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Applying Machine Learning to Enhance Market Factor Analysis and Mispricing. Discovery in Cross Section of Asset Returns

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Abstract

In the recent years many researchers attempted to apply machine learning to prediction of asset returns. In this paper, we showed empirically how predictability of returns decays as the horizon of the prediction increases. We also studied how different cryptocurrency exchanges affect each other's returns. We successfully showed that the Binance USDM futures market is the primary market where the price originates, all other exchanges are typically lags of prices on Binance, therefore, using features computed using Binance data are great regressors for price prediction on other exchanges. We were able to build the model that predicts returns at Binance spot exchange with R^2 and accuracy reaching 0.056 and 0.581 respectively.

Keywords: Cryptocurrency, High Frequency Trading, Machine Learning, Gradient boosting, Pumps and dumps. Big data

1 Introduction

1.1 Previous research on the topic

This research was primarily inspired by my previous paper, in which I successfully predicted assets that would be manipulated at known times, yielding positive returns in back-testing. That paper focused on so-called "pump-and-dump" schemes, illegal manipulations of asset prices. Historically, such manipulations occurred in traditional markets but were quickly outlawed and heavily regulated; by contrast, the cryptocurrency space has seen relatively little oversight of pumps and dumps. Pump-and-dump schemes are organized, fraudulent price manipulations in which insiders accumulate a low-liquidity, small-cap cryptocurrency and then signal others to buy. The resulting price surge is short-lived: once new investors rush in, insiders liquidate their holdings, pocketing substantial profits while latecomers are left holding devalued tokens and forced to sell at a loss. There is no genuine value appreciation or underlying fundamental news driving the spike, it is simply a redistribution of followers' funds to the insiders. Figure 1 illustrates an example of a pump-and-dump event we sought to predict. The one-second candlesticks show no trading volume until 17:00:00, when the price suddenly spikes and then quickly retraces back to its normal level.

Figure 1: Example of Pump and dump: VIBBTC pump on Binance

In that research we used multiple low to mid-frequency features like flow imbalances and past returns, then trained the model to label if the asset will be manipulated or not within the next hour. We also applied a novel method of cross-sectional standardization Equation 1 that was not used in related literature before which involves scaling features by their cross-sectional moments.

$$X_{\text{standardized}} = \frac{X - \bar{X}_{\text{within}}}{\bar{\sigma}_{X_{\text{within}}}} \tag{1}$$

Since our data spanned from 2018 to 2024, the market dynamics changed significantly over time. In order to adjust for this we standardized each numeric feature cross-sectionally within each pump-and-dump event using the Equation 1 above. Such standardisation allowed us to make sure that the distributions of features are aligned across time, this way tree-based models could learn the data much better as they rely on binning the data.

Following the methodology described above, we computed [1] TOP-K accuracy for each model on the test set. The results are presented in Table 1) below:

[1]TOP-K accuracy measures the probability that among K highest logits there will be a true pumped ticker.

	LogisticRegression	RandomForest	CatboostCLF	**CatboostCLF + ES**	CatboostRanker
TOP-1	0.000	0.000	0.033	**0.050**	**0.050**
TOP-3	0.100	0.100	0.150	**0.183**	0.100
TOP-5	0.217	0.217	0.250	**0.300**	0.117
TOP-10	0.333	0.333	0.383	**0.450**	0.150
TOP-20	0.483	0.483	0.517	**0.533**	0.233
TOP-30	0.567	0.567	0.600	**0.650**	0.300

Table 1: Top@K accuracy of models on test sample

From the Table 1 we see that LogisticRegression is comparable to other more complex models like RandomForest and CatBoostClassifier. The superior model turned out to be Catboost-Classifier + ES (early stopping) which was trained with Early Stopping based on the custom evaluation metric - Top@K%-AUC.

These results hinted us that given the right methodology and data we might be able to develop the model predicting cryptocurrency returns in the same way we used classification and ranking to rank assets based on their returns during the manipulation. So this work is continuation and generalization of similar methodology but applied to general cryptocurrency market.

1.2 Related work

We will briefly go over the current state of research on the topic of predictability of asset returns. First, we will start with more established literature.

1.2.1 Market Efficiency. Market Microstructure

Many researchers tried to apply machine learning to the problem of predicting returns in traditional markets. The topic is still debatable to this day with multiple researches leaning towards efficient market hypothesis (EMH). Fama, 1991 introduced 3 types of market efficiency: weak, semi-strong, and strong form market efficiency. In weak form efficient markets, prices only reflect all past price information, whereas in semi-strong form, prices reflect all publicly available information. In strong form efficient markets, prices also reflect all private information.

There is also theoretical literature on short-term predictability of returns. Microstructure theory explains how frictions in trading (bid–ask spreads, latency, inventory risk) generate very short-lived predictability. Kyle, 1985 continuous-auction model shows private information is gradually priced by informed trading, yielding short-lived price impact. In Kyle, 1985 setup there are 3 types of agents:

- Informed trader, who knows the true asset value
- Noise traders, who submit random orders
- Market maker, who sets prices to clear the market and break even on average.

The main idea of Kyle, 1985 continuous-auction model is that private information is priced gradually, through the interaction of an informed trader, uninformed “noise” traders, and a competitive market maker. In equilibrium:

$$P_t = E[V \mid Y_t] = \mu + Y_t\,\lambda, \quad \lambda = \frac{\sigma_V}{2\,\sigma_u} \tag{2}$$

Only a fraction λ of the informed trader’s information is revealed per trading round, the rest is obscured by noise orders, as a result of this prices converge gradually (not instantaneously) to the true value.

Empirical studies by Hasbrouck, 1995 decomposed transaction-level return variance and found that a sizable portion of intraday volatility and serial correlation arises from microstructure effects at the millisecond-to-second scale. We see that there are theoretical models and setups that would allow for predictability of returns. Below we will look at empirical works that attempted to develop methodologies to successfully predict return to some extent.

1.2.2 Empirical approach to prediction cryptocurrency returns

Sun et al., 2020 tried to apply LightGBM implementation of gradient boosting introduced by Ke et al., 2017 to similar problem. Authors used mid-frequency candlestick data from website [2]. In their analysis Sun et al., 2020 also used macro features like prices of indexes like S&P500, Dow Jones 30 index and prices of crude oil futures. Authors developed a model that predicts up and down movements in cryptocurrencies prices in mid-to-long term horizon. Fang et al., 2020 applied Neural Networks like LSTM to forecast short-term cryptocurrency returns. They found out that while a deep-learning model (specifically an LSTM) can achieve very high out-of-sample accuracy up to about 78% on next-tick mid-price direction in BTCUSD, their performance decays rapidly when deployed on live data due to non-stationary microstructure effects. Derbentsev et al., 2019 also attempted to predict returns using daily candlestick data, they compared the performance of linear models like ARIMA to hybrid tree-based models, namely Binary Auto Regressive Tree (BART). Authors found that across cryptocurrencies Bitcoin, Ethereum and Ripple, hybrid model achieved significantly lower

[2] Website “Investing.com” [Online resource]: https://www.investing.com/

RMSE errors: roughly 4% at 14 days, 6% at 21 days and 8% at 30 days, virtually halving the error of ARIMA and improving on ARFIMA by 15–20%.

Hashish et al., 2019 proposed using Hidden Markov Model (HMM) along with LSTM neural networks. This paper stands out among other as authors used L2 level data, which is the state of the whole orderbook, not only best bid, ask but also its depth. Their analysis was performed on the short period of time between August 2018 and September 2018. Using this data they computed features like bid-ask spread, bid-ask volumes in the orderbook, features measuring depth of the orderbook. Hashish et al., 2019 also included technical analysis indicators like SMA, EMA with different windows and Bollinger Bands. Authors used log return of sampled mid price which is $P_{\text{mid}} = \frac{P_{\text{bid}}+P_{\text{ask}}}{2}$ as the target for their model. They found out that using LSTMs along with HMM is superior to using linear models like ARIMA. Hashish et al., 2019 also noted that increasing the forecast step resulted in worse performance across all models. This is important as we are expecting to obtain the same results in our research. Barnwal et al., 2019 introduced a stacked generalization framework that combines three generative classifiers (Naive Bayes, LDA, QDA) and six discriminative classifiers (XGBoost, LightGBM, KNN, logistic elastic net, SVM, Random Forest) under a one-layer neural network meta-learner to forecast cryptocurrency price direction. Their dataset comprises end-of-day Bitcoin prices from August 2017 to July 2018, aggregated across Kraken, Bitstamp, Itbit, and Coinbase via weighted volume, along with 41 technical indicators (trend, momentum, volume, volatility) and three sentiment features derived from Coindesk tweets. Barnwal et al., 2019 concluded that stacking ensemble enables to achieve the highest test-period accuracy ≈ 0.54 and F1 score ≈ 0.55, modestly outperforming all individual classifiers whose accuracies range around 0.50-0.52. Jaquart et al., 2021 as well investigated if ML models can predict short-term Bitcoin price movements over horizons from 1 to 60 minutes, finding that RNNs (LSTM, GRU) and gradient boosting classifiers outperform both random and simpler benchmarks. All models beat 0.5 accuracy, with performance rising for longer horizons (up to ≈ 0.56 at 60 min), and the RNNs and gradient boosting achieving the highest scores.

1.3 Motivation. Research objectives

We see that the literature suggests that if there is alpha in the market we can take advantage of it only if we are fast enough in our decision making. In this research we want to apply our methodology developed in Pumps and dumps paper. We want to find how fast predictability decays over time, what features might be useful for short-mid term prediction of cryptocurrency returns. This topic is important as it can be used by market makers that use short-term return predictions on top of different heuristics.

The paper is organized in the following way: in the next section 2 we will go over the data we collected for our research, we will explain the main hurdles that we had to deal with during collection, preprocessing and using the data. We will also list the set of features used for training the models with their description and intuition. Then we will cover the steps that we took to obtain the results and then in section 3 we will go over the main findings. In section 4 we will summarize the results and touch on what could have been done differently and what we will do in the future.

2 Methodology

2.1 Market data

For the purposes of predicting returns of cryptocurrencies we downloaded historical trading tick-level data for multiple exchanges and markets within exchanges. Our data spans over January 2024 to May 2025. We have both SPOT and USDM-futures trades data for 553 cryptocurrencies traded against USDT stablecoin for Binance and OKX exchanges. Raw data has the following structure:

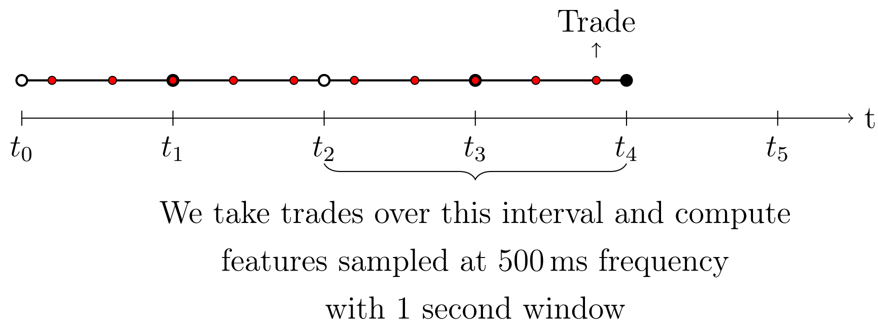
price	quantity	trade_time	is_buyer_maker	symbol
0.681600	14.700000	2025-05-01 00:00:00.414557	False	ADA-USDT
0.681600	31.500000	2025-05-01 00:00:00.642144	False	ADA-USDT
0.681600	7.400000	2025-05-01 00:00:00.857135	False	ADA-USDT
0.681600	11.000000	2025-05-01 00:00:00.857135	False	ADA-USDT
0.681600	474.200000	2025-05-01 00:00:00.857135	False	ADA-USDT

Table 2: Structure of collected data: *price* indicates the execution price at which the order was filled, *quantity* specifies the quantity of the base asset that was traded, and isBuyerMaker is a boolean flag: when True, the buyer's order was already in the book and an incoming sell matched it (i.e. a sell trade), and when False, the seller's order was resting and an incoming buy matched it (i.e. a buy trade).

In this research we focused on studying currencies traded only against USDT quote as typically these orderbooks have the most liquidity and higher trading activity which is essential to us as we are using transaction level data. Although it would have been interesting to extend the research and incorporate other quotes like USDC, FDUSD and other fiat/stablecoin quote assets.

2.2 Feature Engineering

As a result of running our data downloading pipeline, we ended up with 100GBs worth of zipped csv files for multiple exchanges and currencies. Unfortunately, we can't simply feed raw tick data to the boosting model, as it typically requires the data to have a tabular form, therefore, we had to come up with the pipeline that could transform raw compressed tick data to tabular data with features and target column attached. We used Pyarrow[3] to process all of the files and store them in Hive dataset structure with parquet files. Then we created feature generation pipeline on top of hive structured data. We used 500 milliseconds sampling, meaning that we are computing features at steps of 500 milliseconds over different intervals.



Below we will go over groups of features that we decided to use to predict returns.

2.2.1 Flow Imbalance features

Flow imbalance measures how much trading volume is on the buying or selling side, if the value of flow imbalance is closer to 1, this means that the majority of trades were the buying ones, if it is negative and closer to -1, then it is the opposite.

$$\text{Flow Imbalance} = \frac{\sum_{t \in T} \text{quote\_sign USDT}_t}{\sum_{t \in T} \text{quote\_abs USDT}_t} \in [-1, 1] \tag{3}$$

The formula in Equation 3 defines flow imbalance as the signed USDT volume (positive for buys, negative for sells) divided by the total USDT volume. Figure 2) plots this metric for VIBBTC using a five-minute rolling window, both before and after the pump-and-dump event introduced earlier. Notice that prior to the manipulation, the imbalance spikes positively, indicating heavy buying pressure, whereas immediately after the pump announcement it turns negative, reflecting the dumping phase as insiders offload their positions onto incoming traders. We expect that including these imbalance based features to our modeling will improve our ability to detect shifts in long/short skews of the returns and potentially improve our model.

[3]Website Pyarrow [Online resource]: https://arrow.apache.org/docs/python/index.html

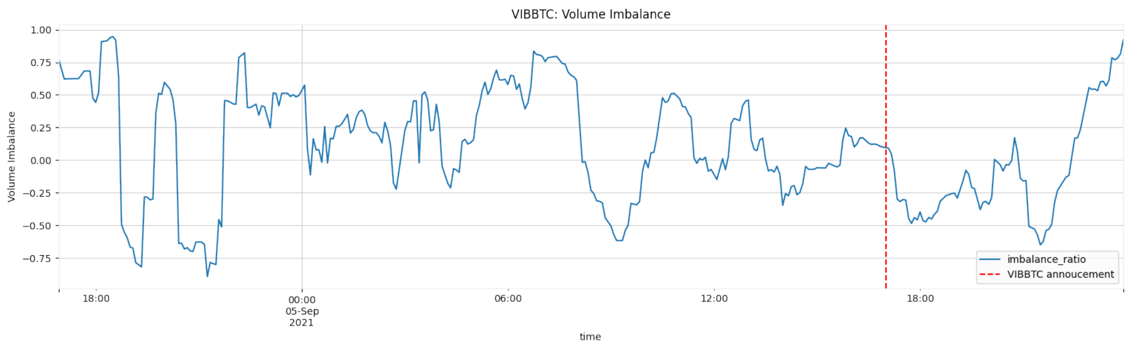


Figure 2: VIBBTC: Flow imbalance

2.2.2 Quote slippage features

Since the data we collected was not aggregated, we could actually assign multiple tick trades to one trader if all of them were executed at the same time up to microseconds. This methodology is used in many papers studying Pumps and dumps manipulations, so we decided to keep it similar to what we had done before and aggregate ticks by time to get trades associated to the same trader. This allowed us to aggregate ticks by time and see if the price of the first tick and the last tick are different, this way we could actually compute price impact and slippage. Slippage typically occurs when the trader wants to execute a big order - buying/selling big amount of asset, if the order is not a limit type order the order will eat into the orderbook and hence the price of ticks will be changing with volume transacted. Below is the formula how we defined loss to slippage Equation 4:

$$\text{Slippage Loss} = \underbrace{\sum_{i=1}^{N} \text{qty\_sign}_i \cdot P_i}_{\text{Quote actually spent}} - \underbrace{\sum_{i=1}^{N} \text{qty\_sign}_i \cdot P_0}_{\substack{\text{Quote could have been spent} \\ \text{if filled at best price}}} \tag{4}$$

This formula measures slippage by comparing the actual amount of quote currency spent to the amount we would have spent if we'd executed at the best bid or ask price (depending on the trade side). As the order fills, it "eats" through successive levels of the order book reflected in the trade-level data and this metric quantifies how far into the book the order "eats" into.

2.2.3 Asset returns features

One of the most intuitive features that we could add to our model is the lags of asset returns. Unfortunately, we did not have direct access to cryptocurrency L1 data with best bid/ask prices. Therefore, in our work we are not predicting the direction of the mid price, we are using a proxy to it computed based on flow of transactions and prices they were executed at.

Below we describe methodology of return calculation Figure 3:

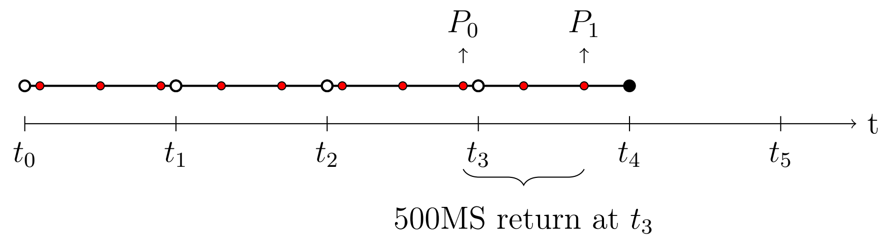


Figure 3: Illustration how returns are computed using transaction data

We are computing returns using the latest available close price P_0 and latest available P_1 before return horizon. For instance, following the example above, to compute 500 ms return at t_3 we are using the trade closest to t_3 from the left and its price P_0, then we are going to the right and looking for the closest trade to the right boundary which is t_4 for 500 ms return and we take its price P_1. Then we adjust the return by the time passed between two trades and we get the following Equation 5, where t_0 and t_1 correspond to timestamps of the left and right trades.

$$\text{Return (pips)} = (\frac{P_1}{P_0} - 1)\frac{0.5}{\text{seconds}(t_1 - t_0)}10^4 \tag{5}$$

In our research we narrowed down the scope to 20 major cryptocurrencies, this was done to improve the accuracy of returns calculated this way. As top cryptocurrencies are more actively traded, therefore, trades will be tightly packed within each interval, so there will be no issue to find left and right trades to compute returns. Adjustment factor will be less and less significant if either trading activity or time horizon increases, this can be see below in Table 3:

Table 3: Mean of seconds$(t_1 - t_0)$ from Equation 5 for Binance SPOT

Feature	BTC	ETH	HBAR
SELF-asset_hold_time-500MS@BINANCE_SPOT	0.639976	0.760697	1.998043
SELF-asset_hold_time-1S@BINANCE_SPOT	1.075336	1.191552	2.477734
SELF-asset_hold_time-2S@BINANCE_SPOT	2.020998	2.099428	3.422041
SELF-asset_hold_time-5S@BINANCE_SPOT	5.000501	5.013268	6.070643
SELF-asset_hold_time-10S@BINANCE_SPOT	9.999981	10.000562	10.617957

As we can see from the Table 3 as the time horizon increases all currencies have tighter intervals, BTC is the most traded cryptocurrency, therefore even at 500MS intervals, hold time on average will be pretty close to 500MS. The less traded the currency is, the more this impact can be seen, for HBAR trades are spaced out far away from one another, hence scaling factor will have affect on returns.

It is also interesting to note that the table above will significantly change for different markets and exchanges. For instance, below Table 4 is for Binance USDM market:

Table 4: Mean of seconds($t_1 - t_0$) from Equation 5 for Binance USDM

Feature	BTC	ETH	HBAR
SELF-asset_hold_time-500MS@BINANCE_USDM	0.550915	0.546265	1.228217
SELF-asset_hold_time-1S@BINANCE_USDM	1.020601	1.016292	1.661764
SELF-asset_hold_time-2S@BINANCE_USDM	2.004197	2.002357	2.538745
SELF-asset_hold_time-5S@BINANCE_USDM	5.000179	5.000035	5.283335
SELF-asset_hold_time-10S@BINANCE_USDM	10.000060	10.000007	10.101561

We see that across all currencies Binance USDM market is more dynamic than Binance SPOT market, hence using Binance USDM features might be useful for prediction of returns on Binance SPOT market. Below we also show the same Table 5 but for the slowest OKX SPOT exchange, this exchange is highly regulated which is why it is unpopular among cryptocurrency traders.

Table 5: Mean of seconds($t_1 - t_0$) from Equation 5 for OKX SPOT

Feature	BTC	ETH	HBAR
SELF-asset_hold_time-500MS@OKX_SPOT	1.050853	1.231412	6.009399
SELF-asset_hold_time-1S@OKX_SPOT	1.489804	1.665044	6.770041
SELF-asset_hold_time-2S@OKX_SPOT	2.373646	2.529405	7.960656
SELF-asset_hold_time-5S@OKX_SPOT	5.149236	5.237105	10.891920
SELF-asset_hold_time-10S@OKX_SPOT	10.033955	10.059024	15.361798

2.2.4 Power law features. Quantile spread of order sizes

We also analyzed trade sizes, we wanted to focus on trades with big volume. We wanted to come up with the feature that would measure that there is very high spread of trading volumes especially in upper quantiles. For this we chose Powerlaw which assumes that high quantile observations follow the probability density function given in Equation 6:

$$f(x, \alpha) = \alpha x^{\alpha-1} \tag{6}$$

We used this method to estimate the value of $\hat{\alpha}_{\mathrm{PL}}$, across the same rolling windows as in Table 6. Since α appears in the exponent of the power-law density, a smaller α causes the PDF to decay more slowly, indicating heavier tails and more extreme large trades. To determine α, we first filtered the data to include only trades above the 95th percentile in size and then estimated the probability density function for those trades. Next, we plotted the logarithm of the estimated PDF against the logarithm of the trade sizes and fitted a straight line to this relationship, the slope of that line is revealing how heavy the tail is and how frequently abnormally large trades occur.

$$\log \hat{f}_{\text{pdf}} = \underbrace{\log \alpha}_{\text{intercept}} + \underbrace{(\alpha - 1)}_{\text{slope}} \log(\text{quote\_abs}) \tag{7}$$

Finally, we took estimated slope which is $\alpha - 1$ and added back 1 to get $\hat{\alpha}_{\text{OLS}}$. Then, this was used a feature in our models measuring the quantile spread. Below in Figure 4 we show how Powerlaw fits to observed data:

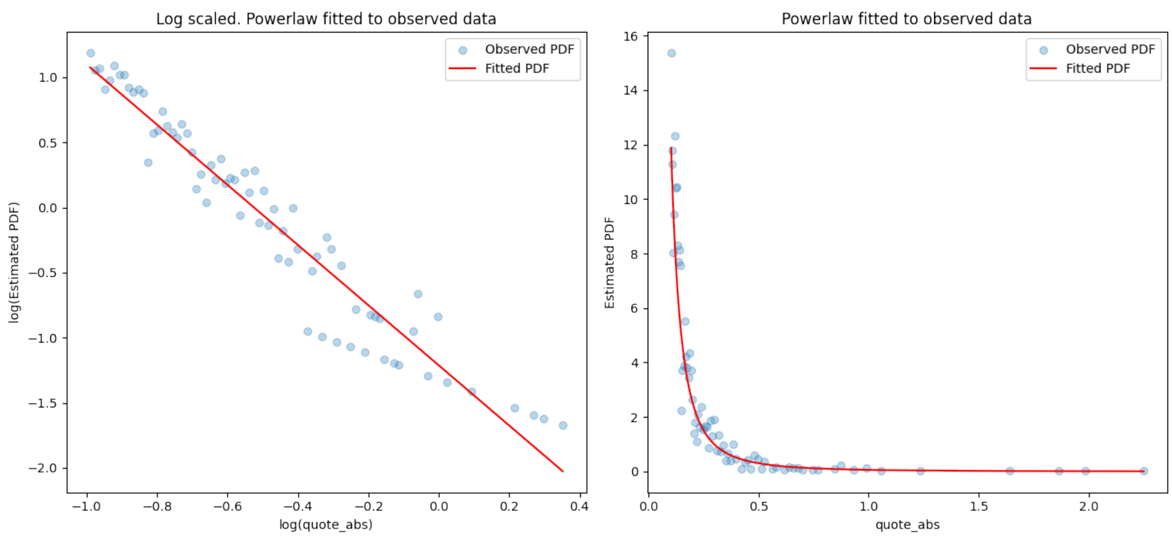


Figure 4: Powerlaw estimation

2.2.5 Exchange Difference

In our analysis we used 2 exchanges and 3 markets: Binance Spot, Binance USDM (perpetual futures against USDT), OKX Spot (different exchange). We anticipate that there will be a leading market: market where the price originates and then flows to other markets with some delay. Therefore, we will take advantage of it by using exchange differences. One of the most straightforward feature is the difference in past returns between exchanges. For instance, someone might buy up a lot of BTC in the spot market such that price spikes, this might affect the price on futures markets for a brief period of time or this might happen the other way round. We will discuss this in section 3.

2.2.6 Feature description

Below we listed all feature used in the model as well as their corresponding descriptions and feature names (6):

Feature	Description	Notation
Asset return	return of the asset calculated over the window of size x	SELF-asset_return-Base-Term-[x]s@Exchange
Flow imbalance	flow imbalance measures if the trading volume is skewed towards buying or selling. This feature is computed over windows of x	SELF-flow_imbalance-Base-Term-[x]s@Exchange
Slippage imbalance	slippage imbalance measures if there was more slippage attributed to buyers or sellers. This feature measures the impatience of either side to fill their positions.	SELF-slippage_imbalance-Base-Term-[x]s@Exchange
Powerlaw alpha	estimated alpha from powerlaw probability density function using the window of size x	SELF-powerlaw_alpha-Base-Term-[x]s@Exchange
Exchange Difference	Different in returns of different windows x between exchanges	SELF-exchange_diff-Exchange-OtherExchange@[x]s
Share of long trades	Share of buying trades in all trades over the window x	SELF-share_of_long_trades-[x]s@Exchange
Currency index	unique id number for each currency	currency_index

Table 6: These are the features included in all models. These features are designed to describe dynamics of price and trading volume. Windows in seconds: $x \in \{0.5, 1, 2, 5, 10, 30, 60, 120, 300\}$. Exchanges used in modeling $\{\text{Binance SPOT}, \text{Binance USDM}, \text{OKX SPOT}\}$. SELF indicates that this feature was calculated for the currency itself, as modeled currencies also have shared features that are supposed to capture market dynamics: BTC and ETH features.

2.3 Modeling

We set up the problem of prediction returns as a simple regression problem where we attempt to predict currencies returns in prediction horizon H. We designed the following pipeline that allowed us to train models:

Algorithm 1 Model methodology

1: Load data into memory for a subset of currencies: BTC, ETH, ADA, TRX, HBAR over the interval between [2025-05-01, 2025-05-10) and train the model, then save feature importance to file
2: Load feature importance and use only 25 best regressors, train the model for all currencies using the data that spans over [2025-04-01, 2025-05-10) with early stopping on a separate validation sample and then save trained booster
3: Load trained booster and load testing data spanning [2025-05-10, 2025-05-25) and compute both regression metrics like R2, MSE, MAE and classification metrics which evaluate our model as a binary classification model predicting if the price goes up or down

This approach allowed us to narrow down the set of regressors from 267 down to 25 which is essential as we have tens of millions of observations, it simply does not fit into memory.

3 Results

In the previous section we went over the whole pipeline, now we are ready to train the models. We trained multiple models with different prediction horizon H which takes the following values in seconds $H \in \{0.5, 1, 2, 3, 5, 10, 30, 60, 120, 300\}$. We used the same methodology described above in Algorithm 1. As a result, we ended up with feature importance as well as evaluation statistics for each forecast horizon H.

3.1 R-2 and H relationship

From Figure 5 we see that there is an optimal prediction horizon $H^* = 3$, where ALL line reaches the maximum R^2 of roughly 0.055. Then, the performance of the model decays faster as we are increasing prediction horizon H. This mirrors the results obtained in Hashish et al., 2019, the predictability decays as H increases, but more interesting is that at the start the performance improves, so for small values of H relationship is not monotonic. The results in tabular form are shown below in Table 8:

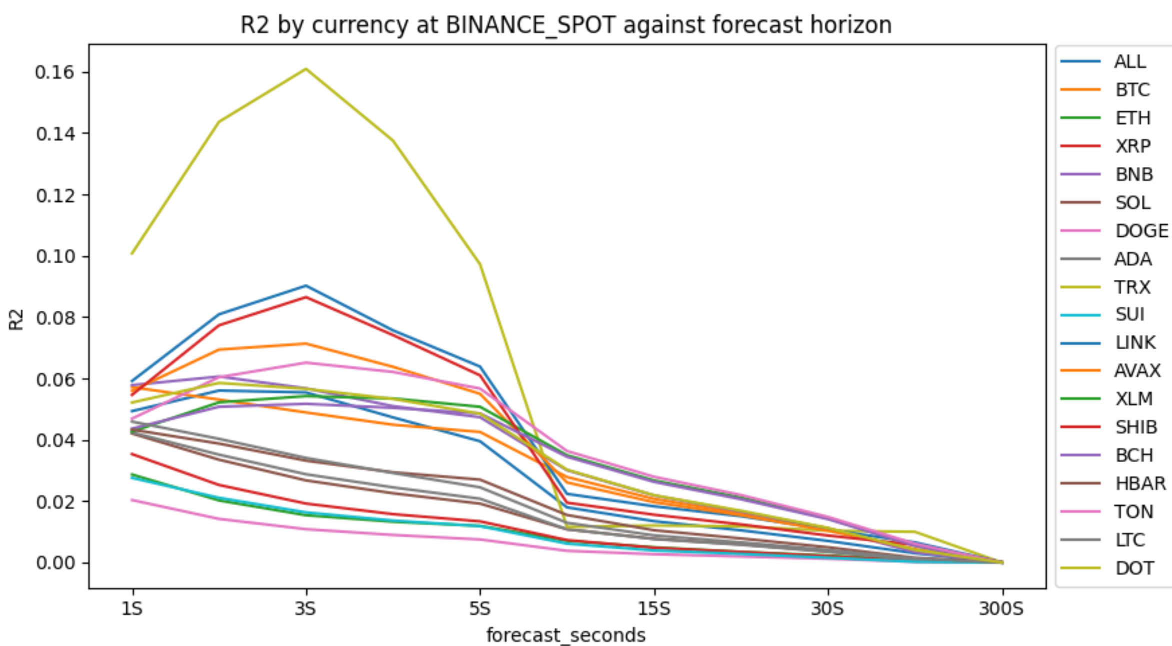


Figure 5: Return R^2 for different H - prediction horizon at Binance Spot

3.2 Feature importance for different H

Since we are using boosted trees, we have access to feature importances for features used during training of the model. Here we are using *gain* importances, meaning that the value of feature importance corresponds to the amount of loss we were able to reduce by splitting the data using this feature, generally, the higher the importance is, the more significant the feature is as it allows us to make better splits that improve in our case mean squared loss. Since distributions of target returns are different for each value of H, the higher the horizon is, the more there is room for prices to change, therefore, feature importances will be overall higher. Typically, we only care about ordering of the features, in order to account for this we scaled feature importances by the sum of all importances within each model. This way we can compare them for different values of H.

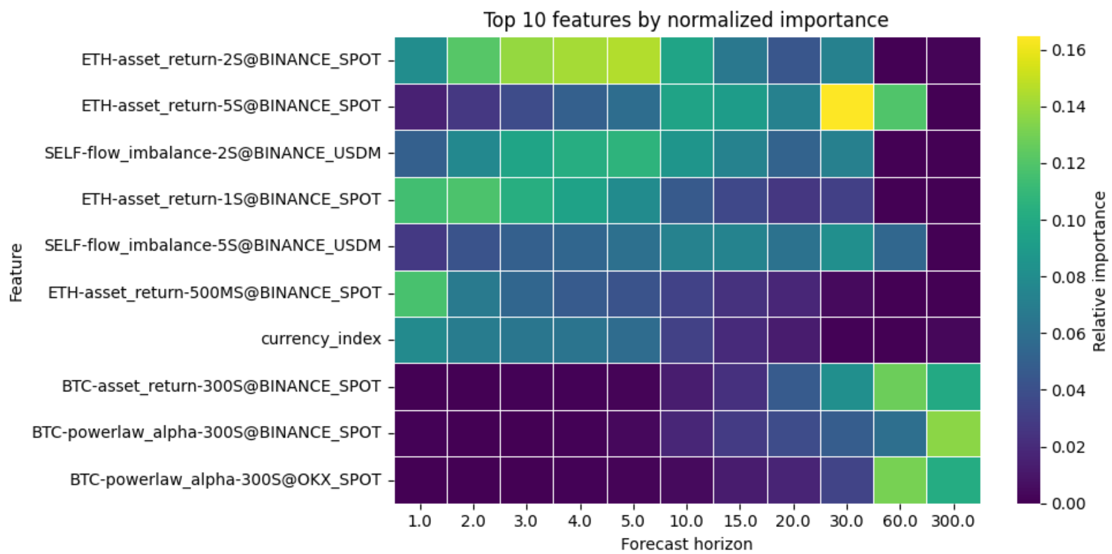


Figure 6: Normalized feature importances against different horizons H

In Figure 6 we see that as time horizon H increases from 1 second to 300 seconds short-term features like *ETH-asset_return-2S@BINANCE_SPOT* become less significant and features with longer windows become more important. Below in Table 7 we listed the most significant features for the best model with time horizon $H^* = 3$:

3.3 Predictability for different exchanges

We are also interested in studying how we can use the same data but to predict returns on different exchanges and markets.

Binance USDM

We ran the same pipeline described in Algorithm 1 for Binance USDM exchange. From Figure 7 we see that R^2 is monotonically decreasing in H - forecast horizon. This is attributed to the fact that the price originates in Binance USDM market and only then propagates to SPOT markets. This USDM market has more liquidity and in general more trading activity which corresponds to data in Table 4.

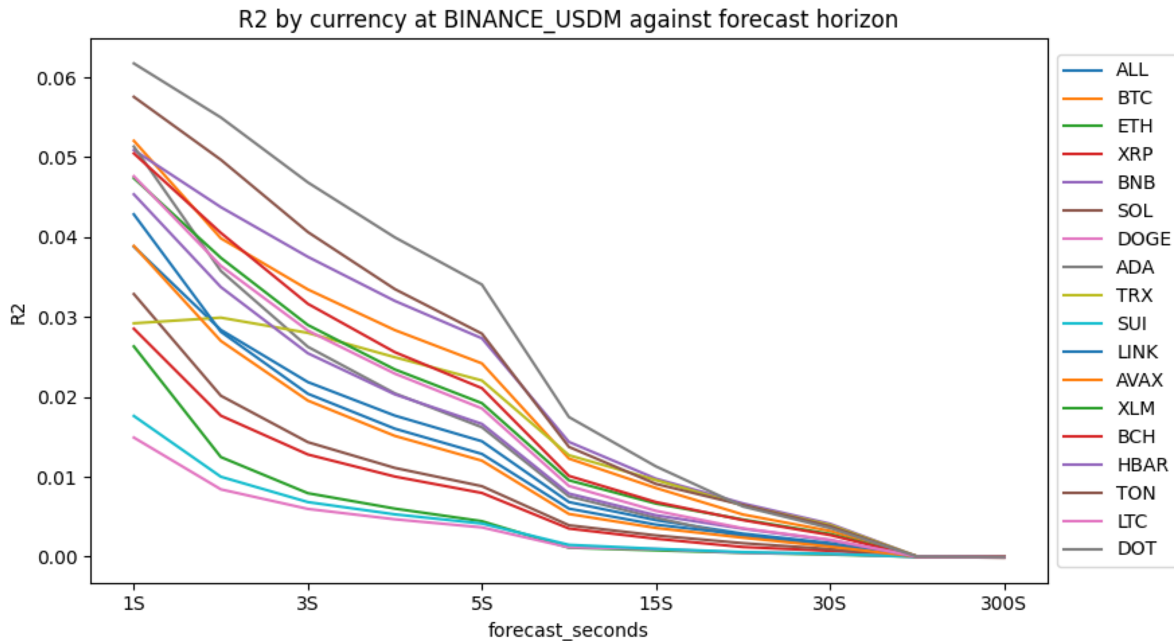


Figure 7: Return R^2 for different H - prediction horizon at Binance USDM

This could explain why we observed non-monotonic behavior of R^2 at Binance Spot. The price originates at futures market and then the most recent trading activity is used for features for spot model and only after a short time spot prices catch up with USDM market. Therefore, we should observe the following:

- Binance Spot model should have *exchange_ diff-BinanceSpot-BinanceUSDM@*[x]s for small values of x as the most significant features
- Binance USDM model should mostly rely on its own features

	BINANCE-SPOT	BINANCE-USDM
1	ETH-asset-return-2S@BINANCE-SPOT	currency-index
2	ETH-asset-return-1S@BINANCE-SPOT	ETH-asset-return-1S@BINANCE-USDM
3	SELF-flow-imbalance-2S@BINANCE-USDM	ETH-asset-return-2S@BINANCE-USDM
4	currency-index	ETH-asset-return-500MS@BINANCE-USDM
5	ETH-asset-return-500MS@BINANCE-SPOT	SELF-asset-return-1S@BINANCE-USDM
6	SELF-flow-imbalance-5S@BINANCE-USDM	SELF-asset-return-2S@BINANCE-USDM
7	SELF-exchange-diff-BINANCE-SPOT-BINANCE-USDM-2S	ETH-asset-return-5S@BINANCE-USDM
8	ETH-asset-return-5S@BINANCE-SPOT	SELF-flow-imbalance-500MS@BINANCE-USDM
9	SELF-flow-imbalance-1S@BINANCE-USDM	SELF-flow-imbalance-1S@BINANCE-USDM
10	SELF-exchange-diff-BINANCE-SPOT-BINANCE-USDM-500MS	BTC-asset-return-500MS@BINANCE-USDM
11	SELF-exchange-diff-BINANCE-SPOT-BINANCE-USDM-1S	SELF-flow-imbalance-1S@BINANCE-SPOT
12	SELF-powerlaw-alpha-300S@BINANCE-USDM	SELF-asset-return-500MS@BINANCE-USDM
13	SELF-flow-imbalance-500MS@BINANCE-USDM	SELF-flow-imbalance-500MS@BINANCE-SPOT
14	BTC-asset-return-500MS@BINANCE-SPOT	SELF-flow-imbalance-2S@BINANCE-USDM
15	SELF-asset-return-2S@BINANCE-SPOT	SELF-flow-imbalance-2S@BINANCE-SPOT

Table 7: Binance SPOT and Binance USDM most significant features for $H = 3$

As we can see from Table 7 model for Binance USDM relies on its own features whereas Binance SPOT uses features like exchange differences.

OKX SPOT

Here we used OKX SPOT as the target exchange. After running the pipeline we got the following results: R^2 follows same patterns as R^2 at Binance SPOT Figure 5, it is also increasing up to $H = 3$ and then decays to 0.

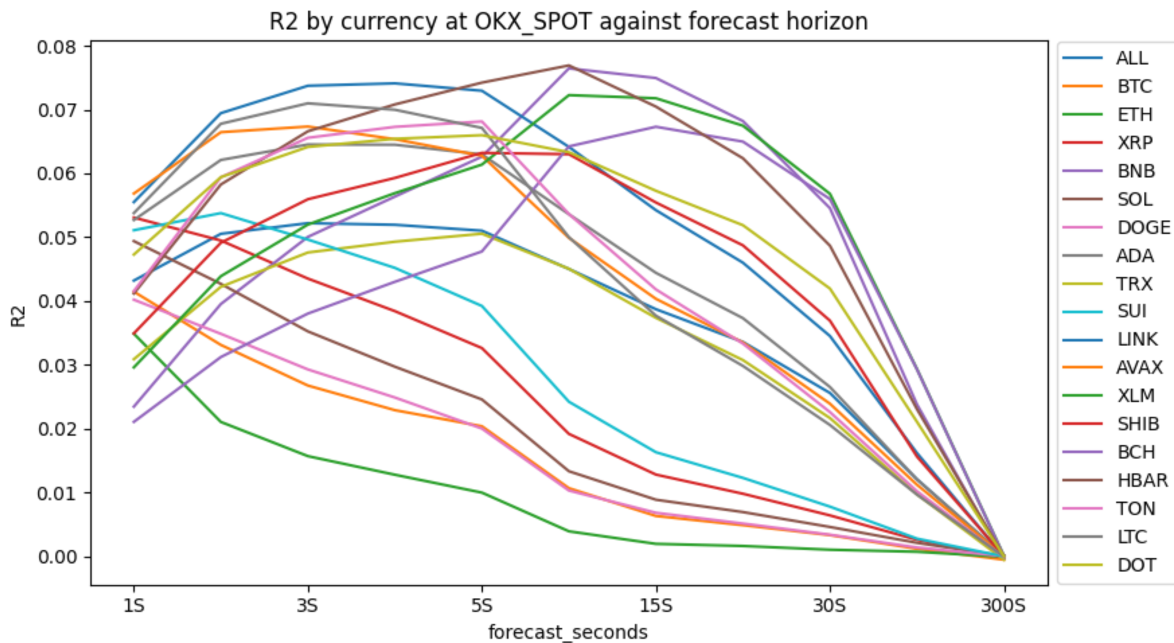


Figure 8: Return R^2 for different H - prediction horizon at OKX SPOT

Comparing OKX SPOT to Binance SPOT results it seems like OKX returns remain predictable for a much longer time. Even after 30 seconds overall R^2 remains ≈ 0.05 which is very high. Interestingly R^2 of BTC and ETH starts to decrease right away while smaller currencies have their optimal prediction forecast step. This effect can also be seen below in Table 8:

3.4 Evaluation metrics for exchanges

		BINANCE-SPOT				BINANCE-USDM				OKX-SPOT			
Currency	Horizon (s)	R2	MAE	F1	Accuracy	R2	MAE	F1	Accuracy	R2	MAE	F1	Accuracy
ALL	1	0.049	0.780	0.367	0.562	**0.039**	0.772	0.451	**0.571**	0.043	0.566	0.262	0.537
	2	0.056	1.273	0.441	0.579	0.028	1.220	0.497	0.571	0.051	0.969	0.349	0.552
	3	**0.055**	1.652	0.473	**0.581**	0.022	1.570	0.511	0.564	0.052	1.304	0.396	0.559
	4	0.047	1.967	0.486	0.577	0.018	1.867	0.517	0.559	**0.052**	1.594	0.426	**0.565**
	5	0.040	2.243	0.490	0.572	0.014	2.129	0.518	0.554	0.051	1.855	0.448	0.567
	10	0.018	3.301	0.500	0.553	0.007	3.137	0.515	0.538	0.045	2.893	0.497	0.570
	15	0.013	4.088	0.505	0.547	0.005	3.903	0.517	0.530	0.039	3.693	0.517	0.567
	20	0.010	4.754	0.507	0.541	0.003	4.554	0.515	0.524	0.034	4.365	0.526	0.564
	30	0.007	5.863	0.509	0.534	0.002	5.640	0.505	0.520	0.026	5.488	0.531	0.557
	60	0.003	8.375	0.503	0.523	0.000	8.085	0.662	0.497	0.012	8.017	0.529	0.541
	300	0.000	18.883	0.650	0.492	-0.000	18.212	0.661	0.504	-0.000	18.298	0.646	0.490
BTC	1	0.057	0.242	0.432	0.557	0.052	0.272	0.468	0.586	0.041	0.278	0.423	0.584
	2	0.053	0.413	0.479	0.575	0.040	0.459	0.497	0.587	0.033	0.464	0.492	0.593
	3	0.049	0.556	0.501	0.582	0.033	0.616	0.512	0.586	0.027	0.620	0.515	0.591
	4	0.045	0.679	0.515	0.584	0.028	0.754	0.519	0.582	0.023	0.755	0.526	0.587
	5	0.043	0.798	0.524	0.585	0.024	0.879	0.523	0.580	0.020	0.876	0.532	0.582
	10	0.028	1.273	0.541	0.580	0.012	1.377	0.523	0.560	0.011	1.357	0.529	0.561
	15	0.021	1.649	0.544	0.572	0.009	1.753	0.524	0.548	0.006	1.722	0.524	0.546
	20	0.016	1.970	0.544	0.563	0.005	2.067	0.530	0.539	0.005	2.027	0.524	0.540
	30	0.011	2.504	0.542	0.552	0.003	2.586	0.516	0.530	0.003	2.534	0.524	0.531
	60	0.004	3.726	0.523	0.531	0.000	3.770	0.665	0.500	0.001	3.695	0.514	0.520
	300	0.000	8.785	0.663	0.506	-0.000	8.698	0.661	0.504	-0.001	8.558	0.651	0.495
ETH	1	0.029	0.733	0.520	0.583	0.026	0.811	0.503	0.553	0.035	0.781	0.495	0.577
	2	0.020	1.206	0.545	0.579	0.012	1.285	0.512	0.537	0.021	1.241	0.526	0.567
	3	0.015	1.579	0.549	0.569	0.008	1.651	0.514	0.530	0.016	1.595	0.531	0.559
	4	0.013	1.894	0.547	0.565	0.006	1.958	0.514	0.525	0.013	1.894	0.534	0.553
	5	0.012	2.172	0.547	0.558	0.004	2.229	0.512	0.521	0.010	2.160	0.532	0.546
	10	0.007	3.236	0.538	0.541	0.001	3.255	0.509	0.511	0.004	3.176	0.518	0.527
	15	0.005	4.040	0.533	0.534	0.001	4.030	0.506	0.508	0.002	3.945	0.514	0.520
	20	0.003	4.723	0.527	0.527	0.000	4.690	0.509	0.506	0.002	4.597	0.514	0.517
	30	0.002	5.863	0.527	0.522	0.000	5.797	0.500	0.506	0.001	5.692	0.511	0.514
	60	0.001	8.472	0.511	0.509	-0.000	8.321	0.673	0.509	0.001	8.192	0.506	0.508
	300	-0.000	19.095	0.672	0.515	-0.000	18.538	0.671	0.514	-0.000	18.363	0.659	0.504
SOL	1	0.042	0.738	0.471	0.579	0.033	0.847	0.505	0.586	0.049	0.679	0.390	0.559
	2	0.033	1.173	0.520	0.585	0.020	1.288	0.512	0.569	0.043	1.115	0.477	0.573
	3	0.027	1.522	0.533	0.578	0.014	1.640	0.513	0.554	0.035	1.463	0.509	0.575
	4	0.023	1.823	0.536	0.574	0.011	1.940	0.513	0.546	0.030	1.759	0.524	0.573
	5	0.019	2.092	0.534	0.565	0.009	2.205	0.513	0.540	0.025	2.022	0.531	0.569
	10	0.011	3.146	0.532	0.547	0.004	3.228	0.513	0.525	0.013	3.043	0.532	0.551
	15	0.008	3.946	0.530	0.538	0.003	3.999	0.514	0.519	0.009	3.815	0.530	0.540
	20	0.006	4.623	0.527	0.532	0.002	4.654	0.510	0.515	0.007	4.465	0.528	0.535
	30	0.004	5.753	0.524	0.525	0.001	5.755	0.499	0.513	0.005	5.556	0.521	0.527
	60	0.001	8.292	0.511	0.513	0.000	8.224	0.663	0.497	0.002	8.004	0.516	0.520
	300	0.000	18.997	0.666	0.509	-0.000	18.688	0.663	0.507	0.000	18.372	0.653	0.498

Table 8: Regression and classification metrics for models with different H (forecast horizon). We show only metrics for ALL (evaluated over all currencies) and the three major cryptocurrencies BTC, ETH, SOL.

4 Conclusion

This research was a follow up on Pumps and Dumps research done in the previous year. The main goal was to extend the methodology and develop a working feature pipeline that would allow us to experiment even further with features and prediction horizons. Initially we wanted to include mid frequency analysis to this work as well, where we would predict returns 1 day ahead using similar features described in Table 6 above, but during research we found out that such approach does not work as it produces predictions with negative R^2 and heavily relies on test sample. In the future we want to improve our code base and allow to read data directly from exchanges websockets. This will allow us to read and save L1 and L2 data, which is not available for download in open sources.

In this research we successfully challenged EMH and added more evidence that there are opportunities to predict returns, at least their direction on smaller time frames. We showed that using tick level data is much better than candlestick data as typically was done in past researches. We were able to build the model that predicts returns with R^2 and accuracy reaching **0.056** and **0.581** respectively. We found interesting patterns that Binance USDM is the most active market where the price originates and propagates to other markets. This effect can be seen in feature importance of models for Binance SPOT and OKX SPOT, where features like exchange difference of returns are one of the most significant for prediction of returns. We also found that there can be an optimal prediction horizon H^*, before it was thought that the smaller the forecast step is, the better the result will be but it is not the case, as the relationship is not monotonic for some currencies. These findings might be useful for market makers that want to integrate Machine Learning to their trading stack. The code with all notebooks and python code is available on our Github.

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5 Supplementary Materials

5.1 Evaluation metrics for all currencies

		BINANCE-SPOT				BINANCE-USDM				OKX-SPOT			
		R2	MAE	F1	Accuracy	R2	MAE	F1	Accuracy	R2	MAE	F1	Accuracy
currency	Horizon (s)												
ADA	1	0.042	0.845	0.379	0.555	0.051	1.029	0.459	0.587	0.053	0.613	0.208	0.530
	2	0.035	1.382	0.459	0.569	0.036	1.533	0.501	0.586	0.062	1.063	0.305	0.548
	3	0.029	1.801	0.488	0.566	0.026	1.920	0.508	0.575	0.065	1.438	0.364	0.558
	4	0.024	2.155	0.501	0.562	0.020	2.251	0.511	0.566	0.064	1.765	0.404	0.567
	5	0.021	2.463	0.505	0.560	0.016	2.544	0.511	0.557	0.063	2.061	0.434	0.572
	10	0.011	3.650	0.511	0.543	0.008	3.682	0.506	0.540	0.054	3.248	0.503	0.582
	15	0.008	4.546	0.513	0.536	0.005	4.552	0.509	0.530	0.044	4.172	0.529	0.580
	20	0.006	5.309	0.515	0.531	0.002	5.296	0.501	0.519	0.037	4.952	0.539	0.576
	30	0.003	6.584	0.513	0.524	0.002	6.531	0.494	0.517	0.027	6.249	0.542	0.566
	60	0.001	9.478	0.507	0.514	0.000	9.326	0.652	0.485	0.012	9.139	0.536	0.545
	300	0.000	21.637	0.660	0.502	-0.000	21.179	0.657	0.499	0.000	20.963	0.646	0.490
ALL	1	0.049	0.780	0.367	0.562	0.039	0.772	0.451	0.571	0.043	0.566	0.262	0.537
	2	0.056	1.273	0.441	0.579	0.028	1.220	0.497	0.571	0.051	0.969	0.349	0.552
	3	0.055	1.652	0.473	0.581	0.022	1.570	0.511	0.564	0.052	1.304	0.396	0.559
	4	0.047	1.967	0.486	0.577	0.018	1.867	0.517	0.559	0.052	1.594	0.426	0.565
	5	0.040	2.243	0.490	0.572	0.014	2.129	0.518	0.554	0.051	1.855	0.448	0.567
	10	0.018	3.301	0.500	0.553	0.007	3.137	0.515	0.538	0.045	2.893	0.497	0.570
	15	0.013	4.088	0.505	0.547	0.005	3.903	0.517	0.530	0.039	3.693	0.517	0.567
	20	0.010	4.754	0.507	0.541	0.003	4.554	0.515	0.524	0.034	4.365	0.526	0.564
	30	0.007	5.863	0.509	0.534	0.002	5.640	0.505	0.520	0.026	5.488	0.531	0.557
	60	0.003	8.375	0.503	0.523	0.000	8.085	0.662	0.497	0.012	8.017	0.529	0.541
	300	0.000	18.883	0.650	0.492	-0.000	18.212	0.661	0.504	-0.000	18.298	0.646	0.490
AVAX	1	0.056	0.951	0.232	0.553	0.039	0.945	0.473	0.576	0.057	0.605	0.232	0.540
	2	0.069	1.566	0.335	0.563	0.027	1.524	0.520	0.571	0.066	1.067	0.333	0.560
	3	0.071	2.036	0.394	0.578	0.020	1.974	0.529	0.560	0.067	1.465	0.391	0.571
	4	0.064	2.423	0.420	0.577	0.015	2.348	0.529	0.551	0.065	1.817	0.429	0.578
	5	0.055	2.760	0.436	0.574	0.012	2.673	0.526	0.545	0.063	2.138	0.456	0.582
	10	0.026	4.041	0.460	0.557	0.005	3.909	0.514	0.529	0.050	3.433	0.517	0.585
	15	0.020	4.977	0.476	0.552	0.004	4.851	0.518	0.523	0.040	4.439	0.536	0.580
	20	0.015	5.769	0.481	0.547	0.002	5.661	0.517	0.519	0.034	5.283	0.544	0.574
	30	0.010	7.083	0.488	0.539	0.001	7.006	0.506	0.515	0.024	6.680	0.545	0.562
	60	0.004	10.063	0.491	0.526	0.000	10.012	0.664	0.498	0.011	9.756	0.540	0.544
	300	0.000	22.759	0.634	0.474	-0.000	22.541	0.658	0.500	0.000	22.258	0.645	0.488
BCH	1	0.044	0.516	0.186	0.529	0.050	0.662	0.437	0.581	0.021	0.382	0.085	0.511
	2	0.051	0.896	0.286	0.555	0.041	1.082	0.510	0.588	0.031	0.692	0.147	0.524
	3	0.052	1.213	0.345	0.560	0.032	1.417	0.532	0.583	0.038	0.975	0.194	0.528
	4	0.050	1.493	0.385	0.566	0.026	1.701	0.539	0.575	0.043	1.224	0.234	0.539
	5	0.049	1.746	0.413	0.574	0.021	1.951	0.539	0.569	0.048	1.463	0.268	0.544
	10	0.034	2.747	0.474	0.574	0.010	2.910	0.528	0.547	0.064	2.457	0.378	0.565
	15	0.026	3.504	0.494	0.568	0.007	3.638	0.528	0.538	0.067	3.248	0.440	0.575
	20	0.021	4.145	0.501	0.561	0.005	4.256	0.525	0.529	0.065	3.852	0.467	0.579
	30	0.014	5.208	0.507	0.550	0.003	5.284	0.513	0.523	0.056	4.877	0.493	0.575
	60	0.005	7.578	0.501	0.531	0.000	7.572	0.664	0.498	0.029	7.339	0.518	0.562
	300	0.000	16.999	0.641	0.481	0.000	16.709	0.659	0.501	0.000	16.850	0.628	0.471

Table 9: Regression and classification metrics for models with different H (forecast horizon). We show metrics for ALL (evaluated over all currencies) and 3 currencies ADA, AVAX, BCH

		BINANCE-SPOT				BINANCE-USDM				OKX-SPOT			
		R2	MAE	F1	Accuracy	R2	MAE	F1	Accuracy	R2	MAE	F1	Accuracy
currency	Horizon (s)												
BNB	1	0.058	0.305	0.441	0.577	0.051	0.340	0.451	0.579	0.023	0.278	0.095	0.501
	2	0.061	0.507	0.515	0.600	0.044	0.561	0.508	0.584	0.040	0.487	0.165	0.514
	3	0.057	0.681	0.540	0.603	0.038	0.745	0.524	0.583	0.050	0.670	0.221	0.523
	4	0.051	0.835	0.553	0.605	0.032	0.908	0.533	0.580	0.056	0.827	0.265	0.535
	5	0.047	0.978	0.556	0.596	0.027	1.054	0.535	0.577	0.063	0.968	0.303	0.545
	10	0.030	1.560	0.564	0.584	0.014	1.634	0.535	0.558	0.076	1.545	0.418	0.572
	15	0.022	2.015	0.559	0.572	0.010	2.075	0.532	0.547	0.075	1.982	0.474	0.583
	20	0.017	2.399	0.555	0.562	0.007	2.448	0.529	0.540	0.068	2.357	0.502	0.587
	30	0.011	3.034	0.548	0.550	0.004	3.062	0.516	0.531	0.055	2.990	0.528	0.583
	60	0.003	4.441	0.524	0.527	0.000	4.431	0.665	0.500	0.024	4.408	0.529	0.561
	300	-0.000	10.247	0.667	0.510	-0.000	10.148	0.666	0.509	-0.000	10.080	0.635	0.478
BTC	1	0.057	0.242	0.432	0.557	0.052	0.272	0.468	0.586	0.041	0.278	0.423	0.584
	2	0.053	0.413	0.479	0.575	0.040	0.459	0.497	0.587	0.033	0.464	0.492	0.593
	3	0.049	0.556	0.501	0.582	0.033	0.616	0.512	0.586	0.027	0.620	0.515	0.591
	4	0.045	0.679	0.515	0.584	0.028	0.754	0.519	0.582	0.023	0.755	0.526	0.587
	5	0.043	0.798	0.524	0.585	0.024	0.879	0.523	0.580	0.020	0.876	0.532	0.582
	10	0.028	1.273	0.541	0.580	0.012	1.377	0.523	0.560	0.011	1.357	0.529	0.561
	15	0.021	1.649	0.544	0.572	0.009	1.753	0.524	0.548	0.006	1.722	0.524	0.546
	20	0.016	1.970	0.544	0.563	0.005	2.067	0.530	0.539	0.005	2.027	0.524	0.540
	30	0.011	2.504	0.542	0.552	0.003	2.586	0.516	0.530	0.003	2.534	0.524	0.531
	60	0.004	3.726	0.523	0.531	0.000	3.770	0.665	0.500	0.001	3.695	0.514	0.520
	300	0.000	8.785	0.663	0.506	-0.000	8.698	0.661	0.504	-0.001	8.558	0.651	0.495
DOGE	1	0.020	1.089	0.479	0.563	0.015	1.185	0.490	0.551	0.040	0.997	0.416	0.565
	2	0.014	1.742	0.517	0.559	0.008	1.809	0.502	0.540	0.035	1.625	0.492	0.576
	3	0.011	2.247	0.526	0.551	0.006	2.286	0.504	0.531	0.029	2.117	0.518	0.574
	4	0.009	2.673	0.525	0.544	0.005	2.690	0.504	0.526	0.025	2.532	0.528	0.570
	5	0.007	3.046	0.521	0.540	0.004	3.045	0.502	0.522	0.020	2.900	0.532	0.565
	10	0.004	4.473	0.519	0.526	0.001	4.408	0.500	0.513	0.010	4.297	0.531	0.547
	15	0.003	5.550	0.518	0.521	0.001	5.444	0.504	0.511	0.007	5.341	0.526	0.537
	20	0.002	6.465	0.516	0.517	0.001	6.329	0.507	0.508	0.005	6.225	0.524	0.532
	30	0.001	7.996	0.516	0.514	0.000	7.810	0.499	0.508	0.003	7.701	0.518	0.526
	60	0.000	11.439	0.510	0.508	-0.000	11.139	0.666	0.501	0.001	11.012	0.517	0.517
	300	-0.000	26.270	0.668	0.510	-0.000	25.418	0.665	0.508	0.000	25.236	0.654	0.499
DOT	1	0.052	0.708	0.263	0.539	0.062	0.926	0.348	0.557	0.047	0.476	0.135	0.523
	2	0.059	1.214	0.374	0.568	0.055	1.457	0.439	0.583	0.059	0.862	0.214	0.538
	3	0.057	1.628	0.431	0.577	0.047	1.865	0.473	0.577	0.064	1.200	0.269	0.547
	4	0.053	1.988	0.463	0.580	0.040	2.206	0.491	0.582	0.065	1.504	0.309	0.555
	5	0.049	2.305	0.481	0.584	0.034	2.506	0.500	0.580	0.066	1.787	0.340	0.559
	10	0.030	3.524	0.512	0.571	0.017	3.656	0.503	0.561	0.063	2.949	0.433	0.576
	15	0.022	4.432	0.520	0.563	0.011	4.528	0.508	0.548	0.057	3.868	0.477	0.580
	20	0.017	5.203	0.521	0.556	0.006	5.283	0.499	0.536	0.052	4.658	0.501	0.581
	30	0.011	6.485	0.521	0.546	0.004	6.531	0.493	0.531	0.042	5.991	0.525	0.578
	60	0.004	9.392	0.511	0.528	0.000	9.332	0.635	0.468	0.021	9.008	0.537	0.559
	300	-0.000	21.363	0.653	0.495	-0.000	20.951	0.649	0.491	-0.000	20.861	0.639	0.483

Table 10: Regression and classification metrics for models with different H (forecast horizon). We show metrics for 4 currencies: BNB, BTC, DOGE, DOT

		BINANCE-SPOT				BINANCE-USDM				OKX-SPOT			
		R2	MAE	F1	Accuracy	R2	MAE	F1	Accuracy	R2	MAE	F1	Accuracy
currency	Horizon (s)												
ETH	1	0.029	0.733	0.520	0.583	0.026	0.811	0.503	0.553	0.035	0.781	0.495	0.577
	2	0.020	1.206	0.545	0.579	0.012	1.285	0.512	0.537	0.021	1.241	0.526	0.567
	3	0.015	1.579	0.549	0.569	0.008	1.651	0.514	0.530	0.016	1.595	0.531	0.559
	4	0.013	1.894	0.547	0.565	0.006	1.958	0.514	0.525	0.013	1.894	0.534	0.553
	5	0.012	2.172	0.547	0.558	0.004	2.229	0.512	0.521	0.010	2.160	0.532	0.546
	10	0.007	3.236	0.538	0.541	0.001	3.255	0.509	0.511	0.004	3.176	0.518	0.527
	15	0.005	4.040	0.533	0.534	0.001	4.030	0.506	0.508	0.002	3.945	0.514	0.520
	20	0.003	4.723	0.527	0.527	0.000	4.690	0.509	0.506	0.002	4.597	0.514	0.517
	30	0.002	5.863	0.527	0.522	0.000	5.797	0.500	0.506	0.001	5.692	0.511	0.514
	60	0.001	8.472	0.511	0.509	-0.000	8.321	0.673	0.509	0.001	8.192	0.506	0.508
	300	-0.000	19.095	0.672	0.515	-0.000	18.538	0.671	0.514	-0.000	18.363	0.659	0.504
HBAR	1	0.043	0.712	0.381	0.558	0.045	0.811	0.430	0.583	0.041	0.563	0.177	0.530
	2	0.039	1.196	0.471	0.581	0.034	1.325	0.497	0.584	0.058	0.990	0.270	0.546
	3	0.033	1.592	0.507	0.581	0.025	1.728	0.517	0.575	0.067	1.347	0.332	0.558
	4	0.029	1.932	0.525	0.578	0.020	2.065	0.522	0.567	0.071	1.658	0.375	0.566
	5	0.027	2.231	0.533	0.579	0.017	2.360	0.522	0.560	0.074	1.939	0.409	0.572
	10	0.015	3.392	0.542	0.559	0.008	3.481	0.514	0.541	0.077	3.063	0.496	0.588
	15	0.010	4.272	0.538	0.549	0.005	4.332	0.516	0.532	0.070	3.944	0.532	0.591
	20	0.008	5.011	0.535	0.540	0.004	5.052	0.519	0.526	0.062	4.694	0.548	0.591
	30	0.005	6.238	0.529	0.532	0.002	6.253	0.507	0.521	0.049	5.949	0.559	0.584
	60	0.002	8.985	0.514	0.518	0.000	8.957	0.663	0.498	0.023	8.739	0.556	0.562
	300	-0.000	20.316	0.665	0.507	-0.000	20.146	0.663	0.505	-0.000	19.932	0.651	0.495
LINK	1	0.059	1.161	0.205	0.538	0.043	0.890	0.460	0.576	0.056	0.579	0.213	0.538
	2	0.081	1.878	0.306	0.556	0.028	1.428	0.506	0.571	0.069	1.015	0.314	0.557
	3	0.090	2.397	0.367	0.575	0.020	1.845	0.516	0.562	0.074	1.385	0.375	0.570
	4	0.076	2.790	0.388	0.569	0.016	2.195	0.519	0.554	0.074	1.710	0.416	0.578
	5	0.064	3.139	0.401	0.569	0.013	2.502	0.518	0.548	0.073	2.007	0.445	0.583
	10	0.022	4.398	0.417	0.546	0.006	3.679	0.509	0.532	0.064	3.206	0.512	0.591
	15	0.018	5.253	0.438	0.545	0.004	4.572	0.514	0.526	0.054	4.148	0.536	0.589
	20	0.015	5.968	0.447	0.543	0.003	5.330	0.516	0.522	0.046	4.947	0.545	0.585
	30	0.011	7.154	0.460	0.537	0.002	6.594	0.504	0.517	0.035	6.274	0.550	0.574
	60	0.007	9.896	0.485	0.532	0.000	9.438	0.659	0.493	0.016	9.224	0.543	0.552
	300	0.000	21.900	0.619	0.460	-0.000	21.381	0.656	0.498	-0.000	21.150	0.644	0.487
LTC	1	0.046	0.738	0.394	0.569	0.048	0.828	0.421	0.579	0.054	0.539	0.213	0.527
	2	0.040	1.208	0.474	0.583	0.036	1.292	0.483	0.581	0.068	0.939	0.320	0.551
	3	0.034	1.577	0.504	0.580	0.028	1.647	0.501	0.574	0.071	1.273	0.386	0.565
	4	0.029	1.891	0.514	0.574	0.023	1.949	0.508	0.567	0.070	1.565	0.429	0.574
	5	0.024	2.168	0.516	0.566	0.019	2.214	0.509	0.560	0.067	1.828	0.459	0.579
	10	0.013	3.237	0.519	0.547	0.009	3.242	0.507	0.542	0.050	2.890	0.522	0.584
	15	0.009	4.048	0.520	0.539	0.006	4.022	0.509	0.532	0.038	3.707	0.539	0.577
	20	0.007	4.733	0.520	0.534	0.004	4.687	0.506	0.525	0.030	4.387	0.544	0.571
	30	0.004	5.881	0.518	0.526	0.002	5.799	0.498	0.521	0.021	5.519	0.543	0.559
	60	0.001	8.485	0.509	0.514	0.000	8.318	0.656	0.490	0.010	8.046	0.532	0.540
	300	-0.000	19.085	0.655	0.496	-0.000	18.606	0.653	0.495	-0.000	18.316	0.642	0.485

Table 11: Regression and classification metrics for models with different H (forecast horizon). We show metrics for 4 currencies: ETH, HBAR, LINK, LTC

		BINANCE-SPOT				BINANCE-USDM				OKX-SPOT			
		R2	MAE	F1	Accuracy	R2	MAE	F1	Accuracy	R2	MAE	F1	Accuracy
currency	forecast-seconds												
SHIB	1	0.055	1.338	0.222	0.551	NaN	NaN	NaN	NaN	0.035	0.590	0.178	0.529
	2	0.077	2.155	0.328	0.592	NaN	NaN	NaN	NaN	0.049	1.062	0.273	0.540
	3	0.086	2.728	0.384	0.601	NaN	NaN	NaN	NaN	0.056	1.468	0.332	0.549
	4	0.074	3.149	0.397	0.576	NaN	NaN	NaN	NaN	0.059	1.827	0.376	0.562
	5	0.061	3.513	0.405	0.574	NaN	NaN	NaN	NaN	0.063	2.156	0.409	0.566
	10	0.019	4.830	0.417	0.543	NaN	NaN	NaN	NaN	0.063	3.487	0.490	0.579
	15	0.016	5.768	0.435	0.542	NaN	NaN	NaN	NaN	0.055	4.537	0.522	0.582
	20	0.012	6.560	0.447	0.537	NaN	NaN	NaN	NaN	0.049	5.425	0.537	0.580
	30	0.009	7.880	0.461	0.530	NaN	NaN	NaN	NaN	0.037	6.902	0.547	0.573
	60	0.006	10.899	0.479	0.535	NaN	NaN	NaN	NaN	0.016	10.172	0.551	0.562
	300	0.000	24.061	0.624	0.464	NaN	NaN	NaN	NaN	0.000	23.193	0.648	0.493
SOL	1	0.042	0.738	0.471	0.579	0.033	0.847	0.505	0.586	0.049	0.679	0.390	0.559
	2	0.033	1.173	0.520	0.585	0.020	1.288	0.512	0.569	0.043	1.115	0.477	0.573
	3	0.027	1.522	0.533	0.578	0.014	1.640	0.513	0.554	0.035	1.463	0.509	0.575
	4	0.023	1.823	0.536	0.574	0.011	1.940	0.513	0.546	0.030	1.759	0.524	0.573
	5	0.019	2.092	0.534	0.565	0.009	2.205	0.513	0.540	0.025	2.022	0.531	0.569
	10	0.011	3.146	0.532	0.547	0.004	3.228	0.513	0.525	0.013	3.043	0.532	0.551
	15	0.008	3.946	0.530	0.538	0.003	3.999	0.514	0.519	0.009	3.815	0.530	0.540
	20	0.006	4.623	0.527	0.532	0.002	4.654	0.510	0.515	0.007	4.465	0.528	0.535
	30	0.004	5.753	0.524	0.525	0.001	5.755	0.499	0.513	0.005	5.556	0.521	0.527
	60	0.001	8.292	0.511	0.513	0.000	8.224	0.663	0.497	0.002	8.004	0.516	0.520
	300	0.000	18.997	0.666	0.509	-0.000	18.688	0.663	0.507	0.000	18.372	0.653	0.498
SUI	1	0.028	0.943	0.490	0.577	0.018	1.080	0.502	0.556	0.051	0.829	0.355	0.563
	2	0.021	1.555	0.535	0.576	0.010	1.683	0.514	0.542	0.054	1.388	0.457	0.580
	3	0.016	2.037	0.543	0.567	0.007	2.143	0.515	0.533	0.050	1.842	0.501	0.587
	4	0.014	2.445	0.542	0.559	0.005	2.529	0.515	0.527	0.045	2.233	0.525	0.587
	5	0.012	2.803	0.540	0.554	0.004	2.870	0.513	0.523	0.039	2.584	0.538	0.585
	10	0.006	4.185	0.532	0.535	0.001	4.190	0.509	0.514	0.024	3.950	0.551	0.570
	15	0.004	5.230	0.525	0.527	0.001	5.203	0.511	0.511	0.016	4.985	0.548	0.558
	20	0.003	6.104	0.523	0.521	0.001	6.054	0.510	0.508	0.012	5.841	0.545	0.551
	30	0.002	7.563	0.522	0.516	0.000	7.479	0.500	0.507	0.008	7.268	0.536	0.540
	60	0.000	10.842	0.508	0.507	-0.000	10.684	0.670	0.505	0.003	10.437	0.527	0.524
	300	-0.000	24.312	0.664	0.507	-0.000	23.826	0.663	0.505	-0.000	23.378	0.650	0.495
TON	1	0.047	0.704	0.212	0.548	0.058	0.679	0.421	0.575	0.042	0.680	0.185	0.525
	2	0.060	1.190	0.318	0.565	0.050	1.118	0.507	0.588	0.059	1.167	0.291	0.553
	3	0.065	1.569	0.382	0.581	0.041	1.471	0.536	0.586	0.066	1.547	0.355	0.562
	4	0.062	1.890	0.415	0.583	0.033	1.773	0.545	0.580	0.067	1.863	0.397	0.574
	5	0.057	2.167	0.434	0.579	0.028	2.040	0.547	0.575	0.068	2.135	0.429	0.580
	10	0.036	3.219	0.476	0.570	0.014	3.063	0.534	0.553	0.054	3.155	0.489	0.585
	15	0.028	3.994	0.492	0.565	0.009	3.836	0.532	0.542	0.042	3.908	0.505	0.580
	20	0.022	4.650	0.497	0.559	0.006	4.488	0.527	0.534	0.033	4.535	0.510	0.573
	30	0.015	5.749	0.500	0.550	0.004	5.573	0.514	0.526	0.023	5.580	0.509	0.561
	60	0.006	8.202	0.497	0.535	0.000	8.002	0.668	0.503	0.010	7.924	0.506	0.542
	300	-0.000	18.066	0.645	0.486	-0.000	17.743	0.668	0.511	-0.000	17.399	0.632	0.476

Table 12: Regression and classification metrics for models with different H (forecast horizon). We show metrics for currencies: SHIB, SOL, SUI, TON

currency	forecast-seconds	BINANCE-SPOT R2	BINANCE-SPOT MAE	BINANCE-SPOT F1	BINANCE-SPOT Accuracy	BINANCE-USDM R2	BINANCE-USDM MAE	BINANCE-USDM F1	BINANCE-USDM Accuracy	OKX-SPOT R2	OKX-SPOT MAE	OKX-SPOT F1	OKX-SPOT Accuracy
TRX	1	0.101	0.979	0.331	0.644	0.029	0.333	0.313	0.529	0.031	0.273	0.177	0.505
	2	0.144	1.409	0.449	0.682	0.030	0.539	0.405	0.552	0.042	0.474	0.278	0.525
	3	0.161	1.646	0.497	0.684	0.028	0.708	0.446	0.555	0.048	0.643	0.345	0.536
	4	0.138	1.801	0.484	0.650	0.025	0.856	0.469	0.558	0.049	0.787	0.390	0.546
	5	0.097	1.906	0.435	0.603	0.022	0.990	0.484	0.559	0.051	0.914	0.425	0.552
	10	0.012	2.330	0.384	0.525	0.013	1.529	0.509	0.551	0.045	1.428	0.504	0.565
	15	0.012	2.629	0.404	0.527	0.010	1.953	0.519	0.544	0.037	1.824	0.531	0.565
	20	0.012	2.886	0.416	0.528	0.006	2.317	0.518	0.537	0.031	2.163	0.542	0.562
	30	0.010	3.349	0.431	0.527	0.004	2.925	0.509	0.530	0.022	2.739	0.546	0.553
	60	0.010	4.457	0.466	0.537	0.000	4.302	0.663	0.498	0.010	4.045	0.533	0.536
	300	-0.000	9.846	0.606	0.446	-0.000	10.076	0.664	0.507	-0.001	9.584	0.653	0.497
XLM	1	0.043	0.645	0.184	0.528	0.047	0.736	0.431	0.579	0.030	0.434	0.115	0.512
	2	0.052	1.109	0.281	0.553	0.037	1.198	0.505	0.584	0.044	0.786	0.190	0.523
	3	0.054	1.487	0.340	0.559	0.029	1.563	0.527	0.578	0.052	1.093	0.244	0.532
	4	0.053	1.820	0.378	0.569	0.023	1.870	0.534	0.572	0.057	1.365	0.286	0.542
	5	0.051	2.114	0.404	0.571	0.019	2.139	0.535	0.566	0.061	1.615	0.321	0.546
	10	0.035	3.245	0.462	0.570	0.010	3.166	0.526	0.545	0.072	2.621	0.419	0.564
	15	0.027	4.073	0.484	0.566	0.007	3.948	0.528	0.537	0.072	3.407	0.469	0.573
	20	0.021	4.769	0.492	0.560	0.005	4.614	0.524	0.531	0.067	4.085	0.498	0.576
	30	0.014	5.916	0.499	0.550	0.003	5.731	0.511	0.524	0.057	5.234	0.527	0.578
	60	0.005	8.491	0.494	0.532	0.000	8.237	0.667	0.502	0.029	7.888	0.546	0.566
	300	0.000	18.807	0.638	0.478	-0.000	18.229	0.664	0.507	0.000	18.247	0.650	0.493
XRP	1	0.035	0.687	0.468	0.573	0.029	0.752	0.493	0.579	0.053	0.616	0.342	0.553
	2	0.025	1.109	0.513	0.576	0.018	1.157	0.507	0.563	0.049	1.012	0.439	0.570
	3	0.019	1.441	0.526	0.568	0.013	1.477	0.510	0.554	0.044	1.328	0.482	0.576
	4	0.016	1.725	0.529	0.563	0.010	1.749	0.512	0.547	0.038	1.598	0.505	0.577
	5	0.013	1.976	0.527	0.556	0.008	1.990	0.510	0.542	0.033	1.838	0.518	0.576
	10	0.007	2.938	0.526	0.540	0.004	2.915	0.509	0.527	0.019	2.772	0.533	0.563
	15	0.005	3.666	0.523	0.531	0.002	3.611	0.508	0.520	0.013	3.482	0.533	0.552
	20	0.003	4.277	0.519	0.525	0.001	4.197	0.507	0.514	0.010	4.073	0.531	0.545
	30	0.002	5.295	0.518	0.520	0.001	5.171	0.498	0.513	0.006	5.056	0.526	0.536
	60	0.000	7.605	0.509	0.511	0.000	7.385	0.663	0.498	0.003	7.277	0.518	0.525
	300	0.000	17.355	0.663	0.505	-0.000	16.734	0.663	0.506	-0.000	16.621	0.650	0.494

Table 13: Regression and classification metrics for models with different H (forecast horizon). We show metrics for currencies: TRX, XLM, XRP