better with less training data.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables R.1-R.18.

The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2018 can be found in Table R.19.

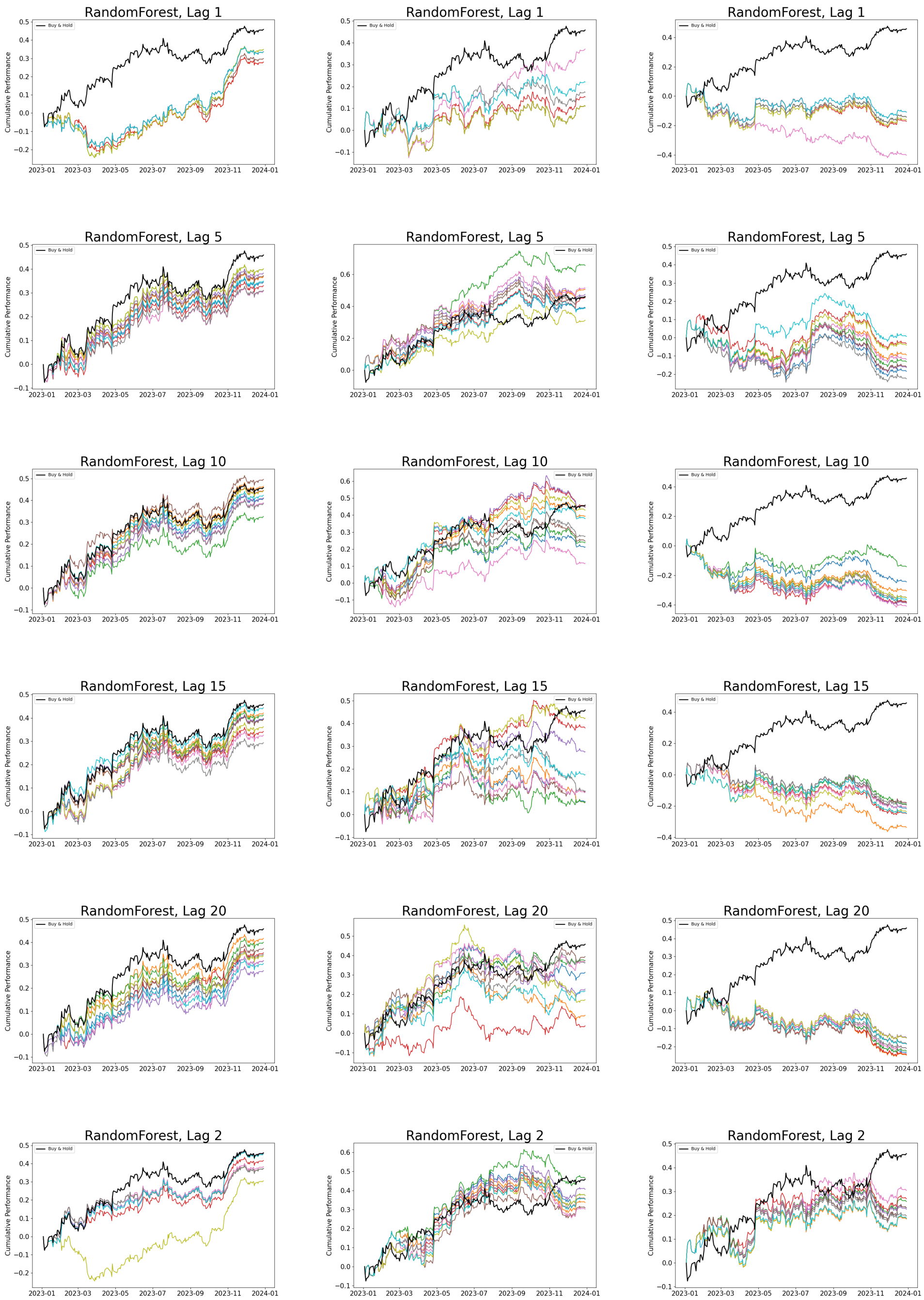
6.2.6 MSFT

MSFT Model Evaluation 2023

In this section, we use the year 2023 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 Models are represented in this section - chosen based on MSE on the train.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.
From start to the end of 2023, the asset had strong incline with one minor drop in value during August 2023. We expect our model to not be able to beat Buy&Hold approach.



(A) Training 2020, 2021, 2022 and Test 2023 (B) Training 2021, 2022 and Test 2023 (C) Training 2022 and Test 2023

FIGURE 6.20: Performances in comparison with benchmark for the year 2023 on different lags using MSFT data each row consists of a different number of lags

The Figure 6.20 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The Figure 6.20 shows that a minority of our models are able to beat the Buy&Hold benchmark at the end of the year.

This result was expected, due to the strong value growth of the asset in the year 2023, seen in Figure 6.11.

Performance Metrics

In this section, the MSE and the Hit ratio is presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.20 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2020-2023	1	0.52381	0.52	1.348217	4.13926E-4	2.48153E-4
2020-2023	5	0.53836	0.56	1.384101	4.08739E-4	2.48563E-4
2020-2023	10	0.53571	0.552	1.640837	4.00587E-4	2.49030E-4
2020-2023	15	0.54233	0.568	1.590595	**3.99190E-4**	2.48741E-4
2020-2023	20	0.54101	0.544	1.281329	3.99480E-4	2.48810E-4
2020-2023	auto	0.54365	0.544	1.498046	4.11900E-4	2.48608E-4
2021-2023	1	0.55467	0.48	0.443264	3.14379E-4	2.48212E-4
2021-2023	5	0.59245	0.532	1.570632	3.11854E-4	2.45091E-4
2021-2023	10	0.62227	0.512	0.846406	2.99513E-4	2.56602E-4
2021-2023	15	0.6163	0.504	0.228714	2.96693E-4	2.50283E-4
2021-2023	20	0.63022	0.548	1.257534	**2.96031E-4**	2.50008E-4
2021-2023	auto	0.57455	0.528	1.502137	3.13272E-4	2.46022E-4
2022-2023	1	0.56175	0.468	-0.567111	4.45133E-4	2.58371E-4
2022-2023	5	0.6494	0.48	-0.738807	4.36887E-4	2.56833E-4
2022-2023	10	0.63745	0.452	-0.978476	4.08552E-4	2.74268E-4
2022-2023	15	0.65339	0.448	-0.865612	4.02798E-4	2.66912E-4
2022-2023	20	0.65737	0.444	-0.941657	**4.01953E-4**	2.65192E-4
2022-2023	auto	0.62948	0.508	0.926432	4.43197E-4	2.57487E-4

TABLE 6.14: Best Model for predicting the Year 2018

The model chosen based on the lowest MSE train is the model that uses the years 2021-2022 as training.

A majority of the models have a positive Sharpe value. The chosen model, without considering past interactions with the equity, results in a Sharpe of -0.09659, meaning inadequate risk for the provided return.

There are no model configuration that inspire confidence in performing well during 2023. Most models don't manage to beat the Buy&Hold approach, due to the strong incline of the equity, they are not able to be better than Buy&Hold. These models are struggling to create gains comparable to the benchmark, as seen in Figure 6.20.

In this specific case, the performance does not consistently improve when including more lags, unlike the finding in SVR Section 6.1. Similar to the finding with the commodity Gold, the RF models have again a high Hit-Rate on the training data, this could be a possible sign of overfitting. And the models seemingly perform better with less lags.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables S.1-S.18.

The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2018 can be found in Table S.19.

6.2.7 Random Walk

In this section we want to present how our model performs on a generated random walk for the year 2024. The model uses the auto Lag based on the standard procedure we followed thru the thesis and is than trained on three years of random walk. What we expect is that the model cannot learn to predict the random walk and generate a profit. For this purpose we illustrate in the Figure 6.21 how a hundred random initiate models would perform.

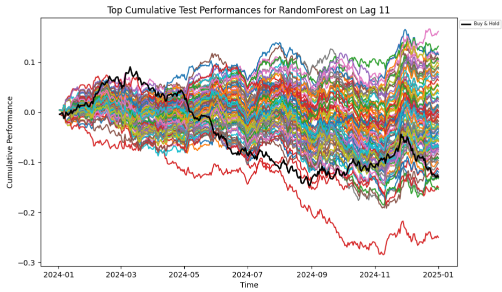


Figure 6.21: Random Walk prediction with 100 random seeds and auto lag.

As awaited the models cannot predict the random walk and therefore form a distribution around zero. Vividly represented with the hundred models in the Figure. This leads us to the assumption that our RF model is trustworthy, as it behaves as expected.

6.3 NN

Parameter	Value
hidden_layer_sizes	(50,23)
activation	relu
solver	adam
alpha	0.0001
batch_size	auto
learning_rate	constant
learning_rate_init	0.001
power_t	0.5
max_iter	200
shuffle	True
random_state	None
tol	1e-4
verbose	False
warm_start	False
momentum	0.9
nesterovs_momentum	True
early_stopping	False
validation_fraction	0.1
beta_1	0.9
beta_2	0.999
epsilon	1e-8
n_iter_no_change	10
max_fun	15000

TABLE 6.15: Neural Network Parameters

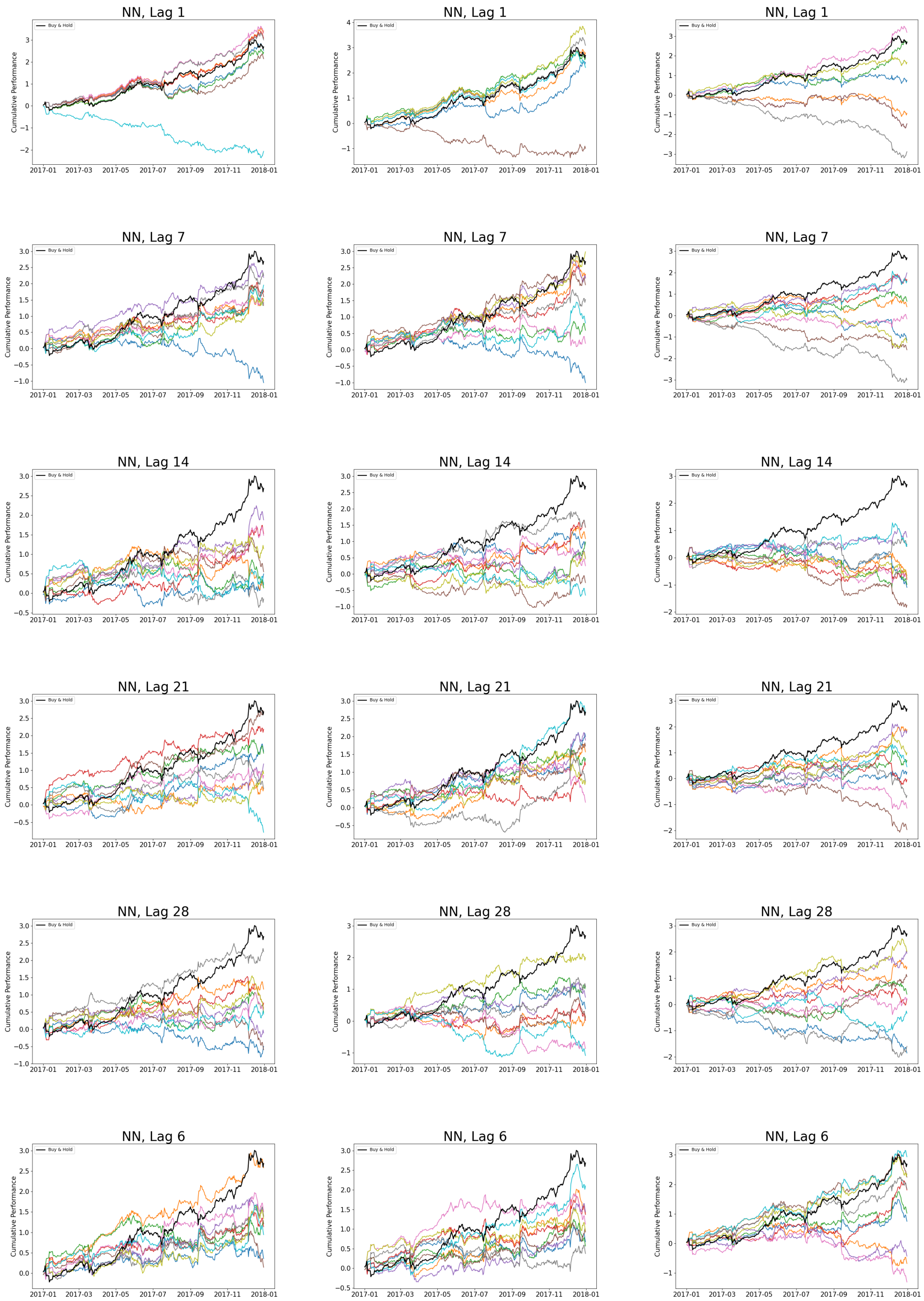
The hyperparameters in Table 6.15 were selected based on the default values provided by the scikit-learn package, the only deviation form the default are the amount of layers and neurons, due to the fact that the default value has one layer with 100 neurons. This choice was made to ensure that the results are reproducible and that we not falsify the results towards benefiting the test performance.

6.3.1 Bitcoin Model Evaluation 2017

In this section, we use the year 2017 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 Models are represented in this section - chosen based on performance on the train dataset.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.
Our model was not able to beat the benchmark Buy&Hold, but some models still manage to create a Benefit for the investor.
In the year 2017, the value of Bitcoin rose steadily. Due to this, the Buy&Hold approach is expected to be the most beneficial, over all the different combinations.



(A) Training 2014, 2015, 2016 and Test 2017 (B) Training 2015, 2016 and Test 2017 (C) Training 2016 and Test 2017

FIGURE 6.22: Performances in comparison with benchmark for the year 2017 on different lags
Each row consists of a different number of lags

The Figure 6.22 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The Figure 6.22 shows that none of our models were able to beat the Buy&Hold benchmark consistently at the end of the year. However, there were some Neural Network models able to beat the benchmark for this year. Especially interesting is the performance of the Models using 2014-2016 as training in combination with Lag 01 managing to match the

benchmark well with 9 out of 10 models. There is one model that could be considered an outlier, reducing this consistency.
Further, increasing the data or increasing the Lag does not seem to increase performance for the year 2017. Additionally, when considering the ACF, with Lag auto (6), the NN is able to consistently achieve a positive return when using the training years [2014, 2015, 2016] and [2015, 2016].

This result with Lag 01 was unexpected, the Buy&Hold benchmark is rarely beaten when the performance is positive, as shown in Figure 6.1. Further, the ACF provides no information that using Lag 01 should perform this well.

Performance Metrics

In this section, the MSE and the Hit ratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.22 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2014-2017	1	0.51497	0.58356	2.679375	9.96754E-4	2.44764E-3
2014-2017	7	0.55127	0.47671	-1.105432	9.48993E-4	2.63489E-3
2014-2017	14	0.49392	0.49863	0.520029	**9.24108E-4**	2.59461E-3
2014-2017	21	0.54233	0.54521	1.626196	9.26770E-4	2.53817E-3
2014-2017	28	0.57673	0.49315	-0.52407	9.41203E-4	2.70724E-3
2014-2017	auto	0.52048	0.51781	0.375152	9.34238E-4	2.57216E-3
2015-2017	1	0.50068	0.5726	2.564747	9.87706E-4	2.45767E-3
2015-2017	7	0.57319	0.47945	-1.055041	9.47115E-4	2.67437E-3
2015-2017	14	0.56908	0.51781	1.003608	9.18480E-4	2.60273E-3
2015-2017	21	0.56772	0.56986	2.110389	9.10444E-4	2.63243E-3
2015-2017	28	0.56908	0.53699	0.40567	**8.86849E-4**	2.67281E-3
2015-2017	auto	0.53762	0.50959	0.709901	9.34360E-4	2.55547E-3
2016-2017	1	0.60383	0.53973	0.788275	6.34055E-4	2.47655E-3
2016-2017	7	0.56011	0.52329	-1.205745	6.20715E-4	2.64771E-3
2016-2017	14	0.57923	0.50685	-1.150984	**5.84190E-4**	2.82959E-3
2016-2017	21	0.59836	0.56164	0.262464	6.18192E-4	2.87410E-3
2016-2017	28	0.57923	0.42192	-1.954442	6.33318E-4	3.01485E-3
2016-2017	auto	0.5765	0.55342	0.787529	6.19907E-4	2.49834E-3

TABLE 6.16: Best Model for predicting the Year 2017

The model chosen based on the lowest MSE train is the model that only uses 2016 as training. However, even fielding the lowest MSE train, it is not a good choice and it's movements cause an active loss, represented by the Sharpe value of -1.150984. Further, it performs poorly, which is reflected in Figure 6.22.

Further, our analysis so far, for other models, especially SVR, has shown that more training data provides a better result for Bitcoin. This is not true in this case, the model performs worse when increasing the Lag or the training years.

In this case, using the Lag provided by the ACF is consistently able to provide a benefit for the investor, while using more than 2016 as training and in one singular case even beating the benchmark.

There is a noticeable difference in spread for the models, when compared to 6.3, increasing uncertainty and decreasing trust in the prediction provided by the Neural Network architecture. This is understandable due to the nature of noisy Time Series data in combination with the Neural Network.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables H.1-H.18.

The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2017 can be found in Table H.19.

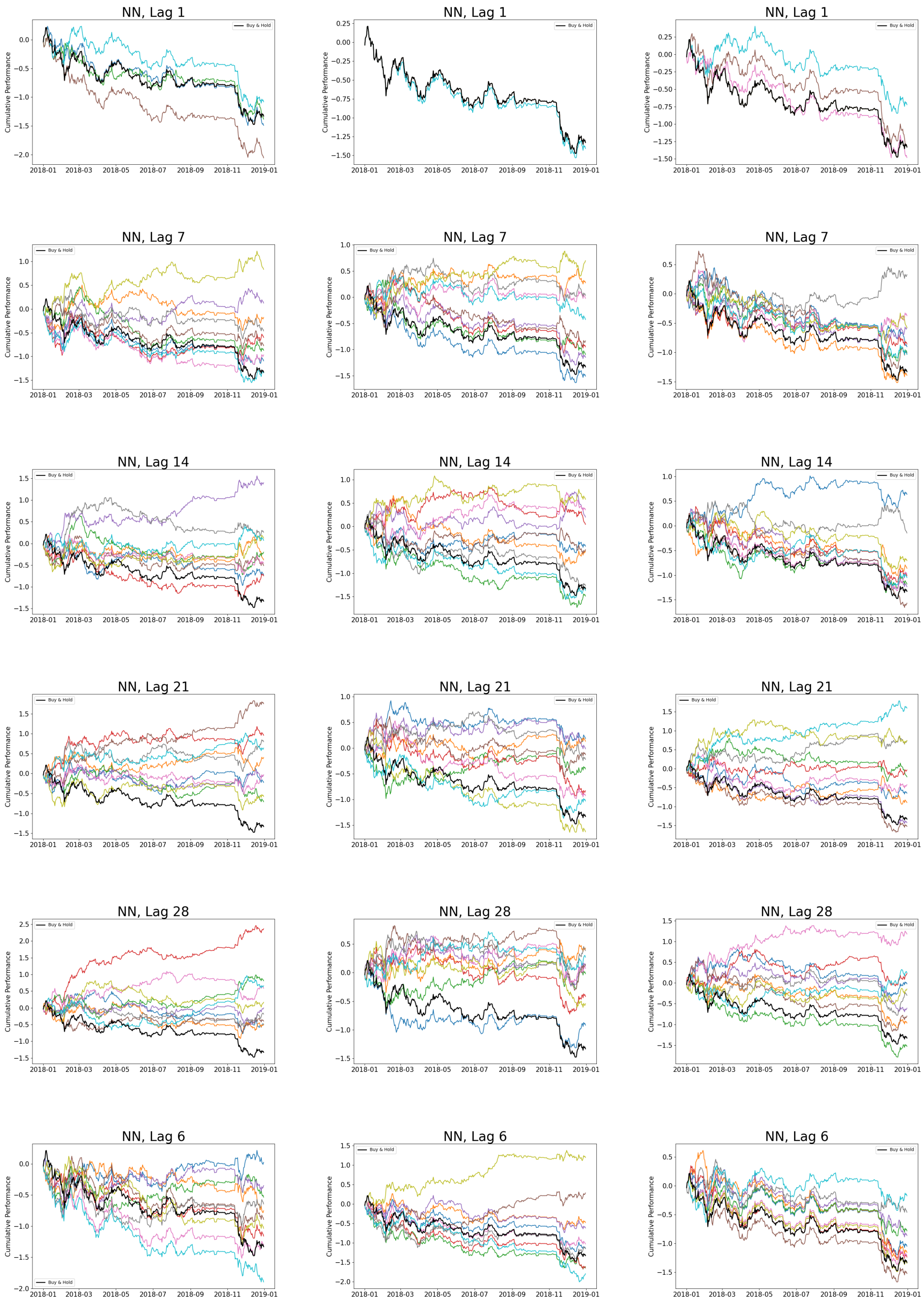
There is a significant amount of correlation available between the train and test MSE for the Neural Network models, reaching to a correlation of up to 84.454% in the best 10 models.

6.3.2 Bitcoin Model Evaluation 2018

In this section, we use the year 2018 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 Models are represented in this section - chosen based on performance on the train dataset.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.
Our model is able to beat the benchmark Buy&Hold and creates a significant benefit when compared to the Buy&Hold approach.
From the start of 2018 to the end of 2018, Bitcoin lost value. Due to this, we expect our model to be able to outperform the benchmark Buy&Hold.



(A) Training 2015, 2016, 2017 and Test 2018 (B) Training 2016, 2017 and Test 2018 (C) Training 2017 and Test 2018

FIGURE 6.23: Performances in comparison with benchmark for the year 2018 on different lags
Each row consists of a different number of lags

The Figure 6.23 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The Figure 6.23 shows that most of our models were able to beat the Buy&Hold benchmark at the end of the year, managing to avoid some losses that the benchmark creates.

This result was expected, due to the loss in value of the asset in the year 2018, seen in Figure 6.1.

Performance Metrics

In this section, the MSE and the Hit ratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.23 corresponds to a model configuration. The best model of all these is chosen and further analyzed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2015-2018	1	0.56843	0.48767	-1.822136	1.45809E-3	1.90766E-3
2015-2018	7	0.56478	0.49315	-1.331577	1.41736E-3	1.88830E-3
2015-2018	14	0.57117	0.49041	-0.881483	1.39486E-3	1.95579E-3
2015-2018	21	0.58394	0.52329	-0.271905	1.37778E-3	1.92494E-3
2015-2018	28	0.57847	0.50137	-0.61696	**1.35412E-3**	1.98572E-3
2015-2018	auto	0.57847	0.50959	0.029401	1.42174E-3	1.87890E-3
2016-2018	1	0.59508	0.50959	-1.62335	1.51768E-3	1.92795E-3
2016-2018	7	0.59918	0.50685	-1.842111	1.50135E-3	1.92344E-3
2016-2018	14	0.61012	0.52329	-0.514507	1.49279E-3	2.00082E-3
2016-2018	21	0.60465	0.51233	0.225044	1.45387E-3	1.88912E-3
2016-2018	28	0.58687	0.52877	-1.116991	**1.43332E-3**	2.13125E-3
2016-2018	auto	0.59234	0.51507	-1.391149	1.50355E-3	1.93452E-3
2017-2018	1	0.6137	0.50959	-1.62335	2.40426E-3	2.04310E-3
2017-2018	7	0.60548	0.49315	-1.102288	2.39229E-3	1.86734E-3
2017-2018	14	0.59452	0.53699	0.773766	2.40086E-3	2.00850E-3
2017-2018	21	0.63288	0.50959	-0.786501	2.33832E-3	2.17019E-3
2017-2018	28	0.60274	0.52329	-0.025695	**2.26941E-3**	2.06666E-3
2017-2018	auto	0.61918	0.51781	-1.280386	2.39510E-3	2.17587E-3

TABLE 6.17: Best Model for predicting the Year 2018

The model chosen based on the lowest MSE train,**1.35412E-3**, is the model that uses the years [2015, 2016, 2017] as training.

Further, our analysis so far, for other models, has shown that more training data provides a better result for Bitcoin. While this was true when using the SVR and when predicting the year 2017 using NN, this is not the case when predicting the year 2018. In this specific case, the performance does not improve when including more lags, unlike the finding in SVR Section 6.1. When looking at Figure 6.2, the movement of 2018 can roughly be seen mirrored in 2015 - with a steady decline of asset value - however the NN is unable to capitalize on this information. What can be seen is a widening of the Performance when increasing the years, especially noticeable in the last row of Figure 6.23, utilizing the Lag provided by the ACF - for Bitcoin this means Lag 06.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables O.1-O.18.

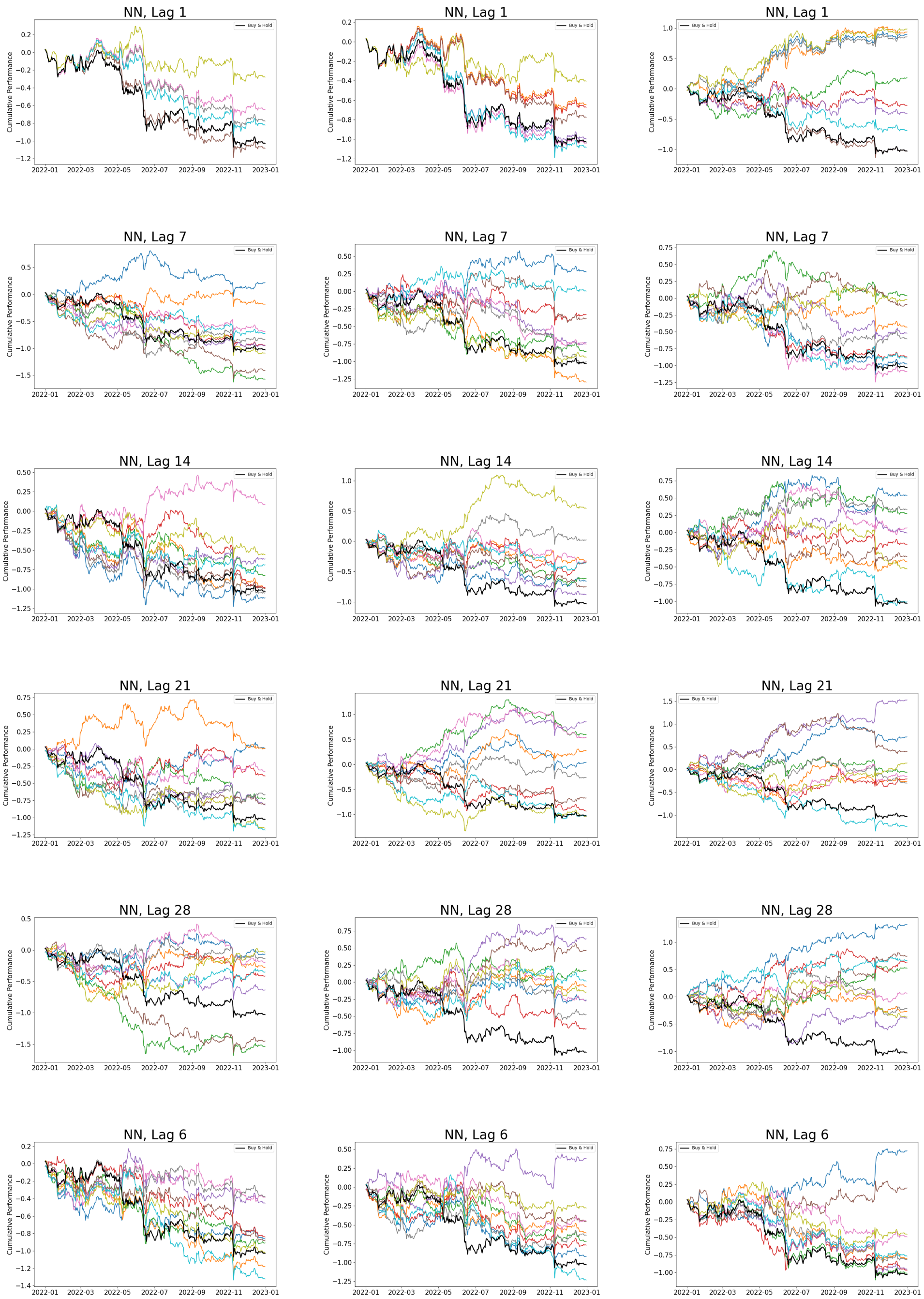
The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2018 can be found in Table O.19.

6.3.3 Bitcoin Model Evaluation 2022

In this section, we use the year 2022 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 Models are represented in this section - chosen based on performance on the train dataset.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.
Our model is able to beat the benchmark Buy&Hold and creates a significant benefit when compared to the Buy&Hold approach.
From the start to the end of 2022, Bitcoin lost value after an initial uptick. Due to this, we expect our model to be able to outperform the benchmark Buy&Hold.



(A) Training 2019, 2020, 2021 and Test 2022 (B) Training 2020, 2021 and Test 2022 (C) Training 2021 and Test 2022

FIGURE 6.24: Performances in comparison with benchmark for the year 2022 on different lags
Each row consists of a different number of lags

The Figure 6.24 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The Figure 6.24 shows that most of our models were able to beat the Buy&Hold benchmark at the end of the year, but not reach a positive Performance.

This result was expected, due to the loss in value of the asset in the year 2022, seen in Figure 6.1.

Performance Metrics

In this section, the MSE and the Hit ratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.5 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2019-2022	1	0.53285	0.46575	-1.602436	1.51818E-3	1.16815E-3
2019-2022	7	0.52281	0.49041	0.337119	1.47277E-3	1.13967E-3
2019-2022	14	0.56387	0.49041	-1.733032	1.44863E-3	1.17265E-3
2019-2022	21	0.53923	0.48493	0.014988	1.43748E-3	1.18814E-3
2019-2022	28	0.57391	0.49041	-0.096209	**1.43698E-3**	1.24079E-3
2019-2022	auto	0.54288	0.44658	-1.342543	1.49310E-3	1.17951E-3
2020-2022	1	0.53762	0.46575	-1.602436	1.66122E-3	1.17269E-3
2020-2022	7	0.55677	0.47671	0.433163	1.61307E-3	1.18237E-3
2020-2022	14	0.54993	0.49589	-1.021952	1.55857E-3	1.18844E-3
2020-2022	21	0.55814	0.48493	0.067879	**1.53502E-3**	1.18985E-3
2020-2022	28	0.54172	0.49589	-0.408083	1.54509E-3	1.18137E-3
2020-2022	auto	0.55814	0.45205	-1.43421	1.61461E-3	1.17697E-3
2021-2022	1	0.48493	0.53973	1.397455	1.75876E-3	1.13127E-3
2021-2022	7	0.50411	0.44658	-1.522274	1.75610E-3	1.20929E-3
2021-2022	14	0.53699	0.52603	0.838545	1.71038E-3	1.20765E-3
2021-2022	21	0.55814	0.48493	0.067879	**1.53502E-3**	1.18985E-3
2021-2022	28	0.53699	0.58082	2.065473	1.73035E-3	1.18382E-3
2021-2022	auto	0.51233	0.53699	1.121805	1.74258E-3	1.14110E-3

Table 6.18: Best Model for predicting the Year 2022

The model chosen based on the lowest MSE train is the model that uses the years [2019, 2020, 2021] as training in combination with Lag 28.

Most models present end up losing money - as does the benchmark. The chosen model, without considering past interactions with the Asset, results in a Sharpe of -0.096209.

No model configuration inspires confidence in performing well during 2022. However, most models provide a dampening of the loss during this year, allowing them to beat the benchmark Buy&Hold.

This is not the case for our chosen model, which performs in the same manner as the benchmark.

In this specific case, the performance does not improve when including more lags, unlike the finding in SVR Section 6.1. The model lacks information to predict the year 2022 properly, due to the reversal of direction. During 2022, the model has negative returns, which did not happen in the available train years.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables J.1-J.18.

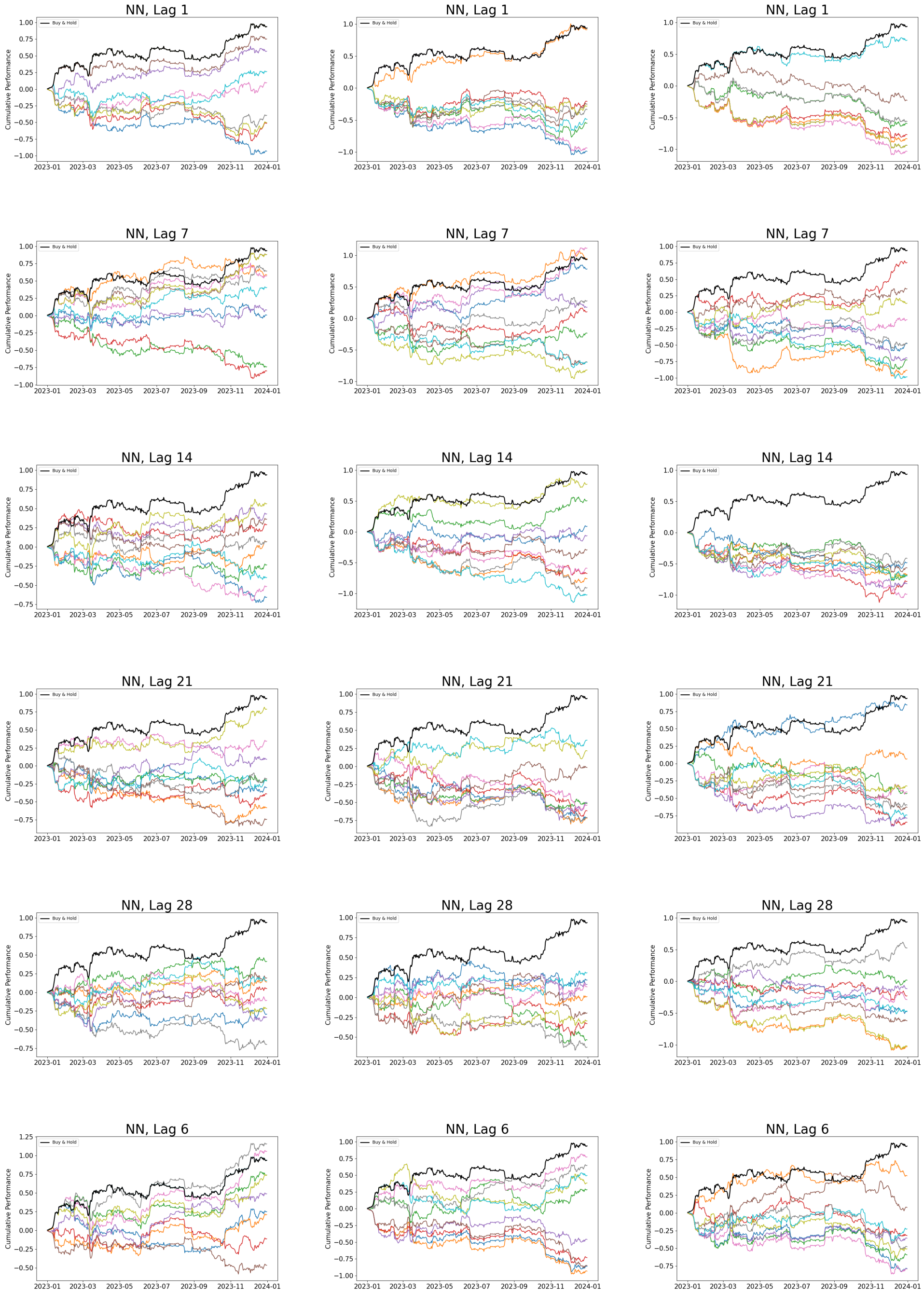
The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2022 can be found in Table J.19. The models for the test year 2022 provide a reduced correlation between train and test MSE - which would encourage taking all models and taking the mean of their prediction. This would stabilize the Neural Network predictions, and make sure that neither loss nor gain is too influential in the end result.

6.3.4 Bitcoin Model Evaluation 2023

In this section, we use the year 2023 as test year, while altering the Lags and the training years and comparing the performance, Hit-Rate and MSE of the different models. The best 10 Models are represented in this section - chosen based on MSE on the train dataset.

Performance Evaluation

As decision metric for the model selection, we chose the train mean squared error. For these choices, the performances of the ten lowest values are then used to create a prediction and plotted against our Buy&Hold benchmark.
From the start to the end of 2023, the asset gained value. We expect our model to not be able to beat Buy&Hold.



(A) Training 2020, 2021, 2022 and Test 2023 (B) Training 2021, 2022 and Test 2023 (C) Training 2022 and Test 2023

FIGURE 6.25: Performances in comparison with benchmark for the year 2023 on different lags
Each row consists of a different number of lags

The Figure 6.25 represents the cumulative performance over different combinations of years, according to table A.1 and a different amount of lag. The Figure 6.25 shows that most of our models were unable to beat the Buy&Hold benchmark at the end of the year, and none were able to do so consistently.

This result was expected, due to the gain in value of the asset in the year 2023, seen in Figure 6.1.

Performance Metrics

In this section, the MSE and the Hit ratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.25 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2020-2023	1	0.48814	0.49589	-2.150101	1.48814E-3	5.20267E-4
2020-2023	7	0.51004	0.49863	0.012595	1.43918E-3	5.16589E-4
2020-2023	14	0.54653	0.48767	-1.511753	1.40689E-3	5.34625E-4
2020-2023	21	0.55657	0.48493	-0.694002	1.39391E-3	5.27933E-4
2020-2023	28	0.55383	0.50137	-0.670214	**1.39158E-3**	5.45073E-4
2020-2023	auto	0.53376	0.49315	0.579342	1.45205E-3	5.17359E-4
2021-2023	1	0.51644	0.49863	-2.286866	1.44296E-3	5.24947E-4
2021-2023	7	0.52192	0.49863	1.811502	1.43488E-3	5.19008E-4
2021-2023	14	0.51233	0.52603	0.203519	1.39480E-3	5.35535E-4
2021-2023	21	0.54932	0.48219	-1.6302	1.36269E-3	5.75405E-4
2021-2023	28	0.55616	0.53699	0.497749	**1.35184E-3**	5.49653E-4
2021-2023	auto	0.53425	0.50137	-1.993365	1.42764E-3	5.46174E-4
2022-2023	1	0.53425	0.50137	-2.166654	1.13000E-3	5.65002E-4
2022-2023	7	0.5589	0.52055	-1.101512	1.12794E-3	5.57112E-4
2022-2023	14	0.55342	0.51781	-1.104562	1.11346E-3	5.63700E-4
2022-2023	21	0.52603	0.53425	1.945296	1.13270E-3	5.41337E-4
2022-2023	28	0.5863	0.51781	-1.097795	**1.11188E-3**	5.90244E-4
2022-2023	auto	0.53151	0.49315	-1.810567	1.12609E-3	5.79146E-4

TABLE 6.19: Best Model for predicting the Year 2023

The model chosen based on the lowest MSE train is the model that uses the year 2022 as training.

Many models have a negative Sharpe value, including the chosen model, without considering past interactions with the Asset. This results in a Sharpe of -1.097795, meaning inadequate risk for the provided return.

No model configuration inspires confidence in performing well during 2023. Most models never manage to beat the Buy&Hold approach, but some are able to beat the benchmark for a very limited time. However, these models lose this gain quickly during the rest of the year, as can be seen in Figure 6.25, with Lag auto.

In this specific case, the performance does not significantly or consistently improve when including more lags, unlike the finding in SVR Section 6.1.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables K.1-K.18.

The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2023 can be found in Table K.19.

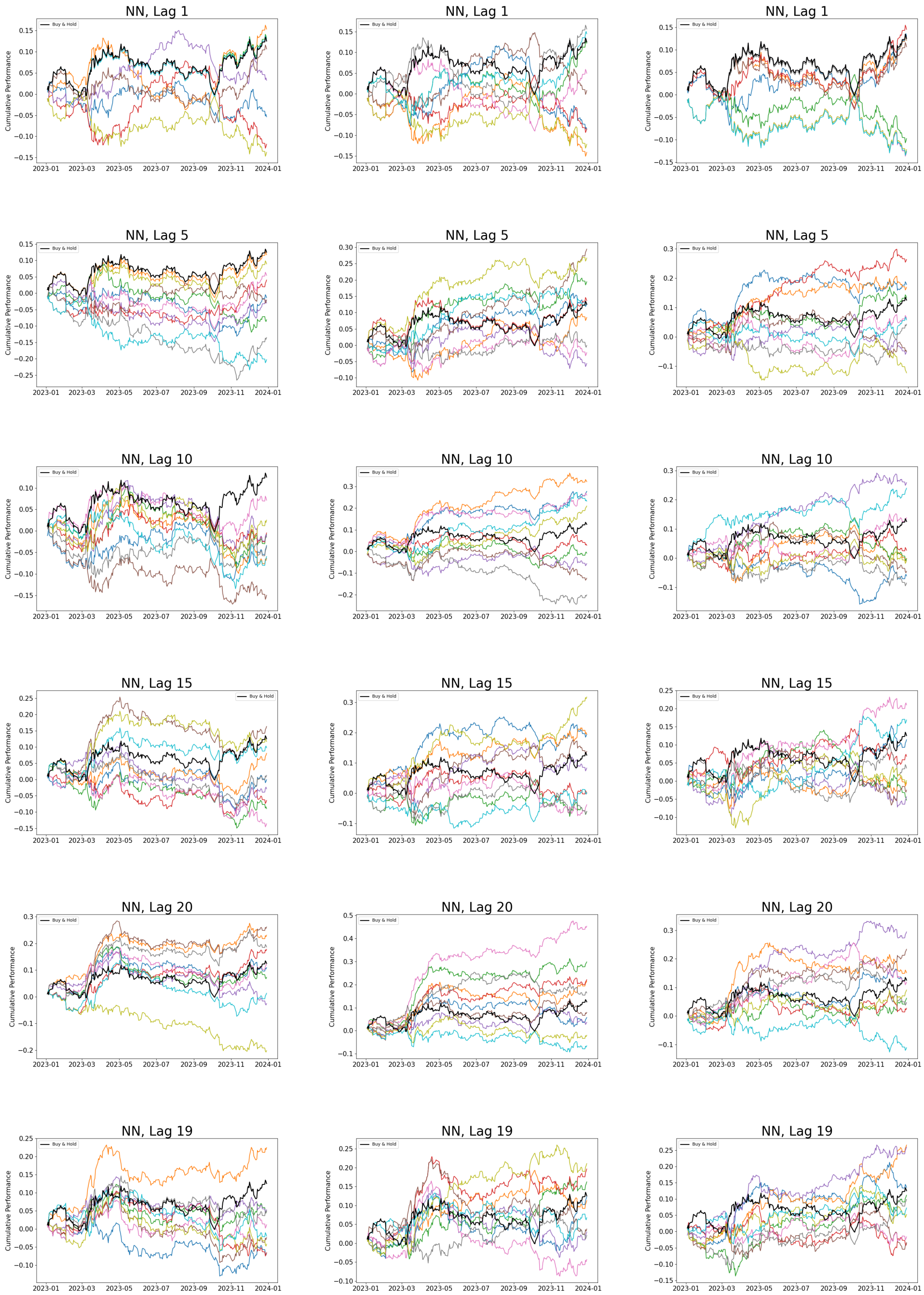
6.3.5 Gold

Gold Model Evaluation 2023

In this section, we use the year 2023 as test year, while altering the lags and the training years to compare the performance, Hit-Rate, sharpe values and MSE of the different models. The best 10 Models are represented in this section - chosen based on MSE on the train dataset.

Performance Evaluation

As decision metric for the model selection the train MSE was crucial. The performances of the ten lowest values are then used to create a prediction and are compared with the benchmark. The Figure 6.26 showcases the performance of the models over different training splits and all available lags.



(A) Training 2020, 2021, 2022 and Test 2023 (B) Training 2021, 2022 and Test 2023 (C) Training 2022 and Test 2023

FIGURE 6.26: Performances in comparison with benchmark for the year 2023 on different lags
each row consists of a different number of lags

With the NNs there is no evident improvement between the different lags and years detectable. Most models appear to have a wide spread over the test period in contrast to the tested SVR, where the models have a minimal spread. In Figure 6.26 we can verify, that the models with a minimal amount of training data can achieve results comparable to the models with more training years and lags. For example models from the third column with 5 lags have a stronger performance than most models from

the first column. Further some of the models determined by the acf perform better with less training data. About half the models in the second column, are capable of beating the benchmark from the third month onwards. If we have a closer look into the lags it seems likely that with more lags the models achieve better results.
In this case the amount of training years has a negative impact on the performance, contrarily the amount of lags - models with less than three years and more lags as training data perform in general better. These models are competing strongly with the benchmark.

Overall, Figure 6.26 demonstrates a general performance improvement for NN models when trained on shorter time frames. This improvement could stem from the architecture of NNs, which may be more adept at capturing essential patterns without overfitting when less historical data is used. Interestingly, the results suggest that NN models benefit from having access to more extensive sets of diverse data points, even if these data points cover shorter time spans. In conclusion, NN models appear to perform better with concise, diverse training datasets and an increased number of lags on the given commodity.

Performance Metrics

In this section, the MSE and the Hit ratio are presented in tabular form. Only the best, selected through the train MSE, are shown. The MSE is done on the Logarithmic and differentiated data. Each plot in Figure 6.26 corresponds to a model configuration. The best model of all these is chosen and further analysed.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2020-2023	1	0.51058	0.45817	-0.406732	1.22210E-4	6.90578E-5
2020-2023	5	0.54497	0.51394	-0.10456	1.21791E-4	7.08848E-5
2020-2023	10	0.50794	0.4741	-0.258968	1.18930E-4	7.13568E-5
2020-2023	15	0.51455	0.48606	-0.003745	1.17056E-4	7.12450E-5
2020-2023	20	0.53571	0.4741	0.830619	1.16294E-4	7.03735E-5
2020-2023	auto	0.50926	0.45418	-0.509616	**1.15322E-4**	7.15121E-5
2021-2023	1	0.52087	0.47012	-0.656301	9.17175E-5	6.91354E-5
2021-2023	5	0.51889	0.5498	0.969429	9.13120E-5	6.85403E-5
2021-2023	10	0.5507	0.56574	2.12211	9.03501E-5	6.75872E-5
2021-2023	15	0.53678	0.54183	1.477278	9.08622E-5	6.80155E-5
2021-2023	20	0.53877	0.50996	0.432654	9.03805E-5	6.84497E-5
2021-2023	auto	0.55467	0.52988	0.933403	**8.86783E-5**	6.83569E-5
2022-2023	1	0.55378	0.51793	0.988995	9.61235E-5	7.04560E-5
2022-2023	5	0.58964	0.53386	1.355107	9.47504E-5	6.77869E-5
2022-2023	10	0.5259	0.48207	-0.465216	9.36514E-5	7.14259E-5
2022-2023	15	0.56574	0.49801	0.865284	9.46239E-5	7.00052E-5
2022-2023	20	0.53785	0.49402	0.949531	9.39970E-5	7.41143E-5
2022-2023	auto	0.56972	0.4741	1.02794	**9.10324E-5**	6.90284E-5

TABLE 6.20: Best Model for predicting the Year 2018

The model chosen based on the lowest MSE train is the model that uses the year 2021 and 2022 as training.

A minority of models have a negative Sharpe value. The chosen models result in a Sharpe of 0.933403, meaning adequate risk for the expected return.

Most model configuration inspires confidence in performing well during 2023. About half of the models manage to outperform the benchmark. Further, these models can keep the gains during the rest of the year, as can be seen in Figure 6.26, with Lag 20.

In this specific case, the performance does not consistently improve when including more lags, unlike the finding in SVR Section 6.1.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables L.1-L.18.

The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2023 can be found in Table L.19.

There is a significant amount of correlation available between the train and test MSE for the Neural Network models, reaching to a correlation of up to 99.578% in the best 10 models. This is an indicator that the MSE train is a valid and reliable metric to use when choosing models for the year 2023.

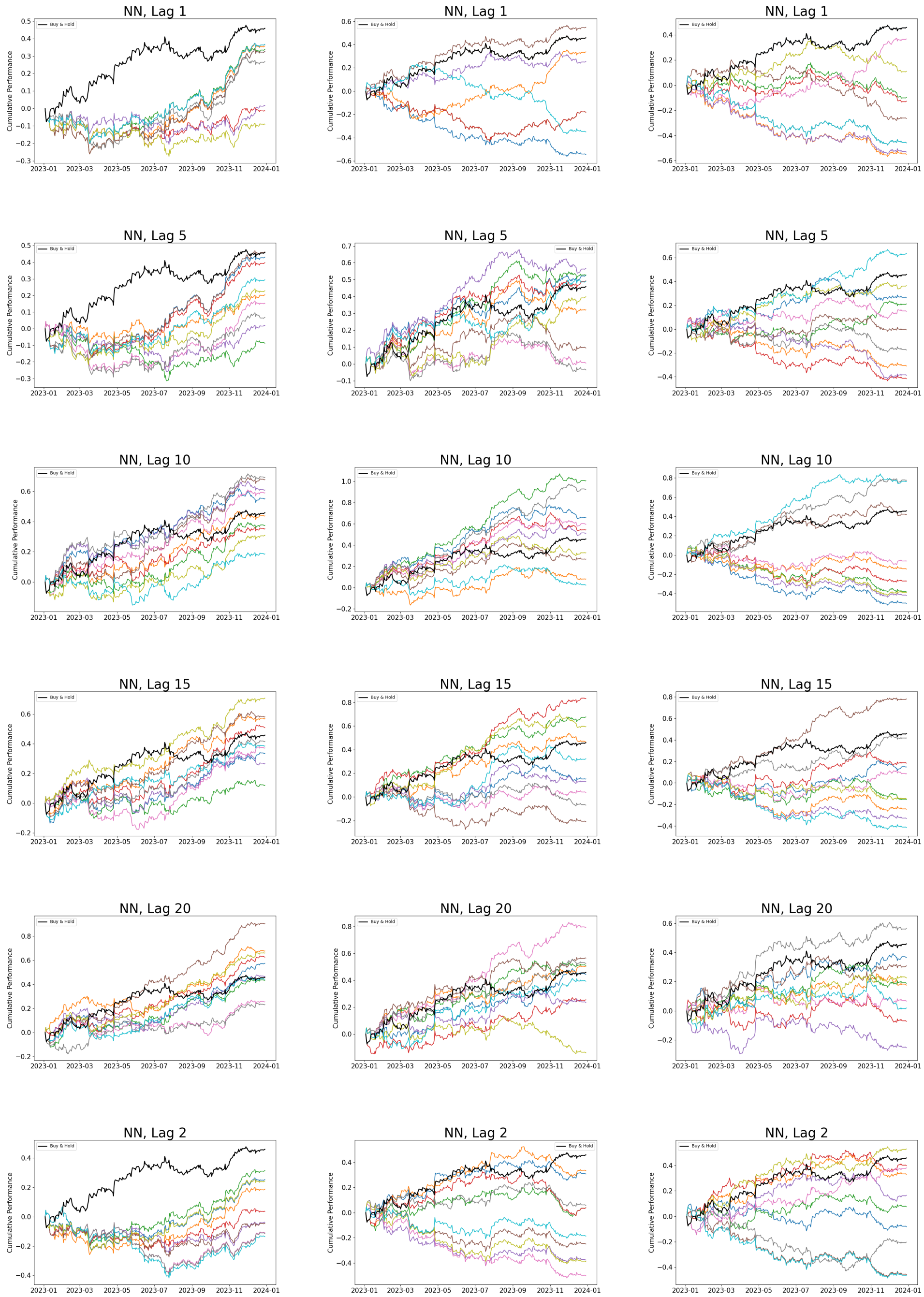
6.3.6 MSFT

MSFT Model Evaluation 2023

In this section, we use the year 2023 as test year, while altering the lags and the training years to compare the performance, Hit-Rate, Sharpe values and MSE of the different models. The best 10 Models are represented in this section - chosen based on performance on the train dataset.

Performance Evaluation

As decision metric for the model selection the train MSE was crucial. The models with the ten lowest values are then used to create a prediction and are compared with the benchmark. The Figure 6.27 showcases the performance of the models over different training splits and all available lags.



(A) Training 2020, 2021, 2022 and Test 2023 (B) Training 2021, 2022 and Test 2023 (C) Training 2022 and Test 2023

FIGURE 6.27: Performances in comparison with benchmark for the year 2023 on different lags
each row consists of a different number of lags

With the NNs there is no evident improvement trend between the different lags and years detectable. Most models appear to have a wide spread over the test period in contrast to the tested SVR, where the models have a minimal spread. In Figure 6.27 we can verify, that the models in the first column have a slimmer performance spread then the models in the second and third column. If we observe the first and last row of the Figure they appear to be identical, this comes from the chosen model by the acf, which is in this case the same as Lag 2.

Most models struggle to beat the benchmark in the first half of the year, contrarily they tend to beat the Buy&Hold towards the end of the year. It appears that models with more than one year as training data have a higher chance of outperforming the benchmark.

With the MSFT as equity, the models seem to be sensitive to the amount of training years as it has an impact on the performance. The more training data and lags are provided, the thinner gets the spread between the models.

Overall, Figure 6.27 demonstrates a general performance improvement for NN models when trained on longer time frames. This improvement could stem from the architecture of NNs, which may be more adept at capturing essential patterns without overfitting when less historical data is used. Interestingly, the results suggest that NN models benefit from having access to more extensive sets of diverse data points, even if these data points cover shorter time spans. In conclusion, NN models appear to perform better with concise, diverse training datasets and an increased number of lags on the given commodity.

Performance Metrics

As previously introduced in 6.1.3 this section presents the MSE and Hit ratio compactly. We explicitly decided against referring each individual table to focus on the relevant findings, but post them in the Appendix F for completeness. The very best out of the ten, selected through the train MSE, are shown. Each plot in Figure 6.27 is represented with its best performing model as a table row in Table 6.21.

Years	Lag	Hit-Rate Train	Hit-Rate Test	Sharpe Test	MSE Train	MSE Test
2020-2023	1	0.52381	0.524	1.306618	4.44393E-4	2.57309E-4
2020-2023	5	0.52646	0.556	1.730434	4.47920E-4	2.55800E-4
2020-2023	10	0.5291	0.508	2.225842	4.20835E-4	2.53724E-4
2020-2023	15	0.51984	0.504	1.346288	4.15570E-4	2.57338E-4
2020-2023	20	0.53042	0.536	2.321512	**4.13663E-4**	2.47987E-4
2020-2023	auto	0.51852	0.516	1.010417	4.51278E-4	2.57159E-4
2021-2023	1	0.50696	0.44	-2.196887	3.35825E-4	2.50125E-4
2021-2023	5	0.50298	0.564	2.117754	3.31700E-4	2.43823E-4
2021-2023	10	0.53479	0.576	2.671136	3.26308E-4	2.45111E-4
2021-2023	15	0.54473	0.504	0.610284	3.25100E-4	2.52381E-4
2021-2023	20	0.51491	0.536	1.781728	**3.24311E-4**	2.47649E-4
2021-2023	auto	0.52684	0.524	1.228553	3.34524E-4	2.50260E-4
2022-2023	1	0.46215	0.552	1.844806	4.97661E-4	2.47189E-4
2022-2023	5	0.50598	0.516	1.052746	4.85468E-4	2.51392E-4
2022-2023	10	0.5498	0.448	-2.017237	4.74669E-4	2.99545E-4
2022-2023	15	0.56574	0.516	0.594542	**4.63252E-4**	2.52849E-4
2022-2023	20	0.53785	0.548	1.461464	4.76136E-4	2.43877E-4
2022-2023	auto	0.55777	0.488	-0.327241	4.88680E-4	2.55576E-4

TABLE 6.21: Best Model for predicting the Year 2018

The model chosen based on the lowest MSE train is the model that uses the year 2021 and 2022 as training and 20 lags.

None of the models with more than one year training data have a negative Sharpe value. The chosen models result in a Sharpe of 1.781728, meaning adequate risk for the expected return.

Some model configuration inspires confidence in performing well during the second half of 2023. A minority of the models manage to outperform the benchmark. Further, most of these models can keep the gains during the end of the year, as it can be seen in Figure 6.27, with Lag 10 and 15.

In this specific case, the performance does not consistently improve when including more lags, unlike the finding in SVR Section 6.1.

More specific metrics to each model, as well as the best 10 models found in each configuration, can be found in the tables M.1-M.18.

The Correlation between the MSE train and MSE Test for the best 10 models for each configuration present in in the test year 2023 can be found in Table M.19.

There is a significant amount of correlation available between the train and test MSE for the Neural Network models, reaching to a correlation of up to 88.947% in the best 10 models.

6.3.7 Random Walk

In this section we want to present how our model performs on a generated random walk for the year 2024. The model uses the auto Lag based on the standard procedure we followed thru the thesis and is than trained on three years of random walk. What we expect is that the model cannot learn to predict the random walk and generate a profit. For this purpose, we illustrate in the Figure 6.28 how a hundred randomly initiated models would perform.

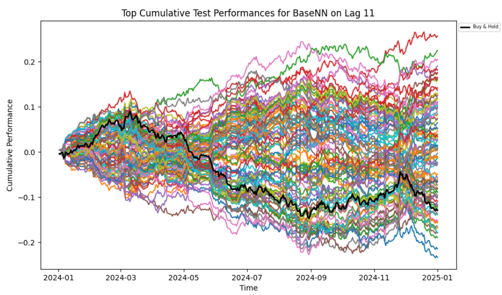
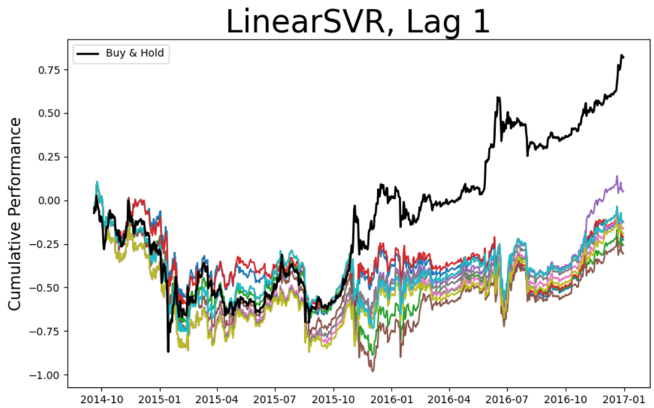


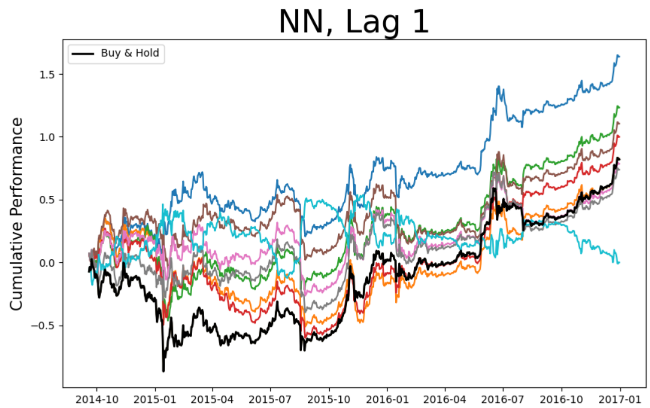
FIGURE 6.28: Random Walk prediction with 100 random seeds and auto lag.

As expected, the models cannot predict the random walk and therefore form a distribution around zero. Vividly represented with the hundred models in the Figure. This leads us to the assumption that our NN model is trustworthy, as it behaves as expected.

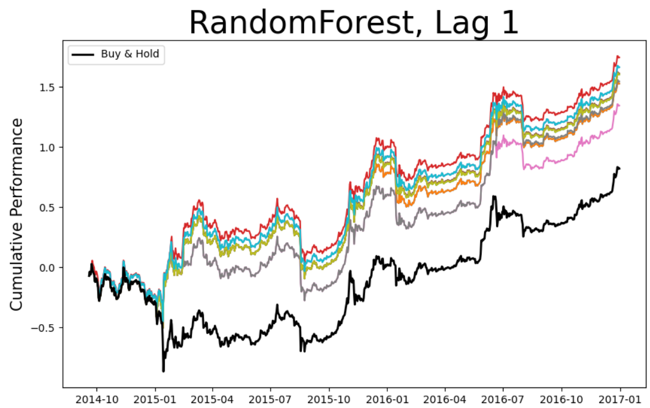
6.4 Summary Results and Training Curves



(A) Training 2014-2016 SVR Lag 1



(B) Training 2014-2016 NN Lag 1



(C) Training 2014-2016 RF Lag 01

FIGURE 6.29: Training Performances of SVR, NN, RF on Lag 1

In Figure 6.29, the different performance curves on the training dataset can be seen. While SVR and NN do not overfit, RF clearly does this by memorizing the different movements present in the training dataset.
This is shown in the always increasing performance of the model - in comparison with

the NN and SVR. NN and SVR are much closer to the actual performance, indicating a learned generalization of the training data, not a memorization.

Chapter 7

Discussion

7.1 Summary of Findings

This study investigated the performance of three machine learning models, SVR, RF and NNs, on predicting asset prices for Bitcoin, Gold, and Microsoft across multiple time frames. The primary goal was to evaluate the models accuracy in predicting asset prices and compare their performance against a Buy&Hold benchmark.

7.1.1 Addressing Research Objectives

Can ML algorithms outperform the Buy&Hold strategy in financial terms?

The results indicate that under certain conditions, ML algorithms, particularly SVR and NN models, have the potential to outperform the Buy&Hold strategy. The SVR model demonstrated robust performance with minimal overfitting, indicating better generalize ability. Similarly, the NN model showed strong predictive capabilities, particularly for Bitcoin and Gold, where it achieved a high correlation between training and testing MSEs. However, the RF model, despite performing well on training, tended to overfit, leading to poorer performance on test data.

What are the risks and limitations of applying ML in trading strategies?

Several risks and limitations were identified in applying ML models to trading strategies:

1. **Overfitting**
   Complex models like RF, which captured noise in the data leading to poor generalization.

2. **Computational Costs**
   Training complex ML models can be computationally expensive and time-consuming.

3. **Market Dynamics**
   The study's reliance on historical price data may not fully capture the dynamic nature of financial markets, which are influenced by numerous external factors such as geopolitical events, market sentiment, and macroeconomic indicators.

Create a reproducible framework for the prediction of financial time-series
The study successfully developed a reproducible framework for financial time-series

prediction, incorporating detailed steps for data preprocessing, model training, and evaluation. The framework includes:

- **Data Preprocessing**
  Techniques such as data cleaning, normalization, and feature engineering to prepare the data for modeling.

- **Model Training**
  Procedures for training RF, SVR, and NN models, including default parameters for a hundred different seeds.

- **Evaluation**
  Comprehensive evaluation metrics, including Mean Squared Error (MSE), Sharpe Ratio, and Hit Rate, to assess model performance.

The reproducibility of the framework is ensured through the use of standardized libraries and detailed documentation of the process, allowing others to replicate the study and build upon its findings.

7.2 Critical Evaluation

The findings suggest that while SVR and NN models can provide valuable insights and potentially outperform traditional strategies in a asset devaluation, they should be used in conjunction with other analytical methods to account for market dynamics not captured by historical data alone. The overfitting observed in RF models highlights the need for better model parameter choices than the defaults, to improve generalization.

7.3 Future Work

To build on the findings of this study, future research should:

1. **Expand the Dataset**
   Include a broader range of assets from different sectors and regions to validate the models' robustness across various markets.

2. **Incorporate Additional Data**
   Integrate macroeconomic variables, sentiment analysis from news and social media, and other exogenous factors to provide a more comprehensive dataset for model training.

3. **Explore Advanced Techniques**
   Investigate hybrid models that combine the strengths of different algorithms. For example, combining RF's feature selection capabilities with NN's predictive power could yield more accurate and stable models.

4. **Enhance Model Interpretability**
   Implement explainable AI methods like LPDs for NNs to improve the transparency and interpretability of ML models, making them more accessible to investors and stakeholders.

7.4 Conclusion

In conclusion, while RF models exhibited a tendency to overfit, SVR and NN models demonstrated more stable and reliable performance across different assets. The study's findings suggest that with further development and integration of additional data sources, ML models can offer significant advantages over traditional trading strategies. Future research should focus on expanding the asset base, incorporating more comprehensive data for example a market sentiment or other economical drivers, exploring hybrid models to enhance the reliability and applicability of ML-based financial predictions.

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List of Figures

List of Tables

Appendix A

Appendix

Split No.	Training Set	Test Set
1	2014, 2015	2016
2	2015, 2016	2017
3	2016, 2017	2018
4	2017, 2018	2019
5	2018, 2019	2020
6	2019, 2020	2021
7	2020, 2021	2022
8	2021, 2022	2023
9	2022, 2023	2024
10	2023, 2024	2025
11	2014, 2015, 2016	2017
12	2015, 2016, 2017	2018
13	2016, 2017, 2018	2019
14	2017, 2018, 2019	2020
15	2018, 2019, 2020	2021
16	2019, 2020, 2021	2022
17	2020, 2021, 2022	2023
18	2021, 2022, 2023	2024
19	2022, 2023, 2024	2025
20	2014, 2015, 2016, 2017	2018
21	2015, 2016, 2017, 2018	2019
22	2016, 2017, 2018, 2019	2020
23	2017, 2018, 2019, 2020	2021
24	2018, 2019, 2020, 2021	2022
25	2019, 2020, 2021, 2022	2023
26	2020, 2021, 2022, 2023	2024
27	2021, 2022, 2023, 2024	2025

Table A.1: Bitcoin Training and Test Set Splits

```
../Bachelorarbeit-2024
├── Download Data.ipynb
├── Globals.py
├── README.md
├── backup_data.py
├── data
│   └── btc_hist.csv
├── images
│   ├── BaseNN
│   │   └── btc_hist.csv
│   │       ├── 14
│   │       │   └── [2014, 2015]-[2016]
│   │       ├── 2
│   │       │   └── [2014, 2015]-[2016]
│   │       │       ├── ACFPlot
│   │       │       │   └── ACF.png
│   │       │       ├── PerformancePlots
│   │       │       │   └── 1.png
│   │       │       ├── TestComparison
│   │       │       │   ├── All_Test.png
│   │       │       │   └── All_Test_Patrick.png
│   │       │       ├── Top-Hitratio
│   │       │       │   ├── Best-Hitratios-Test_Boxplot_[2014, 2015]-[2016]_2.png
│   │       │       │   └── Best-Hitratios-Test_[2014, 2015]-[2016]_2.png
│   │       │       ├── Top-Model-PerformancePlots
│   │       │       │   ├── Aggregated_Performances_[2014, 2015]-[2016]_2.png
│   │       │       │   ├── Best_Performances_[2014, 2015]-[2016]_2.png
│   │       │       │   └── Best_Performances_[2014, 2015]-[2016]_2_Actual_Performance.png
│   │       │       ├── TrainComparison
│   │       │       │   └── All_Train.png
│   │       │       ├── TruePrediction
│   │       │       │   └── 1.png
│   │       │       ├── hitratio
│   │       │       │   └── 1.txt
│   │       │       ├── saved_models
│   │       │       │   └── 1.joblib
│   │       │       └── statistics
│   │       │           ├── mse_corr.json
│   │       │           ├── mse_of_models.json
│   │       │           └── stats.json
│   │       ├── 21
│   │       │   └── [2014, 2015]-[2016]
│   │       ├── 28
│   │       │   └── [2014, 2015]-[2016]
│   │       ├── 7
│   │       │   └── [2014, 2015]-[2016]
│   │       ├── auto
│   │       │   └── [2014, 2015]-[2016]
│   │       └── original_comaprisonplot.png
│   ├── LSTM
│   ├── LinearSVR
│   └── RandomForest
├── model_base.py
├── models
│   ├── LSTM.ipynb
│   ├── NN.ipynb
│   ├── RandomForest-Copy1.ipynb
│   ├── RandomForest.ipynb
│   ├── RandomForest.py
│   └── SVM.ipynb
└── run_experiments.ipynb
```

FIGURE A.1: This is a high-level overview of the file structure consisting of the data created when the pipeline is run. We can't illustrate the final structure because it too spacious.

Appendix B

Appendix SVR - Bitcoin 2017

B.1 Bitcoin SVR - extended Tables - 2017 Test

B.1.1 Lag 01

Table B.1: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
36	0.56766	0.47671	-1.11307	1.00871821E-3	2.49323158E-3
86	0.56407	0.50959	-0.251082	1.00877825E-3	2.48777861E-3
51	0.55569	0.51507	0.023057	1.00904543E-3	2.48587361E-3
14	0.56527	0.48219	-0.968383	1.00911755E-3	2.49382190E-3
99	0.57006	0.48219	-0.995492	1.00922259E-3	2.49209938E-3
50	0.55449	0.52877	0.676778	1.00923228E-3	2.48502042E-3
52	0.56168	0.47945	-1.000357	1.00926299E-3	2.49116610E-3
100	0.56527	0.48493	-0.977173	1.00934543E-3	2.49193713E-3
69	0.56048	0.48219	-0.989267	1.00934651E-3	2.49142615E-3
17	0.56407	0.50959	-0.251082	1.00940511E-3	2.48884172E-3

Table B.2: Metrics using Dataset [2015, 2016]-[2017] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
61	0.56361	0.48493	-0.766952	9.97499115E-4	2.49564076E-3
39	0.56635	0.50411	-0.315223	9.97637958E-4	2.49479709E-3
55	0.56635	0.50411	-0.315223	9.97646946E-4	2.49484169E-3
43	0.56361	0.48219	-0.895418	9.97651020E-4	2.49698736E-3
31	0.56908	0.48493	-0.977173	9.97672886E-4	2.49773227E-3
45	0.55814	0.53973	0.778373	9.97679862E-4	2.48763411E-3
27	0.56361	0.51507	-0.041872	9.97689961E-4	2.49255943E-3
48	0.56224	0.51507	0.023057	9.97698392E-4	2.49206444E-3
50	0.56908	0.48219	-0.989267	9.97781414E-4	2.49803871E-3
6	0.57319	0.48493	-0.993089	9.97781466E-4	2.49872661E-3

Table B.3: Metrics using Dataset [2016]-[2017] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
9	0.60656	0.48493	-0.882748	6.47377019E-4	2.54657307E-3
90	0.60383	0.48767	-0.676062	6.47410680E-4	2.54063033E-3
4	0.60929	0.48493	-0.886117	6.47426722E-4	2.54566830E-3
65	0.60383	0.48493	-0.766952	6.47561817E-4	2.54163563E-3
37	0.60383	0.48219	-0.895418	6.47620736E-4	2.54321834E-3
44	0.60383	0.48219	-0.895418	6.47639563E-4	2.54348578E-3
39	0.59836	0.50959	-0.236199	6.47653085E-4	2.53754062E-3
67	0.60929	0.48493	-0.882748	6.47660416E-4	2.54821112E-3
83	0.60383	0.48219	-0.895418	6.47663101E-4	2.54347103E-3
98	0.60109	0.50959	-0.251082	6.47735901E-4	2.53836784E-3

B.1.2 Lag 07

Table B.4: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
2	0.57298	0.53425	0.04658	9.78587227E-4	2.53352159E-3
4	0.57298	0.49863	-0.646567	9.78700525E-4	2.54020599E-3
31	0.5766	0.50685	-0.343809	9.78727439E-4	2.54037197E-3
82	0.56212	0.52329	-0.14554	9.78827656E-4	2.53627343E-3
52	0.56815	0.49589	-0.706584	9.78862254E-4	2.54708859E-3
12	0.57057	0.54247	0.250537	9.78884714E-4	2.52885731E-3
62	0.56574	0.50411	-0.427448	9.78927943E-4	2.54640137E-3
22	0.56936	0.51507	-0.27578	9.78942842E-4	2.53789268E-3
64	0.56815	0.51781	-0.272379	9.78970905E-4	2.53729598E-3
21	0.57177	0.49041	-0.796039	9.79021692E-4	2.54681266E-3

Table B.5: Metrics using Dataset [2015, 2016]-[2017] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
32	0.56772	0.49589	-0.578067	9.87048819E-4	2.56568151E-3
98	0.57182	0.47671	-1.081102	9.87446593E-4	2.57194150E-3
11	0.57045	0.49315	-0.691744	9.87773964E-4	2.56857280E-3
44	0.56772	0.49041	-0.838312	9.88002874E-4	2.56933839E-3
25	0.57729	0.47397	-1.003847	9.88101198E-4	2.57498186E-3
91	0.57319	0.47123	-1.182962	9.88105913E-4	2.57602695E-3
3	0.57045	0.49041	-0.838312	9.88189508E-4	2.57105780E-3
24	0.58003	0.49863	-0.82893	9.88224609E-4	2.56449250E-3
85	0.57729	0.50137	-0.75509	9.88235108E-4	2.56498493E-3
76	0.56498	0.48767	-0.971184	9.88250362E-4	2.56799963E-3

Table B.6: Metrics using Dataset [2016]-[2017] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
89	0.58197	0.51781	-0.434144	6.24922094E-4	2.61668693E-3
70	0.58743	0.50959	-0.506498	6.25019436E-4	2.61688143E-3
25	0.60656	0.52055	-0.462906	6.25188979E-4	2.61604065E-3
97	0.60656	0.51507	-0.703703	6.25280432E-4	2.61213083E-3
82	0.59836	0.52329	-0.385503	6.25281551E-4	2.61861567E-3
58	0.60656	0.51507	-0.712146	6.25294563E-4	2.61526243E-3
41	0.60383	0.51507	-0.783337	6.25317823E-4	2.61515639E-3
42	0.59836	0.51781	-0.605442	6.25358195E-4	2.61441286E-3
38	0.58743	0.51507	-0.579828	6.25429454E-4	2.61887725E-3
95	0.58743	0.50959	-0.583282	6.25441208E-4	2.62039578E-3

B.1.3 Lag 14

TABLE B.7: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
33	0.59124	0.51507	-0.819408	9.71723440E-4	2.57846429E-3
51	0.58273	0.51233	-0.854815	9.71938444E-4	2.57802569E-3
10	0.58151	0.50959	-1.021541	9.72020697E-4	2.57472394E-3
91	0.59002	0.52329	-0.426336	9.72050439E-4	2.56751562E-3
15	0.58637	0.51507	-0.741783	9.72144682E-4	2.57316445E-3
42	0.58759	0.50959	-0.96569	9.72201300E-4	2.57718289E-3
57	0.58029	0.50411	-1.043969	9.72276897E-4	2.57549120E-3
61	0.58881	0.52055	-0.59187	9.72354346E-4	2.57054298E-3
68	0.58637	0.51233	-0.904745	9.72362634E-4	2.57628611E-3
77	0.59611	0.52603	-0.429846	9.72396875E-4	2.57196037E-3

TABLE B.8: Metrics using Dataset [2015, 2016]-[2017] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
34	0.58413	0.50411	-0.815696	9.78373689E-4	2.60270072E-3
39	0.59781	0.51233	-0.527793	9.78469839E-4	2.59695310E-3
74	0.59097	0.50959	-0.774654	9.78501106E-4	2.60065037E-3
57	0.5896	0.50685	-0.600185	9.78529503E-4	2.60136017E-3
15	0.60739	0.50685	-0.627104	9.78561079E-4	2.59510297E-3
100	0.59644	0.50959	-0.774654	9.78594982E-4	2.59647125E-3
30	0.60328	0.50959	-0.706032	9.78659420E-4	2.59669510E-3
91	0.58413	0.50959	-0.840051	9.78661639E-4	2.59770653E-3
19	0.59371	0.50959	-0.68237	9.78768375E-4	2.59814094E-3
40	0.5896	0.50411	-0.934448	9.78799846E-4	2.60168334E-3

TABLE B.9: Metrics using Dataset [2016]-[2017] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
44	0.61475	0.52055	-0.900578	6.27389881E-4	2.61477711E-3
62	0.60929	0.50685	-1.008858	6.27611160E-4	2.61979577E-3
87	0.62568	0.52329	-0.802594	6.27641629E-4	2.62010772E-3
73	0.64208	0.51233	-0.93538	6.27722546E-4	2.60577220E-3
37	0.64481	0.51507	-1.006732	6.27726436E-4	2.60947961E-3
10	0.61202	0.50685	-0.985659	6.27751148E-4	2.61978196E-3
20	0.62295	0.51781	-0.730043	6.27758835E-4	2.61916971E-3
57	0.61475	0.51781	-0.817224	6.27759198E-4	2.62104758E-3
34	0.62295	0.51781	-0.733454	6.27814768E-4	2.61425711E-3
61	0.62295	0.52055	-0.671864	6.27821958E-4	2.61653350E-3

B.1.4 Lag 21

TABLE B.10: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
74	0.59018	0.53151	0.04815	9.68543440E-4	2.57516369E-3
85	0.58896	0.50959	-0.497172	9.68829422E-4	2.57951359E-3
37	0.58405	0.53151	0.106486	9.68853278E-4	2.57560985E-3
57	0.58773	0.50959	-0.42212	9.69109310E-4	2.58115633E-3
62	0.58528	0.49863	-0.694986	9.69147193E-4	2.58737001E-3
16	0.59141	0.52877	0.21077	9.69179510E-4	2.57797646E-3
63	0.58773	0.51781	-0.115094	9.69244309E-4	2.58325777E-3
91	0.58773	0.51507	-0.33055	9.69262047E-4	2.58025732E-3
71	0.58528	0.51233	-0.161678	9.69285976E-4	2.58317664E-3
27	0.58896	0.52877	0.082212	9.69338084E-4	2.57461238E-3

TABLE B.11: Metrics using Dataset [2015, 2016]-[2017] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
83	0.60739	0.53425	0.034669	9.78438096E-4	2.58140786E-3
96	0.60739	0.54247	0.193307	9.78659919E-4	2.58136559E-3
49	0.59918	0.53151	0.370812	9.78762049E-4	2.58706026E-3
18	0.59918	0.53151	0.278917	9.78762390E-4	2.58610868E-3
9	0.60328	0.53699	0.318113	9.78829076E-4	2.58517392E-3
85	0.61286	0.53425	0.000866	9.78885325E-4	2.58115934E-3
68	0.60602	0.53973	0.171311	9.79049067E-4	2.58376616E-3
60	0.60055	0.53425	0.304537	9.79111436E-4	2.58553635E-3
23	0.60739	0.53973	-0.065542	9.79192973E-4	2.58111656E-3
39	0.59781	0.51507	-0.108569	9.79219025E-4	2.59010631E-3

TABLE B.12: Metrics using Dataset [2016]-[2017] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
96	0.62568	0.53973	-0.208272	6.20803442E-4	2.61145811E-3
74	0.63115	0.55068	0.230424	6.20806284E-4	2.60839701E-3
32	0.63388	0.54521	0.131379	6.20938440E-4	2.60690423E-3
23	0.63661	0.53699	-0.032924	6.20939775E-4	2.60356300E-3
40	0.64208	0.54521	0.16308	6.20941568E-4	2.60618268E-3
81	0.63934	0.53425	-0.298182	6.20961540E-4	2.60213748E-3
94	0.63934	0.53973	0.106874	6.20988372E-4	2.60634705E-3
24	0.63388	0.55068	0.20178	6.21012556E-4	2.60415885E-3
47	0.62568	0.53699	-0.053157	6.21056295E-4	2.60718491E-3
4	0.63661	0.54795	0.137625	6.21056713E-4	2.60392576E-3

B.1.5 Lag 28

TABLE B.13: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
99	0.57921	0.53425	-0.005055	9.60411619E-4	2.60447456E-3
59	0.58416	0.54247	0.078887	9.60426590E-4	2.60410097E-3
13	0.57921	0.53973	0.022337	9.60631610E-4	2.60683987E-3
86	0.58787	0.53973	-0.082032	9.60674674E-4	2.60163889E-3
37	0.58911	0.53151	-0.329506	9.60697718E-4	2.60536065E-3
50	0.58416	0.52877	-0.439563	9.60779969E-4	2.60871153E-3
65	0.58911	0.53151	-0.120444	9.60815958E-4	2.61385391E-3
93	0.57797	0.53425	0.06686	9.60843243E-4	2.60544615E-3
91	0.58663	0.53151	-0.486224	9.60864033E-4	2.60714425E-3
64	0.58787	0.52877	-0.299681	9.60874284E-4	2.60994242E-3

TABLE B.14: Metrics using Dataset [2015, 2016]-[2017] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
23	0.60739	0.54247	0.613579	9.66108212E-4	2.60283207E-3
88	0.59371	0.53973	0.28807	9.66193515E-4	2.60209891E-3
25	0.59918	0.54247	0.220886	9.66243279E-4	2.60003812E-3
68	0.59508	0.53699	-0.227819	9.66270718E-4	2.60249278E-3
40	0.60739	0.53973	0.331906	9.66389530E-4	2.59892212E-3
93	0.59781	0.53425	-0.440729	9.66499693E-4	2.60190700E-3
20	0.59644	0.54247	-0.089515	9.66500190E-4	2.60112603E-3
46	0.60192	0.53699	0.013193	9.66569450E-4	2.60280912E-3
10	0.59781	0.53699	-0.116213	9.66577625E-4	2.60355678E-3
16	0.60602	0.53973	0.319653	9.66589848E-4	2.60199654E-3

TABLE B.15: Metrics using Dataset [2016]-[2017] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
17	0.62568	0.51781	-0.294429	6.17817419E-4	2.60954871E-3
14	0.64208	0.51781	-0.171856	6.17867397E-4	2.60866682E-3
21	0.63388	0.52329	-0.097252	6.18049026E-4	2.60766087E-3
26	0.63934	0.52055	-0.054036	6.18213419E-4	2.60905241E-3
39	0.62022	0.51507	-0.219881	6.18219711E-4	2.60903716E-3
5	0.60109	0.51233	-0.268966	6.18277933E-4	2.60855803E-3
44	0.62022	0.51233	-0.233455	6.18299952E-4	2.61049799E-3
68	0.64481	0.52603	0.158878	6.18374579E-4	2.60217521E-3
8	0.61749	0.50685	-0.362699	6.18376793E-4	2.61236877E-3
80	0.61475	0.50959	-0.481451	6.18383542E-4	2.61422401E-3

B.1.6 Lag auto - 06

TABLE B.16: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
56	0.56386	0.51507	-0.205029	9.73888138E-4	2.51304029E-3
7	0.56265	0.50959	-0.224786	9.74029941E-4	2.51319437E-3
34	0.56867	0.50959	-0.104676	9.74549729E-4	2.51278912E-3
91	0.55904	0.51233	-0.389225	9.74556752E-4	2.50894767E-3
18	0.57108	0.52055	-0.290035	9.74592332E-4	2.50835979E-3
8	0.56145	0.51781	-0.261523	9.74616046E-4	2.51123033E-3
45	0.56747	0.49863	-0.483465	9.74616323E-4	2.51493248E-3
74	0.57108	0.52329	-0.169212	9.74631231E-4	2.50913130E-3
16	0.56386	0.50137	-0.644936	9.74689700E-4	2.51849470E-3
38	0.57108	0.53425	0.01473	9.74714178E-4	2.50351011E-3

TABLE B.17: Metrics using Dataset [2015, 2016]-[2017] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
1	0.56224	0.48493	-0.939861	9.83423696E-4	2.55197199E-3
99	0.56361	0.47671	-1.111213	9.84022267E-4	2.55514372E-3
17	0.57456	0.47123	-1.496689	9.84216948E-4	2.55909077E-3
96	0.57045	0.47945	-0.973048	9.84240311E-4	2.55291725E-3
70	0.57182	0.47123	-1.541466	9.84252856E-4	2.55805118E-3
15	0.56908	0.47397	-1.20441	9.84346988E-4	2.55465256E-3
62	0.56772	0.48493	-0.818749	9.84369460E-4	2.55183450E-3
51	0.56908	0.51507	0.010844	9.84386973E-4	2.54503726E-3
48	0.56635	0.47397	-1.194606	9.84402434E-4	2.55579581E-3
89	0.56361	0.47123	-1.327476	9.84406312E-4	2.55760390E-3

TABLE B.18: Metrics using Dataset [2016]-[2017] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
11	0.60383	0.49041	-1.19223	6.32546337E-4	2.58507390E-3
10	0.5847	0.48493	-1.219154	6.32620260E-4	2.59152999E-3
65	0.60929	0.49589	-1.104315	6.32640784E-4	2.58492187E-3
32	0.62022	0.49041	-1.226004	6.32674440E-4	2.58439242E-3
16	0.62022	0.49589	-1.104315	6.32724170E-4	2.58660935E-3
4	0.61749	0.49589	-1.104315	6.32733081E-4	2.58627742E-3
14	0.61749	0.49041	-1.226004	6.32770649E-4	2.58488706E-3
30	0.61475	0.49863	-1.099961	6.32785230E-4	2.58622082E-3
55	0.60656	0.48767	-1.251366	6.32818319E-4	2.58850141E-3
63	0.60929	0.50137	-1.116694	6.32848328E-4	2.58276900E-3

B.1.7 Bitcoin MSE Correlation 2017

Year	Lag	Correlation
2014-2017	01	-0.647557
2014-2017	07	-0.36719
2014-2017	14	-0.10869
2014-2017	21	0.28561
2014-2017	28	-0.01452
2014-2017	auto - 6	-0.66498
2015-2017	01	0.191428
2015-2017	07	0.45083
2015-2017	14	0.18366
2015-2017	21	0.34052
2015-2017	28	0.16702
2015-2017	auto - 6	0.24643
2016-2017	01	0.899538
2016-2017	07	0.94483
2016-2017	14	0.80833
2016-2017	21	0.83901
2016-2017	28	0.80087
2016-2017	auto - 6	0.87498

TABLE B.19: Correlation MSE Bitcoin

Appendix C

Appendix SVR - Bitcoin 2018

C.1 Bitcoin SVR - extended Tables - 2018 Test

C.1.1 Lag 01

Table C.1: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
16	0.57482	0.51233	-0.960315	1.48195267E-3	1.88489972E-3
28	0.57208	0.50959	-0.994295	1.48218848E-3	1.88064256E-3
41	0.57573	0.51233	-0.922026	1.48218999E-3	1.89123230E-3
93	0.57117	0.50959	-0.994295	1.48229069E-3	1.87934396E-3
20	0.57482	0.51233	-0.960315	1.48231791E-3	1.88683889E-3
64	0.57117	0.50959	-0.994295	1.48239508E-3	1.87916734E-3
78	0.57482	0.51233	-0.960315	1.48240553E-3	1.88696498E-3
23	0.57482	0.51233	-0.960315	1.48241272E-3	1.88539253E-3
88	0.57482	0.50959	-1.057441	1.48249020E-3	1.89011226E-3
21	0.57208	0.51507	-0.895077	1.48254740E-3	1.88577433E-3

Table C.2: Metrics using Dataset [2016, 2017]-[2018] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
68	0.59918	0.51233	-0.960315	1.54651393E-3	1.90911696E-3
40	0.59918	0.51233	-0.978138	1.54666541E-3	1.90083977E-3
62	0.59918	0.51233	-0.960315	1.54667892E-3	1.90859976E-3
52	0.59918	0.51233	-0.960315	1.54686915E-3	1.90921160E-3
1	0.59918	0.50959	-0.994295	1.54705981E-3	1.90296929E-3
79	0.59781	0.50959	-0.994295	1.54710887E-3	1.90032699E-3
4	0.59781	0.50959	-0.994295	1.54713694E-3	1.90025393E-3
81	0.59781	0.50959	-0.994295	1.54715989E-3	1.89736865E-3
8	0.60055	0.51507	-0.895077	1.54716867E-3	1.90752189E-3
39	0.60328	0.50685	-1.007989	1.54717484E-3	1.89441712E-3

Table C.3: Metrics using Dataset [2017]-[2018] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
98	0.6137	0.50959	-1.62335	2.42502827E-3	1.96462194E-3
61	0.6137	0.50959	-1.62335	2.42511547E-3	1.96655046E-3
3	0.6137	0.50959	-1.62335	2.42528872E-3	1.96636384E-3
69	0.6137	0.50959	-1.62335	2.42535308E-3	1.96480691E-3
99	0.6137	0.50959	-1.62335	2.42542642E-3	1.96883525E-3
70	0.6137	0.50959	-1.62335	2.42547514E-3	1.96617365E-3
95	0.6137	0.50959	-1.62335	2.42549319E-3	1.97404958E-3
47	0.6137	0.50959	-1.62335	2.42552242E-3	1.96902125E-3
57	0.6137	0.50959	-1.62335	2.42552590E-3	1.96902798E-3
19	0.6137	0.50959	-1.62335	2.42557072E-3	1.97363333E-3

C.1.2 Lag 07

Table C.4: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
83	0.58303	0.49589	-1.695792	1.47858413E-3	1.90795388E-3
84	0.58394	0.51781	-1.108991	1.47891832E-3	1.90195433E-3
36	0.57938	0.50959	-1.177455	1.47894008E-3	1.90058099E-3
8	0.57755	0.49589	-1.496356	1.47895518E-3	1.90957306E-3
86	0.58212	0.52055	-0.906973	1.47896027E-3	1.90252832E-3
21	0.57847	0.50959	-1.506841	1.47899671E-3	1.89119166E-3
28	0.58212	0.52055	-1.055922	1.47900128E-3	1.90184925E-3
26	0.58212	0.51507	-1.021901	1.47902829E-3	1.90008717E-3
70	0.58303	0.51233	-1.078438	1.47909167E-3	1.90446639E-3
78	0.58029	0.50959	-1.490159	1.47918167E-3	1.89588641E-3

Table C.5: Metrics using Dataset [2016, 2017]-[2018] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
91	0.59918	0.52877	-0.497507	1.55275583E-3	1.90960722E-3
48	0.59644	0.52877	-0.728828	1.55353388E-3	1.90381620E-3
70	0.59508	0.52329	-0.810415	1.55355001E-3	1.91268942E-3
31	0.59644	0.52877	-0.858443	1.55376331E-3	1.90530022E-3
52	0.59644	0.51781	-0.856393	1.55376609E-3	1.91206168E-3
75	0.59508	0.52329	-0.574602	1.55378526E-3	1.91460200E-3
27	0.60055	0.53699	-0.275069	1.55395678E-3	1.90369187E-3
25	0.59508	0.52603	-0.872123	1.55403226E-3	1.90474932E-3
81	0.59371	0.53425	-0.617433	1.55404836E-3	1.90414807E-3
42	0.59644	0.52877	-0.803295	1.55419934E-3	1.90276388E-3

Table C.6: Metrics using Dataset [2017]-[2018] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
8	0.63288	0.50685	-1.258795	2.43024910E-3	1.99040787E-3
34	0.63014	0.50685	-1.254577	2.43058470E-3	2.00162676E-3
32	0.63014	0.50137	-1.360553	2.43088915E-3	2.00392590E-3
18	0.63014	0.50959	-1.157277	2.43148682E-3	1.99717120E-3
20	0.63014	0.50685	-1.254577	2.43171810E-3	2.00017299E-3
42	0.63288	0.50685	-1.258795	2.43173025E-3	1.99225904E-3
21	0.63288	0.50685	-1.258795	2.43199322E-3	1.99409156E-3
75	0.6274	0.50685	-1.23563	2.43214903E-3	2.01646338E-3
66	0.63288	0.50685	-1.254577	2.43217231E-3	1.99714725E-3
100	0.63562	0.50411	-1.338025	2.43224012E-3	2.02228176E-3

C.1.3 Lag 14

Table C.7: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
36	0.60036	0.50959	-1.468239	1.47506485E-3	1.91374208E-3
15	0.6031	0.50685	-1.260775	1.47507588E-3	1.90956125E-3
57	0.59489	0.51507	-1.116182	1.47508421E-3	1.91467613E-3
90	0.60036	0.51507	-1.485557	1.47527482E-3	1.91392458E-3
35	0.59763	0.50959	-1.207598	1.47545572E-3	1.90056704E-3
9	0.59672	0.51781	-1.553954	1.47551089E-3	1.91623421E-3
91	0.59763	0.52329	-0.90257	1.47566991E-3	1.90818864E-3
44	0.59854	0.50685	-1.24794	1.47567648E-3	1.91370322E-3
98	0.5958	0.51781	-0.956061	1.47568047E-3	1.91233837E-3
80	0.60128	0.50685	-1.278072	1.47569135E-3	1.91290353E-3

Table C.8: Metrics using Dataset [2016, 2017]-[2018] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
2	0.60876	0.51781	-1.255623	1.56043249E-3	1.94202117E-3
16	0.61286	0.52055	-1.033543	1.56076871E-3	1.94149212E-3
50	0.61286	0.52055	-1.178036	1.56081021E-3	1.94453657E-3
10	0.61012	0.53425	-0.688059	1.56098227E-3	1.94132193E-3
51	0.6156	0.51781	-1.171838	1.56100736E-3	1.94025136E-3
22	0.61286	0.53425	-0.84819	1.56104946E-3	1.94294448E-3
18	0.61423	0.53151	-0.767877	1.56125705E-3	1.94411031E-3
90	0.61149	0.51781	-1.142828	1.56127118E-3	1.94102582E-3
4	0.6156	0.52877	-0.918676	1.56131684E-3	1.94387015E-3
49	0.61286	0.52329	-1.069214	1.56152296E-3	1.94606679E-3

Table C.9: Metrics using Dataset [2017]-[2018] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
11	0.63836	0.47123	-2.662364	2.43404654E-3	2.04498746E-3
85	0.64384	0.47123	-2.70988	2.43409397E-3	2.04874690E-3
42	0.64384	0.47123	-2.662364	2.43498759E-3	2.05307633E-3
26	0.64384	0.47397	-2.562911	2.43504242E-3	2.05305228E-3
17	0.63836	0.47397	-2.562911	2.43507762E-3	2.04840042E-3
66	0.63836	0.47397	-2.562911	2.43522234E-3	2.05099303E-3
34	0.6411	0.47397	-2.633916	2.43532592E-3	2.04996075E-3
99	0.63836	0.47671	-2.534522	2.43569058E-3	2.05081442E-3
61	0.63836	0.47123	-2.662364	2.43569645E-3	2.05079037E-3
82	0.63836	0.47671	-2.544942	2.43637827E-3	2.05668884E-3

C.1.4 Lag 21

Table C.10: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
17	0.60219	0.49863	-2.148138	1.47135301E-3	1.90946341E-3
95	0.60036	0.49863	-1.951991	1.47150285E-3	1.90903828E-3
100	0.59398	0.49863	-2.200312	1.47152775E-3	1.90855138E-3
2	0.59763	0.50411	-1.832889	1.47163086E-3	1.90902119E-3
42	0.59672	0.49589	-1.988388	1.47169823E-3	1.91095258E-3
65	0.59672	0.49863	-2.205381	1.47172306E-3	1.90860604E-3
98	0.6031	0.50137	-2.14067	1.47173867E-3	1.90644446E-3
12	0.59489	0.50411	-1.662171	1.47175075E-3	1.90801201E-3
54	0.59398	0.49041	-1.971764	1.47175658E-3	1.91551463E-3
61	0.59398	0.51781	-1.712566	1.47177283E-3	1.89918273E-3

Table C.11: Metrics using Dataset [2016, 2017]-[2018] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
51	0.61149	0.51781	-0.010895	1.54272409E-3	1.89754922E-3
64	0.60602	0.50411	-0.402577	1.54281944E-3	1.90058905E-3
60	0.60602	0.50411	-0.814097	1.54311990E-3	1.90421874E-3
87	0.60876	0.51233	-0.206553	1.54320455E-3	1.89916542E-3
59	0.61149	0.51233	-0.348651	1.54334163E-3	1.89744270E-3
55	0.61423	0.51781	0.08799	1.54338423E-3	1.89591976E-3
76	0.60876	0.51233	-0.164643	1.54342361E-3	1.89858343E-3
46	0.60739	0.50685	-0.323536	1.54348897E-3	1.90081011E-3
29	0.60465	0.52329	0.159789	1.54351938E-3	1.89942846E-3
15	0.61286	0.51233	-0.27631	1.54359354E-3	1.89553188E-3

Table C.12: Metrics using Dataset [2017]-[2018] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
39	0.63836	0.48493	-1.50484	2.41634422E-3	1.99938090E-3
54	0.64658	0.48767	-1.37609	2.41728943E-3	2.00097010E-3
28	0.64658	0.49589	-0.976491	2.41774940E-3	2.00812142E-3
100	0.64384	0.47945	-1.525898	2.41780594E-3	1.99824258E-3
70	0.65479	0.49589	-0.961157	2.41826966E-3	2.00356305E-3
30	0.64384	0.49041	-1.089254	2.41843094E-3	2.00242697E-3
22	0.6411	0.49041	-1.150094	2.41846233E-3	2.00278072E-3
92	0.64932	0.49863	-0.932443	2.41863749E-3	2.00721435E-3
53	0.64932	0.49315	-1.033781	2.41865494E-3	2.00438203E-3
89	0.64658	0.49041	-1.13036	2.41869418E-3	2.00141887E-3

C.1.5 Lag 28

Table C.13: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
33	0.59672	0.51233	-0.500631	1.46368428E-3	1.90059018E-3
46	0.59215	0.50685	-0.504931	1.46401091E-3	1.90493754E-3
16	0.59215	0.50685	-0.489424	1.46401102E-3	1.90562861E-3
44	0.59124	0.49589	-0.511071	1.46410748E-3	1.90377455E-3
74	0.59672	0.50959	-0.648271	1.46411195E-3	1.90241186E-3
12	0.59124	0.49589	-0.735519	1.46412602E-3	1.90451156E-3
91	0.59854	0.50685	-0.385828	1.46421388E-3	1.90342945E-3
49	0.59489	0.50959	-0.668499	1.46434183E-3	1.90199562E-3
95	0.59398	0.49315	-0.939621	1.46434327E-3	1.90210747E-3
56	0.5958	0.50959	-0.449842	1.46434449E-3	1.90553526E-3

Table C.14: Metrics using Dataset [2016, 2017]-[2018] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
78	0.61149	0.53151	0.469175	1.53537482E-3	1.90773964E-3
13	0.60739	0.52877	0.502666	1.53560020E-3	1.90531174E-3
6	0.61286	0.53151	0.604519	1.53566633E-3	1.90442037E-3
98	0.60739	0.52329	0.436755	1.53572452E-3	1.89557214E-3
46	0.6156	0.52055	0.435201	1.53590218E-3	1.90452191E-3
23	0.60739	0.52603	0.51061	1.53592827E-3	1.90296093E-3
14	0.60876	0.52603	0.50823	1.53596533E-3	1.90781854E-3
15	0.61423	0.52055	0.40662	1.53600283E-3	1.89788006E-3
11	0.61149	0.52877	0.645337	1.53607936E-3	1.90890489E-3
41	0.60876	0.52877	0.501995	1.53612269E-3	1.90307959E-3

TABLE C.15: Metrics using Dataset [2017]-[2018] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
31	0.6274	0.50137	-1.400095	2.38710876E-3	1.98979889E-3
2	0.63288	0.49315	-1.804755	2.38776343E-3	1.99985218E-3
50	0.63288	0.49863	-1.905018	2.38796974E-3	1.99571332E-3
70	0.63562	0.49589	-1.893321	2.38805021E-3	1.99377322E-3
27	0.63014	0.49315	-2.037802	2.38831083E-3	1.99543790E-3
96	0.63288	0.48493	-2.318645	2.38837623E-3	1.99690604E-3
3	0.63014	0.48493	-2.293568	2.38841324E-3	2.00112126E-3
92	0.63288	0.49863	-1.900759	2.38883840E-3	1.99352978E-3
91	0.63014	0.49041	-2.060591	2.38901962E-3	1.99356555E-3
43	0.63014	0.48219	-2.377822	2.38901970E-3	2.00187792E-3

C.1.6 Lag auto - 6

TABLE C.16: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
15	0.57391	0.51781	-1.102213	1.47060466E-3	1.89126666E-3
1	0.57847	0.50685	-1.400739	1.47063383E-3	1.89637363E-3
80	0.57573	0.52603	-0.742584	1.47076013E-3	1.88697477E-3
13	0.57208	0.52603	-1.035549	1.47084854E-3	1.88828823E-3
20	0.5812	0.50959	-1.31319	1.47087266E-3	1.89616005E-3
51	0.57573	0.52329	-0.730839	1.47092320E-3	1.88267678E-3
58	0.57664	0.50959	-1.574296	1.47099789E-3	1.89158330E-3
48	0.57573	0.51233	-1.495663	1.47105029E-3	1.89039598E-3
36	0.57573	0.51507	-1.327127	1.47106918E-3	1.89215464E-3
94	0.57847	0.51781	-1.26552	1.47110015E-3	1.89101984E-3

TABLE C.17: Metrics using Dataset [2016, 2017]-[2018] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
22	0.59234	0.50411	-1.503453	1.55238205E-3	1.90426038E-3
100	0.59097	0.52055	-1.155505	1.55273766E-3	1.89935257E-3
72	0.5896	0.52329	-0.891195	1.55295873E-3	1.89842389E-3
49	0.58824	0.51781	-1.112552	1.55301630E-3	1.89120253E-3
8	0.59371	0.50411	-1.249849	1.55304124E-3	1.90785969E-3
89	0.59781	0.50137	-1.395271	1.55308336E-3	1.90417868E-3
52	0.58687	0.51507	-1.260922	1.55330455E-3	1.89471686E-3
77	0.5855	0.51507	-1.260922	1.55336546E-3	1.89389175E-3
78	0.5896	0.51781	-1.408009	1.55342500E-3	1.89676830E-3
65	0.59644	0.50411	-1.322351	1.55350557E-3	1.91027871E-3

TABLE C.18: Metrics using Dataset [2017]-[2018] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
85	0.63288	0.50685	-1.258795	2.43272149E-3	1.99068728E-3
70	0.63288	0.50959	-1.178662	2.43343931E-3	2.00146513E-3
67	0.63288	0.50685	-1.258795	2.43351327E-3	1.99523978E-3
44	0.63288	0.50685	-1.297202	2.43361343E-3	1.98808485E-3
98	0.6274	0.50685	-1.19705	2.43369694E-3	2.00931462E-3
32	0.63562	0.50959	-1.178662	2.43370384E-3	2.00073602E-3
56	0.63288	0.50685	-1.204401	2.43377046E-3	2.00417803E-3
82	0.63562	0.50959	-1.178662	2.43384061E-3	1.99776593E-3
2	0.63288	0.50959	-1.178662	2.43384097E-3	1.99605477E-3
23	0.63014	0.50959	-1.178662	2.43385331E-3	1.99680795E-3

C.1.7 Bitcoin MSE Correlation

Year	Lag	Correlation
2015-2018	01	-0.74992
2015-2018	07	-0.79357
2015-2018	14	-0.29346
2015-2018	21	0.15110
2015-2018	28	0.03187
2015-2018	auto - 6	-0.74415
2016-2018	01	-0.92372
2016-2018	07	-0.84331
2016-2018	14	-0.72323
2016-2018	21	-0.47293
2016-2018	28	-0.32047
2016-2018	auto - 6	-0.85270
2017-2018	01	0.961986
2017-2018	07	0.62059
2017-2018	14	0.96595
2017-2018	21	0.90250
2017-2018	28	0.65323
2017-2018	auto - 6	0.91802

TABLE C.19: Correlation MSE Bitcoin

Appendix D

Appendix SVR - Bitcoin 2022

D.1 Bitcoin SVR - extended Tables - 2022 Test

D.1.1 Lag 01

Table D.1: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
88	0.53558	0.46849	-1.156003	1.52948566E-3	1.16413601E-3
70	0.53285	0.47397	-1.002826	1.52950040E-3	1.16276976E-3
58	0.53467	0.47397	-0.829877	1.52959111E-3	1.16256525E-3
79	0.5365	0.47397	-1.005589	1.52959780E-3	1.16663702E-3
94	0.53285	0.47945	-0.888693	1.52960243E-3	1.16371683E-3
77	0.53376	0.47397	-1.002826	1.52960541E-3	1.16434426E-3
35	0.53376	0.47945	-0.888693	1.52961109E-3	1.16340451E-3
45	0.5365	0.48219	-0.540332	1.52961731E-3	1.15893784E-3
34	0.53558	0.47123	-1.044648	1.52961939E-3	1.16594414E-3
75	0.53285	0.47397	-1.002826	1.52962344E-3	1.16437327E-3

Table D.2: Metrics using Dataset [2020, 2021]-[2022] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
49	0.53899	0.47397	-0.829877	1.67083581E-3	1.16711150E-3
41	0.53762	0.47671	-0.744403	1.67085417E-3	1.16680832E-3
3	0.53899	0.47397	-0.829877	1.67085467E-3	1.16715082E-3
84	0.53625	0.47397	-1.002826	1.67086529E-3	1.16959732E-3
27	0.53762	0.47671	-0.744403	1.67087478E-3	1.16744233E-3
21	0.54036	0.47671	-0.744403	1.67087560E-3	1.16696129E-3
86	0.53625	0.47123	-1.047041	1.67087941E-3	1.17023720E-3
47	0.53625	0.47123	-1.047041	1.67088082E-3	1.17023823E-3
29	0.53762	0.47671	-0.744403	1.67088126E-3	1.16730231E-3
25	0.53762	0.47671	-0.744403	1.67088140E-3	1.16741629E-3

TABLE D.3: Metrics using Dataset [2021]-[2022] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
26	0.52329	0.48219	-0.657048	1.75796057E-3	1.14961834E-3
58	0.51781	0.47945	-0.661913	1.75801684E-3	1.14934524E-3
22	0.52603	0.48493	-0.628215	1.75808924E-3	1.15066864E-3
12	0.52603	0.48493	-0.628215	1.75811342E-3	1.15084650E-3
17	0.52329	0.48219	-0.657048	1.75811800E-3	1.15050509E-3
24	0.51781	0.47945	-0.661913	1.75813000E-3	1.14988338E-3
13	0.52877	0.48493	-0.628215	1.75814345E-3	1.15106093E-3
10	0.52329	0.48219	-0.657048	1.75815993E-3	1.15071684E-3
88	0.52329	0.48219	-0.657048	1.75817288E-3	1.15078086E-3
39	0.54247	0.48493	-0.4955	1.75817452E-3	1.14630206E-3

D.1.2 Lag 07

TABLE D.4: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
91	0.53102	0.47671	-0.972067	1.52797139E-3	1.16515671E-3
66	0.53193	0.47945	-1.078667	1.52816275E-3	1.16601199E-3
62	0.53741	0.48219	-0.834974	1.52823166E-3	1.15997840E-3
39	0.53376	0.48493	-0.709763	1.52825898E-3	1.15985931E-3
74	0.53376	0.47671	-0.963223	1.52826725E-3	1.16767697E-3
57	0.53102	0.47945	-1.078667	1.52827278E-3	1.16707203E-3
11	0.53467	0.47945	-0.814494	1.52828785E-3	1.16821605E-3
90	0.54015	0.47671	-0.811598	1.52843806E-3	1.16055634E-3
28	0.53467	0.47671	-0.972067	1.52843973E-3	1.16368657E-3
12	0.53102	0.47671	-1.117751	1.52844629E-3	1.16449718E-3

TABLE D.5: Metrics using Dataset [2020, 2021]-[2022] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
62	0.54446	0.49315	-0.66969	1.66464012E-3	1.16821585E-3
19	0.5472	0.48219	-1.096096	1.66464097E-3	1.17146404E-3
4	0.54993	0.48219	-1.096096	1.66465978E-3	1.17138996E-3
10	0.54993	0.47945	-1.17779	1.66466627E-3	1.17232513E-3
15	0.5513	0.49041	-0.905998	1.66471649E-3	1.17113526E-3
82	0.55267	0.48219	-1.137633	1.66475112E-3	1.17350802E-3
53	0.54993	0.48219	-1.096096	1.66476302E-3	1.17125725E-3
39	0.54036	0.49041	-0.700065	1.66484028E-3	1.16802487E-3
93	0.54583	0.48767	-0.709699	1.66487644E-3	1.16923932E-3
84	0.54583	0.47671	-1.263559	1.66487684E-3	1.17725595E-3

TABLE D.6: Metrics using Dataset [2021]-[2022] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
100	0.54521	0.49041	-0.676895	1.74484551E-3	1.17421545E-3
32	0.5589	0.49589	-0.823597	1.74490250E-3	1.17174836E-3
31	0.55068	0.49863	-0.807677	1.74497223E-3	1.17186638E-3
14	0.55616	0.49315	-0.902387	1.74498080E-3	1.17236615E-3
26	0.54247	0.49041	-0.579826	1.74512810E-3	1.17444357E-3
37	0.54795	0.50137	-0.115493	1.74515122E-3	1.17664787E-3
81	0.55616	0.49041	-0.876113	1.74517368E-3	1.17301173E-3
4	0.54521	0.48767	-0.647047	1.74517694E-3	1.17437136E-3
35	0.56438	0.49041	-1.138537	1.74518532E-3	1.17129646E-3
95	0.53973	0.49589	-0.328781	1.74518731E-3	1.17579517E-3

D.1.3 Lag 14

TABLE D.7: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
12	0.55109	0.46027	-2.248817	1.52321170E-3	1.17436924E-3
95	0.55474	0.46027	-2.194171	1.52338044E-3	1.17135285E-3
69	0.54562	0.45753	-2.238058	1.52338680E-3	1.17810517E-3
35	0.54927	0.45205	-2.396951	1.52347823E-3	1.17552566E-3
85	0.55018	0.46027	-2.564225	1.52353049E-3	1.17232325E-3
52	0.55383	0.46301	-1.889582	1.52357359E-3	1.17518600E-3
51	0.54471	0.45205	-2.668909	1.52357586E-3	1.17548728E-3
1	0.55201	0.46575	-2.212357	1.52358257E-3	1.17327105E-3
22	0.55383	0.45753	-2.570297	1.52361710E-3	1.17222611E-3
90	0.55566	0.47397	-1.512476	1.52362393E-3	1.16966231E-3

TABLE D.8: Metrics using Dataset [2020, 2021]-[2022] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
85	0.56224	0.45479	-2.195653	1.66153111E-3	1.18610502E-3
43	0.55814	0.44932	-2.275541	1.66227267E-3	1.17935175E-3
51	0.56635	0.46849	-2.068134	1.66228710E-3	1.17404943E-3
19	0.56361	0.46027	-2.138369	1.66232374E-3	1.17843043E-3
65	0.56224	0.45205	-2.39642	1.66232719E-3	1.18063261E-3
91	0.55951	0.45479	-2.220284	1.66252448E-3	1.18077894E-3
46	0.57045	0.46027	-2.163867	1.66262136E-3	1.17764253E-3
8	0.55814	0.44932	-2.223244	1.66268830E-3	1.18294241E-3
49	0.56635	0.44932	-2.231245	1.66274466E-3	1.18023664E-3
38	0.56498	0.46301	-2.11959	1.66289296E-3	1.17585058E-3

TABLE D.9: Metrics using Dataset [2021]-[2022] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
85	0.5863	0.46849	-1.864607	1.76684079E-3	1.18628437E-3
41	0.5863	0.47671	-1.625686	1.76717052E-3	1.19052815E-3
51	0.57808	0.47123	-1.870979	1.76740991E-3	1.19315757E-3
10	0.58356	0.47397	-1.756683	1.76749457E-3	1.19396691E-3
67	0.5863	0.47397	-1.705562	1.76793019E-3	1.18787769E-3
37	0.58082	0.47123	-1.71462	1.76794310E-3	1.19115005E-3
60	0.5863	0.46849	-1.864607	1.76812528E-3	1.18672353E-3
98	0.58082	0.47945	-1.542984	1.76834278E-3	1.18305258E-3
5	0.5863	0.47397	-1.660222	1.76834695E-3	1.18717801E-3
52	0.57808	0.47397	-1.648709	1.76835267E-3	1.18298325E-3

D.1.4 Lag 21

TABLE D.10: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
92	0.56478	0.48767	-0.904304	1.51401618E-3	1.17360680E-3
90	0.56661	0.48767	-0.861553	1.51435024E-3	1.17555112E-3
15	0.56843	0.49041	-1.223854	1.51450746E-3	1.17048283E-3
6	0.56661	0.48493	-0.691319	1.51460213E-3	1.17464486E-3
37	0.57391	0.48219	-1.368568	1.51468225E-3	1.16968869E-3
42	0.57847	0.48493	-1.446798	1.51470055E-3	1.17038755E-3
75	0.57026	0.48219	-0.881401	1.51475794E-3	1.18032689E-3
17	0.57391	0.48767	-1.36938	1.51487597E-3	1.16933521E-3
80	0.56843	0.47945	-1.04534	1.51488033E-3	1.17649110E-3
2	0.56661	0.48493	-0.844649	1.51493706E-3	1.17667457E-3

TABLE D.11: Metrics using Dataset [2020, 2021]-[2022] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
34	0.58276	0.52877	-0.731133	1.64623175E-3	1.16953570E-3
7	0.57456	0.52877	-0.711493	1.64701066E-3	1.17816071E-3
38	0.58687	0.51507	-0.587844	1.64752838E-3	1.18104570E-3
10	0.57456	0.52329	-0.405202	1.64762775E-3	1.17769883E-3
95	0.57729	0.52055	-0.605357	1.64788578E-3	1.17843954E-3
41	0.57729	0.54247	-0.066284	1.64795555E-3	1.17457895E-3
92	0.57866	0.50685	-0.621494	1.64805021E-3	1.18474073E-3
27	0.5814	0.49041	-1.026072	1.64805552E-3	1.18646731E-3
16	0.58003	0.50959	-0.552706	1.64808074E-3	1.18347909E-3
74	0.5814	0.50137	-0.454595	1.64811182E-3	1.18640029E-3

Table D.12: Metrics using Dataset [2021]-[2022] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
1	0.59452	0.49041	-0.456662	1.72604761E-3	1.19500988E-3
56	0.58904	0.49041	-0.780572	1.72619541E-3	1.19795848E-3
19	0.59726	0.47945	-1.283436	1.72658572E-3	1.19775248E-3
33	0.58904	0.48493	-1.157097	1.72664415E-3	1.20010115E-3
37	0.59452	0.48219	-0.644197	1.72667586E-3	1.19647959E-3
82	0.58904	0.47945	-1.088324	1.72670020E-3	1.19644904E-3
25	0.59452	0.48219	-0.843037	1.72689678E-3	1.19521724E-3
27	0.5863	0.47945	-1.280159	1.72690541E-3	1.19467415E-3
98	0.59726	0.48767	-0.666984	1.72699428E-3	1.19749371E-3
14	0.58904	0.47671	-1.336189	1.72708515E-3	1.19863370E-3

D.1.5 Lag 28

Table D.13: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
75	0.56752	0.50959	-0.327341	1.50259032E-3	1.17183643E-3
49	0.57299	0.52055	-0.104038	1.50288058E-3	1.17152929E-3
39	0.57117	0.51233	-0.08939	1.50289466E-3	1.17489186E-3
86	0.57664	0.50411	-0.485083	1.50296252E-3	1.18051552E-3
5	0.57664	0.48767	-0.913169	1.50303724E-3	1.17699790E-3
99	0.57573	0.51781	-0.003036	1.50311042E-3	1.17248655E-3
74	0.57208	0.49315	-0.680471	1.50322498E-3	1.17779814E-3
61	0.57391	0.51781	-0.031833	1.50323410E-3	1.17331995E-3
13	0.57664	0.50685	-0.323504	1.50325440E-3	1.17607522E-3
32	0.57208	0.51233	-0.255524	1.50325702E-3	1.17040497E-3

Table D.14: Metrics using Dataset [2020, 2021]-[2022] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
3	0.58824	0.49041	-0.695431	1.63595029E-3	1.17786610E-3
55	0.58276	0.49315	-0.557991	1.63669882E-3	1.17297633E-3
73	0.59097	0.48219	-1.199836	1.63672598E-3	1.17507641E-3
49	0.58687	0.49589	-0.734302	1.63682067E-3	1.17342112E-3
11	0.58413	0.48493	-1.256685	1.63697865E-3	1.17223671E-3
86	0.58276	0.50137	-0.159395	1.63702731E-3	1.16795324E-3
66	0.58824	0.49589	-0.517633	1.63710722E-3	1.18057575E-3
82	0.5855	0.48767	-1.229128	1.63717495E-3	1.17313779E-3
79	0.5896	0.49315	-0.549097	1.63728070E-3	1.16964422E-3
30	0.58687	0.49315	-0.603991	1.63740156E-3	1.17158159E-3

Table D.15: Metrics using Dataset [2021]-[2022] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
94	0.6137	0.48493	0.973491	1.71391785E-3	1.20425916E-3
28	0.60822	0.49041	1.043284	1.71491770E-3	1.20626349E-3
58	0.60548	0.48493	0.959099	1.71499387E-3	1.20326249E-3
42	0.60274	0.48767	1.135821	1.71504774E-3	1.20596094E-3
46	0.59726	0.48767	0.951053	1.71530632E-3	1.20136239E-3
52	0.60274	0.48767	1.135821	1.71552320E-3	1.20500053E-3
72	0.61644	0.48767	1.040911	1.71553747E-3	1.20498694E-3
61	0.59452	0.49041	1.139269	1.71562880E-3	1.20383285E-3
38	0.60548	0.49315	1.176868	1.71564620E-3	1.20314304E-3
88	0.59726	0.48767	0.951053	1.71565028E-3	1.20292747E-3

D.1.6 Lag auto - 6

Table D.16: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
90	0.53011	0.47671	-0.925364	1.52756701E-3	1.16402494E-3
61	0.53193	0.47123	-1.103314	1.52767699E-3	1.16117360E-3
88	0.53376	0.47671	-0.972067	1.52768621E-3	1.16230604E-3
51	0.53467	0.47945	-0.931981	1.52770353E-3	1.16392284E-3
27	0.5292	0.47671	-0.925364	1.52778897E-3	1.16498165E-3
98	0.53285	0.47945	-0.739867	1.52784755E-3	1.16511024E-3
13	0.53285	0.47671	-0.972067	1.52784875E-3	1.16248195E-3
48	0.53467	0.47671	-0.972067	1.52787833E-3	1.16370996E-3
40	0.53285	0.47671	-0.972067	1.52790423E-3	1.16415844E-3
91	0.53467	0.47397	-1.023283	1.52791458E-3	1.16360838E-3

Table D.17: Metrics using Dataset [2020, 2021]-[2022] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
90	0.53899	0.48493	-0.891342	1.66510362E-3	1.17191255E-3
25	0.53899	0.48493	-0.744863	1.66528382E-3	1.16896031E-3
32	0.54172	0.48493	-0.612673	1.66537347E-3	1.17059538E-3
7	0.54036	0.48219	-0.855957	1.66550356E-3	1.16707788E-3
16	0.54036	0.47397	-1.26855	1.66551354E-3	1.17559353E-3
37	0.54036	0.48219	-1.041195	1.66554334E-3	1.17321871E-3
59	0.54036	0.48493	-0.891342	1.66558014E-3	1.16935684E-3
86	0.54172	0.47945	-1.047208	1.66559931E-3	1.17279301E-3
39	0.53899	0.48219	-1.002117	1.66567065E-3	1.16936719E-3
26	0.54446	0.47671	-1.141733	1.66579224E-3	1.17846774E-3

Table D.18: Metrics using Dataset [2021]-[2022] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
90	0.54521	0.45753	-0.769227	1.74013953E-3	1.17172794E-3
41	0.55342	0.47397	-1.008482	1.74014076E-3	1.16948811E-3
76	0.53699	0.46027	-0.751086	1.74020889E-3	1.17339720E-3
86	0.56438	0.48219	-0.784604	1.74021393E-3	1.16857791E-3
77	0.5589	0.48219	-0.86098	1.74024438E-3	1.16712367E-3
9	0.56438	0.48219	-0.784604	1.74026754E-3	1.16884745E-3
69	0.54247	0.46027	-0.751086	1.74029663E-3	1.17281226E-3
31	0.55616	0.47945	-0.774818	1.74031759E-3	1.17094892E-3
64	0.56438	0.48219	-0.780582	1.74032058E-3	1.16712126E-3
2	0.54795	0.47671	-0.694518	1.74033853E-3	1.17009998E-3

D.1.7 Bitcoin MSE Correlation 2022

Year	Lag	Correlation
2019-2022	01	-0.902813
2019-2022	07	-0.80232
2019-2022	14	-0.67682
2019-2022	21	-0.41762
2019-2022	28	-0.58074
2019-2022	auto - 6	-0.80110
2020-2022	01	-0.40818
2020-2022	07	-0.65616
2020-2022	14	0.31945
2020-2022	21	0.06257
2020-2022	28	-0.15547
2020-2022	auto - 6	-0.51614
2021-2022	01	-0.910565
2021-2022	07	-0.71890
2021-2022	14	-0.08878
2021-2022	21	0.07281
2021-2022	28	0.27657
2021-2022	auto - 6	-0.09371

Table D.19: Correlation MSE Bitcoin

Appendix E

Appendix SVR - Bitcoin 2023

E.1 Bitcoin SVR - extended Tables - 2023 Test

E.1.1 Lag 01

Table E.1: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
17	0.52555	0.54795	0.801247	1.49836120E-3	5.18833452E-4
2	0.52281	0.55068	0.52125	1.49837708E-3	5.19703135E-4
88	0.52099	0.54247	0.473087	1.49839875E-3	5.19579151E-4
70	0.52281	0.55068	0.52125	1.49840080E-3	5.19799104E-4
62	0.52464	0.54521	0.573041	1.49840631E-3	5.19170502E-4
21	0.52555	0.55342	0.581369	1.49840918E-3	5.19897247E-4
49	0.52099	0.54247	0.473087	1.49840973E-3	5.19665011E-4
42	0.52372	0.55342	0.619922	1.49841500E-3	5.20008481E-4
56	0.52372	0.55342	0.619922	1.49841694E-3	5.20011287E-4
26	0.52372	0.55068	0.52125	1.49841982E-3	5.19851873E-4

Table E.2: Metrics using Dataset [2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
11	0.53562	0.53425	-1.279332	1.44811643E-3	5.27378832E-4
37	0.53425	0.52877	-1.384823	1.44832269E-3	5.27939281E-4
66	0.54658	0.53973	-0.622454	1.44836069E-3	5.29185350E-4
21	0.5411	0.53425	-0.698573	1.44838464E-3	5.31165274E-4
69	0.53836	0.53151	-1.188445	1.44846885E-3	5.28556053E-4
4	0.52877	0.53425	-1.279332	1.44847004E-3	5.27882167E-4
65	0.53425	0.53151	-1.153378	1.44850411E-3	5.28396730E-4
5	0.52877	0.53425	-1.279332	1.44851570E-3	5.27957311E-4
51	0.53151	0.53425	-1.155349	1.44851785E-3	5.27198346E-4
6	0.53151	0.53425	-1.155349	1.44854610E-3	5.27398998E-4

Table E.3: Metrics using Dataset [2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
40	0.53425	0.50137	-2.166654	1.12660653E-3	5.39928190E-4
1	0.53425	0.50137	-2.166654	1.12661496E-3	5.39951419E-4
64	0.53425	0.50137	-2.166654	1.12662633E-3	5.38723242E-4
8	0.53425	0.50137	-2.166654	1.12669972E-3	5.40125438E-4
25	0.53425	0.50137	-2.166654	1.12671403E-3	5.41751327E-4
74	0.53425	0.50137	-2.166654	1.12674065E-3	5.41642258E-4
6	0.53425	0.50137	-2.166654	1.12682914E-3	5.36337763E-4
38	0.53425	0.50137	-2.166654	1.12685332E-3	5.36355248E-4
55	0.53425	0.50137	-2.166654	1.12688224E-3	5.36373997E-4
49	0.53425	0.50137	-2.166654	1.12688495E-3	5.36375683E-4

E.1.2 Lag 07

Table E.4: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
30	0.53193	0.53699	1.123091	1.49939162E-3	5.18746884E-4
65	0.54288	0.53973	0.994112	1.49951629E-3	5.20345795E-4
31	0.53923	0.54247	1.072828	1.49957402E-3	5.20729857E-4
2	0.53923	0.54247	1.067289	1.49961803E-3	5.20851602E-4
21	0.53832	0.54247	0.832419	1.49964042E-3	5.21033194E-4
81	0.54197	0.53973	1.328714	1.49964648E-3	5.20282216E-4
17	0.53102	0.54521	1.386434	1.49969428E-3	5.18818413E-4
32	0.53558	0.54247	0.470395	1.49972662E-3	5.21574749E-4
71	0.5365	0.52329	0.870088	1.49976137E-3	5.18226848E-4
91	0.53193	0.52603	0.860976	1.49979556E-3	5.18613965E-4

Table E.5: Metrics using Dataset [2021, 2022]-[2023] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
5	0.52877	0.53151	-1.532401	1.44885268E-3	5.32717527E-4
64	0.52466	0.53151	-1.510343	1.44890264E-3	5.31969479E-4
70	0.53288	0.51781	-1.947401	1.44893703E-3	5.33786879E-4
15	0.53151	0.52877	-1.724735	1.44896574E-3	5.31872808E-4
14	0.52466	0.53151	-1.60148	1.44897289E-3	5.33203575E-4
35	0.5274	0.52603	-1.777278	1.44899544E-3	5.32097399E-4
96	0.53014	0.51781	-1.943702	1.44901691E-3	5.31558552E-4
54	0.52466	0.52877	-1.526191	1.44901958E-3	5.32060734E-4
81	0.52192	0.52329	-1.654772	1.44905204E-3	5.32635249E-4
79	0.52192	0.53699	-1.469879	1.44907150E-3	5.31873666E-4

TABLE E.6: Metrics using Dataset [2022]-[2023] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
17	0.57534	0.50959	-0.979588	1.13025110E-3	5.60375138E-4
15	0.56712	0.50685	-1.940897	1.13028559E-3	5.74102635E-4
67	0.57534	0.50411	-1.813043	1.13036038E-3	5.69815588E-4
24	0.58082	0.50411	-1.004894	1.13037907E-3	5.62009057E-4
68	0.57534	0.50685	-0.987096	1.13053843E-3	5.60710237E-4
4	0.58356	0.51233	-0.974862	1.13062753E-3	5.62958677E-4
56	0.57808	0.50685	-0.98588	1.13063047E-3	5.63251154E-4
72	0.57808	0.50959	-0.979588	1.13063258E-3	5.61819309E-4
32	0.58082	0.50959	-0.979588	1.13063664E-3	5.65099474E-4
76	0.58356	0.50411	-0.99162	1.13065462E-3	5.59413354E-4

E.1.3 Lag 14

TABLE E.7: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
21	0.54471	0.56986	1.613486	1.49112185E-3	5.15688999E-4
54	0.54015	0.5589	1.060402	1.49135274E-3	5.15184231E-4
69	0.54745	0.56712	1.527631	1.49149694E-3	5.15009710E-4
41	0.55201	0.56438	0.770564	1.49153535E-3	5.17970646E-4
97	0.54471	0.5726	1.437599	1.49158930E-3	5.15628948E-4
48	0.54745	0.56438	1.058252	1.49159516E-3	5.16613439E-4
98	0.54471	0.5726	1.139792	1.49160358E-3	5.15150759E-4
31	0.53558	0.54247	0.975495	1.49161600E-3	5.14003750E-4
76	0.53923	0.56164	1.192384	1.49166250E-3	5.14643715E-4
50	0.54288	0.56438	1.06015	1.49168155E-3	5.14860223E-4

TABLE E.8: Metrics using Dataset [2021, 2022]-[2023] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
58	0.53973	0.53699	0.014461	1.44783549E-3	5.27966297E-4
70	0.55068	0.54521	0.553006	1.44847132E-3	5.23096462E-4
100	0.53699	0.52877	-0.06548	1.44847762E-3	5.26838077E-4
62	0.53973	0.53699	-0.450092	1.44857140E-3	5.29657228E-4
90	0.53288	0.52055	-0.447581	1.44857244E-3	5.28362720E-4
20	0.53836	0.52055	-0.676744	1.44858746E-3	5.26692630E-4
42	0.53425	0.53973	-0.31265	1.44863184E-3	5.31085841E-4
82	0.52877	0.53699	-0.483039	1.44866219E-3	5.30849381E-4
56	0.54384	0.52329	-0.262889	1.44869565E-3	5.25844860E-4
16	0.53973	0.53699	-0.300595	1.44877944E-3	5.28993007E-4

TABLE E.9: Metrics using Dataset [2022]-[2023] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
43	0.58904	0.50685	-1.535895	1.11393564E-3	5.62399140E-4
97	0.59178	0.51507	-1.216427	1.11455434E-3	5.61515777E-4
95	0.58904	0.51507	-1.198227	1.11456119E-3	5.59055358E-4
14	0.58904	0.51507	-1.316611	1.11495900E-3	5.61730985E-4
74	0.59452	0.51507	-1.346902	1.11505704E-3	5.62708624E-4
46	0.59726	0.50959	-0.798816	1.11509278E-3	5.57184168E-4
23	0.58904	0.51233	-0.616909	1.11530516E-3	5.56856249E-4
33	0.58904	0.51233	-1.145725	1.11550730E-3	5.56977000E-4
56	0.58904	0.51507	-1.316611	1.11553125E-3	5.61391958E-4
34	0.6	0.52603	-0.597566	1.11557391E-3	5.53113532E-4

E.1.4 Lag 21

TABLE E.10: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
9	0.56387	0.56712	0.620037	1.48608496E-3	5.22907958E-4
55	0.55566	0.56712	0.930989	1.48611947E-3	5.21343673E-4
97	0.55657	0.55342	0.876699	1.48612364E-3	5.20953018E-4
30	0.55931	0.56712	0.775194	1.48612754E-3	5.21732483E-4
73	0.56022	0.56712	0.682815	1.48617454E-3	5.21529268E-4
31	0.55657	0.55068	1.010264	1.48627619E-3	5.20476401E-4
43	0.55566	0.5589	0.743576	1.48634725E-3	5.21572671E-4
72	0.55474	0.5589	0.707325	1.48636461E-3	5.21865600E-4
1	0.55657	0.54521	0.763849	1.48639124E-3	5.21288079E-4
96	0.55931	0.56164	0.8279	1.48639592E-3	5.21739181E-4

TABLE E.11: Metrics using Dataset [2021, 2022]-[2023] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
41	0.56301	0.55068	-0.202414	1.42613738E-3	5.27651981E-4
59	0.56164	0.5589	0.292729	1.42622996E-3	5.23075181E-4
20	0.56301	0.54795	-0.315133	1.42658714E-3	5.24744746E-4
79	0.55479	0.55068	0.106208	1.42665120E-3	5.23507429E-4
97	0.56164	0.55616	0.022722	1.42680463E-3	5.22552722E-4
9	0.56027	0.55068	-0.033613	1.42685405E-3	5.24613416E-4
56	0.56164	0.55068	-0.126924	1.42695668E-3	5.25140532E-4
11	0.56712	0.55342	-0.173432	1.42698733E-3	5.26653443E-4
74	0.56301	0.55616	-0.245689	1.42698800E-3	5.25259289E-4
39	0.56438	0.54521	-0.602397	1.42699173E-3	5.26972328E-4

TABLE E.12: Metrics using Dataset [2022]-[2023] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
40	0.58082	0.50685	-0.716931	1.10294289E-3	5.47985338E-4
46	0.57808	0.50959	-0.602194	1.10311600E-3	5.45700135E-4
30	0.58082	0.50685	-0.716931	1.10312583E-3	5.47453404E-4
2	0.57534	0.50959	-0.676142	1.10323505E-3	5.48010015E-4
68	0.5863	0.50685	-0.717511	1.10328892E-3	5.46608060E-4
20	0.57808	0.50959	-0.676142	1.10343228E-3	5.47731339E-4
58	0.58082	0.51507	-0.4381	1.10350928E-3	5.48887737E-4
83	0.56986	0.50685	-0.694984	1.10362168E-3	5.48640134E-4
94	0.57534	0.50685	-0.692458	1.10369708E-3	5.46834646E-4
34	0.58904	0.50959	-0.663367	1.10369809E-3	5.45127137E-4

E.1.5 Lag 28

TABLE E.13: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
72	0.57117	0.5589	1.363742	1.47811531E-3	5.19874492E-4
24	0.57755	0.55616	1.068377	1.47837167E-3	5.19284023E-4
58	0.57664	0.54521	1.118124	1.47840228E-3	5.17300463E-4
51	0.57573	0.54247	0.720817	1.47859943E-3	5.18897615E-4
23	0.56204	0.55342	1.497122	1.47863978E-3	5.21755658E-4
66	0.58029	0.5589	1.09943	1.47864673E-3	5.18681828E-4
3	0.57117	0.55342	1.087469	1.47873705E-3	5.18658940E-4
70	0.57847	0.54795	0.93786	1.47881777E-3	5.18462464E-4
6	0.57391	0.55342	1.008042	1.47883779E-3	5.19813130E-4
37	0.57208	0.55342	0.960911	1.47889258E-3	5.19179127E-4

TABLE E.14: Metrics using Dataset [2021, 2022]-[2023] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
55	0.56712	0.53425	-0.266977	1.41667422E-3	5.30668681E-4
49	0.56027	0.52329	-0.157319	1.41678421E-3	5.29274794E-4
15	0.56164	0.52329	-0.224382	1.41717896E-3	5.30299106E-4
51	0.56164	0.52603	-0.087194	1.41737613E-3	5.31965293E-4
7	0.5726	0.52877	-0.023777	1.41763686E-3	5.29589929E-4
66	0.56849	0.52877	-0.142146	1.41766268E-3	5.30949063E-4
75	0.56301	0.51781	-0.486364	1.41777424E-3	5.32456800E-4
70	0.5726	0.51781	-0.369081	1.41780022E-3	5.30514481E-4
37	0.56986	0.53699	0.026754	1.41782093E-3	5.25790872E-4
13	0.56438	0.52877	-0.251139	1.41790891E-3	5.29658677E-4

TABLE E.15: Metrics using Dataset [2022]-[2023] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
59	0.59178	0.50411	-1.066225	1.10087276E-3	5.72478545E-4
56	0.5863	0.50411	-1.066225	1.10097838E-3	5.72891497E-4
73	0.5863	0.50685	-1.113546	1.10108575E-3	5.66099415E-4
10	0.58904	0.51233	-0.84174	1.10115820E-3	5.68305964E-4
51	0.5863	0.50685	-0.898826	1.10119271E-3	5.70794968E-4
9	0.58356	0.50685	-0.898826	1.10133268E-3	5.70965945E-4
4	0.59726	0.51233	-0.747854	1.10137911E-3	5.76028517E-4
71	0.58356	0.50411	-1.133457	1.10138337E-3	5.72216433E-4
16	0.58356	0.50685	-1.131495	1.10138540E-3	5.67613589E-4
77	0.58904	0.51781	-0.87429	1.10142700E-3	5.68009120E-4

E.1.6 Lag auto - 6

TABLE E.16: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
32	0.5365	0.55342	0.886554	1.50166837E-3	5.21042317E-4
83	0.53923	0.55342	0.949605	1.50168622E-3	5.21342159E-4
6	0.54106	0.55616	0.831732	1.50176076E-3	5.20493396E-4
33	0.53832	0.55342	0.82431	1.50177202E-3	5.20616540E-4
57	0.53741	0.55068	0.798989	1.50185128E-3	5.20179189E-4
92	0.54288	0.55068	0.597476	1.50187104E-3	5.21981757E-4
52	0.53832	0.53699	0.302048	1.50194253E-3	5.22783103E-4
97	0.53741	0.55616	0.952987	1.50194951E-3	5.21021285E-4
74	0.53467	0.55616	1.085922	1.50195679E-3	5.21317306E-4
54	0.53741	0.53151	1.038975	1.50196161E-3	5.18329079E-4

TABLE E.17: Metrics using Dataset [2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
22	0.52192	0.52329	-1.49178	1.45008538E-3	5.30486356E-4
52	0.53425	0.52877	-1.005494	1.45011953E-3	5.31966724E-4
17	0.52603	0.53425	-1.097637	1.45014664E-3	5.30894048E-4
54	0.52877	0.52877	-1.315843	1.45024848E-3	5.31012516E-4
94	0.51918	0.52877	-1.220649	1.45027120E-3	5.30450489E-4
4	0.51644	0.52329	-1.447453	1.45028704E-3	5.30226137E-4
3	0.52055	0.53425	-0.98494	1.45030343E-3	5.30452879E-4
57	0.53288	0.52329	-1.119691	1.45030999E-3	5.32477741E-4
38	0.51096	0.53151	-1.242893	1.45035167E-3	5.30398022E-4
2	0.5274	0.52877	-1.2417	1.45035490E-3	5.31133521E-4

TABLE E.18: Metrics using Dataset [2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
12	0.57534	0.50959	-0.979588	1.13030663E-3	5.60307569E-4
2	0.58356	0.51233	-0.974862	1.13038693E-3	5.64003315E-4
94	0.5726	0.50137	-1.981934	1.13046004E-3	5.72836813E-4
11	0.57534	0.50959	-0.981036	1.13063648E-3	5.63218401E-4
48	0.58356	0.50411	-0.985119	1.13064971E-3	5.58522768E-4
36	0.57534	0.51233	-1.612322	1.13065092E-3	5.68078758E-4
53	0.58356	0.51233	-0.974862	1.13066682E-3	5.63901226E-4
81	0.56986	0.50411	-2.228954	1.13067174E-3	5.73677975E-4
74	0.5863	0.51781	-0.895868	1.13067979E-3	5.67928354E-4
56	0.58082	0.52055	-0.742428	1.13070939E-3	5.66504776E-4

E.1.7 Bitcoin MSE Correlation 2023

Year	Lag	Correlation
2020-2023	01	-0.234334
2020-2023	07	-0.34608
2020-2023	14	-0.18151
2020-2023	21	-0.75679
2020-2023	28	-0.46621
2020-2023	auto - 6	-0.32867
2021-2023	01	-0.600725
2021-2023	07	0.04710
2021-2023	14	0.18366
2021-2023	21	-0.72336
2021-2023	28	-0.70978
2021-2023	auto - 6	-0.51231
2022-2023	01	-0.937929
2022-2023	07	0.94483
2022-2023	14	-0.87563
2022-2023	21	-0.69644
2022-2023	28	-0.48914
2022-2023	auto - 6	-0.84308

TABLE E.19: Correlation MSE Bitcoin

Appendix F

Appendix SVR - GOLD 2023

F.1 Gold SVR - extended Tables - 2023 Test

F.1.1 Lag 01

TABLE F.1: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
55	0.54233	0.51793	0.637068	1.22104134E-4	6.88720523E-5
13	0.53836	0.51793	0.916337	1.22108308E-4	6.88558071E-5
88	0.54233	0.51793	0.637068	1.22109179E-4	6.88488147E-5
24	0.53439	0.51394	1.129515	1.22109542E-4	6.89039185E-5
16	0.52778	0.51394	1.048131	1.22109581E-4	6.88766229E-5
79	0.53175	0.51394	1.048131	1.22110311E-4	6.88664479E-5
27	0.52778	0.50996	1.024753	1.22111228E-4	6.88726787E-5
90	0.54365	0.52191	1.130169	1.22113503E-4	6.88264111E-5
84	0.53439	0.5259	0.966277	1.22114929E-4	6.88950359E-5
43	0.53968	0.52191	0.985667	1.22115439E-4	6.88360199E-5

TABLE F.2: Metrics using Dataset [2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
66	0.5328	0.48207	-0.345404	9.17533704E-5	6.92496659E-5
34	0.51889	0.46215	-0.75897	9.17539825E-5	6.93157362E-5
30	0.5328	0.46614	0.109332	9.17559421E-5	6.91288623E-5
91	0.52286	0.48606	-0.18187	9.17569462E-5	6.92365211E-5
45	0.52883	0.47012	0.116445	9.17570689E-5	6.91285229E-5
81	0.5328	0.46614	0.109332	9.17571964E-5	6.91359468E-5
40	0.5169	0.46215	-0.353295	9.17604572E-5	6.90816832E-5
60	0.52485	0.46614	-0.161696	9.17615822E-5	6.91139004E-5
100	0.5169	0.46614	-0.211759	9.17645642E-5	6.90959150E-5
58	0.5169	0.46614	-0.88171	9.17646057E-5	6.93463579E-5

Table F.3: Metrics using Dataset [2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
96	0.52988	0.46614	0.109332	9.45339010E-5	6.92724830E-5
11	0.53386	0.46614	0.109332	9.45352370E-5	6.92826260E-5
19	0.49801	0.49004	0.385347	9.45387231E-5	6.93433213E-5
88	0.49801	0.48606	0.245035	9.45401209E-5	6.93532016E-5
2	0.49801	0.48606	0.245035	9.45401231E-5	6.93529544E-5
66	0.49801	0.48606	0.245035	9.45418688E-5	6.93648172E-5
85	0.51394	0.48207	0.274163	9.45419928E-5	6.91556245E-5
77	0.51394	0.48207	0.274163	9.45422373E-5	6.91610058E-5
80	0.51394	0.47809	0.221703	9.45429424E-5	6.91727889E-5
78	0.51394	0.47809	0.221703	9.45430295E-5	6.91740237E-5

F.1.2 Lag 05

Table F.4: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
72	0.53307	0.5259	0.43371	1.21771431E-4	6.92853906E-5
20	0.5463	0.55777	1.359513	1.21774482E-4	6.92201895E-5
3	0.54233	0.52988	0.637878	1.21775800E-4	6.92248957E-5
36	0.53571	0.5259	0.750109	1.21778610E-4	6.92587653E-5
25	0.53571	0.5259	0.582915	1.21783467E-4	6.92372318E-5
13	0.53571	0.5259	0.689632	1.21795574E-4	6.92348983E-5
60	0.53307	0.52988	0.475034	1.21807370E-4	6.92075133E-5
35	0.53439	0.51394	0.058801	1.21808594E-4	6.93199518E-5
8	0.54233	0.5259	0.5988	1.21809343E-4	6.91893429E-5
26	0.53704	0.53785	0.380316	1.21821359E-4	6.92343036E-5

Table F.5: Metrics using Dataset [2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
33	0.52485	0.50199	0.280359	9.13257812E-5	6.89965106E-5
65	0.51889	0.49402	-0.093725	9.13264787E-5	6.89635667E-5
84	0.52286	0.50996	0.36781	9.13320041E-5	6.89116430E-5
41	0.5169	0.51793	0.503439	9.13339542E-5	6.89557930E-5
93	0.52087	0.49801	-0.027001	9.13380056E-5	6.89937121E-5
9	0.51889	0.51793	0.814957	9.13399754E-5	6.90337614E-5
63	0.52087	0.50199	0.210835	9.13409866E-5	6.90079014E-5
83	0.52286	0.50598	0.089721	9.13438226E-5	6.88794149E-5
45	0.52087	0.50598	0.408036	9.13447381E-5	6.89063840E-5
74	0.52286	0.50598	0.384947	9.13447690E-5	6.90195667E-5

TABLE F.6: Metrics using Dataset [2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
89	0.50996	0.48606	0.838639	9.40107218E-5	6.94497323E-5
100	0.51394	0.47809	0.560589	9.40300952E-5	6.94547211E-5
41	0.5259	0.50996	1.479714	9.40393427E-5	6.94183294E-5
47	0.51793	0.48606	0.711559	9.40470548E-5	6.94888082E-5
77	0.51394	0.48207	0.620626	9.40639674E-5	6.94498935E-5
24	0.51394	0.48606	0.711559	9.40658649E-5	6.94893974E-5
96	0.52191	0.48207	0.620626	9.40733959E-5	6.95379710E-5
86	0.51394	0.48207	0.672498	9.40774658E-5	6.95664238E-5
81	0.51793	0.48207	0.620626	9.40819150E-5	6.95567114E-5
19	0.54582	0.49801	1.088904	9.40842961E-5	6.93618089E-5

F.1.3 Lag 10

TABLE F.7: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
62	0.53836	0.54183	1.337242	1.20728087E-4	6.86011464E-5
38	0.55159	0.51793	0.496713	1.20739667E-4	6.84682465E-5
58	0.52513	0.50996	0.907138	1.20749353E-4	6.87239694E-5
50	0.5463	0.52191	0.459698	1.20751605E-4	6.85050157E-5
91	0.53571	0.53386	1.347942	1.20773884E-4	6.85934122E-5
52	0.5291	0.50996	0.915539	1.20789340E-4	6.86152156E-5
86	0.54894	0.50996	0.309508	1.20789393E-4	6.84297640E-5
73	0.52381	0.5259	1.206066	1.20792063E-4	6.86014630E-5
45	0.53042	0.5259	1.241622	1.20792179E-4	6.84731850E-5
90	0.52646	0.52988	1.46335	1.20801021E-4	6.87912719E-5

TABLE F.8: Metrics using Dataset [2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
94	0.54871	0.53386	0.93319	9.08196355E-5	6.81656012E-5
16	0.54076	0.52191	0.783329	9.08217066E-5	6.83772126E-5
49	0.54274	0.5259	0.697532	9.08301352E-5	6.82488228E-5
37	0.53479	0.51394	0.592255	9.08315569E-5	6.83476395E-5
76	0.54274	0.52191	0.680305	9.08387198E-5	6.81631901E-5
79	0.54274	0.52191	0.752585	9.08419100E-5	6.82039481E-5
14	0.53678	0.54183	1.096976	9.08490157E-5	6.81219942E-5
52	0.54672	0.54183	0.942851	9.08514588E-5	6.82031721E-5
61	0.5328	0.51394	0.624092	9.08541544E-5	6.83882052E-5
34	0.53678	0.52191	0.629994	9.08549780E-5	6.83687289E-5

TABLE F.9: Metrics using Dataset [2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
32	0.56972	0.49004	0.728877	9.22266680E-5	6.90082841E-5
46	0.55777	0.49402	0.794701	9.22314372E-5	6.89256468E-5
91	0.56574	0.50199	1.037884	9.22387987E-5	6.89690289E-5
77	0.56972	0.49801	0.799171	9.22782619E-5	6.88526550E-5
90	0.57769	0.50199	0.93855	9.22937009E-5	6.88064707E-5
36	0.53386	0.49801	0.923183	9.23081099E-5	6.91819298E-5
19	0.57769	0.51793	1.486761	9.23190337E-5	6.87662202E-5
49	0.57371	0.49801	0.971888	9.23224463E-5	6.88480589E-5
23	0.53785	0.50598	1.034054	9.23238035E-5	6.93455760E-5
31	0.52988	0.49801	0.872677	9.23264698E-5	6.92113101E-5

F.1.4 Lag 15

TABLE F.10: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
20	0.54365	0.55378	1.272785	1.20221998E-4	6.79373372E-5
75	0.55556	0.53386	0.929914	1.20226271E-4	6.80404340E-5
95	0.54365	0.5498	1.375416	1.20255218E-4	6.80088980E-5
59	0.55159	0.53785	1.154712	1.20256601E-4	6.80028366E-5
6	0.55291	0.52988	0.97918	1.20259335E-4	6.80229997E-5
3	0.55026	0.55777	1.466279	1.20261326E-4	6.80186267E-5
41	0.54233	0.5259	0.918051	1.20261640E-4	6.80548803E-5
82	0.53704	0.51394	1.125847	1.20265760E-4	6.81501132E-5
87	0.54894	0.53386	1.027895	1.20268437E-4	6.80562617E-5
12	0.55159	0.53386	0.939644	1.20268824E-4	6.80270048E-5

TABLE F.11: Metrics using Dataset [2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
63	0.53082	0.55378	2.003289	9.09098470E-5	6.74755610E-5
11	0.53877	0.5498	1.824406	9.09144689E-5	6.74891768E-5
71	0.53082	0.5498	1.945267	9.09174148E-5	6.75662100E-5
55	0.52286	0.54582	1.647715	9.09239596E-5	6.75029045E-5
61	0.5328	0.54183	1.64527	9.09272435E-5	6.76482992E-5
72	0.54274	0.5498	1.93833	9.09329478E-5	6.74774937E-5
5	0.53479	0.55378	1.936372	9.09334424E-5	6.75252466E-5
70	0.52485	0.54582	1.102686	9.09339247E-5	6.78364225E-5
13	0.5328	0.54582	2.016568	9.09405977E-5	6.75751262E-5
99	0.52883	0.54183	1.785688	9.09475250E-5	6.76803607E-5

TABLE F.12: Metrics using Dataset [2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
95	0.58167	0.48207	0.823346	9.11700804E-5	6.95169423E-5
48	0.59761	0.46614	0.592581	9.11878029E-5	6.92134579E-5
92	0.57769	0.48606	0.862178	9.12040327E-5	6.94291020E-5
49	0.60558	0.4741	0.933922	9.12053472E-5	6.90812885E-5
82	0.59363	0.48207	0.906082	9.12136486E-5	6.92730195E-5
99	0.59363	0.4741	0.838078	9.12151915E-5	6.93441587E-5
77	0.60558	0.48207	0.713595	9.12182535E-5	6.91425088E-5
25	0.59761	0.4741	0.749187	9.12191125E-5	6.91064761E-5
41	0.60956	0.48606	1.176975	9.12195610E-5	6.90051592E-5
10	0.60558	0.47809	0.720926	9.12209522E-5	6.90412997E-5

F.1.5 Lag 20

TABLE F.13: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
34	0.56481	0.54582	1.52394	1.19248443E-4	6.75710285E-5
14	0.56481	0.54582	1.524173	1.19261783E-4	6.74920555E-5
10	0.56349	0.55777	2.167376	1.19263378E-4	6.75006657E-5
16	0.5754	0.5498	1.580636	1.19268646E-4	6.74839330E-5
60	0.55159	0.52988	1.081554	1.19280633E-4	6.75381020E-5
85	0.55291	0.51394	0.848814	1.19281684E-4	6.75626070E-5
3	0.56481	0.5498	1.80568	1.19286377E-4	6.75215149E-5
47	0.55291	0.50199	0.127812	1.19288570E-4	6.77679754E-5
64	0.57143	0.55378	2.112338	1.19292025E-4	6.74324609E-5
5	0.56481	0.5498	2.04364	1.19293464E-4	6.75573557E-5

TABLE F.14: Metrics using Dataset [2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
70	0.54871	0.52191	0.750957	9.01497934E-5	6.70587461E-5
40	0.53877	0.52988	0.682645	9.01663309E-5	6.71729617E-5
66	0.52883	0.52988	0.687258	9.01751702E-5	6.71977706E-5
7	0.55666	0.52191	0.606279	9.01768378E-5	6.69740758E-5
58	0.56262	0.52988	0.733863	9.01857548E-5	6.68662736E-5
54	0.54871	0.5259	0.834113	9.01964359E-5	6.69666208E-5
38	0.54076	0.52191	0.616798	9.01993641E-5	6.70584094E-5
24	0.55666	0.53386	0.860813	9.02061532E-5	6.68839856E-5
6	0.55666	0.52191	0.496371	9.02072601E-5	6.70650024E-5
47	0.56461	0.53785	1.030145	9.02110375E-5	6.68256310E-5

TABLE F.15: Metrics using Dataset [2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
70	0.61753	0.48207	-0.255076	9.09175978E-5	6.97050905E-5
38	0.61355	0.49004	-0.082517	9.09431545E-5	6.96792027E-5
58	0.61355	0.4741	-0.334755	9.09492823E-5	6.97847603E-5
36	0.62151	0.4741	-0.429329	9.09614370E-5	6.99563065E-5
12	0.60956	0.50598	0.666276	9.09667848E-5	6.95680944E-5
42	0.60956	0.49801	0.526644	9.09686761E-5	6.96793223E-5
27	0.60558	0.49004	0.184018	9.09709692E-5	6.96957899E-5
74	0.61355	0.50199	0.608317	9.09718766E-5	6.95978068E-5
43	0.60956	0.49402	0.222977	9.09810956E-5	6.97404690E-5
46	0.60558	0.48606	-0.14038	9.09870878E-5	6.97517289E-5

F.1.6 Lag auto

TABLE F.16: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
65	0.56481	0.53386	1.739542	1.19298787E-4	6.75456310E-5
64	0.55159	0.50598	0.716297	1.19331878E-4	6.76668415E-5
94	0.56614	0.50598	0.632432	1.19332442E-4	6.75625734E-5
14	0.56614	0.51394	0.835895	1.19339387E-4	6.75698290E-5
25	0.55952	0.50996	0.680301	1.19339735E-4	6.75305794E-5
1	0.56878	0.50199	0.807593	1.19346670E-4	6.75410222E-5
47	0.56746	0.50996	0.741073	1.19347690E-4	6.75294812E-5
60	0.56349	0.50598	0.632432	1.19349297E-4	6.75541547E-5
7	0.56085	0.5259	1.6465	1.19350322E-4	6.74522037E-5
38	0.56746	0.51394	1.035191	1.19359058E-4	6.75208923E-5

TABLE F.17: Metrics using Dataset [2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
39	0.56262	0.55378	1.011934	9.00184868E-5	6.69690164E-5
71	0.5666	0.55378	1.011934	9.00295148E-5	6.69223566E-5
28	0.56461	0.55777	1.159262	9.00404385E-5	6.68876655E-5
26	0.56064	0.5259	0.930214	9.00411925E-5	6.73546939E-5
36	0.55666	0.53386	0.644886	9.00421933E-5	6.70267816E-5
6	0.56064	0.5498	0.884784	9.00459191E-5	6.70385840E-5
24	0.55666	0.53386	1.039248	9.00460724E-5	6.68705845E-5
83	0.56461	0.54183	0.823793	9.00464045E-5	6.69735206E-5
44	0.5666	0.5498	0.939361	9.00493224E-5	6.69916294E-5
95	0.55666	0.53785	1.207663	9.00515199E-5	6.72016054E-5

TABLE F.18: Metrics using Dataset [2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
38	0.57769	0.48606	0.827848	9.01397588E-5	6.93518427E-5
83	0.58964	0.46215	-0.14883	9.01715490E-5	6.94030274E-5
17	0.59363	0.46614	0.345935	9.01911391E-5	6.93465126E-5
84	0.58566	0.47809	0.652646	9.01921815E-5	6.92781988E-5
31	0.57769	0.47012	-0.074228	9.01963717E-5	6.95206421E-5
54	0.56972	0.48207	0.719662	9.02015404E-5	6.92019204E-5
37	0.58566	0.47809	0.607563	9.02022181E-5	6.94760281E-5
56	0.58964	0.47809	0.405469	9.02023772E-5	6.90247572E-5
72	0.58167	0.49004	0.787982	9.02037731E-5	6.90992730E-5
12	0.58167	0.48606	0.810218	9.02069957E-5	6.91599212E-5

F.1.7 Gold MSE Correlation 2023

Year	Lag	Correlation
2020-2023	01	0.947146
2020-2023	05	0.92276
2020-2023	10	0.92766
2020-2023	15	0.95326
2020-2023	20	0.87801
2020-2023	auto - 19	0.94056
2021-2023	01	-0.013432
2021-2023	05	0.25047
2021-2023	10	-0.21320
2021-2023	15	0.10806
2021-2023	20	-0.08645
2021-2023	auto - 19	-0.17485
2022-2023	01	-0.122177
2022-2023	05	0.29629
2022-2023	10	0.74356
2022-2023	15	0.40813
2022-2023	20	-0.18612
2022-2023	auto - 19	-0.15891

TABLE F.19: Correlation MSE Gold

Appendix G

Appendix SVR - MSFT 2023

G.1 MSFT SVR - extended Tables - 2023 Test

G.1.1 Lag 01

Table G.1: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
81	0.53175	0.524	1.289398	4.60859033E-4	2.50889529E-4
60	0.52513	0.528	1.460031	4.60909482E-4	2.50578608E-4
28	0.52513	0.528	1.453391	4.60960553E-4	2.50415148E-4
6	0.53307	0.504	0.629002	4.61013623E-4	2.51828150E-4
45	0.52249	0.532	1.485678	4.61050292E-4	2.50109461E-4
48	0.53175	0.504	0.607221	4.61061915E-4	2.51825376E-4
15	0.53175	0.504	0.607221	4.61070508E-4	2.51829084E-4
100	0.52646	0.528	1.443192	4.61108903E-4	2.50225235E-4
44	0.53175	0.512	1.060127	4.61120371E-4	2.51291998E-4
61	0.53439	0.5	0.569821	4.61131570E-4	2.51876372E-4

Table G.2: Metrics using Dataset [2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
63	0.50298	0.5	0.093265	3.37009329E-4	2.49158035E-4
64	0.49901	0.52	0.183577	3.37025243E-4	2.49995633E-4
43	0.50895	0.52	0.03456	3.37036483E-4	2.50222486E-4
90	0.48708	0.504	-0.495679	3.37039020E-4	2.49719803E-4
92	0.50099	0.512	-0.396281	3.37069104E-4	2.50304151E-4
32	0.49901	0.5	-0.076885	3.37089942E-4	2.49209151E-4
5	0.50099	0.516	0.225242	3.37097280E-4	2.49970333E-4
67	0.49901	0.528	0.685495	3.37126995E-4	2.48685147E-4
24	0.50696	0.528	0.143792	3.37132529E-4	2.50216995E-4
94	0.50099	0.528	0.685495	3.37144281E-4	2.48717013E-4

Table G.3: Metrics using Dataset [2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
45	0.54582	0.452	-1.562388	4.94811655E-4	2.57044042E-4
58	0.55378	0.452	-1.562388	4.94882701E-4	2.56906572E-4
79	0.55378	0.452	-1.562388	4.94900767E-4	2.56852649E-4
82	0.5498	0.452	-1.562388	4.94915948E-4	2.56808133E-4
71	0.55378	0.452	-1.562388	4.94931615E-4	2.56902889E-4
10	0.5498	0.456	-1.608189	4.94958990E-4	2.56685647E-4
72	0.55378	0.46	-1.74704	4.94975803E-4	2.54573540E-4
60	0.5498	0.456	-1.914199	4.94987580E-4	2.56607139E-4
74	0.5498	0.456	-1.608189	4.94994462E-4	2.56832921E-4
87	0.5498	0.456	-1.608189	4.94994545E-4	2.56832831E-4

G.1.2 Lag 05

Table G.4: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
91	0.51323	0.548	1.714516	4.59969782E-4	2.54376574E-4
69	0.51323	0.544	1.655434	4.59972584E-4	2.54169099E-4
76	0.50926	0.532	1.344999	4.59999420E-4	2.53952045E-4
29	0.50794	0.528	1.144753	4.60138427E-4	2.54662024E-4
71	0.50926	0.532	1.05098	4.60215663E-4	2.55169394E-4
89	0.50529	0.548	1.754051	4.60275974E-4	2.53754982E-4
34	0.51323	0.532	0.910386	4.60369527E-4	2.55189201E-4
38	0.5172	0.528	0.631898	4.60389707E-4	2.55281812E-4
40	0.51058	0.536	1.096833	4.60407643E-4	2.54478960E-4
99	0.5119	0.536	1.04065	4.60415071E-4	2.54860472E-4

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Table G.5: Metrics using Dataset [2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
36	0.53479	0.552	0.352627	3.32929017E-4	2.47521598E-4
54	0.53082	0.536	0.140962	3.32963354E-4	2.47607439E-4
25	0.5328	0.536	0.095511	3.32986201E-4	2.47827006E-4
46	0.53678	0.532	0.342067	3.32994964E-4	2.48302714E-4
71	0.53479	0.54	0.117198	3.33002041E-4	2.47469999E-4
1	0.53082	0.54	0.225015	3.33007631E-4	2.47701303E-4
2	0.53082	0.532	0.581507	3.33008376E-4	2.48392083E-4
80	0.5328	0.536	-0.066019	3.33014419E-4	2.47577168E-4
8	0.53082	0.544	0.304169	3.33015166E-4	2.47573206E-4
100	0.53479	0.528	0.451018	3.33032566E-4	2.48135784E-4

Table G.6: Metrics using Dataset [2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
27	0.54183	0.5	-0.834831	4.89160787E-4	2.56541884E-4
82	0.54183	0.512	-0.250669	4.89358631E-4	2.57583735E-4
94	0.5259	0.496	-0.902366	4.89388320E-4	2.55549997E-4
88	0.53386	0.504	-0.593345	4.89418399E-4	2.57459562E-4
61	0.55378	0.492	-0.58081	4.89455915E-4	2.61053393E-4
3	0.53386	0.496	-0.802212	4.89475148E-4	2.56916704E-4
59	0.54183	0.504	-0.30652	4.89477628E-4	2.57851870E-4
79	0.5498	0.488	-0.661189	4.89507575E-4	2.60537281E-4
77	0.53785	0.492	-0.604077	4.89517396E-4	2.60055270E-4
30	0.53785	0.496	-0.505267	4.89551928E-4	2.60149361E-4

G.1.3 Lag 10

Table G.7: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
64	0.53042	0.528	1.978698	4.41595757E-4	2.48242723E-4
78	0.54762	0.524	1.711646	4.41670679E-4	2.47618233E-4
36	0.53571	0.528	1.925541	4.41784458E-4	2.48077989E-4
17	0.53836	0.528	1.822769	4.41824866E-4	2.47936746E-4
71	0.5291	0.516	1.37378	4.41830298E-4	2.48797476E-4
51	0.53042	0.52	1.736616	4.41838030E-4	2.48161216E-4
16	0.53571	0.516	1.397545	4.41905885E-4	2.48488961E-4
8	0.5463	0.524	1.709592	4.42004613E-4	2.47874467E-4
40	0.53836	0.524	1.874315	4.42008673E-4	2.48090832E-4
27	0.54497	0.528	1.638159	4.42013426E-4	2.48034419E-4

Table G.8: Metrics using Dataset [2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
78	0.53082	0.568	1.833599	3.30197899E-4	2.46238558E-4
45	0.53877	0.56	1.835838	3.30223093E-4	2.45829899E-4
16	0.53877	0.576	2.464776	3.30234241E-4	2.45430130E-4
52	0.52883	0.576	2.347053	3.30248622E-4	2.45337877E-4
91	0.5328	0.576	2.082642	3.30285890E-4	2.45851879E-4
19	0.52087	0.58	2.163026	3.30290017E-4	2.45388357E-4
39	0.5169	0.568	1.7119	3.30294657E-4	2.46534458E-4
22	0.54076	0.552	0.910863	3.30298119E-4	2.47137293E-4
73	0.52684	0.576	2.217145	3.30298892E-4	2.45653131E-4
38	0.52684	0.58	2.216627	3.30309059E-4	2.45243858E-4

TABLE G.9: Metrics using Dataset [2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
63	0.56175	0.484	-0.607898	4.81615797E-4	2.61535659E-4
46	0.57769	0.496	-0.691686	4.81684466E-4	2.58716195E-4
49	0.57371	0.472	-0.88605	4.81780653E-4	2.61759751E-4
18	0.56972	0.5	-0.536886	4.81928567E-4	2.58250975E-4
100	0.56574	0.48	-0.743036	4.81969471E-4	2.62745271E-4
94	0.56175	0.496	-0.674697	4.81981951E-4	2.57742086E-4
50	0.56574	0.472	-0.88605	4.82010679E-4	2.61859234E-4
55	0.56972	0.472	-0.862257	4.82011755E-4	2.61743328E-4
52	0.56574	0.476	-0.782371	4.82072668E-4	2.63888843E-4
17	0.55378	0.468	-1.000926	4.82072825E-4	2.65086540E-4

G.1.4 Lag 15

TABLE G.10: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
65	0.54365	0.516	0.977513	4.46355808E-4	2.52808494E-4
57	0.53836	0.52	1.165729	4.46373974E-4	2.52841348E-4
69	0.54762	0.512	1.218453	4.46402093E-4	2.54130237E-4
31	0.54894	0.52	1.34579	4.46429951E-4	2.53792196E-4
26	0.53307	0.524	1.207505	4.46431337E-4	2.52318514E-4
5	0.54365	0.516	1.301508	4.46474932E-4	2.53734965E-4
56	0.55026	0.504	1.125095	4.46498883E-4	2.53940577E-4
3	0.54365	0.512	1.218453	4.46505229E-4	2.54495258E-4
40	0.54365	0.516	1.303181	4.46525884E-4	2.54069163E-4
18	0.55423	0.512	1.122495	4.46561445E-4	2.53950551E-4

TABLE G.11: Metrics using Dataset [2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
78	0.55268	0.512	0.237149	3.34166646E-4	2.51906850E-4
6	0.55666	0.528	0.226162	3.34363510E-4	2.51425796E-4
57	0.56461	0.524	0.247017	3.34378445E-4	2.51468155E-4
84	0.55467	0.508	0.010214	3.34389150E-4	2.52439211E-4
39	0.55268	0.524	-0.062296	3.34411614E-4	2.52097287E-4
11	0.54871	0.516	0.034419	3.34412116E-4	2.51982946E-4
23	0.56859	0.52	0.147849	3.34412395E-4	2.50617479E-4
60	0.55467	0.52	0.102141	3.34467473E-4	2.51461042E-4
19	0.54076	0.512	-0.072295	3.34481455E-4	2.53712724E-4
92	0.56064	0.516	0.098088	3.34485981E-4	2.50977602E-4

TABLE G.12: Metrics using Dataset [2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
52	0.57371	0.504	0.764516	4.72098441E-4	2.60275561E-4
73	0.58167	0.496	0.469449	4.72134535E-4	2.62301934E-4
50	0.57371	0.496	0.675941	4.72151535E-4	2.60433236E-4
5	0.57371	0.5	0.735112	4.72236948E-4	2.60357637E-4
27	0.57371	0.5	0.755598	4.72237202E-4	2.60987297E-4
65	0.58167	0.504	0.55591	4.72264326E-4	2.61135013E-4
98	0.58566	0.508	0.902142	4.72297911E-4	2.61922073E-4
88	0.57769	0.5	0.836313	4.72346014E-4	2.59979764E-4
68	0.57769	0.496	0.483658	4.72362775E-4	2.61975282E-4
17	0.58566	0.488	0.337342	4.72375205E-4	2.62529040E-4

G.1.5 Lag 20

TABLE G.13: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
65	0.54497	0.508	0.667529	4.48125587E-4	2.53400786E-4
77	0.54497	0.508	0.868219	4.48362436E-4	2.53036816E-4
88	0.54762	0.52	1.081827	4.48443035E-4	2.52843650E-4
3	0.53439	0.492	0.051147	4.48460802E-4	2.54536461E-4
98	0.54497	0.512	0.991564	4.48509366E-4	2.53497786E-4
11	0.54365	0.512	0.726514	4.48517857E-4	2.53011642E-4
13	0.5463	0.524	1.471912	4.48531153E-4	2.52672255E-4
66	0.54497	0.52	1.282776	4.48591340E-4	2.52636436E-4
6	0.54233	0.512	0.855103	4.48603608E-4	2.53333898E-4
87	0.55026	0.516	1.078876	4.48634078E-4	2.52549883E-4

TABLE G.14: Metrics using Dataset [2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
62	0.53479	0.552	1.253074	3.33125708E-4	2.46107950E-4
1	0.53678	0.564	1.796733	3.33219286E-4	2.44739511E-4
46	0.54274	0.564	1.796392	3.33233811E-4	2.44739843E-4
8	0.54076	0.556	1.538801	3.33311599E-4	2.45721642E-4
23	0.54076	0.556	1.587054	3.33319350E-4	2.45986810E-4
11	0.54076	0.56	1.60466	3.33321428E-4	2.45393873E-4
9	0.54274	0.56	1.709284	3.33322872E-4	2.45299508E-4
4	0.54274	0.568	2.17406	3.33335883E-4	2.44680870E-4
6	0.54076	0.56	1.709284	3.33397523E-4	2.45310080E-4
64	0.53877	0.56	1.60466	3.33417144E-4	2.45228116E-4

TABLE G.15: Metrics using Dataset [2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
83	0.58566	0.5	0.348047	4.79885781E-4	2.70406959E-4
14	0.58566	0.5	0.348047	4.79964357E-4	2.71987385E-4
31	0.58964	0.496	0.329105	4.79966217E-4	2.70558834E-4
74	0.58964	0.496	0.329105	4.80025921E-4	2.71372659E-4
54	0.58964	0.492	0.3163	4.80070305E-4	2.73882599E-4
79	0.58167	0.5	0.617452	4.80078718E-4	2.71306231E-4
60	0.58964	0.496	0.305189	4.80096193E-4	2.71269580E-4
10	0.58964	0.488	0.305474	4.80109575E-4	2.73263017E-4
64	0.58964	0.496	0.329105	4.80140900E-4	2.71061087E-4
23	0.58566	0.5	0.576563	4.80141768E-4	2.72362211E-4

G.1.6 Lag auto

TABLE G.16: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
13	0.50397	0.52	0.799559	4.60657138E-4	2.54850822E-4
81	0.50794	0.528	1.360252	4.60764788E-4	2.54384929E-4
43	0.50794	0.524	1.284292	4.60785867E-4	2.54297573E-4
44	0.50529	0.48	-0.482904	4.60801540E-4	2.55412693E-4
41	0.51455	0.528	1.360252	4.60810185E-4	2.54239180E-4
8	0.50661	0.524	1.286905	4.60836667E-4	2.54676915E-4
49	0.5	0.484	-0.439266	4.60865370E-4	2.55524001E-4
32	0.50529	0.524	1.284292	4.60880841E-4	2.54281872E-4
35	0.50529	0.524	1.286905	4.60883210E-4	2.54546613E-4
30	0.51058	0.516	1.160967	4.60902522E-4	2.53929184E-4

TABLE G.17: Metrics using Dataset [2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
83	0.50497	0.532	0.595482	3.36743979E-4	2.47528084E-4
66	0.50696	0.508	-0.104943	3.36747160E-4	2.48286081E-4
78	0.50696	0.516	0.21214	3.36751783E-4	2.48260758E-4
2	0.50298	0.532	0.595482	3.36767731E-4	2.47538772E-4
35	0.49304	0.528	0.551023	3.36774801E-4	2.48025944E-4
29	0.49503	0.524	0.496997	3.36778311E-4	2.47871995E-4
48	0.49503	0.544	0.739399	3.36778891E-4	2.47528164E-4
72	0.50497	0.524	0.208492	3.36785127E-4	2.47948529E-4
65	0.50298	0.516	0.058381	3.36788597E-4	2.48074533E-4
42	0.50696	0.504	-0.239261	3.36793355E-4	2.48411329E-4

TABLE G.18: Metrics using Dataset [2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
66	0.52988	0.48	-0.72843	4.91485735E-4	2.52231372E-4
40	0.54183	0.476	-0.924879	4.91582767E-4	2.55381305E-4
26	0.54582	0.476	-0.924879	4.91608570E-4	2.55448661E-4
72	0.53785	0.464	-1.16353	4.91663261E-4	2.55990126E-4
31	0.54582	0.472	-0.955553	4.91667119E-4	2.55589449E-4
90	0.54183	0.468	-0.935073	4.91675695E-4	2.51571957E-4
56	0.54183	0.468	-0.993266	4.91687567E-4	2.55665858E-4
95	0.54582	0.472	-0.955553	4.91708870E-4	2.55627888E-4
3	0.54183	0.476	-0.861669	4.91726980E-4	2.55078920E-4
93	0.53386	0.46	-1.327312	4.91731698E-4	2.57409466E-4

G.1.7 MSFT MSE Correlation 2023

Year	Lag	Correlation
2020-2023	01	0.473794
2020-2023	05	0.77857
2020-2023	10	-0.70008
2020-2023	15	-0.44002
2020-2023	20	-0.49102
2020-2023	auto - 2	0.72208
2021-2023	01	0.889638
2021-2023	05	0.90183
2021-2023	10	0.78936
2021-2023	15	-0.18803
2021-2023	20	0.04213
2021-2023	auto - 2	0.92458
2022-2023	01	0.778761
2022-2023	05	0.91690
2022-2023	10	0.81998
2022-2023	15	0.53179
2022-2023	20	0.82817
2022-2023	auto - 2	0.84467

TABLE G.19: Correlation MSE MSFT

Appendix H

Appendix NN - Bitcoin 2017

H.1 Bitcoin NN - extended Tables - 2017 Test

H.1.1 Lag 01

Table H.1: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
8	0.51497	0.58356	2.679375	9.96754015E-4	2.44763937E-3
84	0.51617	0.60274	3.648725	9.97796171E-4	2.41463439E-3
49	0.51737	0.5863	2.594616	9.98018054E-4	2.43370903E-3
73	0.51856	0.58904	3.278749	9.99331271E-4	2.45636197E-3
15	0.53892	0.6137	2.852823	9.99442213E-4	2.45416707E-3
90	0.51257	0.56986	2.269648	1.00049843E-3	2.45655517E-3
61	0.53174	0.6137	3.53687	1.00090394E-3	2.44810268E-3
86	0.53533	0.6137	3.197361	1.00112331E-3	2.44652423E-3
20	0.53892	0.6137	2.852823	1.00117560E-3	2.43479079E-3
60	0.45749	0.42466	-2.181828	1.00118166E-3	2.46802737E-3

Table H.2: Metrics using Dataset [2015, 2016]-[2017] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
66	0.50068	0.5726	2.564747	9.87706124E-4	2.45766614E-3
49	0.53899	0.60274	2.973059	9.88026396E-4	2.42793418E-3
15	0.55267	0.61918	2.75867	9.89102365E-4	2.45813013E-3
20	0.5472	0.6137	2.852823	9.89995164E-4	2.43335976E-3
79	0.5472	0.6137	2.852823	9.90062024E-4	2.44768842E-3
73	0.45007	0.43562	-1.042712	9.90464819E-4	2.47133394E-3
60	0.5472	0.6137	2.852823	9.91059819E-4	2.43190041E-3
23	0.53078	0.60548	3.290361	9.91357398E-4	2.43240761E-3
17	0.53625	0.6137	3.780943	9.91452393E-4	2.45827483E-3
86	0.54172	0.60274	2.337843	9.91666259E-4	2.44075493E-3

TABLE H.3: Metrics using Dataset [2016]-[2017] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
75	0.60383	0.53973	0.788275	6.34054847E-4	2.47655313E-3
74	0.60656	0.48493	-0.977173	6.36410683E-4	2.47635833E-3
66	0.52459	0.58356	2.89634	6.38315428E-4	2.46237921E-3
23	0.5765	0.6137	2.852823	6.40335183E-4	2.42263490E-3
19	0.51639	0.45205	-1.538132	6.43998965E-4	2.51813180E-3
89	0.51639	0.45205	-1.538132	6.45636960E-4	2.53265283E-3
55	0.55738	0.61096	3.402032	6.47827129E-4	2.43253517E-3
15	0.45082	0.40548	-3.066599	6.49984986E-4	2.52401068E-3
76	0.59016	0.6	1.75378	6.52751635E-4	2.46367071E-3
14	0.5765	0.6137	2.852823	6.53219736E-4	2.42908830E-3

H.1.2 Lag 07

TABLE H.4: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
54	0.55127	0.47671	-1.105432	9.48992858E-4	2.63489088E-3
14	0.57177	0.55616	1.415002	9.49736117E-4	2.47611821E-3
32	0.57057	0.56986	1.488098	9.55626675E-4	2.49808149E-3
42	0.53559	0.56164	1.836214	9.56509457E-4	2.49853654E-3
44	0.56333	0.5589	2.321512	9.59815216E-4	2.48101838E-3
5	0.55247	0.58356	1.685475	9.60320552E-4	2.53048527E-3
88	0.54041	0.51507	1.401716	9.61805827E-4	2.49984294E-3
81	0.54765	0.54795	2.38707	9.61943071E-4	2.51698377E-3
90	0.54644	0.56164	1.540902	9.61953376E-4	2.52289538E-3
15	0.56333	0.56986	2.067627	9.62782687E-4	2.49932348E-3

TABLE H.5: Metrics using Dataset [2015, 2016]-[2017] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
54	0.57319	0.47945	-1.055041	9.47115176E-4	2.67436650E-3
32	0.56908	0.60274	2.439733	9.56148169E-4	2.52019005E-3
14	0.57592	0.54521	0.622547	9.56585291E-4	2.47452433E-3
42	0.53352	0.56986	2.327218	9.58399370E-4	2.48977462E-3
24	0.53762	0.58356	2.302425	9.58596294E-4	2.52374619E-3
88	0.56498	0.5589	2.089121	9.62941596E-4	2.48560116E-3
67	0.54172	0.50137	0.203486	9.63191601E-4	2.55549605E-3
57	0.5855	0.60548	1.613225	9.63394038E-4	2.45200538E-3
81	0.56908	0.61644	3.177369	9.65108562E-4	2.45451522E-3
90	0.56908	0.54521	0.856027	9.65161659E-4	2.48437896E-3

Table H.6: Metrics using Dataset [2016]-[2017] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
4	0.56011	0.52329	-1.205745	6.20714910E-4	2.64771337E-3
14	0.58743	0.56438	0.428595	6.33004656E-4	2.63293119E-3
77	0.54645	0.51233	0.697738	6.34035967E-4	2.63195833E-3
8	0.58743	0.58356	1.769279	6.46860367E-4	2.52723770E-3
15	0.56557	0.5726	2.102573	6.61243199E-4	2.50463771E-3
29	0.50546	0.46301	-1.68744	6.61363352E-4	2.98812582E-3
94	0.48634	0.47945	-0.166674	6.64952834E-4	2.62966563E-3
57	0.43716	0.38356	-3.198599	6.68807429E-4	2.64577180E-3
76	0.58197	0.45753	-1.331255	6.69717208E-4	2.76633823E-3
38	0.57923	0.59452	1.69101	6.73776701E-4	2.51742097E-3

H.1.3 Lag 14

Table H.7: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
99	0.49392	0.49863	0.520029	9.24108013E-4	2.59461412E-3
14	0.56569	0.51781	0.283155	9.42907393E-4	2.64270694E-3
36	0.56204	0.51781	0.141736	9.43503377E-4	2.60608350E-3
83	0.56204	0.55616	1.609402	9.50471243E-4	2.50063732E-3
96	0.58881	0.57534	1.983676	9.55775565E-4	2.52987405E-3
75	0.54745	0.5589	0.577091	9.55904414E-4	2.61806521E-3
69	0.49513	0.56986	1.563341	9.60325084E-4	2.47479924E-3
7	0.57178	0.51781	-0.155337	9.60642461E-4	2.62867364E-3
61	0.56569	0.51781	1.198753	9.60810041E-4	2.54796969E-3
30	0.58273	0.53699	0.233291	9.61350650E-4	2.52376082E-3

Table H.8: Metrics using Dataset [2015, 2016]-[2017] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.56908	0.51781	1.003608	9.18479926E-4	2.60272934E-3
96	0.57456	0.48219	1.137538	9.28951600E-4	2.63386138E-3
99	0.49248	0.51781	1.032291	9.30474658E-4	2.56138843E-3
83	0.58276	0.5589	1.505954	9.40572917E-4	2.49012879E-3
36	0.56361	0.51781	0.515322	9.40602383E-4	2.62547682E-3
42	0.52668	0.48493	-0.281396	9.46484792E-4	2.59926416E-3
61	0.57592	0.50411	0.261212	9.47259863E-4	2.56679789E-3
75	0.55951	0.5726	1.516485	9.48310900E-4	2.57529316E-3
77	0.5896	0.51781	0.483326	9.48543245E-4	2.61228705E-3
30	0.56361	0.49589	-0.688087	9.50296770E-4	2.59260670E-3

TABLE H.9: Metrics using Dataset [2016]-[2017] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.57923	0.50685	-1.150984	5.84190396E-4	2.82959263E-3
75	0.50546	0.50685	-0.695458	6.25414404E-4	2.74393620E-3
36	0.54645	0.47945	-1.038175	6.30663455E-4	2.75979888E-3
30	0.56557	0.51507	-0.839341	6.33272826E-4	2.73357352E-3
96	0.5847	0.51233	0.791127	6.38932843E-4	2.76676843E-3
70	0.54645	0.48493	-1.840846	6.44732042E-4	2.85784116E-3
65	0.59016	0.49589	-0.681458	6.45020526E-4	2.62466112E-3
42	0.52732	0.54795	0.437159	6.46835383E-4	2.68830397E-3
91	0.57923	0.51507	-0.770548	6.54357078E-4	2.79572855E-3
35	0.56284	0.56712	0.520536	6.56695844E-4	2.72901358E-3

H.1.4 Lag 21

TABLE H.10: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
58	0.54233	0.54521	1.626196	9.26769905E-4	2.53817023E-3
90	0.48834	0.49041	0.512655	9.27759355E-4	2.60694814E-3
35	0.53006	0.54795	1.570878	9.33767552E-4	2.53175611E-3
23	0.54601	0.5589	2.308955	9.41372622E-4	2.52392494E-3
67	0.53865	0.52603	1.243926	9.43871251E-4	2.60778183E-3
48	0.57301	0.59726	2.798844	9.52464449E-4	2.61308051E-3
64	0.54724	0.57534	0.897489	9.55359354E-4	2.51474754E-3
79	0.51656	0.50411	0.494029	9.56389698E-4	2.76515520E-3
88	0.55706	0.52603	0.947517	9.57919306E-4	2.55196533E-3
66	0.54479	0.47945	-0.833529	9.59208448E-4	2.62593931E-3

TABLE H.11: Metrics using Dataset [2015, 2016]-[2017] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
67	0.56772	0.56986	2.110389	9.10443992E-4	2.63242802E-3
58	0.54856	0.54521	1.650342	9.15667647E-4	2.62471968E-3
90	0.49384	0.53425	1.450136	9.21629171E-4	2.60942437E-3
88	0.58687	0.50959	1.260632	9.26782392E-4	2.58663015E-3
35	0.53215	0.56712	2.001183	9.28369664E-4	2.52724074E-3
48	0.56088	0.55616	1.824398	9.42797899E-4	2.69788302E-3
66	0.56361	0.49589	0.155168	9.44709204E-4	2.57909203E-3
12	0.57182	0.56164	0.775555	9.46028292E-4	2.60277772E-3
76	0.56498	0.54247	0.769573	9.48422214E-4	2.59138075E-3
72	0.53625	0.58356	2.817903	9.49535783E-4	2.61977986E-3

TABLE H.12: Metrics using Dataset [2016]-[2017] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
82	0.59836	0.56164	0.262464	6.18191891E-4	2.87409926E-3
64	0.5847	0.5726	1.993628	6.32228154E-4	2.51944181E-3
12	0.5765	0.56712	0.738714	6.35885178E-4	2.75106356E-3
62	0.52732	0.49589	-0.046426	6.41426702E-4	2.76262567E-3
90	0.59563	0.59178	1.938869	6.55047190E-4	2.74265850E-3
76	0.44262	0.43562	-2.086487	6.63773510E-4	3.04248678E-3
63	0.54372	0.43562	-1.20283	6.63922381E-4	3.22011143E-3
41	0.5847	0.49589	-0.687083	6.69452041E-4	2.82062371E-3
27	0.57104	0.5726	1.046568	6.72792562E-4	2.73804024E-3
70	0.51093	0.56438	0.475299	6.75422868E-4	3.05944621E-3

H.1.5 Lag 28

TABLE H.13: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
99	0.57673	0.49315	-0.52407	9.41202723E-4	2.70724188E-3
21	0.53713	0.56438	1.220895	9.45246222E-4	2.62046733E-3
14	0.54703	0.56164	0.513041	9.50848570E-4	2.64456869E-3
37	0.55817	0.53699	0.797963	9.58148610E-4	2.66847237E-3
10	0.56559	0.52055	-0.116681	9.58338120E-4	2.67428277E-3
28	0.5755	0.50959	-0.626635	9.65633554E-4	2.73349539E-3
71	0.51361	0.53973	0.67681	9.76812409E-4	2.76579059E-3
24	0.53713	0.5589	2.385676	9.79697837E-4	2.50831775E-3
1	0.53342	0.52329	0.609684	9.80045107E-4	2.68608786E-3
82	0.50124	0.49315	0.457884	9.81684891E-4	2.67761286E-3

TABLE H.14: Metrics using Dataset [2015, 2016]-[2017] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
69	0.56908	0.53699	0.40567	8.86848533E-4	2.67281273E-3
99	0.56498	0.49041	0.166291	9.09772661E-4	2.66857293E-3
21	0.56088	0.56438	1.158679	9.12955096E-4	2.66179968E-3
66	0.54856	0.50411	0.018475	9.19305847E-4	2.61521090E-3
14	0.57592	0.5726	0.787165	9.26617893E-4	2.62169760E-3
91	0.53352	0.51507	0.10172	9.31125225E-4	2.64309905E-3
3	0.52668	0.51233	-0.912836	9.33823718E-4	2.85791776E-3
82	0.5472	0.53973	1.152787	9.34752783E-4	2.61381047E-3
26	0.54309	0.53699	2.11563	9.41573019E-4	2.57260651E-3
85	0.56772	0.49041	-1.142524	9.46739251E-4	2.63491084E-3

TABLE H.15: Metrics using Dataset [2016]-[2017] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
99	0.57923	0.42192	-1.954442	6.33317668E-4	3.01484535E-3
66	0.58197	0.53973	1.508454	6.45717440E-4	2.57837109E-3
85	0.48361	0.49863	0.409536	6.68957807E-4	2.79892032E-3
1	0.49454	0.50411	0.200885	6.70947453E-4	2.79057108E-3
24	0.54098	0.53699	2.060742	6.71212628E-4	2.53765897E-3
82	0.54098	0.51233	1.114921	6.72973669E-4	2.78142736E-3
60	0.53005	0.49041	0.241236	6.74294783E-4	2.99431407E-3
54	0.53552	0.42192	-1.682546	6.79917290E-4	3.09791612E-3
61	0.52459	0.57534	2.132852	6.84097171E-4	2.84189466E-3
23	0.55464	0.50685	-0.355223	6.90444412E-4	3.09091561E-3

H.1.6 Lag auto - 6

TABLE H.16: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
34	0.52048	0.51781	0.375152	9.34237936E-4	2.57216153E-3
29	0.57349	0.58904	2.737696	9.41591620E-4	2.45364698E-3
19	0.57711	0.53151	1.272668	9.42523018E-4	2.51770800E-3
25	0.55663	0.52877	1.197801	9.44419722E-4	2.54660281E-3
17	0.55422	0.5589	1.453502	9.49479711E-4	2.50989238E-3
61	0.51687	0.50685	0.153435	9.51980934E-4	2.53852810E-3
60	0.54578	0.53699	1.584987	9.52112759E-4	2.50332309E-3
32	0.55181	0.56438	1.482661	9.54554542E-4	2.52760173E-3
30	0.56386	0.56986	1.406685	9.59005514E-4	2.44553874E-3
46	0.55422	0.53699	0.992351	9.59038584E-4	2.49056696E-3

TABLE H.17: Metrics using Dataset [2015, 2016]-[2017] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
25	0.53762	0.50959	0.709901	9.34359570E-4	2.55547308E-3
61	0.58413	0.56164	1.47933	9.45516477E-4	2.48761799E-3
17	0.49384	0.52603	0.596157	9.51922260E-4	2.55339158E-3
60	0.54993	0.55342	1.441449	9.55253652E-4	2.50093550E-3
32	0.56772	0.5589	1.515358	9.56116504E-4	2.54159835E-3
29	0.47469	0.52329	0.971385	9.58130430E-4	2.50565145E-3
97	0.56908	0.57534	1.184952	9.61274850E-4	2.55735057E-3
34	0.56361	0.51507	0.395242	9.62608130E-4	2.59885600E-3
44	0.57866	0.52055	1.002545	9.63733646E-4	2.54267118E-3
46	0.57182	0.60274	2.221186	9.65071253E-4	2.46197799E-3

Table H.18: Metrics using Dataset [2016]-[2017] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
60	0.5765	0.55342	0.787529	6.19907499E-4	2.49834239E-3
92	0.58197	0.49589	-0.716998	6.23773141E-4	2.54403834E-3
97	0.58197	0.56712	1.07654	6.37532111E-4	2.61779711E-3
30	0.51093	0.55068	1.910388	6.39891058E-4	2.47762005E-3
81	0.44809	0.47671	-0.452301	6.43501946E-4	2.60660436E-3
61	0.56284	0.59178	2.375268	6.45138313E-4	2.47754868E-3
90	0.48087	0.46301	-1.376624	6.55432537E-4	2.69295097E-3
25	0.57923	0.5726	1.94458	6.58416039E-4	2.59250144E-3
53	0.59016	0.60274	2.498574	6.59152021E-4	2.49381960E-3
36	0.57923	0.5863	3.125361	6.64847559E-4	2.51197202E-3

H.1.7 Bitcoin MSE Correlation 2017

Year	Lag	Correlation
2014-2017	01	0.68908
2014-2017	07	0.57855
2014-2017	14	0.71498
2014-2017	21	0.69387
2014-2017	28	0.79325
2014-2017	auto - 6	0.47532
2015-2017	01	0.548911
2015-2017	07	0.56462
2015-2017	14	0.75051
2015-2017	21	0.65578
2015-2017	28	0.71388
2015-2017	auto - 6	0.75965
2016-2017	01	0.826875
2016-2017	07	0.77274
2016-2017	14	0.79333
2016-2017	21	0.84454
2016-2017	28	0.80551
2016-2017	auto - 6	0.79184

Table H.19: Correlation MSE Bitcoin

Appendix I

Appendix NN - Bitcoin 2018

I.1 Bitcoin NN - extended Tables - 2018 Test

I.1.1 Lag 01

Table I.1: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
84	0.56843	0.48767	-1.822136	1.45808990E-3	1.90766021E-3
49	0.56934	0.50959	-1.62335	1.46482162E-3	1.90059625E-3
75	0.53285	0.46027	-1.687982	1.46510994E-3	1.86633558E-3
66	0.56934	0.50959	-1.62335	1.46606396E-3	1.90435305E-3
15	0.56934	0.50959	-1.62335	1.46780844E-3	1.88330316E-3
52	0.55018	0.45753	-2.522103	1.46812728E-3	1.88016324E-3
60	0.56934	0.50959	-1.62335	1.46930237E-3	1.88613552E-3
31	0.56934	0.50959	-1.62335	1.46931146E-3	1.88027486E-3
87	0.56934	0.50959	-1.62335	1.46937367E-3	1.89236464E-3
70	0.56752	0.50137	-1.317798	1.46937383E-3	1.89073693E-3

Table I.2: Metrics using Dataset [2016, 2017]-[2018] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
84	0.59508	0.50959	-1.62335	1.51768142E-3	1.92795196E-3
20	0.59508	0.50959	-1.62335	1.52520362E-3	1.90069886E-3
56	0.59508	0.50959	-1.62335	1.52608945E-3	1.93040176E-3
60	0.59508	0.50959	-1.62335	1.52616630E-3	1.97235391E-3
49	0.59508	0.50959	-1.62335	1.52702176E-3	1.96493119E-3
67	0.59508	0.50959	-1.62335	1.52883061E-3	1.93020520E-3
83	0.59508	0.50959	-1.62335	1.52976140E-3	1.89891273E-3
75	0.59508	0.50959	-1.62335	1.52994959E-3	2.01546916E-3
86	0.59508	0.50959	-1.62335	1.53002424E-3	1.94574886E-3
87	0.59644	0.50411	-1.721896	1.53027764E-3	1.88040726E-3

TABLE I.3: Metrics using Dataset [2017]-[2018] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
75	0.6137	0.50959	-1.62335	2.40425933E-3	2.04310043E-3
86	0.61096	0.50959	-1.62335	2.41392632E-3	1.96086577E-3
85	0.6137	0.50959	-1.62335	2.42639197E-3	1.90414405E-3
74	0.61644	0.50959	-1.62335	2.42852468E-3	1.99144306E-3
15	0.61644	0.50959	-1.62335	2.43724814E-3	1.94514653E-3
66	0.61918	0.49863	-1.61207	2.43773564E-3	1.87300854E-3
55	0.60548	0.47671	-1.809148	2.44190810E-3	1.90089824E-3
39	0.61918	0.50959	-1.62335	2.44223720E-3	1.87665476E-3
28	0.62192	0.50685	-1.625439	2.44237136E-3	1.99353179E-3
69	0.60548	0.50685	-0.880697	2.44352817E-3	1.87870579E-3

I.1.2 Lag 07

TABLE I.4: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.56478	0.49315	-1.331577	1.41736014E-3	1.88830230E-3
44	0.55748	0.48767	-0.216546	1.41741397E-3	1.87650261E-3
81	0.58303	0.49863	-1.060823	1.42745044E-3	1.87925968E-3
24	0.58212	0.51781	-0.728977	1.42810707E-3	1.89649756E-3
90	0.57208	0.50685	0.151174	1.42925049E-3	1.84866681E-3
73	0.57117	0.50411	-0.941756	1.43041458E-3	1.94611879E-3
42	0.57391	0.47671	-1.177518	1.43407141E-3	1.90488878E-3
32	0.57755	0.49041	-0.561728	1.43447450E-3	1.92128968E-3
72	0.54562	0.49589	1.015881	1.43457569E-3	1.89755243E-3
31	0.5812	0.49589	-1.645275	1.43751759E-3	1.88563034E-3

TABLE I.5: Metrics using Dataset [2016, 2017]-[2018] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.59918	0.50685	-1.842111	1.50135007E-3	1.92344284E-3
88	0.57045	0.51781	0.333315	1.51218371E-3	1.88005166E-3
73	0.57456	0.47945	-1.333627	1.51441728E-3	1.91813346E-3
81	0.60465	0.50411	-1.15583	1.51731403E-3	1.91096629E-3
57	0.60055	0.50685	-1.4003	1.51893391E-3	1.92834475E-3
44	0.55951	0.50411	-1.013807	1.51944468E-3	1.87685811E-3
72	0.59234	0.50685	-0.028795	1.52667335E-3	1.96234936E-3
4	0.58824	0.51507	0.040672	1.52735840E-3	1.86483295E-3
90	0.55951	0.50959	0.847007	1.52921456E-3	1.84116349E-3
32	0.59918	0.51233	-0.518869	1.52933074E-3	2.01583263E-3

TABLE I.6: Metrics using Dataset [2017]-[2018] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.60548	0.49315	-1.102288	2.39229010E-3	1.86734319E-3
4	0.60548	0.50137	-1.701582	2.41037688E-3	1.98813240E-3
73	0.63014	0.50685	-1.222111	2.42987936E-3	2.34155163E-3
88	0.60548	0.52055	-1.045409	2.43351758E-3	2.00079163E-3
44	0.52603	0.50685	-0.698618	2.43995685E-3	1.90993108E-3
82	0.58082	0.50685	-1.249905	2.46469672E-3	1.98089276E-3
2	0.5863	0.50685	-0.457422	2.47184847E-3	1.99591167E-3
32	0.5726	0.51233	0.395291	2.47578939E-3	1.99851123E-3
94	0.5863	0.50137	-0.70726	2.48077043E-3	1.98746190E-3
15	0.62192	0.51233	-1.263684	2.48229571E-3	2.13557046E-3

I.1.3 Lag 14

TABLE I.7: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
69	0.57117	0.49041	-0.881483	1.39485774E-3	1.95579480E-3
83	0.55839	0.48219	-0.460974	1.40841323E-3	1.90379731E-3
36	0.56296	0.52329	-0.244863	1.41143607E-3	1.90868057E-3
14	0.56478	0.52329	-0.909024	1.41567283E-3	1.90954462E-3
58	0.55018	0.51233	1.708311	1.42054365E-3	1.83458427E-3
70	0.5885	0.50137	-0.619757	1.42141786E-3	1.88743779E-3
40	0.56752	0.50685	-0.558402	1.42310818E-3	1.95057606E-3
99	0.56022	0.47397	0.311795	1.42391627E-3	1.89567736E-3
75	0.55839	0.53151	0.148379	1.43402382E-3	1.93083078E-3
47	0.58303	0.52877	0.085124	1.43482271E-3	1.87483854E-3

TABLE I.8: Metrics using Dataset [2016, 2017]-[2018] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
40	0.61012	0.52329	-0.514507	1.49279315E-3	2.00082359E-3
36	0.59371	0.50959	-0.637518	1.49956361E-3	1.99550941E-3
14	0.56772	0.52603	-1.817055	1.50163787E-3	1.97171651E-3
69	0.5171	0.48219	0.052903	1.50433568E-3	1.92492371E-3
83	0.56635	0.49041	0.242341	1.51842546E-3	1.89556256E-3
61	0.56772	0.50411	-0.602829	1.52101837E-3	1.89689185E-3
47	0.59097	0.53151	0.431045	1.52219955E-3	1.92716889E-3
30	0.57319	0.48493	-1.543754	1.52249720E-3	1.89366521E-3
95	0.56772	0.53425	0.705183	1.52307040E-3	1.93757694E-3
75	0.59097	0.51233	-1.671161	1.52417818E-3	1.98167594E-3

TABLE I.9: Metrics using Dataset [2017]-[2018] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
76	0.59452	0.53699	0.773766	2.40085846E-3	2.00849810E-3
75	0.6274	0.49863	-1.052059	2.41874547E-3	2.10799156E-3
83	0.61644	0.49863	-1.441642	2.42697407E-3	2.12410736E-3
70	0.6137	0.50685	-1.23972	2.43217312E-3	2.08401592E-3
96	0.57808	0.48493	-1.508338	2.43260676E-3	2.19428843E-3
30	0.60822	0.45753	-1.916814	2.43606330E-3	1.98092556E-3
14	0.58356	0.52055	-1.196608	2.45270829E-3	2.09479973E-3
69	0.49863	0.46575	-0.178806	2.45778980E-3	1.92956500E-3
53	0.5726	0.50137	-0.862142	2.46777247E-3	2.29047706E-3
91	0.59452	0.51507	-1.281246	2.47041784E-3	2.09877589E-3

I.1.4 Lag 21

TABLE I.10: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
58	0.58394	0.52329	-0.271905	1.37777786E-3	1.92493922E-3
35	0.56296	0.53425	0.490482	1.38068271E-3	1.87327722E-3
67	0.56569	0.48767	-0.862502	1.39455875E-3	1.90485794E-3
88	0.58303	0.55068	1.169352	1.39644103E-3	1.88293852E-3
15	0.56843	0.50959	-0.038907	1.39903965E-3	1.90095597E-3
90	0.53467	0.56712	2.146268	1.40098047E-3	1.92197940E-3
2	0.58029	0.54247	-0.043134	1.40251174E-3	1.87876379E-3
48	0.57755	0.52055	0.974757	1.40712786E-3	1.91504113E-3
45	0.57664	0.49041	-0.699132	1.41004197E-3	1.96611007E-3
23	0.56569	0.53425	0.77938	1.41478383E-3	1.86765366E-3

TABLE I.11: Metrics using Dataset [2016, 2017]-[2018] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
88	0.60465	0.51233	0.225044	1.45387493E-3	1.88912067E-3
58	0.6156	0.52055	0.160626	1.45449660E-3	1.97955782E-3
90	0.55814	0.53151	-0.494339	1.46629492E-3	2.02890980E-3
35	0.59918	0.51507	-1.009062	1.48224090E-3	1.96955932E-3
67	0.59234	0.50685	-0.016081	1.48957178E-3	1.99434294E-3
48	0.60465	0.49315	-0.156507	1.49127911E-3	1.93484042E-3
82	0.60328	0.50411	-1.127456	1.50448520E-3	1.99941937E-3
12	0.58824	0.49589	-0.266917	1.51106665E-3	1.94838479E-3
66	0.58824	0.47397	-1.989637	1.51456525E-3	2.02806326E-3
76	0.60876	0.51781	-1.253906	1.51486015E-3	1.98452985E-3

Table I.12: Metrics using Dataset [2017]-[2018] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
58	0.63288	0.50959	-0.786501	2.33831978E-3	2.17018719E-3
90	0.50959	0.51507	-1.088899	2.37189980E-3	2.08638036E-3
88	0.55616	0.50137	-0.262501	2.37424676E-3	1.98704485E-3
77	0.54521	0.50411	-0.040404	2.39951552E-3	2.13414675E-3
45	0.57808	0.50137	-1.740567	2.42984821E-3	2.22180846E-3
64	0.61096	0.50137	-1.859757	2.43251329E-3	1.99538712E-3
35	0.62466	0.51781	-0.512038	2.43515989E-3	2.12665505E-3
67	0.5589	0.52877	0.893883	2.44035515E-3	2.01435151E-3
94	0.59452	0.54795	0.907037	2.44391517E-3	1.97627112E-3
70	0.58082	0.50685	1.952183	2.44618345E-3	1.85027851E-3

I.1.5 Lag 28

Table I.13: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
26	0.57847	0.50137	-0.61696	1.35412359E-3	1.98571758E-3
54	0.57573	0.50137	-0.595063	1.35757976E-3	2.09644951E-3
66	0.56022	0.52329	0.985825	1.36329903E-3	1.98353765E-3
93	0.56022	0.55342	2.908115	1.36422810E-3	1.86512533E-3
60	0.57117	0.49863	-0.004264	1.36891615E-3	1.92473569E-3
99	0.58029	0.53973	-0.484822	1.37396487E-3	2.03360228E-3
24	0.5812	0.53973	0.711476	1.37745574E-3	1.93653937E-3
18	0.56843	0.50959	-0.229463	1.38147399E-3	1.91769968E-3
82	0.56478	0.52603	0.201644	1.39348613E-3	1.92580796E-3
62	0.55748	0.54795	0.803224	1.39568598E-3	1.98747486E-3

Table I.14: Metrics using Dataset [2016, 2017]-[2018] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
99	0.58687	0.52877	-1.116991	1.43332303E-3	2.13124794E-3
93	0.59644	0.54521	0.523878	1.43421784E-3	1.95988640E-3
66	0.59508	0.54521	-0.022173	1.44017318E-3	2.12627005E-3
24	0.5896	0.52329	-0.506455	1.44341674E-3	1.99715717E-3
82	0.58413	0.53151	0.147239	1.46729541E-3	1.98796078E-3
60	0.56635	0.51781	0.180747	1.47067517E-3	2.10110765E-3
26	0.57182	0.53425	0.090632	1.47177783E-3	2.02132540E-3
21	0.57729	0.50411	0.470287	1.47433306E-3	1.99465033E-3
85	0.5855	0.52603	-0.657979	1.48392437E-3	1.98097783E-3
18	0.58003	0.51781	0.329268	1.49734805E-3	1.96717896E-3

Table I.15: Metrics using Dataset [2017]-[2018] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
24	0.60274	0.52329	-0.025695	2.26941096E-3	2.06666330E-3
66	0.60548	0.52055	-1.177216	2.28698454E-3	2.35807064E-3
69	0.61096	0.49589	-1.870465	2.38707996E-3	2.32702621E-3
26	0.56164	0.53425	0.278819	2.39243397E-3	1.99833556E-3
85	0.5726	0.51233	-0.738328	2.39309582E-3	2.09139706E-3
82	0.59178	0.51781	-0.971388	2.39829086E-3	2.24553051E-3
21	0.61644	0.53973	1.441703	2.41903155E-3	2.08366400E-3
28	0.56438	0.50685	-0.363901	2.42746791E-3	2.19973868E-3
93	0.57808	0.52055	-0.176914	2.45424568E-3	2.15923122E-3
68	0.56712	0.52329	0.298668	2.46999127E-3	2.17444270E-3

I.1.6 Lag auto - 6

Table I.16: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
29	0.57847	0.50959	0.029401	1.42174467E-3	1.87889576E-3
34	0.56387	0.49315	-0.915175	1.42234478E-3	1.88237029E-3
17	0.55201	0.48219	-0.651173	1.42393078E-3	1.87240060E-3
81	0.57117	0.51781	-1.413345	1.43139287E-3	1.93964003E-3
13	0.55383	0.53425	-0.424171	1.43166765E-3	1.89242752E-3
25	0.57482	0.50685	-1.087011	1.43358279E-3	1.94566816E-3
46	0.58212	0.50411	-1.602181	1.43389436E-3	1.89862154E-3
61	0.58394	0.52329	-0.783544	1.43704728E-3	1.85421071E-3
32	0.56204	0.47123	-1.261106	1.43803253E-3	1.90561476E-3
60	0.57482	0.49041	-2.321551	1.44063137E-3	1.91703686E-3

Table I.17: Metrics using Dataset [2016, 2017]-[2018] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
81	0.59234	0.51507	-1.391149	1.50355412E-3	1.93451881E-3
17	0.59371	0.51781	-0.583639	1.50420907E-3	1.94981653E-3
34	0.58276	0.49863	-1.973984	1.50452760E-3	2.00385822E-3
25	0.59097	0.49863	-2.015259	1.50943415E-3	1.94037355E-3
68	0.5814	0.50411	-0.752776	1.50989005E-3	1.87415167E-3
29	0.52804	0.49589	0.343292	1.51120578E-3	1.87804077E-3
32	0.58824	0.50959	-1.256152	1.51191080E-3	1.97400987E-3
80	0.59371	0.50959	-1.404425	1.51646039E-3	1.89365965E-3
61	0.57592	0.52603	1.456101	1.51910970E-3	1.84240173E-3
4	0.58824	0.48219	-2.199682	1.52128577E-3	1.98219217E-3

Table I.18: Metrics using Dataset [2017]-[2018] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
81	0.61918	0.51781	-1.280386	2.39509941E-3	2.17586778E-3
61	0.60274	0.50685	-1.413716	2.39530237E-3	1.94834180E-3
68	0.61918	0.51233	-0.955616	2.39810668E-3	2.15268032E-3
13	0.59178	0.50685	-1.511095	2.40988183E-3	2.04991417E-3
60	0.60548	0.51233	-1.054224	2.41509698E-3	1.94870920E-3
30	0.61096	0.50411	-1.862735	2.42111662E-3	2.01215453E-3
25	0.61918	0.51233	-1.485206	2.42669118E-3	2.19633895E-3
14	0.58356	0.49863	-0.561686	2.42755300E-3	1.94394234E-3
44	0.6274	0.50685	-1.642555	2.43618342E-3	2.12646456E-3
41	0.63288	0.52877	-0.214315	2.43799771E-3	1.96293871E-3

I.1.7 Bitcoin MSE Correlation

Year	Lag	Correlation
2015-2018	01	0.271528
2015-2018	07	0.67711
2015-2018	14	0.82626
2015-2018	21	0.79843
2015-2018	28	0.84722
2015-2018	auto - 6	0.48986
2016-2018	01	0.580112
2016-2018	07	0.67445
2016-2018	14	0.88996
2016-2018	21	0.83316
2016-2018	28	0.87701
2016-2018	auto - 6	0.53539
2017-2018	01	0.583198
2017-2018	07	0.67772
2017-2018	14	0.77809
2017-2018	21	0.73662
2017-2018	28	0.66935
2017-2018	auto - 6	0.75415

Table I.19: Correlation MSE Bitcoin

Appendix J

Appendix NN - Bitcoin 2022

J.1 Bitcoin NN - extended Tables - 2022 Test

J.1.1 Lag 01

Table J.1: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
52	0.53285	0.46575	-1.602436	1.51817858E-3	1.16815465E-3
84	0.53285	0.46575	-1.602436	1.51866760E-3	1.17310140E-3
49	0.53285	0.46575	-1.602436	1.51871134E-3	1.15573931E-3
18	0.53285	0.46575	-1.602436	1.51880540E-3	1.16204823E-3
60	0.53285	0.46575	-1.602436	1.52046649E-3	1.15356444E-3
70	0.53832	0.45753	-1.688173	1.52097141E-3	1.16552154E-3
19	0.53741	0.47397	-1.005589	1.52129171E-3	1.15272948E-3
31	0.53832	0.47397	-1.206688	1.52135367E-3	1.15200366E-3
64	0.53193	0.47945	-0.433252	1.52141093E-3	1.16122186E-3
32	0.5365	0.46849	-1.277147	1.52169605E-3	1.15516911E-3

Table J.2: Metrics using Dataset [2020, 2021]-[2022] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
49	0.53762	0.46575	-1.602436	1.66121981E-3	1.17268656E-3
66	0.54172	0.47397	-1.005589	1.66171918E-3	1.14572271E-3
60	0.53762	0.46575	-1.602436	1.66199257E-3	1.18083404E-3
19	0.54036	0.47123	-1.044648	1.66260013E-3	1.16423294E-3
86	0.53625	0.46575	-1.552078	1.66373092E-3	1.16922238E-3
11	0.54309	0.47397	-1.206688	1.66508805E-3	1.16159752E-3
71	0.53899	0.46575	-1.624646	1.66519015E-3	1.14507476E-3
18	0.53762	0.46575	-1.602436	1.66529635E-3	1.19204901E-3
73	0.54856	0.48219	-0.62931	1.66565013E-3	1.14483533E-3
14	0.54446	0.45753	-1.688173	1.66582300E-3	1.16642169E-3

Table J.3: Metrics using Dataset [2021]-[2022] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
66	0.48493	0.53973	1.397455	1.75875862E-3	1.13127077E-3
74	0.52877	0.55342	1.45649	1.75962587E-3	1.13679139E-3
89	0.52603	0.53425	0.280001	1.75982670E-3	1.14217357E-3
19	0.53973	0.47945	-0.428902	1.76080383E-3	1.14772674E-3
51	0.53973	0.47397	-0.632465	1.76094873E-3	1.15043571E-3
76	0.51781	0.45479	-1.605877	1.77392838E-3	1.19968998E-3
49	0.51233	0.46575	-1.602436	1.77484421E-3	1.17981180E-3
15	0.48219	0.53973	1.33238	1.77616083E-3	1.12835593E-3
94	0.49589	0.55342	1.533679	1.77726269E-3	1.13093408E-3
55	0.51233	0.45479	-1.071467	1.78165458E-3	1.15715912E-3

J.1.2 Lag 07

Table J.4: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
32	0.52281	0.49041	0.337119	1.47277047E-3	1.13966541E-3
63	0.51916	0.46575	-0.287347	1.48752159E-3	1.18644004E-3
38	0.5438	0.43562	-2.465853	1.48777098E-3	1.15582740E-3
81	0.54562	0.46301	-1.472226	1.48864613E-3	1.16874613E-3
90	0.54562	0.45205	-1.485418	1.48939984E-3	1.16280971E-3
25	0.54562	0.42192	-2.210795	1.48974539E-3	1.15149667E-3
16	0.5292	0.44384	-1.077441	1.49032140E-3	1.17075833E-3
34	0.54562	0.47397	-1.308902	1.49101527E-3	1.17335292E-3
35	0.53558	0.43562	-1.700848	1.49114445E-3	1.15644869E-3
24	0.52828	0.44384	-1.135743	1.49189930E-3	1.15625608E-3

Table J.5: Metrics using Dataset [2020, 2021]-[2022] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
90	0.55677	0.47671	0.433163	1.61307468E-3	1.18237106E-3
63	0.54036	0.44658	-2.017338	1.61346126E-3	1.22725962E-3
32	0.54993	0.45205	-1.335269	1.61882452E-3	1.23054547E-3
23	0.52257	0.51233	-0.508952	1.61991468E-3	1.19513289E-3
44	0.50752	0.47123	-1.131713	1.62055846E-3	1.16705201E-3
2	0.53352	0.47945	-0.600126	1.62279913E-3	1.17430549E-3
81	0.54036	0.45479	-1.167771	1.62327816E-3	1.17917185E-3
35	0.53352	0.45753	-1.562501	1.62372743E-3	1.16309345E-3
16	0.53215	0.46027	-1.460144	1.62379671E-3	1.19780375E-3
31	0.54856	0.47397	0.007935	1.62919983E-3	1.23059867E-3

Table J.6: Metrics using Dataset [2021]-[2022] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.50411	0.44658	-1.522274	1.75609584E-3	1.20928713E-3
4	0.52603	0.46849	-0.668499	1.76908457E-3	1.18719333E-3
38	0.51507	0.49041	0.05301	1.77499073E-3	1.15993907E-3
44	0.53699	0.45753	-1.358195	1.79101011E-3	1.29588746E-3
15	0.54521	0.48219	-0.807983	1.79706987E-3	1.21481294E-3
94	0.53425	0.48493	-0.143903	1.80741485E-3	1.15061570E-3
54	0.52603	0.45479	-1.701627	1.81029468E-3	1.28448618E-3
63	0.53425	0.47397	-0.939937	1.81159703E-3	1.24210067E-3
82	0.48219	0.52055	-0.029117	1.82409000E-3	1.14026377E-3
66	0.52603	0.44384	-1.38277	1.82463172E-3	1.21462517E-3

J.1.3 Lag 14

Table J.7: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.56387	0.49041	-1.733032	1.44863498E-3	1.17264619E-3
30	0.54106	0.47397	-1.536496	1.46124003E-3	1.18015111E-3
36	0.54288	0.48493	-1.287584	1.46862549E-3	1.19933954E-3
95	0.53376	0.45205	-1.527896	1.47602046E-3	1.15072963E-3
69	0.5438	0.48219	-0.950747	1.47833563E-3	1.18508339E-3
38	0.56843	0.46301	-1.547206	1.48093377E-3	1.18367577E-3
58	0.53741	0.49589	0.13145	1.48344859E-3	1.15757467E-3
42	0.54927	0.50137	-1.631954	1.48419727E-3	1.20181409E-3
40	0.53741	0.47945	-0.867348	1.48476549E-3	1.14625290E-3
83	0.51734	0.48767	-1.069393	1.48492652E-3	1.17783397E-3

Table J.8: Metrics using Dataset [2020, 2021]-[2022] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.54993	0.49589	-1.021952	1.55857124E-3	1.18843847E-3
36	0.54309	0.51233	-0.511441	1.58025550E-3	1.20690408E-3
30	0.52394	0.49863	-0.948835	1.59112240E-3	1.17979378E-3
42	0.5212	0.51233	-0.530369	1.59576825E-3	1.20121260E-3
83	0.53625	0.47671	-1.371386	1.59911379E-3	1.20485235E-3
38	0.54583	0.48767	-1.162104	1.60049284E-3	1.20134695E-3
51	0.54993	0.46575	-0.501095	1.60909662E-3	1.18344334E-3
43	0.5513	0.49041	0.036245	1.61078946E-3	1.21045437E-3
95	0.51573	0.50137	0.84616	1.61328328E-3	1.12486195E-3
69	0.49521	0.49589	-0.549426	1.61627908E-3	1.17806086E-3

TABLE J.9: Metrics using Dataset [2021]-[2022] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
36	0.53699	0.52603	0.838545	1.71037921E-3	1.20764585E-3
14	0.52055	0.49589	-0.662913	1.73962975E-3	1.20099894E-3
40	0.54247	0.49863	0.421502	1.74489904E-3	1.22457915E-3
70	0.53151	0.49589	-0.268416	1.74728053E-3	1.24213303E-3
83	0.47945	0.50411	-0.010301	1.75748263E-3	1.23475985E-3
30	0.52329	0.51507	-0.535284	1.75781841E-3	1.18770090E-3
42	0.47945	0.49315	0.104768	1.75978782E-3	1.21318647E-3
68	0.51507	0.52055	0.521528	1.76140111E-3	1.24804599E-3
35	0.52055	0.46575	-0.820841	1.76906133E-3	1.25834619E-3
99	0.47397	0.51233	-1.5689	1.76935618E-3	1.25287265E-3

J.1.4 Lag 21

TABLE J.10: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
70	0.53923	0.48493	0.014988	1.43748262E-3	1.18813847E-3
67	0.55657	0.51781	0.012613	1.43899339E-3	1.20173720E-3
90	0.5438	0.46027	-1.12222	1.44469495E-3	1.20102725E-3
37	0.55931	0.48767	-0.612907	1.44886841E-3	1.22494111E-3
66	0.55292	0.49315	-1.26943	1.45493815E-3	1.20767327E-3
58	0.52464	0.45205	-1.24853	1.45974025E-3	1.23523148E-3
11	0.55474	0.48493	-0.517167	1.46331268E-3	1.24499323E-3
20	0.54562	0.46849	-1.037077	1.46578979E-3	1.20446536E-3
28	0.55931	0.46027	-1.800542	1.46756149E-3	1.24204562E-3
88	0.54106	0.46027	-1.842159	1.46849173E-3	1.23365245E-3

TABLE J.11: Metrics using Dataset [2020, 2021]-[2022] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
90	0.55814	0.48493	0.067879	1.53501830E-3	1.18984525E-3
70	0.54856	0.47671	0.424049	1.55086837E-3	1.24133237E-3
67	0.55267	0.52603	0.928099	1.56537227E-3	1.23597770E-3
66	0.54309	0.48219	-1.449933	1.57771391E-3	1.21938953E-3
35	0.54309	0.54521	1.327245	1.58683103E-3	1.20285202E-3
20	0.54856	0.46849	-1.040178	1.59011012E-3	1.21241945E-3
46	0.55404	0.51781	0.840266	1.59312557E-3	1.18932801E-3
39	0.54172	0.50137	-0.407655	1.59381391E-3	1.22160913E-3
88	0.55677	0.45753	-1.617164	1.59725076E-3	1.23227207E-3
56	0.54583	0.46301	-1.581661	1.60412968E-3	1.27169688E-3

TABLE J.12: Metrics using Dataset [2021]-[2022] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
90	0.55342	0.52877	1.113249	1.62187660E-3	1.21951386E-3
70	0.52603	0.47671	-0.418179	1.63817998E-3	1.29918780E-3
64	0.53973	0.47671	-0.094116	1.73006990E-3	1.17072668E-3
66	0.45479	0.52329	-0.317589	1.73066243E-3	1.20729853E-3
72	0.55342	0.55068	2.384729	1.74351413E-3	1.18618112E-3
83	0.52603	0.52877	0.612866	1.75826076E-3	1.21194910E-3
63	0.53151	0.54795	-0.238224	1.76998831E-3	1.25525960E-3
39	0.51781	0.48767	-0.46202	1.77034750E-3	1.36749111E-3
12	0.57534	0.51233	0.223563	1.77043406E-3	1.26584193E-3
73	0.52055	0.44932	-1.944343	1.77943609E-3	1.42503178E-3

J.1.5 Lag 28

TABLE J.13: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
54	0.57391	0.49041	-0.096209	1.43697998E-3	1.24078987E-3
75	0.57847	0.49315	-0.421306	1.43745505E-3	1.20520310E-3
18	0.56113	0.45479	-2.409979	1.43752705E-3	1.25748117E-3
60	0.56204	0.48767	-0.641307	1.43775285E-3	1.25262223E-3
28	0.53102	0.48493	-0.985808	1.44208691E-3	1.17502691E-3
26	0.55109	0.47123	-2.267551	1.44313565E-3	1.25907161E-3
37	0.54836	0.48219	-0.300338	1.44418909E-3	1.19526762E-3
56	0.57755	0.48219	-0.207951	1.44457812E-3	1.24640233E-3
57	0.54471	0.51233	-0.041785	1.45185485E-3	1.21649418E-3
93	0.53832	0.47671	-0.54001	1.45446015E-3	1.23225420E-3

TABLE J.14: Metrics using Dataset [2020, 2021]-[2022] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
28	0.54172	0.49589	-0.408083	1.54508839E-3	1.18136998E-3
99	0.54172	0.50137	-0.10612	1.56496244E-3	1.24033750E-3
93	0.55267	0.49589	0.263924	1.57280440E-3	1.22859281E-3
14	0.53625	0.48767	-1.064224	1.57394231E-3	1.18857794E-3
56	0.56088	0.51507	0.984346	1.57509950E-3	1.20773268E-3
66	0.55267	0.50959	0.724604	1.57567325E-3	1.24050657E-3
75	0.55677	0.49041	-0.424699	1.58190622E-3	1.23246886E-3
50	0.5513	0.47945	-0.739856	1.58820960E-3	1.28341250E-3
37	0.51847	0.49589	-0.227299	1.58880559E-3	1.22301770E-3
60	0.56224	0.48767	0.023565	1.59258063E-3	1.30595972E-3

TABLE J.15: Metrics using Dataset [2021]-[2022] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
81	0.53699	0.58082	2.065473	1.73034812E-3	1.18382396E-3
66	0.52055	0.48767	-0.421205	1.73179299E-3	1.28589163E-3
24	0.52329	0.52603	0.813931	1.73492666E-3	1.26921433E-3
99	0.55342	0.52603	0.968197	1.73645742E-3	1.25065392E-3
30	0.53425	0.49315	-0.607487	1.73717945E-3	1.27635435E-3
57	0.52329	0.50959	1.156287	1.75242018E-3	1.29140718E-3
50	0.56712	0.50137	0.099418	1.75467786E-3	1.37628964E-3
91	0.53973	0.48219	-0.332788	1.75863313E-3	1.24990622E-3
10	0.52329	0.49041	-0.571249	1.76162555E-3	1.32265258E-3
54	0.54795	0.52055	1.032662	1.77464273E-3	1.29455310E-3

J.1.6 Lag auto - 6

TABLE J.16: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
46	0.54288	0.44658	-1.342543	1.49309522E-3	1.17950678E-3
25	0.5365	0.44658	-1.841687	1.49790968E-3	1.20321815E-3
34	0.52555	0.46301	-1.412581	1.49871932E-3	1.17880671E-3
29	0.53102	0.4411	-1.306935	1.49881703E-3	1.14034898E-3
61	0.51825	0.45753	-0.702593	1.50171037E-3	1.15987090E-3
81	0.53558	0.45479	-1.37579	1.50435886E-3	1.15595522E-3
62	0.53376	0.46849	-0.599406	1.50814693E-3	1.15738754E-3
60	0.54836	0.46027	-0.586449	1.50915573E-3	1.17642025E-3
13	0.52828	0.45205	-1.583901	1.51003835E-3	1.16183598E-3
44	0.54197	0.4274	-2.062124	1.51152093E-3	1.16880496E-3

TABLE J.17: Metrics using Dataset [2020, 2021]-[2022] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
25	0.55814	0.45205	-1.43421	1.61461013E-3	1.17697332E-3
46	0.53352	0.44932	-0.945212	1.62702433E-3	1.21864458E-3
97	0.54993	0.44932	-1.122907	1.63497308E-3	1.20288012E-3
99	0.52668	0.48493	-1.19719	1.63689882E-3	1.17356478E-3
29	0.50068	0.50959	0.591374	1.63690801E-3	1.12910975E-3
62	0.513	0.46575	-0.710972	1.64149031E-3	1.15896600E-3
60	0.54993	0.48767	-0.696598	1.64236282E-3	1.16618143E-3
41	0.52668	0.46849	-0.994107	1.64331348E-3	1.15698524E-3
81	0.53352	0.46027	-0.431852	1.64640832E-3	1.23691579E-3
44	0.54036	0.43288	-1.921798	1.64747549E-3	1.17229388E-3

Table J.18: Metrics using Dataset [2021]-[2022] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
81	0.51233	0.53699	1.121805	1.74258407E-3	1.14110317E-3
60	0.56438	0.46027	-1.251363	1.75447379E-3	1.19318504E-3
25	0.52055	0.46849	-1.572528	1.75596364E-3	1.22954711E-3
97	0.56986	0.43288	-1.505671	1.76178539E-3	1.23826876E-3
61	0.52329	0.46575	-1.482359	1.77122539E-3	1.21358272E-3
30	0.48219	0.50411	0.305096	1.77174259E-3	1.13308262E-3
99	0.53425	0.47123	-0.769888	1.77233166E-3	1.23090198E-3
53	0.53973	0.43014	-1.271457	1.77353875E-3	1.23001141E-3
41	0.52329	0.46849	-0.711486	1.78116150E-3	1.18233522E-3
44	0.52603	0.46849	-1.191257	1.79260560E-3	1.25382544E-3

J.1.7 Bitcoin MSE Correlation 2022

Year	Lag	Correlation
2019-2022	01	0.2682
2019-2022	07	0.71864
2019-2022	14	0.74513
2019-2022	21	0.62166
2019-2022	28	0.80278
2019-2022	auto - 6	0.59869
2020-2022	01	0.551039
2020-2022	07	0.67357
2020-2022	14	0.78330
2020-2022	21	0.68338
2020-2022	28	0.83975
2020-2022	auto - 6	0.53119
2021-2022	01	0.884886
2021-2022	07	0.84885
2021-2022	14	0.85400
2021-2022	21	0.81904
2021-2022	28	0.78737
2021-2022	auto - 6	0.89708

Table J.19: Correlation MSE Bitcoin

Appendix K

Appendix NN - Bitcoin 2023

K.1 Bitcoin NN - extended Tables - 2023 Test

K.1.1 Lag 01

Table K.1: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
52	0.48814	0.49589	-2.150101	1.48814462E-3	5.20267036E-4
84	0.51369	0.49863	2.166654	1.48838691E-3	5.14659649E-4
60	0.51369	0.49863	2.166654	1.48919504E-3	5.14050337E-4
49	0.52555	0.52877	-1.180068	1.48948767E-3	5.19813100E-4
70	0.52099	0.50685	1.310402	1.48958156E-3	5.18439901E-4
18	0.51551	0.49315	1.736481	1.49096407E-3	5.14034318E-4
64	0.52737	0.53973	0.221518	1.49118959E-3	5.19141505E-4
31	0.53467	0.53425	-0.904139	1.49119739E-3	5.20318858E-4
15	0.52464	0.53425	-1.155349	1.49155032E-3	5.23582399E-4
20	0.52555	0.52877	0.60744	1.49209441E-3	5.17105124E-4

Table K.2: Metrics using Dataset [2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
49	0.51644	0.49863	-2.286866	1.44296211E-3	5.24947414E-4
75	0.49452	0.51507	2.1122	1.44390365E-3	5.16718300E-4
14	0.53425	0.53151	-1.265193	1.44428232E-3	5.20280120E-4
35	0.5411	0.53151	-0.480508	1.44564831E-3	5.27508087E-4
60	0.48904	0.49863	2.166654	1.44630548E-3	5.14206436E-4
85	0.53425	0.55068	-0.577347	1.44658096E-3	5.20887363E-4
17	0.51781	0.50137	-2.166654	1.44681083E-3	5.24665529E-4
56	0.5411	0.53151	-0.770721	1.44696879E-3	5.23521755E-4
67	0.5274	0.52603	-0.644734	1.44705506E-3	5.19448214E-4
15	0.53151	0.53425	-1.126091	1.44727497E-3	5.22559985E-4

TABLE K.3: Metrics using Dataset [2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
66	0.53425	0.50137	-2.166654	1.12999887E-3	5.65002164E-4
19	0.54247	0.49589	-1.924941	1.13044524E-3	5.51576487E-4
49	0.52329	0.49589	-1.365044	1.13076663E-3	5.34593182E-4
23	0.55068	0.49863	-1.773609	1.13090724E-3	5.25298728E-4
76	0.53699	0.50137	-2.166654	1.13282850E-3	5.74701861E-4
20	0.52603	0.44932	-0.52125	1.13313143E-3	5.18543852E-4
89	0.53973	0.49589	-2.388136	1.13343271E-3	5.71028365E-4
12	0.51507	0.48493	-1.289575	1.14284622E-3	5.33480229E-4
75	0.53425	0.50137	-2.166654	1.14477307E-3	6.13127910E-4
50	0.44932	0.49863	1.660477	1.14728852E-3	5.13725642E-4

K.1.2 Lag 07

TABLE K.4: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
32	0.51004	0.49863	0.012595	1.43917774E-3	5.16589463E-4
81	0.51734	0.49863	1.35134	1.45058131E-3	5.19022453E-4
23	0.50365	0.48219	-1.707875	1.45216766E-3	5.28321004E-4
25	0.50912	0.49315	-1.848049	1.45446248E-3	5.28961772E-4
63	0.51825	0.50137	0.182915	1.45552521E-3	5.37047148E-4
90	0.53558	0.50137	2.033918	1.45559343E-3	5.15636836E-4
38	0.51186	0.49589	1.318775	1.45601472E-3	5.15033307E-4
44	0.52646	0.49863	1.482496	1.45682248E-3	5.18318238E-4
31	0.5219	0.52877	2.033859	1.45732155E-3	5.16776703E-4
87	0.52007	0.52055	0.928581	1.45787232E-3	5.17496221E-4

TABLE K.5: Metrics using Dataset [2021, 2022]-[2023] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
90	0.52192	0.49863	1.811502	1.43488328E-3	5.19008190E-4
81	0.50411	0.49863	2.191892	1.43731470E-3	5.15607344E-4
38	0.5	0.49315	-0.536596	1.43812197E-3	5.22030299E-4
14	0.49589	0.49041	0.242775	1.43947763E-3	5.20285301E-4
44	0.52466	0.51233	0.412604	1.43990135E-3	5.19976561E-4
88	0.51781	0.50137	-1.592105	1.43993424E-3	5.43872286E-4
96	0.49178	0.52329	2.587987	1.44032289E-3	5.14468907E-4
51	0.50137	0.50137	0.641404	1.44233845E-3	5.14303051E-4
23	0.51233	0.48767	-1.886386	1.44511376E-3	5.53456431E-4
35	0.51096	0.50411	-1.600932	1.44653859E-3	5.35764991E-4

TABLE K.6: Metrics using Dataset [2022]-[2023] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.5589	0.52055	-1.101512	1.12793684E-3	5.57112214E-4
38	0.5589	0.48493	-2.043651	1.14069070E-3	5.78885516E-4
82	0.51507	0.49863	-1.677587	1.14952489E-3	5.64671463E-4
4	0.49315	0.49041	1.735798	1.16384467E-3	5.16395394E-4
51	0.55068	0.50411	-1.606419	1.16518502E-3	6.07388509E-4
8	0.49863	0.51507	0.815498	1.16537804E-3	5.21786061E-4
94	0.54247	0.52603	-0.262967	1.16704112E-3	5.70789277E-4
83	0.55342	0.49863	-1.085098	1.17654499E-3	6.04604464E-4
54	0.50685	0.53425	0.310219	1.18225292E-3	5.70441323E-4
66	0.50959	0.47945	-2.27408	1.18957833E-3	5.68911633E-4

K.1.3 Lag 14

TABLE K.7: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.54653	0.48767	-1.511753	1.40689235E-3	5.34624763E-4
69	0.55383	0.52329	0.155789	1.42072479E-3	5.36720918E-4
30	0.53011	0.49041	-0.538983	1.42560564E-3	5.30881299E-4
95	0.52281	0.52329	0.666161	1.42806674E-3	5.25099781E-4
36	0.52099	0.50411	0.986436	1.43137502E-3	5.26265953E-4
58	0.50639	0.52055	0.82802	1.43494977E-3	5.22573970E-4
64	0.51825	0.49589	-1.185183	1.43729746E-3	5.42979075E-4
83	0.52555	0.52329	0.153788	1.44027231E-3	5.37419826E-4
43	0.53011	0.51233	1.292061	1.44405095E-3	5.24540178E-4
51	0.53102	0.49041	-0.918315	1.44508322E-3	5.35069470E-4

TABLE K.8: Metrics using Dataset [2021, 2022]-[2023] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
40	0.51233	0.52603	0.203519	1.39479708E-3	5.35534542E-4
14	0.5411	0.49863	-1.752201	1.40687973E-3	5.56663748E-4
58	0.53973	0.54247	1.162676	1.41578615E-3	5.27472983E-4
38	0.50685	0.47123	-1.55968	1.42051624E-3	5.49528227E-4
83	0.5	0.53425	-0.147169	1.42237969E-3	5.41042931E-4
30	0.52603	0.51781	-0.674731	1.42357199E-3	5.55746918E-4
69	0.5274	0.50411	-1.365054	1.42398670E-3	5.66646683E-4
36	0.54247	0.49041	-2.104764	1.42431740E-3	5.64407221E-4
95	0.50274	0.54521	1.784417	1.42578712E-3	5.31943810E-4
64	0.52192	0.48767	-2.371401	1.42631709E-3	5.65374651E-4

Table K.9: Metrics using Dataset [2022]-[2023] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
40	0.55342	0.51781	-1.104562	1.11345850E-3	5.63700313E-4
75	0.51781	0.49041	-1.544121	1.12858079E-3	5.62268315E-4
14	0.53151	0.50685	-1.567213	1.14126533E-3	6.09919126E-4
30	0.53151	0.51233	-1.799908	1.14220773E-3	5.53066072E-4
70	0.55616	0.50685	-1.885489	1.15132147E-3	6.76973536E-4
83	0.54795	0.52603	-1.298482	1.15560277E-3	6.08345009E-4
36	0.52603	0.48767	-2.281078	1.16743830E-3	5.87408162E-4
35	0.50685	0.50685	-0.946943	1.16895307E-3	5.51344262E-4
42	0.56438	0.50959	-1.583045	1.17949468E-3	6.62390844E-4
96	0.56986	0.51507	-1.599243	1.19456903E-3	6.54070361E-4

K.1.4 Lag 21

Table K.10: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
90	0.55657	0.48493	-0.694002	1.39390813E-3	5.27932976E-4
67	0.53376	0.49863	-1.340669	1.40188736E-3	5.74173202E-4
70	0.54288	0.51233	-0.447845	1.40600729E-3	5.53854051E-4
37	0.54927	0.50411	-0.897587	1.41486694E-3	5.62701011E-4
46	0.53285	0.48493	0.208536	1.43136732E-3	5.44422228E-4
66	0.53741	0.47123	-1.713979	1.43233683E-3	5.29268911E-4
20	0.52281	0.51781	0.790859	1.43243874E-3	5.17531246E-4
39	0.53467	0.47397	-0.404632	1.43261082E-3	5.41893776E-4
88	0.54562	0.51233	1.820138	1.43426978E-3	5.15480811E-4
58	0.51642	0.49863	-0.483213	1.43551372E-3	5.70448860E-4

Table K.11: Metrics using Dataset [2021, 2022]-[2023] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
70	0.54932	0.48219	-1.6302	1.36268907E-3	5.75405181E-4
90	0.55753	0.49041	-1.655931	1.36374565E-3	6.08367827E-4
67	0.5411	0.48219	-1.183524	1.39271408E-3	6.04646054E-4
58	0.52329	0.47945	-1.417563	1.39693050E-3	5.69278600E-4
12	0.55068	0.52055	-1.155234	1.39934454E-3	5.66300602E-4
46	0.54795	0.50137	-0.039103	1.40689495E-3	5.60295643E-4
39	0.53562	0.49863	-1.23627	1.40808847E-3	5.65914139E-4
72	0.57534	0.48219	-1.638758	1.41352370E-3	5.84517386E-4
20	0.55068	0.52877	0.490244	1.41405547E-3	5.50368847E-4
88	0.5589	0.54795	0.830761	1.41406921E-3	5.25744372E-4

Table K.12: Metrics using Dataset [2022]-[2023] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
82	0.52603	0.53425	1.945296	1.13270232E-3	5.41337002E-4
64	0.46849	0.47671	0.153174	1.14399010E-3	5.31550907E-4
70	0.51507	0.49589	-0.987755	1.15011389E-3	5.95805165E-4
72	0.57534	0.50137	-1.952065	1.15088702E-3	8.09133232E-4
15	0.5726	0.49863	-1.813329	1.15587392E-3	6.47662086E-4
66	0.55616	0.50959	-1.449007	1.15883251E-3	6.43232550E-4
35	0.5726	0.49589	-0.942169	1.16192383E-3	5.69840829E-4
12	0.52055	0.49863	-1.372463	1.16679145E-3	6.40473056E-4
62	0.58082	0.52877	-0.743818	1.17137183E-3	6.51270699E-4
27	0.50959	0.46849	-1.710478	1.18000753E-3	6.06717272E-4

K.1.5 Lag 28

Table K.13: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
26	0.55383	0.50137	-0.670214	1.39158089E-3	5.45073329E-4
28	0.54015	0.50137	0.318653	1.39368596E-3	5.33797313E-4
66	0.54015	0.52877	0.95491	1.39626152E-3	5.32159142E-4
30	0.54562	0.51233	0.117629	1.40093047E-3	5.33509964E-4
37	0.53011	0.49589	-0.763628	1.40139839E-3	5.32814592E-4
75	0.55109	0.52055	0.445882	1.40565760E-3	5.38441330E-4
18	0.54288	0.52603	-0.245553	1.40724872E-3	5.42644294E-4
93	0.54836	0.49589	-1.609122	1.40769449E-3	5.77111607E-4
56	0.53832	0.50685	-0.498029	1.40857032E-3	5.67135613E-4
43	0.52828	0.46849	0.353611	1.41104457E-3	5.34120264E-4

Table K.14: Metrics using Dataset [2021, 2022]-[2023] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
56	0.55616	0.53699	0.497749	1.35183871E-3	5.49653052E-4
66	0.55068	0.52329	0.022307	1.36060494E-3	5.52178678E-4
54	0.53836	0.48767	-1.226522	1.36122079E-3	5.69893876E-4
99	0.57808	0.51233	-0.756109	1.36222221E-3	5.69520684E-4
69	0.54247	0.51507	0.374629	1.36287999E-3	5.41209685E-4
37	0.53562	0.51233	-0.451202	1.36585183E-3	5.59303966E-4
28	0.53425	0.52877	0.304588	1.38967770E-3	5.39265537E-4
93	0.53699	0.51781	-1.439207	1.38996974E-3	5.84505676E-4
14	0.53562	0.50137	-0.67985	1.39359237E-3	5.43101331E-4
10	0.53836	0.51233	0.710425	1.39509025E-3	5.57961517E-4

TABLE K.15: Metrics using Dataset [2022]-[2023] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
24	0.5863	0.51781	-1.097795	1.11187644E-3	5.90244367E-4
66	0.58082	0.50411	-2.384179	1.12113209E-3	7.91617039E-4
85	0.55616	0.53151	0.043082	1.15777313E-3	5.75016787E-4
82	0.57808	0.50685	-0.524982	1.15881541E-3	5.99009741E-4
28	0.53699	0.51781	-0.265679	1.18486690E-3	5.73349483E-4
39	0.53973	0.52603	-1.430889	1.20434890E-3	7.32058571E-4
93	0.54521	0.53151	-0.660755	1.20588544E-3	6.39923717E-4
30	0.56164	0.50685	1.21198	1.20755611E-3	5.61198317E-4
77	0.54247	0.50411	-2.356914	1.21294937E-3	7.93718049E-4
91	0.51781	0.50959	-1.074283	1.21501642E-3	6.56050400E-4

K.1.6 Lag auto - 6

TABLE K.16: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
29	0.53376	0.49315	0.579342	1.45205000E-3	5.17358666E-4
81	0.5146	0.50959	0.488881	1.46429880E-3	5.18022823E-4
46	0.51734	0.51507	1.70963	1.46505548E-3	5.14685658E-4
61	0.50821	0.48767	-0.253385	1.46622362E-3	5.26088001E-4
60	0.52372	0.51507	1.129421	1.47125058E-3	5.18512057E-4
32	0.5	0.48493	-1.069077	1.47404010E-3	5.23962840E-4
56	0.52099	0.53973	2.45031	1.47435729E-3	5.15056950E-4
50	0.52099	0.51781	2.683352	1.47636142E-3	5.15568284E-4
62	0.51551	0.50137	1.703273	1.47674059E-3	5.13312690E-4
25	0.51551	0.50411	2.172977	1.47675495E-3	5.18166086E-4

TABLE K.17: Metrics using Dataset [2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
25	0.53425	0.50137	-1.993365	1.42763989E-3	5.46174276E-4
29	0.51918	0.49863	-2.158534	1.43149674E-3	5.63522882E-4
61	0.49589	0.49589	0.651797	1.43270071E-3	5.19227479E-4
13	0.49726	0.51507	-1.689638	1.43951148E-3	5.34078846E-4
4	0.52055	0.51233	-1.05919	1.44066124E-3	5.46791618E-4
60	0.51096	0.49041	-1.964336	1.44132591E-3	5.37207798E-4
97	0.49315	0.50685	1.784834	1.44327371E-3	5.20660734E-4
50	0.49589	0.50959	1.490322	1.44350481E-3	5.20017056E-4
56	0.50685	0.48767	0.884082	1.44381232E-3	5.14820463E-4
46	0.50274	0.49863	1.13963	1.44491989E-3	5.13963072E-4

TABLE K.18: Metrics using Dataset [2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
81	0.53151	0.49315	-1.810567	1.12609035E-3	5.79146359E-4
30	0.50137	0.46301	1.199278	1.13971550E-3	5.18631579E-4
13	0.5589	0.50411	-1.362441	1.14007167E-3	5.71854440E-4
61	0.52877	0.46575	-0.73645	1.14282849E-3	5.28055031E-4
10	0.51507	0.50959	-0.823351	1.14413797E-3	5.63808286E-4
41	0.53425	0.52877	0.173774	1.15183130E-3	5.49023728E-4
97	0.53699	0.51781	-1.826659	1.15408549E-3	5.87476686E-4
35	0.54521	0.49315	-1.095423	1.15546522E-3	5.95902430E-4
53	0.45753	0.52055	-1.167857	1.15936458E-3	5.41259111E-4
92	0.55068	0.53425	-0.522008	1.16569475E-3	5.56554604E-4

K.1.7 Bitcoin MSE Correlation 2023

Year	Lag	Correlation
2020-2023	01	0.099566
2020-2023	07	0.63719
2020-2023	14	0.68617
2020-2023	21	0.51986
2020-2023	28	0.55478
2020-2023	auto - 6	0.45976
2021-2023	01	0.57093
2021-2023	07	0.66656
2021-2023	14	0.63418
2021-2023	21	0.62657
2021-2023	28	0.66006
2021-2023	auto - 6	0.81423
2022-2023	01	0.808631
2022-2023	07	0.73682
2022-2023	14	0.76437
2022-2023	21	0.68724
2022-2023	28	0.83044
2022-2023	auto - 6	0.78505

TABLE K.19: Correlation MSE Bitcoin

Appendix L

Appendix NN - Gold 2023

L.1 Gold NN - extended Tables - 2023 Test

L.1.1 Lag 01

Table L.1: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
79	0.51058	0.45817	-0.406732	1.22210334E-4	6.90578293E-5
86	0.50661	0.51793	1.165542	1.22219397E-4	6.90878180E-5
4	0.54497	0.51394	1.000475	1.22412957E-4	6.88392804E-5
78	0.49471	0.48606	-0.899268	1.22450112E-4	6.93557674E-5
35	0.51455	0.48207	0.246912	1.22536887E-4	6.92707339E-5
75	0.53571	0.51394	0.808631	1.22579098E-4	6.88673460E-5
14	0.54762	0.50996	0.950565	1.22599760E-4	6.89407129E-5
56	0.54894	0.50996	0.950565	1.22600615E-4	6.89450658E-5
17	0.45238	0.48207	-1.04442	1.22650747E-4	6.98199206E-5
53	0.54497	0.51394	0.97182	1.22650842E-4	6.89453590E-5

Table L.2: Metrics using Dataset [2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
8	0.52087	0.47012	-0.656301	9.17174544E-5	6.91353796E-5
75	0.50099	0.48207	-1.072848	9.19182168E-5	6.98388819E-5
19	0.53678	0.50996	0.927269	9.21636032E-5	6.89501630E-5
72	0.4672	0.48207	-0.637068	9.22628096E-5	6.99676085E-5
24	0.5328	0.50996	0.950565	9.26458585E-5	6.89908062E-5
31	0.49901	0.51394	0.060213	9.29571346E-5	7.14648356E-5
10	0.51491	0.49801	0.376443	9.30454105E-5	6.93312782E-5
55	0.49503	0.52191	1.187996	9.30640277E-5	6.95120437E-5
29	0.46521	0.49402	-0.923597	9.35482101E-5	7.26355134E-5
65	0.54672	0.51394	1.100954	9.41078793E-5	7.01276000E-5

Table L.3: Metrics using Dataset [2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
74	0.55378	0.51793	0.988995	9.61234892E-5	7.04559968E-5
69	0.49801	0.51394	0.917101	9.86516752E-5	7.04459058E-5
99	0.4502	0.47809	-0.738569	9.92001012E-5	7.36215534E-5
76	0.5498	0.51793	1.103404	9.96673557E-5	7.22132612E-5
23	0.5259	0.50996	0.950565	1.00115798E-4	7.18591411E-5
12	0.49801	0.50598	0.8098	1.00185442E-4	7.17413286E-5
89	0.4741	0.49004	-0.965816	1.01615332E-4	7.95918614E-5
55	0.52191	0.50598	0.923597	1.02430031E-4	7.32355255E-5
75	0.47012	0.49402	-0.923597	1.03302617E-4	8.15647835E-5
19	0.47012	0.49004	-0.950565	1.07221437E-4	8.61293693E-5

L.1.2 Lag 05

Table L.4: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
3	0.54497	0.51394	-0.10456	1.21791374E-4	7.08847932E-5
82	0.55159	0.51394	0.891498	1.21807546E-4	6.99772717E-5
67	0.52513	0.4741	-0.613804	1.21871609E-4	6.94047127E-5
39	0.47222	0.50598	0.305739	1.21901431E-4	7.13740136E-5
100	0.53836	0.49402	-0.2265	1.21933090E-4	6.92391766E-5
64	0.47354	0.49402	-0.156219	1.22041586E-4	7.06919076E-5
11	0.53704	0.50996	0.413442	1.22177855E-4	7.07869382E-5
60	0.52249	0.44223	-1.027198	1.22180651E-4	7.19368776E-5
53	0.5463	0.51793	0.678872	1.22383632E-4	7.14413216E-5
31	0.48545	0.45418	-1.544288	1.22551583E-4	7.20118915E-5

Table L.5: Metrics using Dataset [2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
3	0.51889	0.5498	0.969429	9.13120237E-5	6.85402820E-5
81	0.51491	0.54183	0.644721	9.14289853E-5	6.86493408E-5
82	0.52485	0.56972	1.477972	9.17255827E-5	6.83787386E-5
73	0.53082	0.50996	1.037972	9.19813117E-5	6.82521446E-5
53	0.49901	0.50996	-0.424402	9.21602126E-5	7.02809168E-5
8	0.5328	0.58566	2.251967	9.25067004E-5	6.89471535E-5
33	0.47316	0.5259	-0.173001	9.27070259E-5	7.14300663E-5
85	0.48509	0.52191	-0.005168	9.30001353E-5	7.03912262E-5
84	0.53082	0.55777	2.039917	9.30086565E-5	6.78438395E-5
17	0.48509	0.5498	0.941719	9.30314426E-5	6.90980717E-5

Table L.6: Metrics using Dataset [2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
3	0.58964	0.53386	1.355107	9.47504384E-5	6.77868535E-5
15	0.4502	0.56574	1.284908	9.58904261E-5	6.72538573E-5
48	0.51793	0.51793	1.016702	9.64163313E-5	6.92516610E-5
26	0.49402	0.5498	2.013263	9.67120391E-5	7.02155506E-5
53	0.49801	0.49801	-0.379406	9.69168244E-5	7.37748668E-5
51	0.49801	0.46215	-0.381384	9.71952160E-5	7.17010982E-5
66	0.48207	0.48207	0.481738	9.73549310E-5	7.01451903E-5
60	0.50996	0.51793	0.325118	9.83270876E-5	7.25061535E-5
64	0.51394	0.47809	-0.929018	9.84338808E-5	7.30450122E-5
96	0.55378	0.50598	0.439154	9.92179486E-5	7.21634934E-5

L.1.3 Lag 10

Table L.7: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
48	0.50794	0.4741	-0.258968	1.18930063E-4	7.13567789E-5
50	0.52249	0.47809	-0.481304	1.18979404E-4	7.08679969E-5
29	0.54497	0.50199	-0.068052	1.19038257E-4	6.97840162E-5
35	0.5172	0.49402	-0.035604	1.19095426E-4	7.18475528E-5
62	0.55026	0.48606	-0.106184	1.19103442E-4	7.01474131E-5
91	0.51058	0.47012	-1.138248	1.19162990E-4	7.31491973E-5
57	0.56746	0.50199	0.541927	1.19299508E-4	7.11737180E-5
97	0.49206	0.48606	-0.28146	1.19562230E-4	7.18925265E-5
39	0.53175	0.47012	0.190509	1.19839241E-4	7.21774643E-5
34	0.51984	0.47012	-0.451643	1.19917780E-4	7.01186922E-5

Table L.8: Metrics using Dataset [2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
35	0.5507	0.56574	2.12211	9.03501467E-5	6.75871560E-5
93	0.57256	0.56972	2.474878	9.14127837E-5	6.70300312E-5
10	0.52485	0.48606	-0.059514	9.14944249E-5	6.85869832E-5
81	0.51889	0.53785	0.216058	9.17813909E-5	7.02492995E-5
48	0.49503	0.51793	-0.427558	9.19118029E-5	7.04146564E-5
7	0.49702	0.49801	-0.936978	9.23155315E-5	7.26736630E-5
62	0.54473	0.5498	1.988954	9.30977325E-5	6.79768898E-5
39	0.5169	0.43825	-1.528999	9.32832202E-5	7.29187414E-5
90	0.55666	0.58964	1.598307	9.33189246E-5	6.75045856E-5
38	0.52883	0.56175	1.772423	9.33895604E-5	6.89464006E-5

Table L.9: Metrics using Dataset [2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
97	0.5259	0.48207	-0.465216	9.36514453E-5	7.14258926E-5
35	0.48606	0.52191	-0.007395	9.46266721E-5	7.04459647E-5
92	0.50996	0.49801	-0.023461	9.59670330E-5	7.61536477E-5
81	0.54183	0.50199	0.201766	9.66996082E-5	7.16165901E-5
93	0.50996	0.56972	1.974529	9.69652826E-5	7.06399717E-5
39	0.51793	0.47809	-0.342564	9.76001601E-5	7.74655179E-5
41	0.48207	0.51394	1.048353	9.76666425E-5	7.08463125E-5
29	0.52191	0.48207	-0.651321	9.78271169E-5	7.50519271E-5
47	0.4741	0.50598	-0.067439	9.85578508E-5	7.67100388E-5
60	0.54582	0.58964	1.824949	9.93325800E-5	6.69353612E-5

L.1.4 Lag 15

Table L.10: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
88	0.51455	0.48606	-0.003745	1.17056053E-4	7.12449896E-5
6	0.52646	0.54183	0.609614	1.17494965E-4	6.99578611E-5
56	0.54233	0.4741	-0.678747	1.17547369E-4	7.02108594E-5
80	0.52381	0.49801	-0.488309	1.18219744E-4	7.08227129E-5
23	0.53439	0.49402	-0.219055	1.18439046E-4	7.06960711E-5
8	0.55952	0.5259	1.239363	1.18599642E-4	7.01231212E-5
29	0.5119	0.46215	-1.033624	1.19192195E-4	7.38324081E-5
24	0.57011	0.50598	0.097995	1.19301608E-4	7.26083031E-5
15	0.54497	0.51394	0.886648	1.19326250E-4	7.18123986E-5
32	0.5582	0.51793	0.738725	1.19430661E-4	7.01775153E-5

Table L.11: Metrics using Dataset [2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
88	0.53678	0.54183	1.477278	9.08622463E-5	6.80155122E-5
56	0.54473	0.54582	1.478417	9.21634468E-5	6.75317812E-5
20	0.48509	0.50199	-0.465874	9.26306242E-5	7.21035343E-5
15	0.54473	0.49402	-0.007811	9.33777828E-5	7.17891087E-5
57	0.51093	0.51793	0.627006	9.34873755E-5	7.25759904E-5
8	0.49702	0.54183	1.046692	9.35030566E-5	7.09821229E-5
18	0.50497	0.52191	-0.291874	9.41346958E-5	7.10051171E-5
44	0.48907	0.50996	-0.456125	9.43597027E-5	7.29930356E-5
24	0.54274	0.53785	2.432778	9.51067595E-5	6.93592129E-5
82	0.51093	0.52191	0.014939	9.55208671E-5	7.05365961E-5

TABLE L.12: Metrics using Dataset [2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
24	0.56574	0.49801	0.865284	9.46238758E-5	7.00052220E-5
69	0.51394	0.49402	-0.036832	9.61681058E-5	7.26937049E-5
15	0.51793	0.47012	-0.402194	9.85069515E-5	7.65405314E-5
6	0.4502	0.57371	0.516165	9.85549167E-5	7.11262173E-5
53	0.50996	0.50199	-0.329823	9.88880618E-5	8.03705533E-5
18	0.5498	0.50996	-0.190609	1.00295882E-4	7.67888919E-5
58	0.56972	0.53785	1.6004	1.01330032E-4	7.11829283E-5
54	0.49801	0.47012	0.270793	1.02431652E-4	7.62489190E-5
8	0.45817	0.51394	0.00802	1.02669230E-4	7.94293409E-5
62	0.52988	0.5498	1.281553	1.02786612E-4	7.13819023E-5

L.1.5 Lag 20

TABLE L.13: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
76	0.53571	0.4741	0.830619	1.16294051E-4	7.03735062E-5
51	0.56614	0.53386	1.759836	1.16720126E-4	6.93014089E-5
93	0.56217	0.49004	0.554621	1.16765164E-4	7.09314071E-5
68	0.55423	0.53386	1.352136	1.16801756E-4	7.07459853E-5
77	0.55291	0.49402	-0.190881	1.16935305E-4	7.10625195E-5
99	0.57275	0.5498	1.998506	1.17084961E-4	6.90061783E-5
16	0.5582	0.49004	0.935645	1.17243532E-4	7.04153108E-5
100	0.56085	0.51394	1.419958	1.17384711E-4	6.81868339E-5
20	0.52646	0.43028	-1.535025	1.17604140E-4	7.21274516E-5
15	0.52778	0.48606	0.100161	1.17844607E-4	7.20752492E-5

TABLE L.14: Metrics using Dataset [2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
77	0.53877	0.50996	0.432654	9.03805412E-5	6.84497418E-5
39	0.54473	0.53785	1.636714	9.09368837E-5	6.87060654E-5
4	0.54672	0.51793	2.285039	9.15889853E-5	6.84356995E-5
100	0.55268	0.54183	1.685744	9.16291375E-5	6.64680731E-5
20	0.52485	0.50598	0.275149	9.18794517E-5	7.10540084E-5
87	0.53082	0.47809	0.601283	9.20282333E-5	6.99320623E-5
55	0.54871	0.5498	3.51963	9.23888965E-5	6.56560038E-5
54	0.53678	0.5498	1.244808	9.26954467E-5	7.08508627E-5
26	0.50895	0.49801	-0.152291	9.27458824E-5	7.43396196E-5
76	0.5169	0.46614	-0.499305	9.34455428E-5	7.47379669E-5

Table L.15: Metrics using Dataset [2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
87	0.53785	0.49402	0.949531	9.39969923E-5	7.41143157E-5
26	0.52191	0.47012	1.149645	9.56930990E-5	7.50942116E-5
16	0.50199	0.47809	0.470114	9.66283689E-5	7.65320053E-5
76	0.50598	0.43825	0.203477	9.66671984E-5	7.62085001E-5
55	0.52988	0.5498	2.252761	9.66799260E-5	6.80913503E-5
77	0.51793	0.56574	1.780876	9.67450061E-5	6.92805569E-5
100	0.50598	0.53785	0.899652	9.93411092E-5	7.95604575E-5
20	0.50199	0.50598	0.354597	1.00058531E-4	8.18656242E-5
17	0.51394	0.49004	0.688012	1.00648840E-4	7.43664965E-5
93	0.51394	0.45817	-0.844976	1.01415298E-4	7.97997746E-5

L.1.6 Lag auto

Table L.16: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
91	0.50926	0.45418	-0.509616	1.15322075E-4	7.15121337E-5
73	0.55688	0.52988	1.71116	1.15716061E-4	7.04102316E-5
82	0.52778	0.47809	0.370824	1.16204777E-4	7.12748344E-5
72	0.5119	0.47012	-0.499358	1.16345758E-4	7.26500610E-5
53	0.51587	0.49402	0.400489	1.16936297E-4	7.19074368E-5
28	0.54365	0.48207	-0.182712	1.17277891E-4	6.93611739E-5
75	0.51455	0.48207	0.086007	1.17535315E-4	7.07440065E-5
33	0.58466	0.49801	0.374782	1.18065962E-4	7.06439884E-5
37	0.53836	0.48606	-0.320332	1.18121723E-4	7.33960064E-5
38	0.52778	0.4741	-0.15171	1.18284618E-4	7.08658277E-5

Table L.17: Metrics using Dataset [2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
76	0.55467	0.52988	0.933403	8.86783094E-5	6.83568533E-5
53	0.52087	0.52988	0.854523	9.01381184E-5	6.98607267E-5
91	0.52883	0.51394	1.233291	9.02736175E-5	6.84352092E-5
28	0.5507	0.55378	1.494824	9.03662535E-5	6.63924120E-5
36	0.52286	0.49801	0.222465	9.14120529E-5	7.00608809E-5
88	0.53877	0.49004	0.283797	9.35464066E-5	7.39301116E-5
37	0.5328	0.4741	-0.330021	9.36818217E-5	7.33449580E-5
75	0.50696	0.51394	0.153765	9.37967119E-5	7.37249807E-5
5	0.49304	0.5498	1.604742	9.42110486E-5	7.04935720E-5
49	0.52485	0.48207	0.51059	9.47942736E-5	6.83946936E-5

TABLE L.18: Metrics using Dataset [2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
53	0.56972	0.4741	1.02794	9.10323555E-5	6.90284380E-5
76	0.52988	0.51394	2.028968	9.11868086E-5	7.17581972E-5
91	0.54183	0.52191	0.847019	9.17801569E-5	6.96461334E-5
82	0.54183	0.48606	-0.280227	9.47684502E-5	7.41423956E-5
28	0.50199	0.58167	1.980357	9.51192816E-5	6.66874348E-5
52	0.55777	0.50598	-0.255563	9.57073859E-5	7.42198533E-5
75	0.52988	0.50996	-0.122392	9.74679724E-5	7.20577919E-5
83	0.51793	0.52988	0.749793	9.81341645E-5	6.94199983E-5
49	0.54582	0.48606	0.397651	1.01081303E-4	7.87785297E-5
5	0.50996	0.51793	0.549676	1.01713865E-4	8.25497274E-5

L.1.7 Gold MSE Correlation 2023

Year	Lag	Correlation
2020-2023	01	0.995716
2020-2023	05	0.94951
2020-2023	10	0.97218
2020-2023	15	0.97219
2020-2023	20	0.96597
2020-2023	auto - 19	0.96310
2021-2023	01	0.994483
2021-2023	05	0.98389
2021-2023	10	0.98359
2021-2023	15	0.97783
2021-2023	20	0.97730
2021-2023	auto - 19	0.98042
2022-2023	01	0.997702
2022-2023	05	0.99474
2022-2023	10	0.99371
2022-2023	15	0.99475
2022-2023	20	0.99332
2022-2023	auto - 19	0.99405

TABLE L.19: Correlation MSE Gold

Appendix M

Appendix NN - MSFT 2023

M.1 MSFT NN - extended Tables - 2023 Test

M.1.1 Lag 01

Table M.1: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
75	0.52381	0.524	1.306618	4.44392560E-4	2.57308954E-4
65	0.52381	0.528	1.43338	4.54392341E-4	2.54394069E-4
76	0.52249	0.52	1.353815	4.54733039E-4	2.52219032E-4
35	0.52646	0.476	-0.056245	4.55274930E-4	2.57406660E-4
88	0.53439	0.496	0.062861	4.55855884E-4	2.62973189E-4
39	0.52513	0.524	1.306618	4.55989422E-4	2.54890097E-4
28	0.52381	0.532	1.472866	4.57076642E-4	2.53824898E-4
85	0.51984	0.52	1.073012	4.57128848E-4	2.53440912E-4
86	0.53175	0.476	-0.361096	4.57538771E-4	2.56189568E-4
50	0.52381	0.528	1.472649	4.57638283E-4	2.51504815E-4

Table M.2: Metrics using Dataset [2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
72	0.50696	0.44	-2.196887	3.35825177E-4	2.50124901E-4
75	0.48907	0.536	1.353602	3.35994496E-4	2.48770743E-4
29	0.49304	0.488	-0.726131	3.36626847E-4	2.52504394E-4
19	0.49105	0.488	-0.726131	3.36742522E-4	2.52821646E-4
10	0.49503	0.536	1.018593	3.37166409E-4	2.48402257E-4
24	0.49901	0.556	2.21615	3.37433070E-4	2.47084550E-4
11	0.49503	0.552	1.844806	3.37601933E-4	2.46307111E-4
37	0.49503	0.552	1.844806	3.37612782E-4	2.46549092E-4
1	0.49503	0.552	1.844806	3.37642685E-4	2.46327155E-4
49	0.50497	0.468	-1.406927	3.37869884E-4	2.52615973E-4

TABLE M.3: Metrics using Dataset [2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
23	0.46215	0.552	1.844806	4.97661161E-4	2.47188689E-4
89	0.5259	0.444	-2.21615	4.98308685E-4	2.80188383E-4
49	0.51394	0.5	-0.389718	5.00160534E-4	2.50167336E-4
55	0.49801	0.504	-0.509405	5.00588078E-4	2.50309927E-4
51	0.54183	0.44	-2.142266	5.00712703E-4	2.74635724E-4
21	0.50598	0.488	-1.060121	5.03115190E-4	2.55112157E-4
76	0.49004	0.532	1.472866	5.04290805E-4	2.51151081E-4
75	0.53785	0.448	-1.844806	5.05054455E-4	2.89386819E-4
12	0.49004	0.512	0.439455	5.05933574E-4	2.51371674E-4
78	0.53785	0.448	-1.844806	5.08456995E-4	2.94173077E-4

M.1.2 Lag 05

TABLE M.4: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
53	0.52646	0.556	1.730434	4.47920202E-4	2.55799818E-4
26	0.5172	0.52	0.816015	4.48798191E-4	2.59022479E-4
96	0.52646	0.484	-0.350598	4.49507977E-4	2.65970947E-4
3	0.52778	0.552	1.593048	4.49533561E-4	2.58268514E-4
31	0.5291	0.496	0.072464	4.50438622E-4	2.62220810E-4
40	0.5172	0.556	1.857072	4.50914985E-4	2.56406849E-4
39	0.5119	0.512	0.60341	4.51093475E-4	2.60785615E-4
13	0.49735	0.508	0.270177	4.51397485E-4	2.59663372E-4
60	0.51587	0.532	0.91101	4.52295855E-4	2.57397336E-4
100	0.51058	0.536	1.177122	4.52603664E-4	2.57676120E-4

TABLE M.5: Metrics using Dataset [2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
3	0.50298	0.564	2.117754	3.31699612E-4	2.43822560E-4
81	0.49901	0.556	1.286049	3.31923984E-4	2.47194485E-4
11	0.50298	0.576	2.128681	3.32073074E-4	2.46667357E-4
73	0.52087	0.564	1.984416	3.32180879E-4	2.44505325E-4
85	0.52883	0.572	2.286545	3.32319106E-4	2.44313690E-4
70	0.5169	0.508	0.375874	3.32452706E-4	2.50427128E-4
67	0.51889	0.508	0.01806	3.32751669E-4	2.51841560E-4
53	0.51889	0.496	-0.14324	3.33511755E-4	2.53841954E-4
89	0.50497	0.556	1.599991	3.33891798E-4	2.49025407E-4
55	0.49304	0.588	1.973125	3.34070808E-4	2.44564176E-4

Table M.6: Metrics using Dataset [2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
100	0.50598	0.516	1.052746	4.85467665E-4	2.51391677E-4
15	0.56972	0.472	-1.238318	4.88055022E-4	2.76017026E-4
96	0.51793	0.548	0.846641	4.94038281E-4	2.51741058E-4
53	0.56175	0.456	-1.670571	4.96063213E-4	2.96281086E-4
66	0.5259	0.476	-1.553518	4.96178273E-4	2.54388472E-4
26	0.50598	0.496	-0.023948	4.97112409E-4	2.64320391E-4
8	0.50996	0.504	0.596984	4.97448878E-4	2.71865497E-4
30	0.54582	0.476	-0.699318	4.98999480E-4	2.95484387E-4
70	0.49402	0.548	1.464123	4.99193267E-4	2.45054864E-4
69	0.47012	0.56	2.569009	4.99723838E-4	2.49578609E-4

M.1.3 Lag 10

Table M.7: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
45	0.5291	0.508	2.225842	4.20835306E-4	2.53723701E-4
89	0.53704	0.508	1.760862	4.21134987E-4	2.55837991E-4
94	0.53704	0.52	1.505822	4.25084231E-4	2.52269437E-4
79	0.52116	0.528	1.413117	4.26542701E-4	2.63729900E-4
39	0.51984	0.512	2.463481	4.26969112E-4	2.54922194E-4
57	0.53968	0.544	2.750732	4.27008104E-4	2.55219461E-4
10	0.53307	0.544	2.386844	4.27069602E-4	2.46553285E-4
92	0.50529	0.532	2.812728	4.27249491E-4	2.58935160E-4
68	0.53175	0.516	1.239117	4.27497372E-4	2.55933722E-4
21	0.52116	0.488	0.741608	4.29210820E-4	2.67146419E-4

Table M.8: Metrics using Dataset [2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
35	0.53479	0.576	2.671136	3.26308190E-4	2.45110589E-4
47	0.53082	0.536	0.325403	3.28238136E-4	2.48926496E-4
93	0.51491	0.596	4.158772	3.28374392E-4	2.41377244E-4
91	0.53479	0.592	2.198228	3.28830912E-4	2.43425432E-4
62	0.53877	0.548	2.067017	3.28949387E-4	2.43810937E-4
48	0.52286	0.528	1.077973	3.29783258E-4	2.51255481E-4
81	0.54076	0.556	2.410641	3.31093736E-4	2.43669393E-4
10	0.52883	0.608	3.809094	3.31311681E-4	2.39734464E-4
39	0.50895	0.54	1.317058	3.31879957E-4	2.47101932E-4
97	0.53082	0.508	0.096233	3.32255194E-4	2.59196747E-4

TABLE M.9: Metrics using Dataset [2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
35	0.5498	0.448	-2.017237	4.74668595E-4	2.99545119E-4
92	0.53386	0.468	-0.579453	4.77045477E-4	2.68280227E-4
29	0.56972	0.48	-1.530693	4.78501215E-4	2.71254718E-4
93	0.53386	0.476	-1.077127	4.81487319E-4	2.64063590E-4
47	0.53386	0.46	-1.682488	4.84146902E-4	2.72901866E-4
48	0.50199	0.532	1.691512	4.84728403E-4	2.49216734E-4
76	0.54582	0.5	-0.242695	4.85027438E-4	2.90075631E-4
97	0.5259	0.596	3.159925	4.86871636E-4	2.40982938E-4
50	0.5498	0.452	-1.565646	4.89160968E-4	2.92182820E-4
62	0.52191	0.596	3.102744	4.89456070E-4	2.43143047E-4

M.1.4 Lag 15

TABLE M.10: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
65	0.51984	0.504	1.346288	4.15570403E-4	2.57337591E-4
6	0.52116	0.528	2.301139	4.18805623E-4	2.47797007E-4
66	0.5463	0.496	0.483135	4.18858880E-4	2.60876556E-4
88	0.52381	0.508	2.050262	4.19525855E-4	2.55964984E-4
54	0.50397	0.484	1.068446	4.19915027E-4	2.63441819E-4
32	0.53571	0.504	2.35308	4.20396231E-4	2.50163939E-4
29	0.52249	0.52	1.496344	4.20600532E-4	2.62250842E-4
37	0.52646	0.528	1.672906	4.21158496E-4	2.53631607E-4
57	0.53704	0.564	2.875719	4.21969957E-4	2.44492160E-4
34	0.53968	0.504	1.549947	4.23467989E-4	2.51929221E-4

TABLE M.11: Metrics using Dataset [2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
29	0.54473	0.504	0.610284	3.25100452E-4	2.52380995E-4
88	0.51093	0.536	1.868887	3.25550529E-4	2.46066180E-4
56	0.50696	0.592	2.74419	3.28868203E-4	2.45094331E-4
15	0.51491	0.596	3.404733	3.30640533E-4	2.38141698E-4
44	0.51093	0.516	0.522615	3.31007385E-4	2.50464300E-4
6	0.5328	0.48	-0.840411	3.31408622E-4	2.66231810E-4
20	0.54274	0.48	0.151045	3.31902195E-4	2.62052310E-4
64	0.51093	0.476	-0.277174	3.32250772E-4	2.61769463E-4
11	0.54076	0.576	2.404563	3.32324180E-4	2.42615539E-4
8	0.50497	0.528	1.292342	3.33308302E-4	2.44185196E-4

TABLE M.12: Metrics using Dataset [2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
29	0.56574	0.516	0.594542	4.63252365E-4	2.52848615E-4
6	0.56175	0.488	-0.976136	4.71319908E-4	2.80305956E-4
56	0.58167	0.492	-0.618004	4.75435408E-4	2.79932917E-4
15	0.53785	0.54	0.736905	4.77381939E-4	2.62060947E-4
69	0.57769	0.48	-1.32171	4.81383033E-4	2.79264700E-4
88	0.47809	0.592	3.177643	4.92356030E-4	2.50014185E-4
24	0.5259	0.54	0.342965	4.96648964E-4	2.70783520E-4
58	0.4741	0.556	1.673998	4.98062968E-4	2.62912574E-4
8	0.50598	0.48	-0.591315	4.98779780E-4	2.92438145E-4
11	0.58167	0.452	-1.660727	5.01874397E-4	2.99507656E-4

M.1.5 Lag 20

TABLE M.13: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
43	0.53042	0.536	2.321512	4.13662611E-4	2.47987456E-4
53	0.53704	0.544	2.747381	4.13982256E-4	2.49748009E-4
20	0.53175	0.516	1.7456	4.18881719E-4	2.58566501E-4
26	0.53571	0.516	2.532118	4.19690416E-4	2.53324751E-4
77	0.5172	0.512	1.875182	4.20038331E-4	2.59155137E-4
76	0.54101	0.568	3.709195	4.20403658E-4	2.47811749E-4
28	0.54233	0.484	1.022038	4.20551606E-4	2.52616884E-4
58	0.53175	0.508	0.92729	4.21602840E-4	2.57143025E-4
32	0.53968	0.54	2.678787	4.21668789E-4	2.55302333E-4
45	0.54233	0.508	1.782715	4.23748657E-4	2.51551396E-4

TABLE M.14: Metrics using Dataset [2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
99	0.51491	0.536	1.781728	3.24311063E-4	2.47649412E-4
77	0.52087	0.52	2.026903	3.27136819E-4	2.45343990E-4
93	0.49503	0.548	2.056047	3.27399871E-4	2.47619837E-4
20	0.54274	0.528	1.018005	3.27434531E-4	2.52544908E-4
82	0.51491	0.508	0.937425	3.27676869E-4	2.55574774E-4
54	0.50298	0.584	2.278587	3.30172201E-4	2.46497730E-4
39	0.50298	0.596	3.242377	3.30833243E-4	2.44260936E-4
55	0.52485	0.548	2.11516	3.31253756E-4	2.46238898E-4
25	0.53678	0.472	-0.562123	3.31308940E-4	2.61064332E-4
26	0.49304	0.556	1.576159	3.31327943E-4	2.48142443E-4

Table M.15: Metrics using Dataset [2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
26	0.53785	0.548	1.461464	4.76136367E-4	2.43877198E-4
55	0.51793	0.504	0.704521	4.77515755E-4	2.64213237E-4
93	0.56574	0.52	0.755577	4.79397003E-4	2.90931966E-4
25	0.56175	0.46	-0.286244	4.81112422E-4	2.90228478E-4
76	0.58566	0.464	-1.01068	4.82094033E-4	2.75711280E-4
92	0.56972	0.568	1.236791	4.88054273E-4	2.62252459E-4
17	0.5498	0.48	0.266317	4.88358606E-4	2.88148554E-4
50	0.52191	0.56	2.276481	4.91976756E-4	2.54008646E-4
61	0.54183	0.52	0.903437	4.92782247E-4	2.70900652E-4
77	0.50598	0.512	0.078983	4.92985043E-4	2.62302494E-4

M.1.6 Lag auto

Table M.16: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
62	0.51852	0.516	1.010417	4.51277615E-4	2.57158545E-4
63	0.51455	0.504	0.746706	4.51300073E-4	2.58427997E-4
76	0.51984	0.524	1.25653	4.51861851E-4	2.58750440E-4
68	0.52646	0.484	0.141664	4.51888733E-4	2.59890211E-4
6	0.53042	0.492	-0.157509	4.52558202E-4	2.63946811E-4
5	0.53439	0.476	-0.190833	4.52805820E-4	2.61903322E-4
32	0.51984	0.484	-0.440254	4.52960403E-4	2.64372875E-4
20	0.52249	0.476	-0.458485	4.53213980E-4	2.68378798E-4
92	0.5172	0.508	0.970221	4.53440840E-4	2.58643902E-4
40	0.52513	0.476	-0.546535	4.53447572E-4	2.65489873E-4

Table M.17: Metrics using Dataset [2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
5	0.52684	0.524	1.228553	3.34523748E-4	2.50259807E-4
47	0.52883	0.524	1.332185	3.34543089E-4	2.47149173E-4
68	0.49702	0.512	0.15506	3.34856770E-4	2.46139798E-4
85	0.49702	0.524	0.151989	3.34857027E-4	2.45521114E-4
94	0.50895	0.456	-1.511017	3.35573607E-4	2.50879102E-4
48	0.50099	0.476	-0.997355	3.36314227E-4	2.54483049E-4
22	0.50497	0.444	-2.019573	3.36681444E-4	2.53763912E-4
34	0.5169	0.5	0.229633	3.36934892E-4	2.51840980E-4
98	0.49503	0.456	-1.563607	3.37214603E-4	2.56141385E-4
17	0.49702	0.46	-0.745998	3.37482065E-4	2.56487089E-4

if the performance is positive is the sharpe as well?

TABLE M.18: Metrics using Dataset [2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
48	0.55777	0.488	-0.327241	4.88680304E-4	2.55575812E-4
12	0.54183	0.516	1.321638	4.88699275E-4	2.52097717E-4
95	0.52191	0.504	0.298762	4.91044026E-4	2.49824171E-4
59	0.52191	0.528	1.597818	4.91154147E-4	2.47061084E-4
32	0.48606	0.524	0.66074	4.93270981E-4	2.43254116E-4
9	0.53785	0.448	-1.844806	4.94096276E-4	2.68395697E-4
76	0.48606	0.548	1.527154	4.94278699E-4	2.46142379E-4
64	0.45418	0.484	-0.810809	4.97604562E-4	2.51280131E-4
18	0.46215	0.56	2.133201	4.99573959E-4	2.43821911E-4
66	0.54183	0.452	-1.880188	5.01985088E-4	2.67049476E-4

M.1.7 MSFT MSE Correlation 2023

Year	Lag	Correlation
2020-2023	01	0.766404
2020-2023	05	0.50027
2020-2023	10	0.76988
2020-2023	15	0.80988
2020-2023	20	0.76554
2020-2023	auto - 2	0.71185
2021-2023	01	0.950378
2021-2023	05	0.88947
2021-2023	10	0.89124
2021-2023	15	0.82773
2021-2023	20	0.86038
2021-2023	auto - 2	0.88580
2022-2023	01	0.928207
2022-2023	05	0.82131
2022-2023	10	0.76008
2022-2023	15	0.62257
2022-2023	20	0.74405
2022-2023	auto - 2	0.83790

TABLE M.19: Correlation MSE MSFT

Appendix N

Appendix RF - Bitcoin 2017

N.1 Bitcoin RF - extended Tables - 2017 Test

N.1.1 Lag 01

TABLE N.1: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
73	0.54012	0.6	2.496862	9.19136084E-4	2.45148349E-3
97	0.54012	0.6	2.496862	9.20557030E-4	2.44964988E-3
92	0.54132	0.6	2.496862	9.20815464E-4	2.45627411E-3
9	0.54491	0.59452	2.334097	9.21215559E-4	2.46123897E-3
90	0.54371	0.6	2.496862	9.21400520E-4	2.45181419E-3
21	0.54251	0.6	2.496862	9.21884162E-4	2.45020346E-3
14	0.53892	0.6	2.505704	9.22182350E-4	2.45758041E-3
40	0.54012	0.59726	2.162754	9.22571536E-4	2.45485636E-3
82	0.54132	0.6	2.496862	9.22848305E-4	2.46521555E-3
10	0.54371	0.6	2.496862	9.22848763E-4	2.45952488E-3

TABLE N.2: Metrics using Dataset [2015, 2016]-[2017] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
29	0.54993	0.6	2.496862	8.96986720E-4	2.45844394E-3
82	0.5513	0.6	2.496862	8.97484704E-4	2.46243088E-3
71	0.54993	0.6	2.496862	8.97746972E-4	2.46313867E-3
78	0.54993	0.6	2.496862	8.97977665E-4	2.45527316E-3
93	0.54993	0.6	2.496862	8.98331981E-4	2.46133210E-3
30	0.54993	0.6	2.496862	8.98493287E-4	2.46667582E-3
70	0.5472	0.6	2.505704	8.98669098E-4	2.45424610E-3
66	0.54856	0.6	2.496862	8.98712439E-4	2.45886737E-3
23	0.5513	0.6	2.496862	8.98777315E-4	2.46143153E-3
38	0.54993	0.60274	2.536642	8.98829095E-4	2.46325545E-3

Table N.3: Metrics using Dataset [2016]-[2017] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
62	0.5847	0.60274	2.971037	5.66443717E-4	2.48297984E-3
71	0.59016	0.60274	3.080639	5.66473259E-4	2.47792830E-3
78	0.5847	0.60274	2.971037	5.66875830E-4	2.48369977E-3
70	0.5847	0.60274	2.971037	5.66901021E-4	2.47983999E-3
12	0.58743	0.60548	3.115338	5.66958300E-4	2.47147643E-3
81	0.5847	0.60274	2.971037	5.67099804E-4	2.47844818E-3
50	0.58743	0.60274	2.971037	5.67138819E-4	2.47662850E-3
100	0.5847	0.60274	2.971037	5.67218887E-4	2.47841277E-3
9	0.58743	0.60274	2.971037	5.67279151E-4	2.47721423E-3
23	0.5847	0.60274	2.971037	5.67335121E-4	2.47811278E-3

N.1.2 Lag 07

Table N.4: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
31	0.57419	0.56986	1.62289	8.91508295E-4	2.46689255E-3
26	0.57419	0.55342	0.928397	8.91577295E-4	2.45967208E-3
66	0.5766	0.55068	0.972101	8.91827933E-4	2.46421513E-3
96	0.56936	0.56712	1.379183	8.91861696E-4	2.46030278E-3
52	0.5766	0.56164	1.202768	8.91961777E-4	2.45392907E-3
70	0.57298	0.56438	1.570369	8.92110010E-4	2.46342616E-3
43	0.57057	0.56438	1.477876	8.92127962E-4	2.46828367E-3
39	0.5766	0.56986	1.856612	8.92141787E-4	2.46038189E-3
44	0.57419	0.56712	1.376202	8.92143267E-4	2.46439045E-3
28	0.57539	0.55342	0.751084	8.92336071E-4	2.47162434E-3

Table N.5: Metrics using Dataset [2015, 2016]-[2017] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
78	0.57729	0.57808	1.734	8.82529698E-4	2.46271573E-3
82	0.57319	0.5589	0.878769	8.82917062E-4	2.47066963E-3
34	0.58003	0.56986	1.409113	8.83418769E-4	2.47338588E-3
29	0.57592	0.56986	1.291171	8.83422887E-4	2.47137747E-3
88	0.57592	0.56164	1.008462	8.83618842E-4	2.47147188E-3
40	0.58003	0.56164	0.987376	8.83852816E-4	2.46786739E-3
71	0.57045	0.55342	0.96606	8.83940391E-4	2.46702021E-3
1	0.5855	0.5726	1.365839	8.84378258E-4	2.46708688E-3
23	0.57729	0.5589	1.417127	8.84548872E-4	2.46809087E-3
5	0.57182	0.55068	0.756124	8.84750491E-4	2.46509100E-3

TABLE N.6: Metrics using Dataset [2016]-[2017] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
3	0.5929	0.59452	1.585973	5.51336029E-4	2.54289106E-3
47	0.60656	0.5726	1.171221	5.51480138E-4	2.53355768E-3
2	0.60383	0.59178	1.674832	5.51734600E-4	2.53574874E-3
54	0.60383	0.58356	1.062448	5.52103592E-4	2.54104233E-3
100	0.60929	0.60274	1.735165	5.52185807E-4	2.53355604E-3
84	0.60109	0.58904	1.38248	5.52199526E-4	2.53576070E-3
9	0.59836	0.57534	0.783103	5.52214451E-4	2.53577184E-3
35	0.60109	0.59726	1.718632	5.52234627E-4	2.54225985E-3
38	0.60383	0.5863	1.391287	5.52396684E-4	2.53833241E-3
79	0.60383	0.58356	1.605347	5.52419148E-4	2.52800442E-3

N.1.3 Lag 14

TABLE N.7: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
92	0.57056	0.5863	2.220976	8.81059091E-4	2.47481115E-3
80	0.57178	0.56438	1.945261	8.81417515E-4	2.48098888E-3
51	0.56813	0.58356	2.263072	8.81701671E-4	2.46852063E-3
13	0.57299	0.58904	3.013982	8.81922262E-4	2.46987219E-3
62	0.57664	0.56986	1.756466	8.81999296E-4	2.47639927E-3
39	0.57178	0.58082	2.366708	8.82201514E-4	2.48103715E-3
7	0.57543	0.60548	2.848417	8.82506590E-4	2.47810289E-3
10	0.56813	0.56164	1.537425	8.82957394E-4	2.48422740E-3
64	0.56569	0.58082	2.414308	8.82980074E-4	2.47374458E-3
17	0.56934	0.5863	2.396837	8.82994481E-4	2.47376301E-3

TABLE N.8: Metrics using Dataset [2015, 2016]-[2017] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
96	0.56498	0.54795	0.989481	8.58985726E-4	2.47655933E-3
33	0.56908	0.55068	1.203817	8.60563990E-4	2.48941790E-3
34	0.56908	0.54795	0.718947	8.60798601E-4	2.49175058E-3
24	0.57319	0.56438	1.429296	8.61583406E-4	2.48062621E-3
25	0.56635	0.5589	0.950422	8.61671898E-4	2.48680008E-3
56	0.57319	0.5589	0.800933	8.61680533E-4	2.49720253E-3
85	0.56772	0.55616	0.922812	8.62292316E-4	2.47833440E-3
23	0.57456	0.56438	1.133962	8.62327871E-4	2.48190230E-3
1	0.57045	0.55342	0.890275	8.63143492E-4	2.49122051E-3
2	0.57182	0.54247	0.756667	8.63148149E-4	2.49414722E-3

Table N.9: Metrics using Dataset [2016]-[2017] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
69	0.5929	0.5863	1.081931	5.21058266E-4	2.63684342E-3
85	0.59016	0.5863	1.318512	5.21716955E-4	2.64499346E-3
62	0.59016	0.57534	1.034404	5.21985079E-4	2.64273293E-3
9	0.58743	0.5726	1.073626	5.21989819E-4	2.64239979E-3
48	0.5929	0.56438	0.289082	5.22081199E-4	2.64615218E-3
86	0.59836	0.57808	1.110639	5.22488525E-4	2.62557002E-3
84	0.59563	0.56438	1.044783	5.22510225E-4	2.64265991E-3
49	0.5929	0.5726	0.764002	5.22788054E-4	2.62148469E-3
70	0.59016	0.56164	0.80718	5.22799476E-4	2.63869556E-3
3	0.59016	0.5726	0.878435	5.22965273E-4	2.64401267E-3

N.1.4 Lag 21

Table N.10: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
40	0.55706	0.56712	1.744477	8.70360342E-4	2.47820486E-3
83	0.56196	0.56438	1.757549	8.70713864E-4	2.47171489E-3
68	0.56074	0.58356	2.347225	8.70957264E-4	2.47391340E-3
25	0.55951	0.56986	1.821489	8.71107730E-4	2.47302004E-3
29	0.56442	0.56986	1.762398	8.71180370E-4	2.47372696E-3
18	0.56319	0.56164	1.731211	8.71249121E-4	2.47771797E-3
87	0.56442	0.57534	1.949339	8.71354999E-4	2.47961299E-3
74	0.56442	0.5726	1.879536	8.71383317E-4	2.46891332E-3
12	0.56564	0.58082	2.243944	8.71529293E-4	2.46686569E-3
38	0.55951	0.57534	1.693715	8.71573332E-4	2.46928932E-3

Table N.11: Metrics using Dataset [2015, 2016]-[2017] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
96	0.56635	0.55068	1.206944	8.60100581E-4	2.47166139E-3
33	0.56635	0.54795	1.03985	8.61140387E-4	2.48381909E-3
34	0.56908	0.54795	0.796245	8.61315096E-4	2.48697564E-3
24	0.57456	0.56164	1.374282	8.62640320E-4	2.47604210E-3
56	0.57319	0.55068	0.676668	8.62740770E-4	2.49667750E-3
70	0.56498	0.55342	1.016768	8.62808371E-4	2.48688881E-3
1	0.56772	0.54521	0.830433	8.62856977E-4	2.48597300E-3
23	0.56908	0.5589	1.034951	8.63370405E-4	2.48203212E-3
85	0.56772	0.5589	1.049579	8.63402680E-4	2.47733484E-3
7	0.56361	0.54521	0.442996	8.63456358E-4	2.49011380E-3

Table N.12: Metrics using Dataset [2016]-[2017] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
96	0.59016	0.5589	0.010523	5.15340219E-4	2.61888520E-3
9	0.5929	0.56438	0.276111	5.15554085E-4	2.62214184E-3
85	0.5847	0.54521	-0.078595	5.15834664E-4	2.62051102E-3
69	0.59016	0.56164	0.747013	5.15882126E-4	2.61800932E-3
68	0.5929	0.56712	0.652211	5.15892126E-4	2.61258607E-3
48	0.5929	0.5589	0.281284	5.15939379E-4	2.61522753E-3
2	0.5929	0.56712	0.451618	5.16070146E-4	2.61474214E-3
53	0.5847	0.58356	1.475029	5.16162085E-4	2.60577953E-3
12	0.58743	0.56164	0.564898	5.16361549E-4	2.61893628E-3
37	0.5929	0.55616	0.768261	5.16370053E-4	2.61174184E-3

N.1.5 Lag 28

Table N.13: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
93	0.57797	0.52603	-0.047502	8.65270900E-4	2.50015132E-3
57	0.57178	0.53425	-0.1007	8.65981652E-4	2.49284086E-3
2	0.58416	0.53973	0.551398	8.66277336E-4	2.48159019E-3
49	0.58168	0.53973	0.28911	8.66600838E-4	2.49013296E-3
41	0.58045	0.54795	0.632309	8.67086487E-4	2.48467093E-3
35	0.57426	0.53973	0.663648	8.67343518E-4	2.49486456E-3
69	0.58416	0.51507	0.045273	8.67344934E-4	2.48566256E-3
97	0.58168	0.53973	0.250927	8.68050537E-4	2.49699825E-3
47	0.57426	0.54247	0.283058	8.68095711E-4	2.49810453E-3
26	0.5854	0.50959	-0.221986	8.68583684E-4	2.49214824E-3

Table N.14: Metrics using Dataset [2015, 2016]-[2017] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
96	0.57866	0.53151	0.610094	8.56028802E-4	2.50103177E-3
34	0.58003	0.51233	-0.383671	8.56333568E-4	2.51378050E-3
70	0.57182	0.53151	0.29023	8.56786383E-4	2.51466189E-3
33	0.57592	0.50959	-0.150655	8.57114930E-4	2.51041619E-3
71	0.58413	0.51781	-0.072288	8.57364898E-4	2.51623596E-3
56	0.57729	0.52329	0.664916	8.57381869E-4	2.52062076E-3
77	0.57866	0.51781	0.339939	8.58354404E-4	2.50716577E-3
85	0.57866	0.52603	0.468952	8.58390951E-4	2.50855528E-3
23	0.57592	0.52877	-0.033274	8.58445375E-4	2.50335196E-3
7	0.57319	0.53151	0.312395	8.58577194E-4	2.50664042E-3

TABLE N.15: Metrics using Dataset [2016]-[2017] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
9	0.59016	0.55342	-0.153543	5.07800753E-4	2.63124337E-3
85	0.58743	0.56164	0.417813	5.09134246E-4	2.62876145E-3
68	0.5847	0.55342	0.218698	5.09209863E-4	2.61930237E-3
96	0.59836	0.54795	0.213379	5.09283837E-4	2.63139468E-3
25	0.58743	0.54247	-0.011241	5.09767024E-4	2.63280554E-3
4	0.58743	0.53973	-0.428318	5.09900567E-4	2.62916694E-3
3	0.59016	0.56164	0.530581	5.10245636E-4	2.60594916E-3
13	0.5929	0.56164	1.09891	5.10276495E-4	2.63307266E-3
100	0.59016	0.54521	-0.290056	5.10286794E-4	2.61868057E-3
23	0.59016	0.56986	0.548695	5.10386825E-4	2.62318619E-3

N.1.6 Lag auto - 6

TABLE N.16: Metrics using Dataset [2014, 2015, 2016]-[2017] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
80	0.5759	0.57808	1.657537	8.90450264E-4	2.47033387E-3
9	0.57831	0.58082	1.95846	8.90964495E-4	2.46409424E-3
16	0.57711	0.5726	2.097742	8.91001415E-4	2.46405406E-3
49	0.57349	0.5726	1.834944	8.91569740E-4	2.45972853E-3
99	0.58072	0.57808	2.135154	8.91758448E-4	2.46156915E-3
75	0.5747	0.57534	2.023673	8.91774014E-4	2.45806211E-3
44	0.57711	0.5863	2.612095	8.92088355E-4	2.47234316E-3
96	0.57711	0.58082	2.233447	8.92118209E-4	2.45785966E-3
81	0.57711	0.57808	1.83773	8.92572797E-4	2.46544947E-3
43	0.5759	0.56164	1.527446	8.92607231E-4	2.46898788E-3

TABLE N.17: Metrics using Dataset [2015, 2016]-[2017] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
71	0.57729	0.57534	1.648338	8.82936274E-4	2.46323647E-3
88	0.57729	0.57808	1.481437	8.82982825E-4	2.46961606E-3
30	0.57456	0.58904	1.897385	8.83527764E-4	2.46450340E-3
82	0.57866	0.57808	1.515581	8.83544037E-4	2.47071829E-3
29	0.57866	0.56438	1.184524	8.83687903E-4	2.46811384E-3
34	0.5855	0.5863	1.700109	8.83794007E-4	2.47389130E-3
25	0.57319	0.58904	1.66451	8.84000901E-4	2.46716376E-3
23	0.57729	0.58082	1.953446	8.84005438E-4	2.46279896E-3
40	0.5855	0.57808	1.249276	8.84160993E-4	2.46633749E-3
67	0.57729	0.56164	0.793447	8.84678286E-4	2.46916098E-3

Table N.18: Metrics using Dataset [2016]-[2017] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
3	0.58743	0.57534	0.936494	5.51354003E-4	2.53884439E-3
2	0.59836	0.58356	1.36825	5.52138719E-4	2.53718526E-3
47	0.60383	0.5726	1.179063	5.52396596E-4	2.53096657E-3
37	0.59563	0.5863	1.664457	5.52412828E-4	2.52787930E-3
27	0.59016	0.59178	1.481651	5.52538259E-4	2.53608121E-3
100	0.5929	0.58904	1.573842	5.52676259E-4	2.53079250E-3
39	0.59836	0.57808	1.031668	5.52806237E-4	2.52877929E-3
9	0.5929	0.59178	1.566059	5.52934896E-4	2.53086447E-3
81	0.59836	0.59726	2.018599	5.53021086E-4	2.53430580E-3
64	0.59836	0.58356	1.207959	5.53082111E-4	2.53911126E-3

N.1.7 Bitcoin MSE Correlation 2017

Year	Lag	Correlation
2014-2017	01	0.438484
2014-2017	07	0.269436
2014-2017	14	0.457702
2014-2017	21	0.356639
2014-2017	28	0.169246
2014-2017	auto - 6	0.380722
2015-2017	01	0.291654
2015-2017	07	0.331039
2015-2017	14	0.170833
2015-2017	21	0.144196
2015-2017	28	0.003882
2015-2017	auto - 6	0.367879
2016-2017	01	-0.380746
2016-2017	07	0.106278
2016-2017	14	-0.398356
2016-2017	21	-0.470476
2016-2017	28	-0.26437
2016-2017	auto - 6	0.128207

Table N.19: Correlation MSE Bitcoin

Appendix O

Appendix RF - Bitcoin 2018

O.1 Bitcoin RF - extended Tables - 2018 Test

O.1.1 Lag 01

Table O.1: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
82	0.56843	0.50959	-1.825405	1.38082077E-3	1.98214648E-3
39	0.57026	0.50959	-1.825405	1.38084131E-3	1.96416076E-3
92	0.56843	0.50959	-1.825405	1.38103851E-3	1.98965743E-3
11	0.57208	0.49863	-1.742088	1.38135622E-3	1.97565789E-3
83	0.56934	0.50959	-1.825405	1.38136847E-3	1.96675096E-3
74	0.56934	0.50959	-1.825405	1.38139153E-3	1.97340048E-3
96	0.57026	0.50959	-1.825405	1.38140637E-3	1.98302554E-3
57	0.57117	0.50959	-1.825405	1.38143967E-3	1.96672488E-3
4	0.57026	0.50959	-1.825405	1.38148026E-3	1.95885772E-3
30	0.57117	0.50959	-1.825405	1.38148378E-3	1.97407469E-3

Table O.2: Metrics using Dataset [2016, 2017]-[2018] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
50	0.59644	0.47397	-2.452551	1.43930706E-3	1.93255317E-3
29	0.59234	0.48219	-1.698216	1.43962945E-3	1.92640021E-3
69	0.59644	0.47397	-2.452551	1.44003063E-3	1.92930196E-3
66	0.60055	0.48767	-1.79509	1.44004096E-3	1.92734055E-3
51	0.59644	0.48493	-1.440741	1.44031492E-3	1.92374412E-3
93	0.59234	0.48219	-1.698216	1.44035106E-3	1.92425097E-3
12	0.59508	0.48219	-1.698216	1.44054783E-3	1.92487619E-3
39	0.59234	0.48219	-1.698216	1.44055486E-3	1.92132871E-3
77	0.59644	0.47397	-2.452551	1.44062336E-3	1.92962160E-3
41	0.59644	0.47397	-2.452551	1.44070845E-3	1.92281610E-3

TABLE O.3: Metrics using Dataset [2017]-[2018] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
81	0.6274	0.49041	-1.164585	2.20097482E-3	1.97016970E-3
73	0.63014	0.49863	-1.032407	2.20099080E-3	1.96232858E-3
53	0.63014	0.49315	-0.837664	2.20168922E-3	1.97375570E-3
85	0.62466	0.49041	-1.164585	2.20324455E-3	1.96675358E-3
79	0.62466	0.49041	-1.164585	2.20333360E-3	1.96161608E-3
18	0.6274	0.49041	-1.164585	2.20340599E-3	1.97394288E-3
67	0.63014	0.49041	-0.917562	2.20343067E-3	1.96400163E-3
16	0.63014	0.49041	-0.917562	2.20373249E-3	1.96917970E-3
91	0.63014	0.49041	-0.917562	2.20376217E-3	1.96095258E-3
60	0.6274	0.49041	-0.917562	2.20381761E-3	1.96335454E-3

O.1.2 Lag 07

TABLE O.4: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
42	0.57391	0.52603	-0.496278	1.36434133E-3	1.88915933E-3
96	0.57482	0.52329	-0.693909	1.36435151E-3	1.89478137E-3
74	0.57482	0.52055	-0.844735	1.36467058E-3	1.89522261E-3
57	0.57299	0.52603	-0.687946	1.36474393E-3	1.89233595E-3
52	0.57482	0.52055	-0.860192	1.36504858E-3	1.89526684E-3
65	0.57573	0.51781	-1.064597	1.36544485E-3	1.88762392E-3
86	0.57117	0.52055	-0.934493	1.36546814E-3	1.90077835E-3
82	0.57391	0.52055	-0.795842	1.36553731E-3	1.89880356E-3
72	0.57391	0.52603	-0.496278	1.36554091E-3	1.89187875E-3
55	0.57299	0.52603	-0.687946	1.36578052E-3	1.89367264E-3

TABLE O.5: Metrics using Dataset [2016, 2017]-[2018] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
1	0.60192	0.52603	-0.296544	1.39980241E-3	1.87410430E-3
48	0.60739	0.52055	-0.554657	1.39987325E-3	1.87051038E-3
78	0.60328	0.52603	-0.296544	1.39992862E-3	1.87726246E-3
19	0.60739	0.52603	-0.296544	1.40003169E-3	1.87953247E-3
50	0.60602	0.52329	-0.646668	1.40007371E-3	1.88027686E-3
49	0.60739	0.52603	-0.296544	1.40026220E-3	1.87698822E-3
88	0.60876	0.52603	-0.296544	1.40028396E-3	1.87289356E-3
35	0.59918	0.52329	-0.524007	1.40039116E-3	1.86759726E-3
33	0.60192	0.52603	-0.296544	1.40062552E-3	1.88160168E-3
28	0.60465	0.51781	-0.712172	1.40076978E-3	1.88282788E-3

Table O.6: Metrics using Dataset [2017]-[2018] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
56	0.63288	0.52877	-0.325132	2.11304052E-3	1.90751825E-3
85	0.63288	0.52877	-0.352855	2.11432546E-3	1.90855774E-3
68	0.63014	0.52603	-0.417639	2.11433244E-3	1.91115676E-3
27	0.6274	0.52877	-0.352855	2.11495751E-3	1.90096909E-3
99	0.63014	0.52877	-0.352855	2.11544870E-3	1.90165507E-3
66	0.63014	0.52877	-0.325132	2.11594993E-3	1.91027526E-3
54	0.63562	0.52877	-0.352855	2.11635800E-3	1.89741893E-3
74	0.63014	0.53151	-0.260365	2.11639883E-3	1.90960641E-3
47	0.63014	0.53151	-0.260365	2.11663807E-3	1.91267833E-3
79	0.63562	0.52877	-0.352855	2.11672843E-3	1.91497656E-3

O.1.3 Lag 14

Table O.7: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
74	0.57938	0.51781	-0.789956	1.35865850E-3	1.88895032E-3
96	0.57847	0.51507	-0.802036	1.35875975E-3	1.88848125E-3
57	0.57755	0.51781	-0.789956	1.35907154E-3	1.88920575E-3
42	0.57847	0.51233	-0.968809	1.35985590E-3	1.89297157E-3
23	0.57847	0.52055	-0.762242	1.35990212E-3	1.88726096E-3
51	0.57938	0.50959	-1.375483	1.35990450E-3	1.89166181E-3
77	0.5812	0.50685	-1.220223	1.35994542E-3	1.89236522E-3
30	0.58212	0.51507	-0.802036	1.36022018E-3	1.89388344E-3
33	0.57847	0.51507	-0.802036	1.36025703E-3	1.88998318E-3
81	0.58394	0.51507	-0.934573	1.36030458E-3	1.89052919E-3

Table O.8: Metrics using Dataset [2016, 2017]-[2018] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
19	0.60602	0.52603	-0.241495	1.39311006E-3	1.87703838E-3
48	0.60328	0.52329	-0.460645	1.39328966E-3	1.86405913E-3
78	0.60602	0.52329	-0.460645	1.39357448E-3	1.87486508E-3
38	0.60602	0.52329	-0.460645	1.39365483E-3	1.87825319E-3
50	0.60328	0.52329	-0.468919	1.39368822E-3	1.87435467E-3
42	0.60602	0.52055	-0.68826	1.39383620E-3	1.87416925E-3
1	0.60465	0.52603	-0.241495	1.39393331E-3	1.87631025E-3
49	0.60602	0.52329	-0.460645	1.39396878E-3	1.87614070E-3
35	0.60328	0.52603	-0.404124	1.39418877E-3	1.86864689E-3
54	0.60328	0.52603	-0.432977	1.39424045E-3	1.88027351E-3

TABLE O.9: Metrics using Dataset [2017]-[2018] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
56	0.63014	0.53151	-0.149091	2.09925136E-3	1.89892409E-3
74	0.6274	0.53151	-0.260365	2.10177515E-3	1.90567123E-3
19	0.63836	0.52877	-0.17656	2.10293035E-3	1.89360171E-3
53	0.63288	0.52603	-0.326734	2.10303522E-3	1.90275667E-3
79	0.63288	0.53151	-0.149091	2.10418858E-3	1.90227135E-3
81	0.63014	0.52877	-0.24156	2.10431377E-3	1.90795674E-3
92	0.63562	0.52603	-0.326734	2.10478175E-3	1.90312777E-3
25	0.63562	0.52877	-0.17656	2.10503835E-3	1.90532122E-3
82	0.63288	0.53151	-0.149091	2.10530782E-3	1.89693626E-3
21	0.63288	0.53151	-0.149091	2.10532654E-3	1.90597485E-3

O.1.4 Lag 21

TABLE O.10: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
74	0.57847	0.51507	-0.822238	1.35903642E-3	1.89351687E-3
96	0.57847	0.51507	-0.822238	1.35964992E-3	1.89469922E-3
51	0.57938	0.50959	-1.209199	1.36017198E-3	1.89128135E-3
57	0.57755	0.51507	-0.822238	1.36089747E-3	1.89296488E-3
39	0.57938	0.51781	-0.794698	1.36120913E-3	1.89420373E-3
23	0.57664	0.51507	-0.822238	1.36202072E-3	1.89063013E-3
77	0.57847	0.50411	-1.32322	1.36202601E-3	1.89667550E-3
66	0.58029	0.51507	-0.822238	1.36220543E-3	1.89454542E-3
52	0.57938	0.51781	-0.794698	1.36224402E-3	1.89803064E-3
89	0.58029	0.51781	-0.794518	1.36233933E-3	1.89509540E-3

TABLE O.11: Metrics using Dataset [2016, 2017]-[2018] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
49	0.60739	0.51781	-0.511263	1.38436882E-3	1.89557084E-3
13	0.60465	0.52055	-0.367651	1.38475029E-3	1.89613874E-3
1	0.60465	0.52055	-0.483589	1.38540327E-3	1.89487796E-3
81	0.60602	0.52329	-0.451318	1.38549626E-3	1.89189363E-3
78	0.60465	0.52603	-0.419097	1.38581322E-3	1.89185803E-3
83	0.60465	0.52329	-0.396246	1.38595227E-3	1.89354984E-3
93	0.60602	0.51781	-0.702946	1.38605500E-3	1.89557440E-3
40	0.60602	0.52329	-0.451318	1.38629203E-3	1.89499496E-3
42	0.60465	0.51781	-0.517908	1.38641245E-3	1.89269597E-3
48	0.60602	0.51781	-0.456178	1.38646499E-3	1.88308328E-3

TABLE O.12: Metrics using Dataset [2017]-[2018] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
95	0.63288	0.53151	-0.174958	2.08488776E-3	1.92197719E-3
82	0.63014	0.53151	-0.174958	2.08907004E-3	1.91386072E-3
92	0.6274	0.52329	-0.391513	2.08982149E-3	1.91307511E-3
19	0.63014	0.53151	-0.149091	2.08995613E-3	1.90779144E-3
90	0.63014	0.52603	-0.419097	2.09046838E-3	1.92193621E-3
56	0.63014	0.52877	-0.213844	2.09050531E-3	1.91564144E-3
25	0.63014	0.53151	-0.260365	2.09109091E-3	1.91707827E-3
67	0.63014	0.53151	-0.149091	2.09217264E-3	1.90613160E-3
68	0.63014	0.53151	-0.174958	2.09230954E-3	1.91641090E-3
79	0.63014	0.52877	-0.325132	2.09315448E-3	1.92195180E-3

O.1.5 Lag 28

TABLE O.13: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
74	0.57847	0.51507	-0.822238	1.36037047E-3	1.89019956E-3
96	0.57938	0.51781	-0.789956	1.36083017E-3	1.89393551E-3
67	0.58029	0.52055	-0.762421	1.36182568E-3	1.89177760E-3
89	0.57938	0.51781	-0.794518	1.36223834E-3	1.89785268E-3
57	0.57847	0.52055	-0.762242	1.36226584E-3	1.893663545E-3
51	0.58029	0.50685	-1.312184	1.36241221E-3	1.89235015E-3
5	0.58212	0.51781	-0.845139	1.36244361E-3	1.89854747E-3
77	0.58029	0.50685	-1.312184	1.36266084E-3	1.89759885E-3
1	0.58212	0.51781	-0.789956	1.36277436E-3	1.89170417E-3
52	0.58029	0.51781	-0.911577	1.36279417E-3	1.89691561E-3

TABLE O.14: Metrics using Dataset [2016, 2017]-[2018] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
97	0.60602	0.52055	-0.622124	1.38324220E-3	1.89311868E-3
1	0.60602	0.52329	-0.451318	1.38386399E-3	1.89652393E-3
50	0.60739	0.52055	-0.490233	1.38390070E-3	1.89644042E-3
35	0.60739	0.52603	-0.301096	1.38396239E-3	1.88981495E-3
81	0.60602	0.52329	-0.451318	1.38403352E-3	1.89594723E-3
13	0.60465	0.52055	-0.547965	1.38420439E-3	1.89689641E-3
60	0.60602	0.52329	-0.451318	1.38428721E-3	1.89978746E-3
49	0.60739	0.52329	-0.520287	1.38444851E-3	1.90460754E-3
59	0.60739	0.52603	-0.419097	1.38542357E-3	1.90185525E-3
40	0.60602	0.52329	-0.451318	1.38564145E-3	1.89828624E-3

TABLE O.15: Metrics using Dataset [2017]-[2018] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
95	0.63562	0.52877	-0.268889	2.07159196E-3	1.93843781E-3
82	0.63288	0.53151	-0.20413	2.07341952E-3	1.92357849E-3
22	0.63014	0.53151	-0.20413	2.07479894E-3	1.93090545E-3
53	0.63288	0.52877	-0.354313	2.07562462E-3	1.92672073E-3
67	0.63014	0.52877	-0.354313	2.07586738E-3	1.92259549E-3
20	0.63836	0.53151	-0.20413	2.07619668E-3	1.92474856E-3
18	0.63836	0.52877	-0.268889	2.07647180E-3	1.94026189E-3
32	0.63562	0.52877	-0.268889	2.07692573E-3	1.93120993E-3
60	0.63562	0.52603	-0.304173	2.07699845E-3	1.93355113E-3
25	0.63562	0.52603	-0.304173	2.07709882E-3	1.93932599E-3

O.1.6 Lag auto - 6

TABLE O.16: Metrics using Dataset [2015, 2016, 2017]-[2018] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
42	0.57391	0.52329	-0.693909	1.36449490E-3	1.89306889E-3
74	0.57573	0.52329	-0.693909	1.36463828E-3	1.89570961E-3
96	0.57482	0.52329	-0.693909	1.36514737E-3	1.89510622E-3
57	0.57299	0.52055	-1.0365	1.36554783E-3	1.89571967E-3
52	0.57482	0.52055	-0.817595	1.36593458E-3	1.89633209E-3
55	0.57391	0.52055	-1.0365	1.36597906E-3	1.89508513E-3
82	0.57391	0.52055	-0.913531	1.36606104E-3	1.89936156E-3
92	0.57391	0.52055	-0.913531	1.36607938E-3	1.90183493E-3
86	0.57299	0.52055	-0.98311	1.36627610E-3	1.90005457E-3
65	0.57482	0.51781	-0.986128	1.36634679E-3	1.88579091E-3

TABLE O.17: Metrics using Dataset [2016, 2017]-[2018] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
49	0.60876	0.51507	-0.739878	1.39934271E-3	1.87728457E-3
35	0.60055	0.52329	-0.524007	1.39955592E-3	1.86703019E-3
50	0.60328	0.52329	-0.484293	1.40042167E-3	1.88220428E-3
28	0.60602	0.51507	-0.931821	1.40053368E-3	1.87962700E-3
48	0.60465	0.51781	-0.705037	1.40057771E-3	1.87301428E-3
1	0.60192	0.52329	-0.33183	1.40070751E-3	1.87649629E-3
78	0.60328	0.52329	-0.515731	1.40075520E-3	1.87816069E-3
54	0.60192	0.51781	-0.905229	1.40088208E-3	1.87981801E-3
88	0.60602	0.52329	-0.446764	1.40098014E-3	1.87379319E-3
42	0.60328	0.51233	-0.959568	1.40129106E-3	1.87659596E-3

TABLE O.18: Metrics using Dataset [2017]-[2018] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
56	0.63014	0.52329	-0.646668	2.12069050E-3	1.89994213E-3
68	0.62192	0.52603	-0.419097	2.12309963E-3	1.90346732E-3
90	0.62466	0.52603	-0.419097	2.12335899E-3	1.90217831E-3
79	0.6274	0.52329	-0.646668	2.12422884E-3	1.90358997E-3
71	0.63014	0.52603	-0.419097	2.12511019E-3	1.90020517E-3
47	0.63014	0.51781	-0.712172	2.12527229E-3	1.90396328E-3
67	0.6274	0.52603	-0.419097	2.12572862E-3	1.89078994E-3
20	0.6274	0.52329	-0.496749	2.12590561E-3	1.89891334E-3
66	0.6274	0.52603	-0.419097	2.12601079E-3	1.90305173E-3
27	0.62192	0.52603	-0.419097	2.12622244E-3	1.89353366E-3

O.1.7 Bitcoin MSE Correlation

Year	Lag	Correlation
2015-2018	01	-0.440123
2015-2018	07	-0.004219
2015-2018	14	-0.048855
2015-2018	21	0.000407
2015-2018	28	0.05927
2015-2018	auto - 6	-0.04778
2016-2018	01	-0.138661
2016-2018	07	0.14758
2016-2018	14	0.096731
2016-2018	21	-0.01229
2016-2018	28	-0.044847
2016-2018	auto - 6	0.191356
2017-2018	01	0.207652
2017-2018	07	0.028251
2017-2018	14	0.011133
2017-2018	21	0.021088
2017-2018	28	-0.058196
2017-2018	auto - 6	0.028635

TABLE O.19: Correlation MSE Bitcoin

Appendix P

Appendix RF - Bitcoin 2022

P.1 Bitcoin RF - extended Tables - 2022 Test

P.1.1 Lag 01

Table P.1: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
28	0.54106	0.46575	-1.624646	1.48644713E-3	1.15820748E-3
13	0.53832	0.46575	-1.624646	1.48812869E-3	1.15992837E-3
25	0.54015	0.46575	-1.624646	1.48826253E-3	1.15853766E-3
85	0.54015	0.46575	-1.624646	1.48836592E-3	1.15865855E-3
82	0.53832	0.46575	-1.624646	1.48841474E-3	1.15944625E-3
68	0.54015	0.46575	-1.624646	1.48843290E-3	1.15624927E-3
44	0.53832	0.46575	-1.624646	1.48848082E-3	1.15814410E-3
96	0.54106	0.46575	-1.624646	1.48866406E-3	1.15944422E-3
94	0.53832	0.46575	-1.624646	1.48874585E-3	1.15751069E-3
66	0.53832	0.46575	-1.624646	1.48885168E-3	1.15845686E-3

Table P.2: Metrics using Dataset [2020, 2021]-[2022] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
96	0.5472	0.46575	-1.624646	1.61369216E-3	1.15562539E-3
7	0.5472	0.46575	-1.624646	1.61450945E-3	1.15626401E-3
98	0.56498	0.47397	-1.504898	1.61466050E-3	1.15415545E-3
78	0.56635	0.47397	-1.413281	1.61487135E-3	1.15525689E-3
63	0.54583	0.46575	-1.624646	1.61512365E-3	1.15599361E-3
13	0.5472	0.46575	-1.624646	1.61518192E-3	1.15377293E-3
90	0.5472	0.46575	-1.624646	1.61529460E-3	1.15605282E-3
55	0.5472	0.46575	-1.624646	1.61560030E-3	1.15707394E-3
16	0.54856	0.46575	-1.624646	1.61587363E-3	1.15555937E-3
4	0.56224	0.47123	-1.470926	1.61595770E-3	1.15591392E-3

TABLE P.3: Metrics using Dataset [2021]-[2022] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
47	0.6137	0.49863	-0.248663	1.65319603E-3	1.14028506E-3
73	0.57808	0.49863	-0.137651	1.65401349E-3	1.13840061E-3
16	0.60548	0.49863	-0.149709	1.65458113E-3	1.14118704E-3
3	0.60274	0.49863	-0.198442	1.65462277E-3	1.13915724E-3
71	0.60548	0.49589	-0.189407	1.65467647E-3	1.13659262E-3
57	0.6	0.49589	-0.267301	1.65470775E-3	1.14014174E-3
8	0.6	0.51233	0.17794	1.65499250E-3	1.13546829E-3
34	0.60548	0.49863	-0.198442	1.65511816E-3	1.13803908E-3
38	0.61096	0.49863	-0.210134	1.65524071E-3	1.13961426E-3
84	0.58082	0.49863	-0.094938	1.65532638E-3	1.13709926E-3

P.1.2 Lag 07

TABLE P.4: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
97	0.53923	0.45479	-1.477272	1.33786084E-3	1.16482629E-3
66	0.54015	0.45479	-1.477272	1.33897145E-3	1.16515170E-3
7	0.5438	0.45753	-1.158087	1.33966930E-3	1.16550696E-3
22	0.54106	0.45479	-1.477272	1.34134639E-3	1.16334326E-3
72	0.54106	0.45753	-1.158087	1.34174520E-3	1.16732233E-3
27	0.54106	0.45479	-1.477272	1.34234554E-3	1.16556813E-3
87	0.5438	0.45205	-1.520827	1.34286384E-3	1.16164279E-3
10	0.54106	0.45205	-1.520827	1.34305974E-3	1.16523844E-3
2	0.54288	0.44932	-1.604003	1.34311064E-3	1.16443474E-3
19	0.54015	0.45479	-1.477272	1.34317108E-3	1.16531450E-3

TABLE P.5: Metrics using Dataset [2020, 2021]-[2022] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
97	0.54993	0.45753	-1.086619	1.36939973E-3	1.21464321E-3
11	0.54993	0.45753	-1.089719	1.37158354E-3	1.20928696E-3
12	0.54993	0.45479	-1.186205	1.37209864E-3	1.22964680E-3
9	0.54993	0.45753	-1.086619	1.37226477E-3	1.19718754E-3
21	0.54856	0.45479	-1.186205	1.37286432E-3	1.21288877E-3
100	0.54993	0.45479	-1.137617	1.37292019E-3	1.21061483E-3
27	0.5472	0.45753	-1.505138	1.37337328E-3	1.20930247E-3
64	0.54993	0.45479	-1.137617	1.37355102E-3	1.21329036E-3
30	0.54993	0.45479	-1.137617	1.37356749E-3	1.20896427E-3
31	0.54856	0.45479	-1.186205	1.37361276E-3	1.21596304E-3

TABLE P.6: Metrics using Dataset [2021]-[2022] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
39	0.62192	0.46027	-1.188249	1.57191457E-3	1.17066971E-3
55	0.60548	0.46849	-0.804476	1.57211495E-3	1.16716516E-3
47	0.61096	0.45205	-1.192171	1.57259176E-3	1.16281604E-3
89	0.61918	0.47397	-0.306051	1.57273257E-3	1.16942055E-3
90	0.61644	0.46301	-0.950297	1.57314165E-3	1.16165655E-3
72	0.61644	0.46849	-1.010973	1.57319795E-3	1.16843091E-3
62	0.6137	0.45205	-1.128514	1.57369407E-3	1.16537421E-3
31	0.6	0.46575	-0.473033	1.57434997E-3	1.16526674E-3
85	0.62466	0.46575	-0.838678	1.57445024E-3	1.16705221E-3
35	0.59726	0.46027	-1.137303	1.57500912E-3	1.16920420E-3

P.1.3 Lag 14

TABLE P.7: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
97	0.54288	0.45753	-1.472763	1.33789899E-3	1.16803713E-3
66	0.54562	0.45205	-1.479197	1.33899234E-3	1.16836017E-3
7	0.54562	0.45205	-1.479197	1.34041218E-3	1.16744881E-3
22	0.54288	0.45479	-1.477272	1.34190225E-3	1.16645580E-3
72	0.5438	0.45479	-1.474688	1.34226829E-3	1.16992393E-3
4	0.54471	0.45479	-1.477272	1.34297322E-3	1.16962985E-3
19	0.54471	0.45205	-1.479197	1.34316569E-3	1.16450934E-3
10	0.5438	0.45205	-1.479197	1.34329195E-3	1.16324427E-3
27	0.5438	0.45205	-1.479197	1.34338958E-3	1.16919475E-3
78	0.54471	0.45479	-1.477272	1.34412383E-3	1.16366931E-3

TABLE P.8: Metrics using Dataset [2020, 2021]-[2022] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
11	0.5513	0.45205	-1.254133	1.36506276E-3	1.22106136E-3
9	0.55267	0.45205	-1.254133	1.36508815E-3	1.20231859E-3
38	0.54993	0.45205	-1.35869	1.36663524E-3	1.21596074E-3
97	0.55267	0.45205	-1.254133	1.36680538E-3	1.21665429E-3
75	0.5554	0.45205	-1.254133	1.36710389E-3	1.21027856E-3
60	0.55267	0.45205	-1.254133	1.36733038E-3	1.20358532E-3
64	0.55267	0.45205	-1.254133	1.36767153E-3	1.21277628E-3
46	0.54856	0.45205	-1.254133	1.36807674E-3	1.21490056E-3
21	0.5513	0.45205	-1.254133	1.36812105E-3	1.22145534E-3
85	0.5554	0.45205	-1.254133	1.36832568E-3	1.21390717E-3

Table P.9: Metrics using Dataset [2021]-[2022] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.55342	0.45753	-1.077759	1.53002576E-3	1.18572723E-3
11	0.5589	0.46849	-0.94072	1.53019750E-3	1.17712647E-3
40	0.55342	0.45205	-1.20161	1.53058191E-3	1.18559521E-3
23	0.56164	0.46301	-0.990047	1.53131806E-3	1.18171117E-3
39	0.56164	0.46027	-1.101158	1.53139844E-3	1.18421933E-3
16	0.56712	0.46027	-1.031739	1.53176774E-3	1.18572586E-3
9	0.56164	0.46301	-0.990047	1.53197154E-3	1.18261845E-3
85	0.55068	0.45753	-1.119016	1.53222194E-3	1.18573768E-3
6	0.55616	0.45753	-1.119016	1.53223064E-3	1.18259067E-3
69	0.55616	0.46301	-0.990047	1.53226038E-3	1.18336496E-3

Table P.10: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
97	0.54562	0.46027	-1.419327	1.33822033E-3	1.16594761E-3
22	0.54471	0.46575	-1.266054	1.34024711E-3	1.16422558E-3
7	0.54836	0.45753	-1.46944	1.34051519E-3	1.16662448E-3
72	0.5438	0.46301	-1.379201	1.34141269E-3	1.16736930E-3
27	0.54562	0.46027	-1.429291	1.34166796E-3	1.16768317E-3
66	0.5438	0.46301	-1.379201	1.34190140E-3	1.16843459E-3
52	0.54288	0.46301	-1.379201	1.34235007E-3	1.17037173E-3
91	0.54562	0.46027	-1.429291	1.34270081E-3	1.16612084E-3
2	0.5438	0.46027	-1.429291	1.34279822E-3	1.16545760E-3
4	0.54745	0.46027	-1.419327	1.34310936E-3	1.16163607E-3

Table P.11: Metrics using Dataset [2020, 2021]-[2022] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
64	0.5554	0.45205	-1.254133	1.36234596E-3	1.21756194E-3
11	0.55814	0.45205	-1.254133	1.36328256E-3	1.21749060E-3
12	0.55677	0.45479	-1.310686	1.36377978E-3	1.22281739E-3
97	0.5554	0.44932	-1.366412	1.36389038E-3	1.22761884E-3
9	0.5554	0.45205	-1.254133	1.36453922E-3	1.21962764E-3
60	0.55267	0.45205	-1.254133	1.36485428E-3	1.20633703E-3
41	0.55677	0.45205	-1.254133	1.36506118E-3	1.21062347E-3
38	0.5554	0.45205	-1.677327	1.36544621E-3	1.22524854E-3
90	0.55404	0.45205	-1.677327	1.36606543E-3	1.21344926E-3
67	0.55677	0.44932	-1.366412	1.36634320E-3	1.21839532E-3

TABLE P.12: Metrics using Dataset [2021]-[2022] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
35	0.5589	0.46301	-1.126992	1.52290402E-3	1.16290530E-3
23	0.55342	0.46575	-1.05831	1.52350328E-3	1.17131336E-3
55	0.56438	0.46027	-1.089762	1.52379036E-3	1.16807215E-3
6	0.55342	0.46027	-1.08673	1.52430241E-3	1.16729458E-3
14	0.56164	0.46575	-0.991207	1.52432638E-3	1.16862912E-3
100	0.55616	0.46301	-1.092072	1.52440837E-3	1.17426745E-3
90	0.55342	0.46575	-0.91819	1.52460370E-3	1.16704532E-3
31	0.5589	0.46849	-1.112932	1.52513408E-3	1.16907662E-3
16	0.5589	0.46301	-1.077977	1.52530424E-3	1.17307433E-3
77	0.55616	0.45479	-1.364638	1.52583929E-3	1.16920594E-3

P.1.4 Lag 28

TABLE P.13: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
97	0.54653	0.45753	-1.46944	1.33789741E-3	1.17374075E-3
72	0.54653	0.46301	-1.379201	1.33823946E-3	1.17665833E-3
7	0.54745	0.45753	-1.46944	1.33851709E-3	1.17453419E-3
2	0.55018	0.45753	-1.46944	1.33939136E-3	1.16857325E-3
22	0.54653	0.46027	-1.537837	1.33945628E-3	1.17097279E-3
66	0.54471	0.46575	-1.269897	1.34016710E-3	1.18068600E-3
85	0.54745	0.46301	-1.379201	1.34032956E-3	1.17180454E-3
52	0.54653	0.46301	-1.379201	1.34040389E-3	1.17806455E-3
4	0.54562	0.46301	-1.309974	1.34096251E-3	1.17443287E-3
27	0.54836	0.45753	-1.46944	1.34104003E-3	1.17964259E-3

TABLE P.14: Metrics using Dataset [2020, 2021]-[2022] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
11	0.55267	0.44658	-1.733308	1.35203672E-3	1.23020104E-3
97	0.56224	0.44932	-1.325907	1.35484063E-3	1.22397949E-3
64	0.55814	0.45205	-1.254133	1.35562968E-3	1.22448374E-3
100	0.55677	0.45205	-1.233044	1.35687514E-3	1.22838874E-3
60	0.55814	0.44932	-1.347388	1.35717893E-3	1.21670790E-3
12	0.55814	0.45479	-1.310686	1.35753648E-3	1.24393006E-3
9	0.56361	0.44932	-1.316116	1.35762402E-3	1.21854133E-3
31	0.55677	0.44932	-1.411723	1.35766104E-3	1.22549509E-3
30	0.55951	0.45205	-1.677327	1.35833960E-3	1.22571925E-3
98	0.55951	0.44932	-1.347388	1.35838753E-3	1.21947450E-3

Table P.15: Metrics using Dataset [2021]-[2022] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
31	0.58356	0.43836	-1.463382	1.51583143E-3	1.16805800E-3
100	0.5726	0.44384	-1.307023	1.51634535E-3	1.17121563E-3
26	0.57808	0.44932	-1.237797	1.51713101E-3	1.16293685E-3
77	0.58356	0.43836	-1.54769	1.51714644E-3	1.17040854E-3
56	0.57808	0.43836	-1.6018	1.51721890E-3	1.16988712E-3
55	0.58356	0.44384	-1.346655	1.51729107E-3	1.16841808E-3
81	0.5726	0.4411	-1.649289	1.51749126E-3	1.16879006E-3
35	0.56986	0.4411	-1.431806	1.51757577E-3	1.16289638E-3
16	0.57534	0.44658	-1.32969	1.51779315E-3	1.17273660E-3
85	0.5726	0.45205	-1.385338	1.51788840E-3	1.17087540E-3

P.1.5 Lag auto - 6

Table P.16: Metrics using Dataset [2019, 2020, 2021]-[2022] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
7	0.5438	0.45479	-1.198119	1.32983918E-3	1.17945810E-3
97	0.54015	0.45205	-1.241539	1.33230899E-3	1.18322139E-3
77	0.5438	0.44932	-1.561021	1.33478354E-3	1.18085617E-3
66	0.54288	0.44932	-1.561021	1.33496651E-3	1.18148377E-3
22	0.54197	0.45205	-1.241539	1.33601348E-3	1.17550336E-3
27	0.54106	0.44932	-1.324444	1.33647245E-3	1.18080688E-3
49	0.54197	0.45205	-1.241539	1.33699526E-3	1.17767848E-3
87	0.54653	0.45205	-1.527079	1.33727922E-3	1.17278332E-3
40	0.5438	0.45205	-1.241539	1.33734445E-3	1.17743821E-3
71	0.54471	0.45479	-1.129403	1.33767435E-3	1.17874339E-3

Table P.17: Metrics using Dataset [2020, 2021]-[2022] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
27	0.54856	0.45479	-1.137617	1.36847888E-3	1.23202989E-3
9	0.54993	0.45479	-1.137617	1.36862529E-3	1.24125226E-3
11	0.5513	0.45479	-1.128159	1.37005800E-3	1.23553536E-3
97	0.5513	0.45205	-1.229305	1.37027549E-3	1.24521519E-3
12	0.5513	0.45205	-1.237252	1.37042604E-3	1.25429790E-3
21	0.54856	0.45479	-1.137617	1.37187413E-3	1.23906257E-3
78	0.55267	0.45205	-1.229305	1.37189898E-3	1.23499161E-3
59	0.54993	0.45479	-1.137617	1.37199349E-3	1.24713365E-3
38	0.54856	0.45753	-1.129914	1.37225504E-3	1.24955239E-3
57	0.54993	0.45479	-1.137617	1.37235931E-3	1.23998912E-3

TABLE P.18: Metrics using Dataset [2021]-[2022] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
50	0.61918	0.47123	-0.071396	1.57070591E-3	1.16139060E-3
39	0.62192	0.45205	-0.358381	1.57126579E-3	1.16278036E-3
98	0.64384	0.46301	-0.415965	1.57146708E-3	1.16062065E-3
99	0.62466	0.45753	-0.542129	1.57226476E-3	1.15944803E-3
43	0.62192	0.46027	-0.285961	1.57244167E-3	1.16297121E-3
89	0.6137	0.43288	-0.839269	1.57250026E-3	1.16347115E-3
14	0.62192	0.45205	-0.461456	1.57250804E-3	1.16694373E-3
84	0.62466	0.45753	-0.595571	1.57297632E-3	1.15782741E-3
72	0.62192	0.46575	-0.184467	1.57300703E-3	1.16260495E-3
64	0.62192	0.46027	-0.308892	1.57301097E-3	1.15996446E-3

P.1.6 Bitcoin MSE Correlation 2022

Year	Lag	Correlation
2019-2022	01	0.013721
2019-2022	07	-0.552283
2019-2022	14	-0.578592
2019-2022	21	-0.50289
2019-2022	28	-0.58476
2019-2022	auto - 6	-0.525095
2020-2022	01	0.04458
2020-2022	07	-0.380461
2020-2022	14	-0.128859
2020-2022	21	-0.340272
2020-2022	28	-0.349915
2020-2022	auto - 6	-0.21256
2021-2022	01	0.177381
2021-2022	07	-0.032669
2021-2022	14	-0.309385
2021-2022	21	-0.141023
2021-2022	28	-0.167404
2021-2022	auto - 6	0.067202

TABLE P.19: Correlation MSE Bitcoin

Appendix Q

Appendix RF - Bitcoin 2023

Q.1 Bitcoin RF - extended Tables - 2023 Test

Q.1.1 Lag 01

Table Q.1: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
20	0.55839	0.54247	0.271531	1.46411925E-3	5.14068556E-4
9	0.56569	0.53151	-0.031093	1.46413413E-3	5.14222005E-4
60	0.54745	0.52329	-0.173694	1.46413620E-3	5.14725059E-4
63	0.56296	0.53973	0.706768	1.46425426E-3	5.14376795E-4
72	0.55931	0.53425	0.3366	1.46425524E-3	5.14216578E-4
10	0.56478	0.52055	0.165922	1.46445615E-3	5.14206771E-4
13	0.56113	0.52055	0.259489	1.46464159E-3	5.14492134E-4
73	0.54836	0.53151	0.144259	1.46465597E-3	5.13579139E-4
16	0.55748	0.53425	0.488809	1.46469683E-3	5.13925678E-4
69	0.55566	0.54247	0.346822	1.46491994E-3	5.14569014E-4

Table Q.2: Metrics using Dataset [2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
14	0.56575	0.53425	-0.784964	1.38963335E-3	5.22741199E-4
91	0.56301	0.52329	-0.979044	1.38982184E-3	5.22773154E-4
43	0.56027	0.52877	-0.969094	1.38988684E-3	5.22663062E-4
49	0.56164	0.53699	-0.713012	1.38997793E-3	5.23193851E-4
80	0.56712	0.53425	-0.890872	1.39004152E-3	5.22480239E-4
18	0.56712	0.52877	-0.983946	1.39008308E-3	5.21608563E-4
30	0.56575	0.52329	-1.205299	1.39010055E-3	5.23200193E-4
4	0.55753	0.53151	-0.839989	1.39032641E-3	5.22019801E-4
98	0.5589	0.53425	-0.797906	1.39037606E-3	5.23393033E-4
58	0.56164	0.53425	-0.678064	1.39038222E-3	5.22626881E-4

TABLE Q.3: Metrics using Dataset [2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
84	0.5589	0.50137	-2.123771	1.03726888E-3	5.37814485E-4
14	0.5726	0.49589	-1.79683	1.03868709E-3	5.39238835E-4
30	0.5726	0.52329	-1.357829	1.03899511E-3	5.38587397E-4
91	0.56438	0.50137	-2.123771	1.04003535E-3	5.40371880E-4
71	0.56986	0.52603	-1.351896	1.04027229E-3	5.38056370E-4
94	0.55616	0.49863	-2.220901	1.04044791E-3	5.40675325E-4
58	0.56164	0.50959	-1.759774	1.04052776E-3	5.39153010E-4
66	0.5589	0.50137	-2.123771	1.04057466E-3	5.39291614E-4
62	0.56986	0.52603	-1.351896	1.04059529E-3	5.38382608E-4
55	0.56712	0.51781	-1.501182	1.04059774E-3	5.39531315E-4

Q.1.2 Lag 07

TABLE Q.4: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
4	0.52007	0.50137	1.888714	1.32899042E-3	5.16861915E-4
73	0.51916	0.50137	1.888714	1.32949795E-3	5.15790614E-4
67	0.51825	0.50137	1.888714	1.32979530E-3	5.16797267E-4
41	0.52099	0.50137	1.888714	1.32982636E-3	5.16607475E-4
49	0.51916	0.50137	1.888714	1.33013552E-3	5.16045237E-4
12	0.51734	0.50137	1.888714	1.33069161E-3	5.17083597E-4
6	0.51916	0.50137	1.888714	1.33151455E-3	5.16121115E-4
86	0.51734	0.50137	1.888714	1.33152923E-3	5.16356527E-4
3	0.51916	0.50137	1.888714	1.33170528E-3	5.17783827E-4
31	0.51825	0.50137	1.888714	1.33176334E-3	5.16918724E-4

TABLE Q.5: Metrics using Dataset [2021, 2022]-[2023] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
36	0.58356	0.49589	-1.813016	1.36769485E-3	5.24936074E-4
23	0.58356	0.48767	-2.128861	1.36781362E-3	5.25746736E-4
4	0.58082	0.50411	-2.171611	1.36789405E-3	5.25377602E-4
34	0.58904	0.51781	-1.027903	1.36795644E-3	5.25052466E-4
63	0.5863	0.50411	-1.627232	1.36813748E-3	5.24790806E-4
54	0.57945	0.50411	-2.224473	1.36835302E-3	5.26948868E-4
67	0.58767	0.49589	-1.931379	1.36842510E-3	5.25632603E-4
18	0.59041	0.50685	-2.251688	1.36847536E-3	5.25296912E-4
40	0.58219	0.51507	-1.541167	1.36858551E-3	5.24423435E-4
93	0.57945	0.50411	-2.070237	1.36860806E-3	5.25847604E-4

Table Q.6: Metrics using Dataset [2022]-[2023] on Lag 7

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
8	0.56164	0.50411	-2.099321	1.00726963E-3	5.54087254E-4
70	0.55616	0.50411	-2.093662	1.00796228E-3	5.53524405E-4
34	0.5589	0.50685	-2.082743	1.00854475E-3	5.49444465E-4
83	0.56164	0.50959	-1.833055	1.00889421E-3	5.52044325E-4
58	0.55068	0.50685	-2.105538	1.00891051E-3	5.54353085E-4
1	0.56164	0.50411	-1.933096	1.00899216E-3	5.51281224E-4
95	0.5726	0.50685	-2.082743	1.00901692E-3	5.53432950E-4
4	0.56712	0.50959	-1.727852	1.00919561E-3	5.52750682E-4
55	0.55616	0.50685	-2.082743	1.00927255E-3	5.51058413E-4
76	0.56438	0.50685	-1.953679	1.00927946E-3	5.53016572E-4

Q.1.3 Lag 14

Table Q.7: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
73	0.52646	0.49863	1.866433	1.32742994E-3	5.16288356E-4
67	0.52372	0.49863	1.866433	1.32881811E-3	5.16165635E-4
12	0.52372	0.49863	1.866433	1.32912141E-3	5.16824532E-4
41	0.52737	0.49863	1.866433	1.32929356E-3	5.16594767E-4
31	0.52372	0.49863	1.866433	1.32956614E-3	5.17133955E-4
4	0.52646	0.49863	1.866433	1.32972013E-3	5.16538728E-4
86	0.52464	0.49863	1.866433	1.33065626E-3	5.16292248E-4
49	0.52555	0.49863	1.866433	1.33074697E-3	5.15827543E-4
80	0.5219	0.49863	1.866433	1.33109061E-3	5.17057506E-4
3	0.52099	0.49863	1.866433	1.33136994E-3	5.17633560E-4

Table Q.8: Metrics using Dataset [2021, 2022]-[2023] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
34	0.59178	0.52329	-1.328316	1.35001408E-3	5.26254984E-4
36	0.6	0.52329	-1.362637	1.35053190E-3	5.25748463E-4
40	0.59315	0.52877	-0.722835	1.35076763E-3	5.25645780E-4
99	0.59863	0.53151	-0.574555	1.35080214E-3	5.25241460E-4
61	0.57945	0.52603	-0.707611	1.35117577E-3	5.25677550E-4
54	0.59041	0.51781	-1.067023	1.35128224E-3	5.26892143E-4
60	0.60822	0.52329	-0.961512	1.35148588E-3	5.25962518E-4
94	0.59863	0.52329	-1.056796	1.35159695E-3	5.26227896E-4
59	0.59452	0.52877	-0.738516	1.35168672E-3	5.26679877E-4
16	0.57123	0.51233	-1.416466	1.35169569E-3	5.25366699E-4

TABLE Q.9: Metrics using Dataset [2022]-[2023] on Lag 14

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
53	0.59726	0.52329	-1.602202	9.84224778E-4	5.50516111E-4
76	0.59452	0.52055	-1.936958	9.85627815E-4	5.49826010E-4
18	0.59178	0.53151	-1.633092	9.86647903E-4	5.49200741E-4
65	0.59178	0.52329	-2.032411	9.88109185E-4	5.48695782E-4
50	0.58904	0.53151	-1.375606	9.88173082E-4	5.49336563E-4
30	0.58904	0.52603	-1.75842	9.88195749E-4	5.49428947E-4
48	0.5863	0.52329	-2.017929	9.88462549E-4	5.49328840E-4
94	0.59178	0.52603	-1.73997	9.88591170E-4	5.50416489E-4
73	0.5863	0.52055	-1.822271	9.88664056E-4	5.46246945E-4
78	0.59452	0.53425	-1.60428	9.88719047E-4	5.46068506E-4

TABLE Q.10: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
67	0.52646	0.49589	1.838701	1.32079466E-3	5.16016832E-4
31	0.52555	0.49863	1.866433	1.32156497E-3	5.16559249E-4
4	0.52464	0.49863	1.866433	1.32168365E-3	5.16273954E-4
86	0.52372	0.49863	1.866433	1.32208954E-3	5.15853086E-4
12	0.52828	0.49863	1.866433	1.32230674E-3	5.16083365E-4
17	0.52646	0.49589	1.838701	1.32279908E-3	5.16584866E-4
73	0.52737	0.49589	1.838701	1.32281317E-3	5.15781926E-4
6	0.52646	0.49863	1.866433	1.32358099E-3	5.16352002E-4
49	0.52646	0.49589	1.838701	1.32377349E-3	5.16001271E-4
3	0.52372	0.49863	1.866433	1.32450492E-3	5.16693312E-4

TABLE Q.11: Metrics using Dataset [2021, 2022]-[2023] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
16	0.55753	0.49315	-2.311925	1.33912817E-3	5.28708556E-4
54	0.55479	0.48767	-2.583817	1.33914412E-3	5.30448694E-4
40	0.55616	0.49041	-2.330081	1.33932052E-3	5.29871030E-4
35	0.55205	0.48493	-2.541869	1.33963117E-3	5.30776767E-4
71	0.55068	0.49315	-2.206851	1.33970332E-3	5.30475505E-4
61	0.55753	0.48767	-2.316687	1.33972541E-3	5.30122704E-4
33	0.55342	0.49041	-2.284246	1.33994483E-3	5.30528138E-4
94	0.54658	0.48767	-2.228308	1.34000447E-3	5.30432260E-4
99	0.56027	0.49315	-2.088512	1.34003041E-3	5.29312692E-4
34	0.56301	0.49589	-2.140406	1.34018932E-3	5.30500959E-4

TABLE Q.12: Metrics using Dataset [2022]-[2023] on Lag 21

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
53	0.57534	0.50411	-1.994182	9.77616715E-4	5.50629173E-4
28	0.5726	0.50411	-1.994182	9.78879034E-4	5.51687546E-4
30	0.57808	0.50137	-2.166654	9.79332328E-4	5.50901673E-4
71	0.56986	0.50137	-2.166654	9.79409128E-4	5.47646383E-4
94	0.57534	0.50137	-2.166654	9.79508811E-4	5.53017212E-4
69	0.57808	0.50411	-1.994182	9.79737160E-4	5.50000943E-4
55	0.5726	0.50137	-2.166654	9.79939088E-4	5.48928429E-4
18	0.57534	0.50137	-2.166654	9.80141092E-4	5.50900008E-4
73	0.57808	0.49863	-2.177754	9.80467973E-4	5.47456560E-4
58	0.56986	0.50411	-1.994182	9.80478427E-4	5.52256869E-4

Q.1.4 Lag 28

TABLE Q.13: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
12	0.53102	0.50137	1.877861	1.31078931E-3	5.17026049E-4
31	0.5292	0.49863	1.866433	1.31094479E-3	5.16776964E-4
67	0.53102	0.49589	1.838701	1.31115590E-3	5.17250462E-4
4	0.52737	0.50137	1.877861	1.31141951E-3	5.16844755E-4
43	0.53011	0.49863	1.850123	1.31296812E-3	5.16448816E-4
49	0.53467	0.50137	1.877861	1.31303776E-3	5.17338714E-4
17	0.52372	0.49589	1.838701	1.31309643E-3	5.17597005E-4
37	0.5292	0.50137	1.877861	1.31352909E-3	5.17018629E-4
86	0.53285	0.50137	1.877861	1.31367504E-3	5.16557540E-4
7	0.53376	0.50137	1.877861	1.31441201E-3	5.17824629E-4

TABLE Q.14: Metrics using Dataset [2021, 2022]-[2023] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
54	0.55479	0.49315	-2.417834	1.33074172E-3	5.30982185E-4
85	0.55205	0.49315	-2.355354	1.33087293E-3	5.30019013E-4
71	0.54932	0.49863	-2.105631	1.33137758E-3	5.31760556E-4
73	0.5589	0.49315	-2.399299	1.33207675E-3	5.30912004E-4
61	0.57397	0.49315	-2.113842	1.33220227E-3	5.31223743E-4
50	0.55753	0.49863	-2.136826	1.33235582E-3	5.30759013E-4
93	0.56027	0.48767	-2.570861	1.33242083E-3	5.31685282E-4
4	0.55205	0.50137	-2.059633	1.33242163E-3	5.29923040E-4
60	0.55479	0.49589	-2.305179	1.33242814E-3	5.30239047E-4
99	0.56438	0.49589	-2.333217	1.33253622E-3	5.30303803E-4

TABLE Q.15: Metrics using Dataset [2022]-[2023] on Lag 28

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
76	0.57808	0.50685	-2.007552	9.59275446E-4	5.51285127E-4
98	0.58356	0.50411	-1.999297	9.60919210E-4	5.49567977E-4
71	0.5863	0.50137	-2.282937	9.61134295E-4	5.50653848E-4
54	0.5863	0.50137	-2.212202	9.61159468E-4	5.51963124E-4
8	0.57808	0.50411	-2.110116	9.61391514E-4	5.52590065E-4
73	0.58904	0.49589	-2.429571	9.61569265E-4	5.47901734E-4
94	0.58356	0.50411	-2.110116	9.61883801E-4	5.51474705E-4
29	0.58904	0.50685	-1.897574	9.61894688E-4	5.52908725E-4
37	0.58356	0.50137	-2.212202	9.61915688E-4	5.50694037E-4
70	0.57808	0.50411	-2.06977	9.61986575E-4	5.51709896E-4

Q.1.5 Lag auto - 6

TABLE Q.16: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
73	0.51734	0.50137	1.888714	1.33005362E-3	5.17357154E-4
77	0.51734	0.50137	1.888714	1.33087066E-3	5.18218101E-4
67	0.51734	0.50137	1.888714	1.33172601E-3	5.18997514E-4
4	0.51916	0.49863	1.468641	1.33311127E-3	5.18807031E-4
3	0.52007	0.50137	1.888714	1.33357233E-3	5.18842243E-4
81	0.52007	0.50137	1.888714	1.33395577E-3	5.17497054E-4
5	0.51734	0.50137	1.888714	1.33403045E-3	5.18768908E-4
41	0.51825	0.50137	1.888714	1.33452463E-3	5.18304401E-4
31	0.51734	0.50137	1.888714	1.33471829E-3	5.18898731E-4
86	0.51825	0.50137	1.888714	1.33477489E-3	5.18154546E-4

TABLE Q.17: Metrics using Dataset [2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
63	0.59041	0.51781	-1.005181	1.36866939E-3	5.27259577E-4
99	0.59726	0.51781	-1.690564	1.36921015E-3	5.29218384E-4
18	0.59315	0.51781	-1.417908	1.36941021E-3	5.26791402E-4
36	0.58493	0.52877	-1.496189	1.36944792E-3	5.27437270E-4
12	0.59178	0.51507	-1.157367	1.36948034E-3	5.28878199E-4
73	0.58767	0.52329	-1.370651	1.36956503E-3	5.27952996E-4
10	0.59315	0.51781	-1.421551	1.36966352E-3	5.26996509E-4
96	0.59452	0.52329	-0.850713	1.36975641E-3	5.27630708E-4
23	0.58767	0.51507	-1.570095	1.36978517E-3	5.27732517E-4
29	0.57671	0.50685	-1.364474	1.36980812E-3	5.26790992E-4

TABLE Q.18: Metrics using Dataset [2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
70	0.56164	0.49863	-1.961963	1.01575651E-3	5.49484498E-4
1	0.56438	0.50685	-1.659451	1.01618596E-3	5.48984929E-4
5	0.56986	0.51233	-1.61449	1.01668387E-3	5.47977770E-4
30	0.56164	0.50685	-1.820158	1.01685690E-3	5.47349506E-4
88	0.55342	0.50137	-2.122365	1.01698902E-3	5.46703408E-4
89	0.56438	0.51233	-1.61449	1.01706649E-3	5.48261378E-4
9	0.5589	0.49863	-2.172562	1.01723576E-3	5.48457097E-4
8	0.56712	0.50137	-1.86525	1.01736786E-3	5.48746863E-4
82	0.5589	0.50411	-1.85124	1.01745138E-3	5.51102639E-4
95	0.56712	0.50685	-1.75469	1.01745222E-3	5.48048395E-4

Q.1.6 Bitcoin MSE Correlation 2023

Year	Lag	Correlation
2020-2023	01	-0.084685
2020-2023	07	0.007779
2020-2023	14	0.028434
2020-2023	21	0.208493
2020-2023	28	0.099938
2020-2023	auto - 6	-0.11049
2021-2023	01	0.100458
2021-2023	07	-0.063716
2021-2023	14	-0.041425
2021-2023	21	-0.16392
2021-2023	28	-0.1221
2021-2023	auto - 6	-0.10017
2022-2023	01	-0.127143
2022-2023	07	-0.421718
2022-2023	14	-0.142851
2022-2023	21	-0.074952
2022-2023	28	-0.131913
2022-2023	auto - 6	-0.349809

TABLE Q.19: Correlation MSE Bitcoin

Appendix R

Appendix RF - Gold 2023

R.1 Gold RF - extended Tables - 2023 Test

R.1.1 Lag 01

Table R.1: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
98	0.56085	0.52191	1.141643	1.16170332E-4	6.87957104E-5
9	0.5582	0.51793	1.083263	1.16185218E-4	6.87427467E-5
63	0.56481	0.5259	1.161165	1.16231824E-4	6.86510936E-5
27	0.56217	0.51793	1.088238	1.16255812E-4	6.88395942E-5
67	0.55952	0.51793	1.088238	1.16275969E-4	6.87487958E-5
4	0.55423	0.52191	1.141643	1.16287330E-4	6.87238992E-5
25	0.56614	0.52191	0.928664	1.16289605E-4	6.87967796E-5
28	0.5582	0.5259	1.161165	1.16296451E-4	6.86632274E-5
49	0.5582	0.51394	0.93692	1.16309043E-4	6.86830647E-5
53	0.56349	0.52191	0.780568	1.16315338E-4	6.87384493E-5

Table R.2: Metrics using Dataset [2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
92	0.55666	0.52988	1.433017	8.68137629E-5	6.85765299E-5
50	0.5666	0.53785	1.388507	8.68229057E-5	6.86889679E-5
69	0.5507	0.51793	1.112984	8.68767521E-5	6.87826204E-5
53	0.56461	0.52988	1.61295	8.68795649E-5	6.86670660E-5
94	0.56262	0.5259	1.116607	8.68845434E-5	6.86691480E-5
37	0.55865	0.53785	1.831048	8.69019287E-5	6.85220613E-5
72	0.5666	0.5498	1.935044	8.69145681E-5	6.85875995E-5
76	0.56262	0.53785	1.832133	8.69176114E-5	6.86544371E-5
28	0.57455	0.53785	1.678865	8.69246013E-5	6.86737117E-5
88	0.55666	0.53386	1.430546	8.69408927E-5	6.87109437E-5

Table R.3: Metrics using Dataset [2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
36	0.58566	0.54582	0.948131	8.45620337E-5	6.95250964E-5
70	0.61355	0.54183	0.978422	8.45792879E-5	6.96867778E-5
61	0.58964	0.53785	0.752007	8.45820548E-5	6.95507854E-5
76	0.60956	0.53785	0.87706	8.45894588E-5	6.96100671E-5
97	0.61753	0.54183	0.978422	8.46041378E-5	6.93239716E-5
91	0.58964	0.54582	0.948131	8.46101244E-5	6.95045509E-5
58	0.59363	0.54183	0.828396	8.46153897E-5	6.95946386E-5
35	0.61355	0.54183	0.978422	8.46247938E-5	6.96800712E-5
39	0.59761	0.54183	0.829195	8.46255803E-5	6.95553333E-5
8	0.59363	0.54582	1.018516	8.46387272E-5	6.96900342E-5

R.1.2 Lag 05

Table R.4: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
97	0.55952	0.46215	0.046971	1.14234352E-4	6.91794450E-5
98	0.56217	0.49402	0.977124	1.14255087E-4	6.90939579E-5
25	0.56878	0.45418	-0.086693	1.14281859E-4	6.91565176E-5
63	0.5754	0.46215	0.357466	1.14292412E-4	6.91052369E-5
45	0.5582	0.45817	0.121422	1.14299710E-4	6.91961839E-5
9	0.5582	0.47809	0.156574	1.14302493E-4	6.91778779E-5
86	0.57407	0.47012	-0.758879	1.14305645E-4	6.92755409E-5
28	0.56085	0.46215	0.436234	1.14369602E-4	6.92739595E-5
57	0.56878	0.4502	-0.177811	1.14376527E-4	6.90751903E-5
81	0.57143	0.45817	0.577733	1.14399143E-4	6.91970536E-5

Table R.5: Metrics using Dataset [2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
18	0.60437	0.54582	0.820131	8.51528707E-5	7.25207158E-5
72	0.59642	0.55378	0.902479	8.51929433E-5	7.20333160E-5
79	0.60835	0.55378	0.840018	8.51951697E-5	7.16492296E-5
51	0.59841	0.54582	0.870342	8.52044753E-5	7.18972091E-5
13	0.60437	0.56574	1.029556	8.52359123E-5	7.15817797E-5
76	0.60835	0.56175	0.974344	8.52489246E-5	7.20070544E-5
7	0.60437	0.55777	0.980241	8.52557779E-5	7.21000034E-5
70	0.60239	0.55378	1.025924	8.52625692E-5	7.19700676E-5
100	0.60835	0.54582	0.692062	8.52628684E-5	7.27622139E-5
12	0.61034	0.54582	0.806761	8.52844431E-5	7.20372096E-5

Table R.6: Metrics using Dataset [2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
42	0.67729	0.55777	2.056779	8.28714675E-5	6.78935298E-5
68	0.69721	0.55777	2.013971	8.28784044E-5	6.81087957E-5
87	0.67331	0.54183	1.420444	8.29363644E-5	6.77038926E-5
47	0.67331	0.54582	1.407996	8.29505858E-5	6.76273871E-5
30	0.66932	0.54183	1.627809	8.29903967E-5	6.78354825E-5
45	0.68924	0.54183	1.557492	8.30049861E-5	6.75713490E-5
97	0.69323	0.5498	1.724619	8.30064793E-5	6.77943751E-5
39	0.69323	0.54183	1.471118	8.30185466E-5	6.77501028E-5
63	0.66534	0.54582	1.24323	8.30227792E-5	6.80843008E-5
40	0.67729	0.53386	1.387144	8.30443520E-5	6.81010469E-5

Table R.7: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
49	0.58333	0.50199	0.302506	1.12045561E-4	6.88578527E-5
30	0.57937	0.51394	1.108839	1.12133820E-4	6.87859706E-5
44	0.58466	0.50996	0.528718	1.12158892E-4	6.87951200E-5
42	0.58201	0.50199	0.302525	1.12159650E-4	6.89045920E-5
87	0.5754	0.51394	0.762261	1.12175933E-4	6.88383198E-5
67	0.58201	0.50598	0.77941	1.12203531E-4	6.88105203E-5
26	0.5754	0.50199	0.428436	1.12210707E-4	6.88307332E-5
38	0.57804	0.48606	0.083522	1.12227789E-4	6.89178146E-5
83	0.57804	0.49004	0.160914	1.12232163E-4	6.89384912E-5
66	0.57937	0.50199	0.333225	1.12241225E-4	6.88586548E-5

Table R.8: Metrics using Dataset [2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
51	0.66004	0.51394	-0.656915	8.45424837E-5	7.22810457E-5
47	0.64612	0.53386	0.123277	8.45576048E-5	7.22273001E-5
76	0.65408	0.54582	0.245474	8.45642077E-5	7.20069301E-5
71	0.6501	0.50598	-0.438237	8.45675044E-5	7.25865950E-5
4	0.66004	0.50199	-0.709628	8.46002771E-5	7.24556838E-5
79	0.64414	0.52988	0.27589	8.46011948E-5	7.18424876E-5
18	0.64414	0.52191	-0.278852	8.46060277E-5	7.27787918E-5
5	0.66998	0.53386	0.319832	8.46224491E-5	7.19101684E-5
46	0.65606	0.49801	-1.00703	8.46448053E-5	7.31604489E-5
70	0.65209	0.51394	-0.197861	8.46473635E-5	7.22723478E-5

Table R.9: Metrics using Dataset [2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
7	0.72112	0.55777	1.490271	8.05784282E-5	6.89170071E-5
5	0.73705	0.56175	1.430104	8.07995357E-5	6.86456004E-5
97	0.72112	0.55777	1.279323	8.08189562E-5	6.88513142E-5
44	0.72112	0.52988	0.943728	8.08681228E-5	6.85283439E-5
42	0.71713	0.56574	1.911609	8.08714529E-5	6.87581279E-5
68	0.74502	0.54582	1.444051	8.08947350E-5	6.87492489E-5
55	0.749	0.56175	1.039936	8.08978079E-5	6.87958951E-5
13	0.749	0.54582	1.881478	8.09314259E-5	6.85231656E-5
81	0.71315	0.53785	1.005219	8.09511783E-5	6.87848450E-5
19	0.72908	0.53386	1.301775	8.09550112E-5	6.87137821E-5

R.1.3 Lag 15

Table R.10: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
94	0.58862	0.49402	0.448793	1.11945301E-4	6.89369604E-5
49	0.59788	0.51394	1.209852	1.11965621E-4	6.89414678E-5
42	0.60185	0.51793	0.854036	1.12015597E-4	6.89250600E-5
7	0.57672	0.49801	0.68354	1.12016321E-4	6.90140526E-5
67	0.58995	0.49402	1.029959	1.12031755E-4	6.88380635E-5
38	0.58995	0.48606	0.399616	1.12036727E-4	6.89651242E-5
91	0.60053	0.5259	1.236105	1.12040470E-4	6.88684624E-5
44	0.59788	0.5259	1.54986	1.12054298E-4	6.89192980E-5
57	0.6045	0.50598	0.774465	1.12056318E-4	6.88673439E-5
97	0.59921	0.50199	0.839365	1.12057200E-4	6.89308603E-5

Table R.11: Metrics using Dataset [2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
76	0.66004	0.5498	0.55267	8.43622090E-5	7.09654547E-5
47	0.67992	0.53785	0.317517	8.43808435E-5	7.11967247E-5
18	0.65408	0.53785	0.492558	8.44318482E-5	7.17373800E-5
4	0.67793	0.54582	0.927313	8.44382794E-5	7.13130627E-5
51	0.66998	0.56175	0.80927	8.44386220E-5	7.13664766E-5
78	0.68588	0.53785	1.118981	8.44606141E-5	7.17150651E-5
24	0.67396	0.55777	0.897538	8.44898533E-5	7.16693389E-5
79	0.66203	0.53785	0.936479	8.44958406E-5	7.09375570E-5
44	0.67396	0.55777	0.996059	8.45038587E-5	7.09134807E-5
11	0.66203	0.56175	1.065557	8.45047716E-5	7.10665478E-5

Table R.12: Metrics using Dataset [2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
26	0.72908	0.52191	1.006211	8.01917227E-5	6.87836893E-5
15	0.74104	0.51394	1.195535	8.02409002E-5	6.87913724E-5
78	0.71713	0.5498	1.445478	8.02899116E-5	6.87820328E-5
96	0.72112	0.51394	0.617977	8.03189012E-5	6.91428818E-5
13	0.71713	0.5259	1.306546	8.03271655E-5	6.85045073E-5
79	0.71713	0.51793	1.366379	8.03433057E-5	6.88575857E-5
23	0.7251	0.52988	1.384374	8.03471787E-5	6.86522846E-5
63	0.71315	0.5259	1.549946	8.03494454E-5	6.88683579E-5
2	0.69323	0.53386	1.478334	8.03511517E-5	6.86728371E-5
7	0.70916	0.53386	0.925526	8.03729260E-5	6.85230321E-5

R.1.4 Lag 20

Table R.13: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
78	0.59921	0.51394	0.537645	1.11381684E-4	6.89007988E-5
67	0.59392	0.51793	1.37733	1.11416085E-4	6.88166625E-5
36	0.58069	0.48207	0.555111	1.11425688E-4	6.89394621E-5
44	0.59656	0.52988	1.690872	1.11457020E-4	6.89011462E-5
94	0.60053	0.49801	0.866677	1.11465805E-4	6.89290330E-5
57	0.60185	0.50996	1.093577	1.11479856E-4	6.88089843E-5
91	0.59788	0.52988	1.656726	1.11494802E-4	6.88380691E-5
83	0.58862	0.49004	0.461767	1.11499300E-4	6.89184363E-5
31	0.58201	0.51394	0.790878	1.11509373E-4	6.90115322E-5
3	0.60053	0.51793	1.147254	1.11510453E-4	6.89064464E-5

Table R.14: Metrics using Dataset [2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
4	0.666	0.5259	1.021837	8.32843446E-5	7.10404016E-5
18	0.66203	0.53785	0.99682	8.33397885E-5	7.11272918E-5
79	0.67793	0.52191	1.080039	8.33468150E-5	7.06826994E-5
5	0.66799	0.51793	1.005886	8.33695526E-5	7.02703462E-5
78	0.66998	0.50199	0.473536	8.33866084E-5	7.14161585E-5
51	0.6501	0.52191	0.924869	8.33911225E-5	7.09440384E-5
68	0.69781	0.5259	0.861415	8.34368407E-5	7.14168726E-5
76	0.66402	0.50996	0.677737	8.34445954E-5	7.05146022E-5
85	0.66402	0.53386	1.050792	8.34458967E-5	7.11268491E-5
52	0.68191	0.5259	1.270723	8.34685323E-5	7.06094093E-5

Table R.15: Metrics using Dataset [2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
23	0.7012	0.52988	1.44778	7.85867164E-5	6.87682508E-5
57	0.70916	0.52191	1.473766	7.86310208E-5	6.93705476E-5
38	0.71713	0.51793	1.703121	7.86529023E-5	6.89370275E-5
26	0.71315	0.50598	0.969099	7.86574276E-5	6.91886016E-5
5	0.70916	0.53785	1.696219	7.86621907E-5	6.88611054E-5
65	0.7251	0.50598	1.619075	7.86766078E-5	6.89782729E-5
29	0.72908	0.54183	1.871953	7.86783821E-5	6.81645666E-5
86	0.71315	0.52191	1.49622	7.87053599E-5	6.88494908E-5
63	0.70916	0.52191	1.187825	7.87142557E-5	6.92198729E-5
96	0.72112	0.54183	1.602884	7.87205859E-5	6.90837136E-5

R.1.5 Lag auto

Table R.16: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
78	0.59788	0.50996	0.350069	1.11398233E-4	6.89106092E-5
36	0.58069	0.48207	0.592105	1.11404884E-4	6.89381437E-5
67	0.59656	0.51394	1.193246	1.11408304E-4	6.88334279E-5
91	0.59524	0.50598	0.671066	1.11435358E-4	6.88519869E-5
49	0.58069	0.50199	0.77034	1.11458784E-4	6.88874449E-5
9	0.58466	0.51793	1.231491	1.11472353E-4	6.89648824E-5
44	0.5873	0.51793	1.213777	1.11479380E-4	6.89265914E-5
35	0.58598	0.49402	0.659778	1.11480000E-4	6.89336058E-5
3	0.60185	0.50199	0.610838	1.11484352E-4	6.89158758E-5
97	0.59524	0.52191	1.214339	1.11487181E-4	6.88795319E-5

Table R.17: Metrics using Dataset [2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
4	0.67197	0.5259	0.906165	8.33411297E-5	7.14495296E-5
5	0.67197	0.51394	0.944796	8.33837255E-5	7.06908101E-5
51	0.66004	0.5259	0.992897	8.34523388E-5	7.12287925E-5
18	0.66799	0.54183	1.138163	8.34679448E-5	7.17073637E-5
78	0.67396	0.49801	0.135747	8.34761118E-5	7.18283030E-5
76	0.66799	0.52191	0.766351	8.34966835E-5	7.10656767E-5
79	0.67396	0.51793	0.708422	8.35356948E-5	7.09934214E-5
68	0.69185	0.52988	0.816788	8.35480329E-5	7.15991116E-5
52	0.68787	0.53386	1.321819	8.35509335E-5	7.12355688E-5
85	0.67197	0.54183	1.07525	8.35545121E-5	7.11903089E-5

Table R.18: Metrics using Dataset [2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
96	0.71315	0.5259	1.378139	7.86186137E-5	6.91203114E-5
23	0.69721	0.54183	1.575307	7.86201642E-5	6.88168810E-5
98	0.70916	0.53785	1.698091	7.86731196E-5	6.88612896E-5
57	0.70518	0.51394	1.403774	7.86791778E-5	6.93504165E-5
65	0.72908	0.50996	1.71692	7.86991271E-5	6.90355781E-5
63	0.70518	0.51394	1.057806	7.86996887E-5	6.92057422E-5
5	0.71315	0.54183	1.555635	7.87082072E-5	6.89891604E-5
38	0.70916	0.51394	1.04028	7.87295337E-5	6.90023728E-5
29	0.72112	0.53386	2.059897	7.87407903E-5	6.82849166E-5
79	0.7012	0.53386	1.78871	7.87427232E-5	6.90537891E-5

R.1.6 Gold MSE Correlation 2023

Year	Lag	Correlation
2020-2023	01	-0.187338
2020-2023	05	-0.169864
2020-2023	10	0.095847
2020-2023	15	0.039621
2020-2023	20	-0.038286
2020-2023	auto - 19	0.057832
2021-2023	01	-0.108416
2021-2023	05	0.287519
2021-2023	10	0.235874
2021-2023	15	0.253662
2021-2023	20	0.362447
2021-2023	auto - 19	0.298517
2022-2023	01	0.21308
2022-2023	05	-0.211805
2022-2023	10	-0.319203
2022-2023	15	-0.074194
2022-2023	20	-0.139909
2022-2023	auto - 19	-0.128602

Table R.19: Correlation MSE Gold

Appendix S

Appendix RF - MSFT 2023

S.1 MSFT RF - extended Tables - 2023 Test

S.1.1 Lag 01

S.1.2 Lag 05

S.1.3 Lag 10

S.1.4 Lag 15

S.1.5 Lag 20

S.1.6 Lag auto

S.1.7 MSFT MSE Correlation 2023

TABLE S.1: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
72	0.52381	0.52	1.348217	4.13926208E-4	2.48152782E-4
92	0.52249	0.52	1.120436	4.14050010E-4	2.48455223E-4
93	0.52381	0.536	1.399433	4.14127074E-4	2.48568742E-4
54	0.52116	0.52	1.120436	4.14139664E-4	2.48750037E-4
29	0.52116	0.52	1.348217	4.14147847E-4	2.48833444E-4
47	0.5172	0.516	1.19954	4.14240736E-4	2.48873747E-4
11	0.52116	0.52	1.348217	4.14275174E-4	2.48527216E-4
2	0.52116	0.52	1.348217	4.14427250E-4	2.48750406E-4
57	0.52381	0.536	1.399433	4.14427626E-4	2.48566724E-4
22	0.51852	0.52	1.348217	4.14450265E-4	2.48572049E-4

TABLE S.2: Metrics using Dataset [2021, 2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
30	0.55467	0.48	0.443264	3.14378808E-4	2.48211649E-4
69	0.55666	0.48	0.443264	3.14384134E-4	2.48624427E-4
6	0.55467	0.48	0.443264	3.14458265E-4	2.48308976E-4
48	0.54672	0.492	0.610731	3.14494280E-4	2.48388041E-4
57	0.55467	0.48	0.443264	3.14541907E-4	2.48345041E-4
54	0.55666	0.48	0.443264	3.14583584E-4	2.48522707E-4
15	0.57058	0.524	1.491118	3.14583974E-4	2.49065024E-4
24	0.55865	0.48	0.695157	3.14619488E-4	2.48949508E-4
10	0.55467	0.48	0.443264	3.14653698E-4	2.48415095E-4
96	0.55467	0.5	0.882737	3.14678311E-4	2.48992564E-4

TABLE S.3: Metrics using Dataset [2022]-[2023] on Lag 1

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
86	0.56175	0.468	-0.567111	4.45132789E-4	2.58370860E-4
79	0.56175	0.468	-0.567111	4.45167088E-4	2.59980980E-4
1	0.56175	0.468	-0.567111	4.45510803E-4	2.60943559E-4
55	0.57769	0.464	-0.685676	4.45603984E-4	2.60934480E-4
81	0.56574	0.472	-0.434343	4.45626793E-4	2.60465534E-4
37	0.56175	0.468	-0.567111	4.45779101E-4	2.59258700E-4
10	0.56972	0.448	-1.611166	4.45785968E-4	2.59945646E-4
35	0.56175	0.468	-0.567111	4.45866433E-4	2.60460716E-4
3	0.56175	0.464	-0.645402	4.45875731E-4	2.59174793E-4
84	0.56574	0.472	-0.434343	4.45887757E-4	2.60914315E-4

TABLE S.4: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
98	0.53836	0.56	1.384101	4.08739345E-4	2.48562880E-4
72	0.53836	0.56	1.476568	4.08791178E-4	2.48503325E-4
30	0.53042	0.568	1.608662	4.08886967E-4	2.48398264E-4
67	0.53968	0.556	1.324102	4.08902021E-4	2.48663283E-4
99	0.54101	0.564	1.538246	4.08937515E-4	2.48606763E-4
92	0.53968	0.56	1.492252	4.08964955E-4	2.48602376E-4
47	0.54101	0.556	1.232929	4.08999635E-4	2.48588847E-4
11	0.54233	0.552	1.244393	4.09046264E-4	2.48620791E-4
93	0.53968	0.568	1.608662	4.09077050E-4	2.48634343E-4
65	0.53968	0.56	1.402393	4.09083661E-4	2.48732246E-4

TABLE S.5: Metrics using Dataset [2021, 2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
24	0.59245	0.532	1.570632	3.11853985E-4	2.45091249E-4
68	0.58847	0.54	2.030532	3.11885802E-4	2.44741898E-4
30	0.59841	0.556	2.652149	3.11899877E-4	2.44990317E-4
79	0.59245	0.536	1.817618	3.11944105E-4	2.45367702E-4
64	0.58847	0.544	1.905207	3.11944117E-4	2.44749507E-4
10	0.59046	0.54	1.862542	3.11952141E-4	2.45373984E-4
6	0.59841	0.548	2.065825	3.11974036E-4	2.44656817E-4
12	0.59443	0.54	1.849282	3.11983152E-4	2.45631068E-4
74	0.59841	0.536	1.250716	3.12011573E-4	2.44955354E-4
35	0.5825	0.532	1.552873	3.12017026E-4	2.45120316E-4

TABLE S.6: Metrics using Dataset [2022]-[2023] on Lag 5

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
54	0.6494	0.48	-0.738807	4.36887310E-4	2.56833210E-4
55	0.63745	0.492	-0.376951	4.37554474E-4	2.55700028E-4
60	0.63745	0.492	-0.527686	4.37606328E-4	2.57492399E-4
47	0.63745	0.5	-0.130031	4.37696321E-4	2.55732066E-4
3	0.62151	0.476	-0.655253	4.37768807E-4	2.55462106E-4
2	0.62948	0.488	-0.637055	4.37843025E-4	2.55219954E-4
92	0.6255	0.492	-0.475568	4.37845824E-4	2.56700471E-4
78	0.62151	0.484	-0.901828	4.37848640E-4	2.55847671E-4
69	0.63745	0.5	-0.164173	4.37853317E-4	2.55491731E-4
75	0.63745	0.492	0.026347	4.37973959E-4	2.54795522E-4

TABLE S.7: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
100	0.53571	0.552	1.640837	4.00587413E-4	2.49029598E-4
78	0.53968	0.552	1.869912	4.00679409E-4	2.48678862E-4
72	0.53307	0.556	1.30819	4.00696818E-4	2.48659701E-4
98	0.53571	0.568	1.791816	4.00737830E-4	2.48924301E-4
52	0.54762	0.564	1.652418	4.00739971E-4	2.48792262E-4
11	0.54365	0.568	1.998304	4.00817255E-4	2.48779847E-4
60	0.53042	0.548	1.562216	4.00834773E-4	2.48841271E-4
86	0.53439	0.548	1.545783	4.00843093E-4	2.48752170E-4
42	0.53968	0.568	1.783973	4.00874983E-4	2.49066002E-4
5	0.53307	0.56	1.701962	4.00932215E-4	2.48790985E-4

Table S.8: Metrics using Dataset [2021, 2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
81	0.62227	0.512	0.846406	2.99512976E-4	2.56601570E-4
44	0.61431	0.548	1.582366	2.99604294E-4	2.56290430E-4
69	0.62227	0.528	0.954066	2.99621628E-4	2.55616506E-4
19	0.63221	0.548	1.811479	2.99621644E-4	2.54019469E-4
30	0.59841	0.536	1.794918	2.99667642E-4	2.56258703E-4
24	0.63221	0.528	0.987021	2.99685802E-4	2.56374679E-4
72	0.62028	0.524	0.459294	2.99803463E-4	2.57714617E-4
1	0.62425	0.544	1.100822	2.99820082E-4	2.56015145E-4
79	0.61829	0.548	1.723472	2.99856009E-4	2.55809705E-4
23	0.63022	0.54	1.521368	2.99905614E-4	2.55652301E-4

Table S.9: Metrics using Dataset [2022]-[2023] on Lag 10

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
47	0.63745	0.452	-0.978476	4.08551698E-4	2.74268123E-4
66	0.63745	0.44	-1.220336	4.08962121E-4	2.73923646E-4
56	0.62948	0.464	-0.567536	4.09030817E-4	2.75629446E-4
73	0.62151	0.44	-1.542834	4.09081092E-4	2.73797705E-4
64	0.63745	0.436	-1.562363	4.09262171E-4	2.74634405E-4
22	0.64143	0.444	-1.519888	4.09331583E-4	2.74229141E-4
35	0.65339	0.436	-1.643468	4.09372598E-4	2.76142424E-4
41	0.63745	0.444	-1.40736	4.09407001E-4	2.73059344E-4
88	0.63745	0.448	-1.412994	4.09436303E-4	2.76656430E-4
75	0.64143	0.444	-1.46129	4.09505230E-4	2.73291894E-4

Table S.10: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
98	0.54233	0.568	1.590595	3.99190372E-4	2.48740558E-4
60	0.53439	0.56	1.692704	3.99381948E-4	2.48691193E-4
100	0.53968	0.556	1.658937	3.99493629E-4	2.48994861E-4
54	0.53704	0.56	1.372508	3.99630145E-4	2.48739145E-4
11	0.54233	0.556	1.598461	3.99801337E-4	2.48649432E-4
88	0.53439	0.552	1.580288	3.99833983E-4	2.48953974E-4
52	0.54365	0.556	1.308376	3.99865290E-4	2.48854859E-4
67	0.54762	0.556	1.177397	3.99875027E-4	2.48818177E-4
2	0.54762	0.564	1.454639	3.99991512E-4	2.48678784E-4
86	0.53439	0.56	1.78504	3.99999897E-4	2.48618813E-4

Table S.11: Metrics using Dataset [2021, 2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
43	0.6163	0.504	0.228714	2.96692799E-4	2.50283434E-4
79	0.61034	0.516	0.211354	2.97118881E-4	2.49896839E-4
69	0.62823	0.516	0.214215	2.97151078E-4	2.50330288E-4
52	0.60437	0.54	1.525937	2.97152995E-4	2.49515951E-4
91	0.61829	0.54	1.105529	2.97267218E-4	2.49690668E-4
24	0.64016	0.512	0.403369	2.97285446E-4	2.49684828E-4
37	0.63022	0.5	0.390089	2.97323750E-4	2.50021914E-4
51	0.61034	0.52	0.412952	2.97334583E-4	2.49905634E-4
26	0.61431	0.536	1.700362	2.97340732E-4	2.49638482E-4
72	0.62823	0.528	0.700337	2.97381049E-4	2.50456391E-4

Table S.12: Metrics using Dataset [2022]-[2023] on Lag 15

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
73	0.65339	0.448	-0.865612	4.02798069E-4	2.66912312E-4
95	0.6494	0.448	-1.346969	4.03063965E-4	2.66241137E-4
78	0.65339	0.448	-0.759709	4.03172167E-4	2.65842489E-4
22	0.65737	0.444	-0.994393	4.03248683E-4	2.66063388E-4
15	0.64542	0.452	-0.72379	4.03289848E-4	2.67798507E-4
100	0.66534	0.452	-0.72379	4.03525916E-4	2.64162736E-4
66	0.66534	0.448	-0.831945	4.03533247E-4	2.65116493E-4
41	0.66135	0.452	-0.776102	4.03621505E-4	2.64872401E-4
56	0.66135	0.448	-0.94322	4.03642818E-4	2.65863335E-4
47	0.6494	0.444	-0.984149	4.03878065E-4	2.65353056E-4

Table S.13: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
60	0.54101	0.544	1.281329	3.99480366E-4	2.48810062E-4
98	0.5463	0.564	1.675408	3.99496104E-4	2.48835398E-4
100	0.55556	0.552	1.606614	3.99527066E-4	2.49057150E-4
54	0.5463	0.564	1.421316	3.99579015E-4	2.48952660E-4
86	0.55688	0.54	1.10641	3.99776898E-4	2.48763250E-4
11	0.5463	0.552	1.498841	3.99806563E-4	2.48792824E-4
39	0.54101	0.544	1.285713	3.99933537E-4	2.48851488E-4
21	0.54365	0.548	1.39525	3.99938056E-4	2.48726511E-4
94	0.54497	0.548	1.370192	3.99946659E-4	2.49029277E-4
52	0.56614	0.54	1.231735	3.99968416E-4	2.49078480E-4

TABLE S.14: Metrics using Dataset [2021, 2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
43	0.63022	0.548	1.257534	2.96030691E-4	2.50007735E-4
91	0.61829	0.516	0.371822	2.96366702E-4	2.49804058E-4
52	0.61233	0.544	1.506121	2.96510264E-4	2.49308485E-4
2	0.60636	0.516	0.151202	2.96531711E-4	2.50885843E-4
16	0.62624	0.528	0.909446	2.96556739E-4	2.49784898E-4
79	0.60835	0.544	1.586385	2.96601191E-4	2.50198190E-4
69	0.62425	0.552	1.498283	2.96607335E-4	2.49990973E-4
13	0.64016	0.532	1.460745	2.96619216E-4	2.49280096E-4
48	0.6163	0.516	0.693008	2.96621922E-4	2.49918227E-4
29	0.63618	0.548	0.87564	2.96689010E-4	2.48892171E-4

TABLE S.15: Metrics using Dataset [2022]-[2023] on Lag 20

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
73	0.65737	0.444	-0.941657	4.01953311E-4	2.65192175E-4
95	0.64143	0.444	-0.994393	4.02455300E-4	2.65230585E-4
15	0.65737	0.448	-0.900172	4.02580835E-4	2.66408925E-4
39	0.64542	0.444	-0.977264	4.02884695E-4	2.65497490E-4
54	0.68526	0.46	-0.599271	4.03027640E-4	2.65732643E-4
78	0.6494	0.452	-0.735237	4.03031837E-4	2.64249678E-4
100	0.64143	0.448	-0.841955	4.03032283E-4	2.62613602E-4
3	0.64143	0.444	-0.839631	4.03471065E-4	2.64751903E-4
66	0.67331	0.452	-0.611198	4.03622480E-4	2.63444562E-4
40	0.63745	0.448	-0.745563	4.03622990E-4	2.66812978E-4

TABLE S.16: Metrics using Dataset [2020, 2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
54	0.54365	0.544	1.498046	4.11899678E-4	2.48608050E-4
93	0.54497	0.544	1.498046	4.11951592E-4	2.48335266E-4
11	0.54233	0.544	1.498046	4.11954121E-4	2.48358651E-4
99	0.54497	0.536	1.676106	4.12038610E-4	2.48495425E-4
70	0.53704	0.548	1.85069	4.12091636E-4	2.48500609E-4
22	0.55026	0.544	1.498046	4.12098819E-4	2.48488845E-4
92	0.5463	0.548	1.539036	4.12101730E-4	2.48352677E-4
29	0.54894	0.544	1.498046	4.12139416E-4	2.48518975E-4
67	0.52778	0.532	1.223973	4.12156460E-4	2.48487415E-4
6	0.55159	0.54	1.819929	4.12221229E-4	2.48418573E-4

Table S.17: Metrics using Dataset [2021, 2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
24	0.57455	0.528	1.502137	3.13272037E-4	2.46021521E-4
30	0.58648	0.52	1.34948	3.13528809E-4	2.44613285E-4
93	0.57654	0.528	1.869001	3.13685324E-4	2.45298958E-4
88	0.57455	0.52	1.427606	3.13698417E-4	2.44808802E-4
6	0.57853	0.532	1.632334	3.13717308E-4	2.44982905E-4
69	0.6004	0.52	1.237092	3.13720612E-4	2.45159296E-4
32	0.58052	0.52	1.207774	3.13753735E-4	2.44757389E-4
96	0.57654	0.52	1.418506	3.13753987E-4	2.45038305E-4
92	0.57853	0.528	1.501957	3.13837065E-4	2.44786748E-4
47	0.59642	0.524	1.418992	3.13915733E-4	2.45226223E-4

Table S.18: Metrics using Dataset [2022]-[2023] on Lag auto

Seed	Hit Ratio Train	Hit Ratio Test	Sharpe Test	MSE Train	MSE Test
79	0.62948	0.508	0.926432	4.43197453E-4	2.57487425E-4
35	0.60956	0.5	0.737413	4.43595486E-4	2.57591923E-4
86	0.61753	0.516	1.031936	4.43636860E-4	2.56337423E-4
98	0.59761	0.512	1.079189	4.43916278E-4	2.57106341E-4
55	0.61355	0.504	0.902109	4.43936639E-4	2.58318891E-4
92	0.60558	0.508	0.926432	4.43942376E-4	2.58236505E-4
2	0.61753	0.512	1.219135	4.43946208E-4	2.55851459E-4
10	0.61355	0.5	0.788744	4.44140469E-4	2.56803768E-4
32	0.62151	0.5	0.749511	4.44277745E-4	2.58537346E-4
26	0.61753	0.496	0.752602	4.44293514E-4	2.56497882E-4

Year	Lag	Correlation
2020-2023	01	0.074904
2020-2023	05	0.036315
2020-2023	10	-0.034747
2020-2023	15	-0.063431
2020-2023	20	-0.083635
2020-2023	auto - 2	0.064183
2021-2023	01	-0.432229
2021-2023	05	0.139665
2021-2023	10	-0.389572
2021-2023	15	-0.252483
2021-2023	20	-0.22215
2021-2023	auto - 2	-0.220659
2022-2023	01	-0.192959
2022-2023	05	-0.280502
2022-2023	10	-0.066511
2022-2023	15	-0.10995
2022-2023	20	-0.135263
2022-2023	auto - 2	-0.165911

Table S.19: Correlation MSE MSFT