Predicting Cryptocurrency Short-Term Returns

Sarah Hollingsworth

Data 612

Franklin University

1. Introduction

The purpose of this project is to forecast the short-term returns of cryptocurrency over varying time intervals to see if trends can be identified in the market. With the recent attention being given to such platforms as Robinhood, where self-directed investors used the Robinhood application to trade stocks such as GameStop, Nokia, and BlackBerry. In so doing, they hyperinflated the price of each of these stocks beyond their market value. (Leonhardt, 2021) This has led to more scrutiny of the stock market, which is already subject to oversight from the Security and Exchange Commission. The same is not true for the open market where cryptocurrency is currently exchanged, with over $40 billion in cryptocurrency changing hands daily, volatility is high and regulation low. The applications of forecasting the price of cryptocurrency can include providing more accurate investment forecasting, identifying hyperinflation of stocks, and potentially fraudulent trades in the market.

Cryptocurrency is not a new phenomenon as the first cryptocurrency, Ecash was introduced to the marketplace in 1988 by David Chaum. (Phillips, 1998) Cryptocurrency is traded on a decentralized peer to peer network, the currency is created with two key cryptography only shared by the creator and receiver. (Koh, 2019) As mentioned above, volatility is high in the cryptocurrency market, in large part due to decentralization of the currency and the value is indistinct as it is not backed by assets. (Giudici, Milne, & Vinogradov, 2019) Cryptocurrency exchanges, unlike stock markets, are not regulated by the Securities Act of 1933 or the Securities Exchange Act of 1934. Both laws clearly define how stocks are traded and who can trade those stocks. Currently in the United States cryptocurrency exchanges are regulated under the Bank Secrecy Act, which includes anti-money laundering and counter terrorism financing. (Smith, 2021) The Bank Secrecy Act was established to regulate the circumstances in which financial institutions are required to report transactions and other activities which in part or in whole could be considered criminal in nature. It does not regulate the pricing or exchange of cryptocurrency or other publicly traded securities. The value of cryptocurrency is designated by the ability to trace the origins of the currency and the privacy of the currency provided to the owner. (Phillips, 1998) While this provides trust to the owner, it also negates a third party such as a financial institution or government entity from the transaction. By eliminating this third party, the currency is no longer certifiable from a source outside of the transaction. (Koh, 2019) Since cryptocurrency is not controlled by a central authority, it also is not required to be supported by physical assets in the same manner as traditional currencies.

For all the reasons listed above, cryptocurrency is highly volatile not only as a currency but also in the open market exchange. Since Bitcoin was introduced in 2009, there has been a wide variety of literature regarding the creation of predictive models for cryptocurrency including its volatility. Nair sets forth the pairs trading strategy utilized in the traditional stock market, can be applied to cryptocurrency markets. By finding pairs of cryptocurrencies which are highly correlated, a highly effective pairs trading strategy can be implemented to increase profits for the investor while minimizing risk. (Nair, 2021) Other approaches include the application of a non-Gaussian probability distribution, which can account for data which is not unimodal. The volatility of the cryptocurrency markets inherently means the value of the currency is not unimodal and more accurate predictions can be achieved through this technique. The results put forth show not only accuracy in forecasting of cryptocurrency, but also how these same techniques can be utilized for larger investment strategies. (Hotz-Behofsits, Huber, & Zörner, 2018) The above-mentioned techniques are beyond the scope of this project; however, the same principles will be utilized to create an accurate predictive model for cryptocurrency which accounts for volatility.

2. Data and Experiments

To create our models, the trading information on fourteen cryptocurrencies including Bitcoin, Bitcoin Cash, Ethereum, and Dogecoin was downloaded from Kaggle. Our data includes the Open, Close, High, and Low price in US dollars of the cryptocurrency for a one-minute time period between January 1, 2018 and September 20, 2021. For the same one-minute time period the count of all trades which occurred, the volume of cryptocurrency units traded, and the Volume Weighted Average Price (VWAP) were also included. VWAP is a derived statistic which measures the ratio of a cryptocurrency's price to the total trade volume. (VWAP definition, 2019) The Asset Name and Asset ID are unique values assigned to each cryptocurrency and helps to identify the cryptocurrency represented in the row of data. The target variable is the fifteen-minute calculated value of the residual returns for the cryptocurrency and is included for the one-minute time interval in each row.

Since the purpose of our model is to predict short-term returns for the cryptocurrency market, the models will focus on predicting returns for each cryptocurrency and in doing so attempt to reduce potential noise caused by volatility in the market. When determining if a cryptocurrency should be bought or sold, there are many different factors which may impact the trader's decision. In our models, we will focus on the association between volume and VWAP and the open, high, low, and close price of cryptocurrency and the impact this has on predicting short-term returns. Consideration was also given to time intervals and if the accuracy of the models was improved or hindered based on longer or shorter time intervals. Fourteen subsets were created, grouping each by the specific cryptocurrency and then grouping again by one-hour and one-day time intervals.

To execute our models, Ordinary Least Squares (OLS) was chosen for our linear regression model as it evaluates the correlation between multiple independent variables and the dependent variable. (Escoto, Blanco, Argamosa, & Medina, 2021) This is done by minimizing the difference between the estimated values and the observed values, to achieve the best fitted model. Five variations of the models were produced and the results for all fourteen cryptocurrencies were compared by the coefficient of determination (R-Squared). When deciding which variables to include in the models, particular attention was given to the Volume and VWAP variables, as both have direct impact on the trading market. The volume of cryptocurrency traded can indicate several things, including market rise or decline, if a price is healthy, and the availability of cryptocurrency to be traded. (Hassan, Nassar, & Keleta, 2021) If investors feel the market is trending towards a bear market, they may sell instead of risking loss in price of the cryptocurrency. On the other hand, if the volume traded is steady over longer time periods, this can indicate a cryptocurrency that is stable and can produce long term returns. In a similar manner, VWAP can point towards the health of the overall market and is used by traders to determine by the price of a cryptocurrency price if it is worth buying or selling. (VWAP definition, 2019) This can directly influence the price of a cryptocurrency, as it may rise or fall based on the trades being placed.

When evaluating the results, for all but two of the cryptocurrencies, the best performing model included the independent variables Count, Volume, Open, High, Low and Close. In this model it was also assumed the Open, High, Low and Close variables were directly related to the VWAP variable, and thus each variable was multiplied by VWAP. As discussed above the relationship between VWAP and the other variables offered a better model to predict our short-term returns. The correlation between these variables was confirmed by the R-Squared of EOS.IO, Ethereum Classic, Monero, TRON, and IOTA, which were 0.405685, 0.30403, 0.42903, 0.328598, and 0.323824 respectively. While some of the cryptocurrencies performed well, others underperformed expectations and should not be utilized in trying to predict short-term returns. Among these were Bitcoin and Ethereum, which are well established cryptocurrencies with consistently increasing prices over the course of the time series we are exploring. (Tables A5, A11) There were two cryptocurrencies, Dogecoin and Maker, which performed better with a separate model where the independent variable VWAP was included along with the Open, High, Low, and Close variables which were multiplied by the Volume variable. With an R-Squared score of 0.410712, Dogecoin shows a stronger relationship between short-term returns and the impact volume has on the open, high, low, and close price of a cryptocurrency. (Table A27) This could be an indicator for the other cryptocurrencies, and further exploration is needed of the relationship between volume and short-term returns of cryptocurrencies.

When looking at predicting short-term returns, the time interval we are trying to predict over is just as important as the predictor variables. For all cryptocurrencies, apart from one, the model's R-Squared improved when the data was grouped by one-day time intervals. There were two cryptocurrencies, IOTA and Maker, which did not change or were smaller for the one-day time interval. The IOTA cryptocurrency had an R-Squared of 0.269653 in the one-hour time interval and 0.323624 in the one-day time interval. (Table A23) The consistency between both time intervals is of significance and could be used as a gauge for the cryptocurrency market overall. Also of note, Maker cryptocurrency had an R-Squared of 0.086571 in the one-hour time interval and 0.031028 in the one-day time interval. (Table A25) The R-Squared value is particularly low for both time intervals and shows there are potential external factors which may impact this cryptocurrency. This could also be due to volatility of the Maker cryptocurrency itself, where the price increased or decreased significantly over the duration of a day or days versus the hourly change in the price.

3. Conclusion

In conclusion, when predicting short-term returns in the cryptocurrency market, the impact both volume and VWAP have on short-term returns is of great importance and should be included in any future models. The model which multiplied the Open, High, Low, and Close by the VWAP variable, was the most satisfactory in predicting short-term returns due to the accuracy over multiple cryptocurrencies. While this result was anticipated, the number of cryptocurrencies which were affected by VWAP was higher than expected. There could be several reasons for this, most likely the actions of traders for cryptocurrency markets in many ways mirror the traditional stock market where VWAP is used for large volume trades done by mutual funds and other large stockholders. When buying or selling, the VWAP is the best indicator of how cryptocurrencies are trending and the potential for a trader to make or lose money. On the other hand, the impact volume had on predicting the short-term returns of Dogecoin and Maker was surprising. The original hypothesis was more cryptocurrencies are impacted by the volume being traded because this could potentially indicate a run or sell-off of a cryptocurrency. This was not the case, and further research should be conducted to determine if the volume of these cryptocurrencies could be a foreshadowing of other short-term returns. Prior to creating our models there was an assumption short-term returns could be predicted in smaller time intervals. This was disproven once the models were run with the one-hour and one-day time intervals, where the cryptocurrencies performed better except for Maker cryptocurrency in one-day intervals. In large part this could be due to the OLS linear regression model chosen and could be improved with different models or by also including additional variables which may impact short-term returns. Overall, the influence of volume, VWAP and time intervals on predicting short-term returns cannot be overstated and should be considered in any future prediction models.

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Appendix A

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
bitcoin_cash_hour1	0.00E+00	-315475.593	-315408.454	32604	0.132512	0.132325
bitcoin_cash_hour2	0.00E+00	-315428.463	-315378.109	32606	0.13115	0.131017
bitcoin_cash_hour3	0.00E+00	-315430.903	-315363.764	32604	0.131322	0.131135
bitcoin_cash_hour4	0.00E+00	-315573.337	-315472.628	32600	0.13532	0.135028
bitcoin_cash_hour5	0.00E+00	-316639.665	-316538.956	32600	0.163135	0.162853
bitcoin_cash_day1	3.54E-65	-17347.904	-17306.1879	1351	0.21045	0.206359
bitcoin_cash_day2	3.52E-50	-17273.1681	-17241.8811	1353	0.163355	0.160264
bitcoin_cash_day3	6.49E-52	-17285.4957	-17243.7797	1351	0.173347	0.169064
bitcoin_cash_day4	1.43E-65	-17357.569	-17294.995	1347	0.220647	0.214282
bitcoin_cash_day5	4.69E-73	-17393.1335	-17330.5595	1347	0.240778	0.234578

Table A1. Summary statistics for the OLS linear regression models for Bitcoin Cash Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
bitcoin_cash_hour1	32606	0.1203	0	NaN	NaN	NaN
bitcoin_cash_hour2	32602	0.119736	4	5.64E-04	878.593657	0.00E+00
bitcoin_cash_hour3	32601	0.119714	1	2.21E-05	137.461471	1.11E-31
bitcoin_cash_hour4	32602	0.116488	-1	3.23E-03	-20104.9846	NaN
bitcoin_cash_hour5	32600	0.115848	2	6.40E-04	1993.77771	0.00E+00
bitcoin_cash_day1	1353	0.000238	31247	1.16E-01	23.056315	0.00E+00
bitcoin_cash_day2	1349	0.000223	4	1.49E-05	23.221114	1.39E-18
bitcoin_cash_day3	1348	0.000223	1	8.08E-08	0.503662	4.78E-01
bitcoin_cash_day4	1349	0.000218	-1	4.09E-06	-25.491453	NaN
bitcoin_cash_day5	1347	0.000216	2	2.28E-06	7.1123	8.46E-04

Table A2. ANOVA statistics for the OLS linear regression models for Bitcoin Cash Cryptocurrency

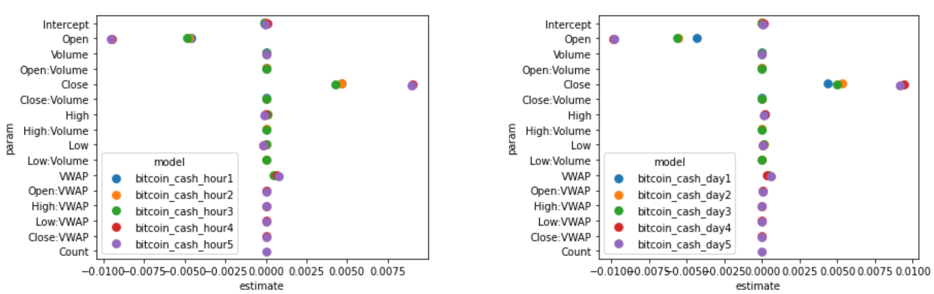

Figure A1. Plot of estimates and parameters for OLS linear regression models for Bitcoin Cash Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
binance_coin_hour1	0.00E+00	-297605.823	-297555.486	32513	0.055267	0.055122
binance_coin_hour2	0.00E+00	-297651.19	-297567.294	32509	0.056816	0.056555
binance_coin_hour3	0.00E+00	-297650.561	-297558.276	32508	0.056856	0.056566
binance_coin_hour4	0.00E+00	-298530.91	-298447.014	32509	0.08199	0.081736
binance_coin_hour5	0.00E+00	-298823.835	-298723.16	32507	0.090334	0.090026
binance_coin_day1	3.60E-38	-16601.3712	-16570.0842	1353	0.127981	0.124759
binance_coin_day2	3.14E-36	-16598.7445	-16546.5994	1349	0.131422	0.125628
binance_coin_day3	6.46E-36	-16598.577	-16541.2175	1348	0.132593	0.126158
binance_coin_day4	1.15E-29	-16567.1123	-16514.9672	1349	0.110968	0.105037
binance_coin_day5	1.45E-37	-16607.8184	-16545.2444	1347	0.139738	0.132713

Table A3. Summary statistics for the OLS linear regression models for Binance Coin Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
binance_coin_hour1	32513	0.201812	0	NaN	NaN	NaN
binance_coin_hour2	32509	0.201481	4	3.31E-04	289.269823	7.23E-245
binance_coin_hour3	32508	0.201473	1	8.49E-06	29.701652	5.08E-08
binance_coin_hour4	32509	0.196104	-1	5.37E-03	-18772.9584	NaN
binance_coin_hour5	32507	0.194321	2	1.78E-03	3116.17662	0.00E+00
binance_coin_day1	1353	0.000391	31154	1.94E-01	21.765641	0.00E+00
binance_coin_day2	1349	0.000389	4	1.54E-06	1.346991	2.50E-01
binance_coin_day3	1348	0.000388	1	5.24E-07	1.832676	1.76E-01
binance_coin_day4	1349	0.000398	-1	-9.6838E-06	33.859947	NaN
binance_coin_day5	1347	0.000385	2	1.29E-05	22.524145	2.39E-10

Table A4. ANOVA statistics for the OLS linear regression models for Binance Coin Cryptocurrency

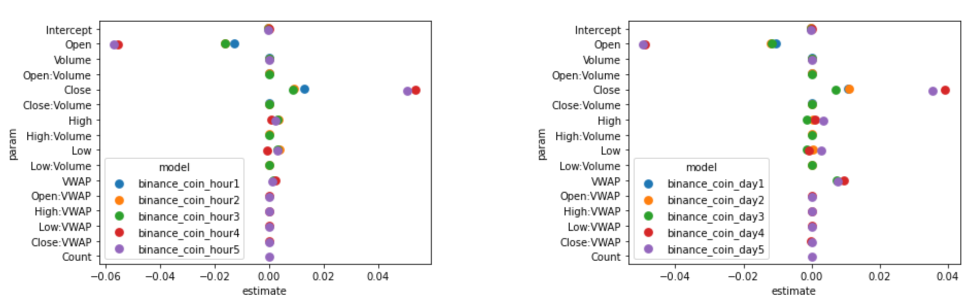

Figure A2. Plot of estimates and parameters for OLS linear regression models for Binance Cash Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
bitcoin_hour1	0.00E+00	-368445.753	-368395.398	32607	0.123011	0.122877
bitcoin_hour2	0.00E+00	-368550.733	-368466.808	32603	0.126044	0.125803
bitcoin_hour3	0.00E+00	-368558.996	-368466.679	32602	0.126319	0.126051
bitcoin_hour4	0.00E+00	-368710.444	-368626.519	32603	0.130313	0.130073
bitcoin_hour5	0.00E+00	-369011.395	-368910.685	32601	0.138408	0.138117
bitcoin_day1	2.67E-43	-19316.1773	-19284.8903	1353	0.143287	0.140121
bitcoin_day2	1.52E-43	-19324.5065	-19272.3615	1349	0.15352	0.147872
bitcoin_day3	4.15E-43	-19323.9268	-19266.5673	1348	0.154404	0.148131
bitcoin_day4	2.75E-43	-19323.2766	-19271.1315	1349	0.152753	0.147101
bitcoin_day5	1.84E-46	-19341.4711	-19278.897	1347	0.166478	0.159671

Table A5. Summary statistics for the OLS linear regression models for Bitcoin Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
bitcoin_hour1	32607	0.023676	0	NaN	NaN	NaN
bitcoin_hour2	32603	0.023594	4	8.19E-05	534.979873	0.00E+00
bitcoin_hour3	32602	0.023587	1	7.42E-06	194.018011	5.64E-44
bitcoin_hour4	32603	0.023479	-1	1.08E-04	-2818.39883	NaN
bitcoin_hour5	32601	0.02326	2	2.19E-04	2855.5439	0.00E+00
bitcoin_day1	1353	0.000053	31248	2.32E-02	19.410407	0.00E+00
bitcoin_day2	1349	0.000052	4	6.33E-07	4.133945	2.47E-03
bitcoin_day3	1348	0.000052	1	5.47E-08	1.428872	2.32E-01
bitcoin_day4	1349	0.000052	-1	-1.02E-07	2.667494	NaN
bitcoin_day5	1347	0.000052	2	8.49E-07	11.089586	1.67E-05

Table A6. ANOVA statistics for the OLS linear regression models for Bitcoin Cryptocurrency

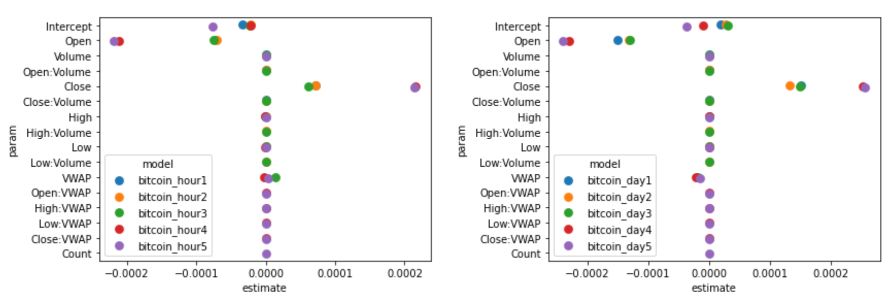

Figure A3. Plot of estimates and parameters for OLS linear regression models for Bitcoin Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
eos_io_hour1	0.00E+00	-320658.21	-320607.855	32606	0.254929	0.254815
eos_io_hour2	0.00E+00	-320762.422	-320678.498	32602	0.257489	0.257284
eos_io_hour3	0.00E+00	-320792.704	-320700.388	32601	0.258223	0.257996
eos_io_hour4	0.00E+00	-320982.119	-320898.194	32602	0.262474	0.26227
eos_io_hour5	0.00E+00	-321147.48	-321046.771	32600	0.266294	0.266047
eos_io_day1	8.47E-139	-17911.9951	-17880.7081	1353	0.382366	0.380083
eos_io_day2	5.29E-137	-17915.7275	-17863.5825	1349	0.387675	0.38359
eos_io_day3	2.29E-138	-17924.8083	-17867.4488	1348	0.392647	0.388142
eos_io_day4	3.77E-142	-17939.7992	-17887.6542	1349	0.398426	0.394412
eos_io_day5	1.14E-143	-17952.2987	-17889.7246	1347	0.405685	0.400832

Table A7. Summary statistics for the OLS linear regression models for EOS.IO Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
eos_io_hour1	32606	0.102455	0	NaN	NaN	NaN
eos_io_hour2	32602	0.102103	4	0.000352	827.337033	0.00E+00
eos_io_hour3	32601	0.102002	1	0.000101	949.954782	1.22E-205
eos_io_hour4	32602	0.101418	-1	0.000585	-5496.41411	NaN
eos_io_hour5	32600	0.100892	2	0.000525	2469.9454	0.00E+00
eos_io_day1	1353	0.000149	31247	0.100743	30.318049	0.00E+00
eos_io_day2	1349	0.000148	4	0.000001	3.008276	1.74E-02
eos_io_day3	1348	0.000146	1	0.000001	11.269787	8.10E-04
eos_io_day4	1349	0.000145	-1	0.000001	-13.095947	NaN
eos_io_day5	1347	0.000143	2	0.000002	8.226729	2.81074

Table A8. ANOVA statistics for the OLS linear regression models for EOS.IO Cryptocurrency

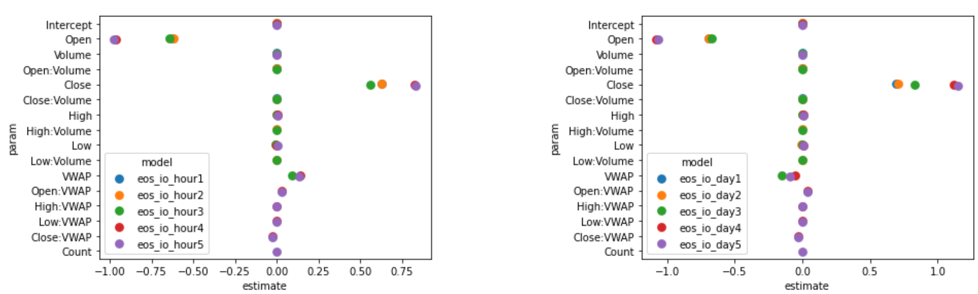

Figure A4. Plot of estimates and parameters for OLS linear regression models for EOS.IO Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
eth_class_hour1	0.00E+00	-300952.595	-300902.241	32606	0.118091	0.117956
eth_class_hour2	0.00E+00	-300982.36	-300898.435	32602	0.119111	0.118868
eth_class_hour3	0.00E+00	-301018.751	-300926.435	32601	0.120148	0.119878
eth_class_hour4	0.00E+00	-301748.089	-301664.165	32602	0.139554	0.139316
eth_class_hour5	0.00E+00	-302056.266	-301955.556	32600	0.147751	0.147463
eth_class_day1	7.01E-62	-17033.3059	-17002.0189	1353	0.196346	0.193376
eth_class_day2	3.54E-73	-17095.2552	-17043.1102	1349	0.236665	0.231572
eth_class_day3	1.96E-72	-17093.7426	-17036.3831	1348	0.236938	0.231278
eth_class_day4	5.16E-82	-17136.9014	-17084.7564	1349	0.259702	0.254763
eth_class_day5	4.80E-98	-17216.8146	-17154.2405	1347	0.30403	0.298347

Table A9. Summary statistics for the OLS linear regression models for Ethereum Classic Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
eth_class_hour1	32606	0.187479	0	NaN	NaN	NaN
eth_class_hour2	32602	0.187262	4	2.17E-04	296.893561	2.93E-251
eth_class_hour3	32601	0.187042	1	2.20E-04	1205.89743	1.73E-259
eth_class_hour4	32602	0.182917	-1	4.13E-03	-22579.7292	NaN
eth_class_hour5	32600	0.181174	2	1.74E-03	4768.96217	0.00E+00
eth_class_day1	1353	0.000284	31247	1.81E-01	31.685512	0.00E+00
eth_class_day2	1349	0.00027	4	1.43E-05	19.508365	1.28E-15
eth_class_day3	1348	0.00027	1	9.68E-08	0.529811	4.67E-01
eth_class_day4	1349	0.000262	-1	8.05E-06	-44.057472	NaN
eth_class_day5	1347	0.000246	2	1.57E-05	42.896843	8.70E-19

Table A10. ANOVA statistics for the OLS linear regression models for Ethereum Classic Cryptocurrency

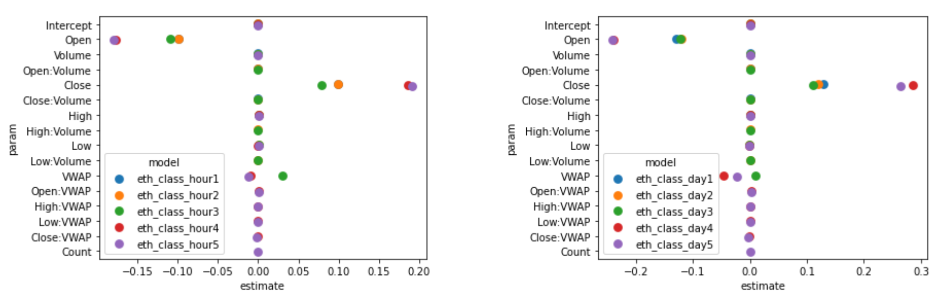

Figure A5. Plot of estimates and parameters for OLS linear regression models for Ethereum Classic Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
eth_hour1	0.00E+00	-357594.523	-357544.169	32605	0.081329	0.081189
eth_hour2	0.00E+00	-357617.862	-357533.938	32601	0.082212	0.081958
eth_hour3	0.00E+00	-357626.835	-357534.519	32600	0.082521	0.082239
eth_hour4	0.00E+00	-357479.274	-357395.35	32601	0.078303	0.078049
eth_hour5	0.00E+00	-357879.795	-357779.086	32599	0.089666	0.089358
eth_day1	4.09E-30	-18974.9731	-18943.6861	1353	0.103321	0.100007
eth_day2	6.61E-34	-18999.0794	-18946.9344	1349	0.124257	0.118414
eth_day3	3.55E-34	-19001.668	-18944.3084	1348	0.127209	0.120734
eth_day4	1.97E-32	-18991.9778	-18939.8327	1349	0.119668	0.113795
eth_day5	4.93E-34	-19002.1863	-18939.6123	1347	0.128825	0.12171

Table A11. Summary statistics for the OLS linear regression models for Ethereum Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
eth_hour1	32605	0.032998	0	NaN	NaN	NaN
eth_hour2	32601	0.032967	4	3.17E-05	161.341376	5.39E-137
eth_hour3	32600	0.032956	1	1.11E-05	225.828621	7.17E-51
eth_hour4	32601	0.033107	-1	-1.51E-04	3084.49119	NaN
eth_hour5	32599	0.032699	2	4.08E-04	4155.09518	0.00E+00
eth_day1	1353	0.000068	31246	3.26E-02	21.263687	0.00E+00
eth_day2	1349	0.000067	4	1.59E-06	8.092632	1.90E-06
eth_day3	1348	0.000066	1	2.24E-07	4.564161	3.28E-02
eth_day4	1349	0.000067	-1	-5.73E-07	11.658574	NaN
eth_day5	1347	0.000066	2	6.95E-07	7.07849	8.75E-04

Table A12. ANOVA statistics for the OLS linear regression models for Ethereum Cryptocurrency

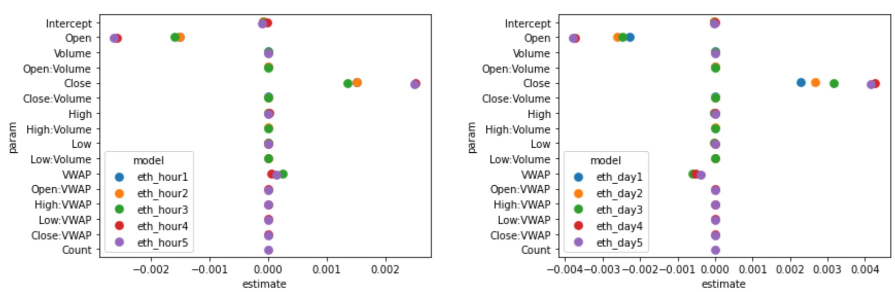

Figure A6. Plot of estimates and parameters for OLS linear regression models for Ethereum Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
litecoin_hour1	0.00E+00	-339086.943	-339036.589	32605	0.127129	0.126996
litecoin_hour2	0.00E+00	-339112.247	-339028.323	32601	0.12802	0.12778
litecoin_hour3	0.00E+00	-339185.668	-339093.352	32600	0.130035	0.129768
litecoin_hour4	0.00E+00	-338777.074	-338693.15	32601	0.119012	0.118769
litecoin_hour5	0.00E+00	-339273.41	-339172.701	32599	0.132425	0.132133
litecoin_day1	2.68E-44	-18480.8782	-18449.5912	1353	0.146229	0.143074
litecoin_day2	2.02E-43	-18483.942	-18431.7969	1349	0.153151	0.147501
litecoin_day3	1.36E-43	-18486.2687	-18428.9092	1348	0.155843	0.149581
litecoin_day4	1.76E-45	-18493.7782	-18441.6332	1349	0.159259	0.153649
litecoin_day5	2.26E-47	-18505.8702	-18443.2962	1347	0.169155	0.16237

Table A13. Summary statistics for the OLS linear regression models for Litecoin Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
litecoin_hour1	32605	0.058206	0	NaN	NaN	NaN
litecoin_hour2	32601	0.058146	4	5.94E-05	209.896346	4.05E-178
litecoin_hour3	32600	0.058012	1	1.34E-04	1898.23058	0.00E+00
litecoin_hour4	32601	0.058747	-1	-7.35E-04	10387.2479	NaN
litecoin_hour5	32599	0.057853	2	8.94E-04	6320.08773	0.00E+00
litecoin_day1	1353	0.000098	31246	5.78E-02	26.120998	0.00E+00
litecoin_day2	1349	0.000097	4	7.94E-07	2.80573	2.46E-02
litecoin_day3	1348	0.000097	1	3.09E-07	4.364206	3.69E-02
litecoin_day4	1349	0.000096	-1	3.92E-07	-5.53713	NaN
litecoin_day5	1347	0.000095	2	1.14E-06	8.022356	3.44E-04

Table A14. ANOVA statistics for the OLS linear regression models for Litecoin Cryptocurrency

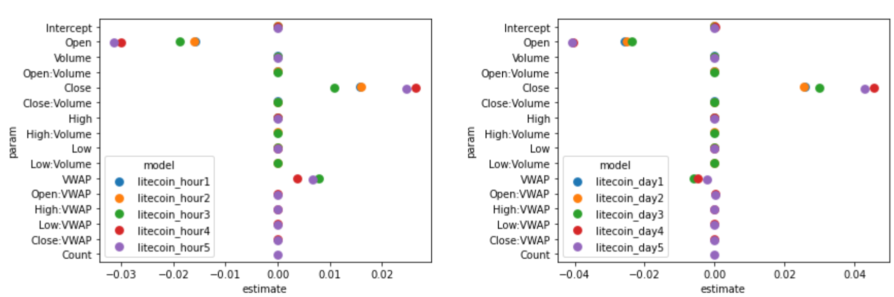

Figure A7. Plot of estimates and parameters for OLS linear regression models for Litecoin Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
monero_hour1	0.00E+00	-287096.396	-287046.088	32353	0.180095	0.179968
monero_hour2	0.00E+00	-287183.933	-287100.087	32349	0.182512	0.182285
monero_hour3	0.00E+00	-287416.061	-287323.83	32348	0.188406	0.188155
monero_hour4	0.00E+00	-289674.944	-289591.098	32349	0.243082	0.242871
monero_hour5	0.00E+00	-289703.13	-289602.514	32347	0.243834	0.243577
monero_day1	6.91E-84	-16206.0749	-16174.7879	1353	0.254769	0.252015
monero_day2	1.71E-90	-16246.9985	-16194.8535	1349	0.28112	0.276324
monero_day3	2.10E-93	-16262.9416	-16205.5821	1348	0.290549	0.285286
monero_day4	2.55E-157	-16559.9917	-16507.8467	1349	0.429004	0.425194
monero_day5	2.79E-155	-16556.0534	-16493.4794	1347	0.42903	0.424367

Table A15. Summary statistics for the OLS linear regression models for Monero Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
monero_hour1	32353	0.265583	0	NaN	NaN	NaN
monero_hour2	32349	0.2648	4	7.83E-04	658.832532	0.00E+00
monero_hour3	32348	0.262891	1	1.91E-03	6425.42105	0.00E+00
monero_hour4	32349	0.245181	-1	1.77E-02	-59611.3821	NaN
monero_hour5	32347	0.244937	2	2.44E-04	410.206974	1.18E-176
monero_day1	1353	0.000522	30994	2.44E-01	26.542721	0.00E+00
monero_day2	1349	0.000504	4	1.85E-05	15.541407	1.95E-12
monero_day3	1348	0.000497	1	6.61E-06	22.2446	2.65E-06
monero_day4	1349	0.0004	-1	9.70E-05	-326.63348	NaN
monero_day5	1347	0.0004	2	1.82E-08	0.030575	9.70E-01

Table A16. ANOVA statistics for the OLS linear regression models for Monero Cryptocurrency

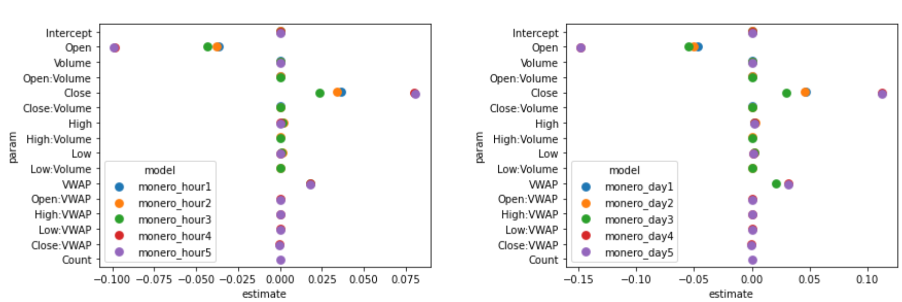

Figure A8. Plot of estimates and parameters for OLS linear regression models for Monero Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
TRON_hour1	0.00E+00	-300995.479	-300945.301	31659	0.19168	0.191552
TRON_hour2	0.00E+00	-301136.112	-301052.483	31655	0.195465	0.195236
TRON_hour3	0.00E+00	-301634.079	-301542.086	31654	0.208068	0.207818
TRON_hour4	0.00E+00	-303135.747	-303052.117	31655	0.2447	0.244485
TRON_hour5	0.00E+00	-303284.089	-303183.733	31653	0.248325	0.248064
TRON_day1	5.79E-92	-16684.0778	-16652.9519	1317	0.281441	0.278713
TRON_day2	5.28E-95	-16708.6282	-16656.7516	1313	0.298904	0.294098
TRON_day3	1.84E-94	-16708.3564	-16651.2921	1312	0.299819	0.294483
TRON_day4	1.37E-102	-16744.2582	-16692.3816	1313	0.317534	0.312856
TRON_day5	2.41E-105	-16761.8837	-16699.6318	1311	0.328598	0.322965

Table A17. Summary statistics for the OLS linear regression models for TRON Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
TRON_hour1	31659	0.137944	0	NaN	NaN	NaN
TRON_hour2	31655	0.137298	4	6.46E-04	884.898491	0.00E+00
TRON_hour3	31654	0.135147	1	2.15E-03	11785.1322	0.00E+00
TRON_hour4	31655	0.128896	-1	6.25E-03	- 34254.0634	NaN
TRON_hour5	31653	0.128277	2	6.19E-04	1694.87795	0.00E+00
TRON_day1	1317	0.000256	30336	1.28E-01	23.123639	0.00E+00
TRON_day2	1313	0.00025	4	6.22E-06	8.524853	8.63E-07
TRON_day3	1312	0.00025	1	3.26E-07	1.787121	1.82E-01
TRON_day4	1313	0.000243	-1	6.31E-06	-34.589264	NaN
TRON_day5	1311	0.000239	2	3.94E-06	10.802711	2.221679e-

Table A18. ANOVA statistics for the OLS linear regression models for TRON Cryptocurrency

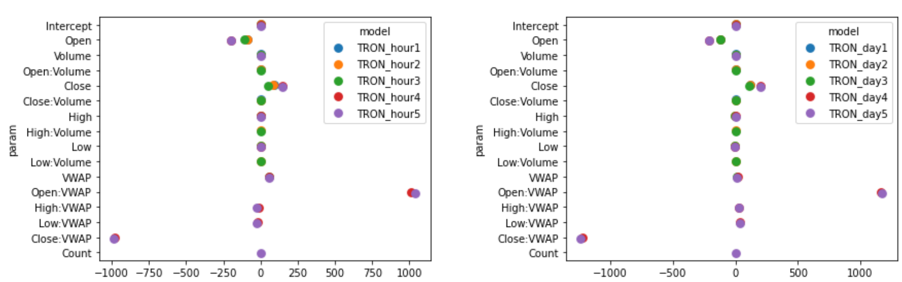

Figure A9. Plot of estimates and parameters for OLS linear regression models for TRON Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
stellar_hour1	0.00E+00	-277549.345	-277499.309	30921	0.082583	0.082434
stellar_hour2	0.00E+00	-277617.098	-277533.704	30917	0.084827	0.08456
stellar_hour3	0.00E+00	-277714.142	-277622.409	30916	0.087753	0.087458
stellar_hour4	0.00E+00	-278359.827	-278276.433	30917	0.106543	0.106283
stellar_hour5	0.00E+00	-278521.894	-278421.821	30915	0.111328	0.111012
stellar_day1	5.43E-15	-14908.114	-14877.0381	1306	0.056555	0.052943
stellar_day2	1.31E-15	-14914.6545	-14862.8614	1302	0.066953	0.060504
stellar_day3	9.84E-27	-14970.4822	-14913.5098	1301	0.107185	0.100323
stellar_day4	1.88E-28	-14977.7362	-14925.9431	1302	0.110753	0.104606
stellar_day5	5.41E-31	-14992.3705	-14930.2188	1300	0.123294	0.115876

Table A19. Summary statistics for the OLS linear regression models for Stellar Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
stellar_hour1	30921	0.229187	0	NaN	NaN	NaN
stellar_hour2	30917	0.228626	4	0.000561	221.726417	5.72E-188
stellar_hour3	30916	0.227895	1	0.000731	1156.33782	7.32E-249
stellar_hour4	30917	0.223201	-1	0.004694	-7425.37395	NaN
stellar_hour5	30915	0.222006	2	0.001195	945.380003	0.00E+00
stellar_day1	1306	0.000884	29609	0.221121	11.813171	0.00E+00
stellar_day2	1302	0.000875	4	0.00001	3.854666	4.05E-03
stellar_day3	1301	0.000837	1	0.000038	59.656675	2.24E-14
stellar_day4	1302	0.000834	-1	0.000003	-5.291051	NaN
stellar_day5	1300	0.000822	2	0.000012	9.297798	9.79E-05

Table A20. ANOVA statistics for the OLS linear regression models for Stellar Cryptocurrency

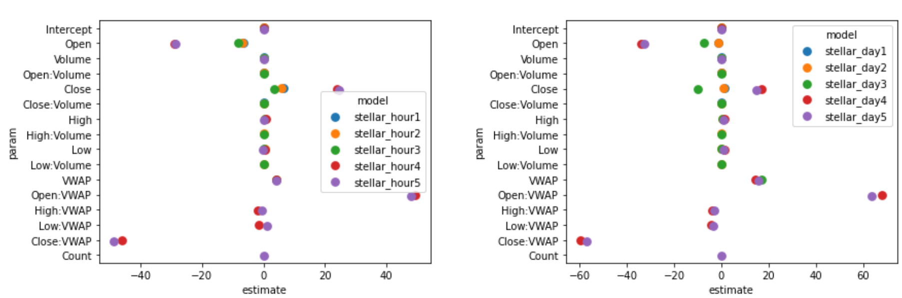

Figure A10. Plot of estimates and parameters for OLS linear regression models for Stellar Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
cardano_hour1	0.00E+00	-290234.814	-290184.949	30052	0.061915	0.061759
cardano_hour2	0.00E+00	-290268.691	-290185.583	30048	0.063221	0.062941
cardano_hour3	0.00E+00	-290297.689	-290206.27	30047	0.064187	0.063875
cardano_hour4	0.00E+00	-290957.574	-290874.465	30048	0.084447	0.084172
cardano_hour5	0.00E+00	-291240.79	-291141.059	30046	0.093153	0.092821
cardano_day1	1.49E-37	-15960.4044	-15929.6046	1247	0.136063	0.132599
cardano_day2	4.61E-39	-15974.3013	-15922.9683	1243	0.15103	0.144883
cardano_day3	4.25E-39	-15975.8895	-15919.4233	1242	0.153457	0.146641
cardano_day4	3.23E-48	-16018.031	-15966.698	1243	0.180148	0.174211
cardano_day5	4.58E-51	-16034.8322	-15973.2326	1241	0.193646	0.186498

Table A21. Summary statistics for the OLS linear regression models for Cardano Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
cardano_hour1	30052	0.112678	0	NaN	NaN	NaN
cardano_hour2	30048	0.112521	4	1.57E-04	244.255057	7.85E-207
cardano_hour3	30047	0.112405	1	1.16E-04	722.319369	3.04E-157
cardano_hour4	30048	0.109972	-1	2.43E-03	-15155.8287	NaN
cardano_hour5	30046	0.108926	2	1.05E-03	3256.66364	0.00E+00
cardano_day1	1247	0.000213	28799	1.09E-01	23.509805	0.00E+00
cardano_day2	1243	0.00021	4	3.70E-06	5.758519	1.36E-04
cardano_day3	1242	0.000209	1	6.00E-07	3.736361	5.35E-02
cardano_day4	1243	0.000203	-1	6.60E-06	-41.077009	NaN
cardano_day5	1241	0.000199	2	3.34E-06	10.38697	3.36E-05

Table A22. ANOVA statistics for the OLS linear regression models for Cardano Cryptocurrency

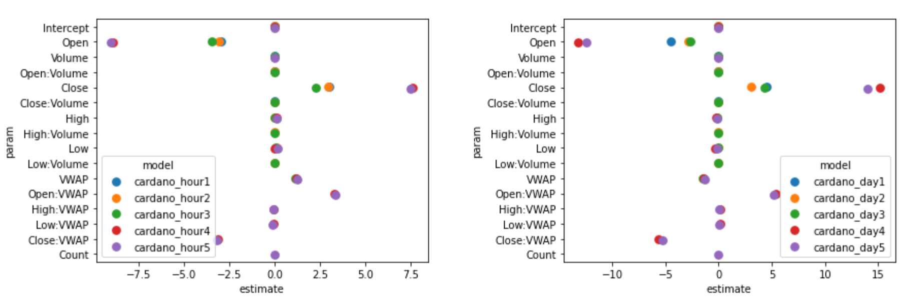

Figure A11. Plot of estimates and parameters for OLS linear regression models for Cardano Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
IOTA_hour1	0.00E+00	-266667.474	-266617.723	29487	0.172505	0.172365
IOTA_hour2	0.00E+00	-266700.239	-266617.32	29483	0.173648	0.173396
IOTA_hour3	0.00E+00	-267024.571	-266933.36	29482	0.182741	0.182464
IOTA_hour4	0.00E+00	-270191.107	-270108.188	29483	0.265891	0.265666
IOTA_hour5	0.00E+00	-270338.637	-270239.134	29481	0.269653	0.26938
IOTA_day1	8.41E-62	-14850.7092	-14820.0157	1225	0.214236	0.211029
IOTA_day2	3.26E-60	-14851.8073	-14800.6515	1221	0.220022	0.214273
IOTA_day3	1.09E-68	-14893.8693	-14837.5979	1220	0.247447	0.241278
IOTA_day4	1.69E-87	-14980.6026	-14929.4467	1221	0.297504	0.292326
IOTA_day5	1.33E-95	-15023.2451	-14961.8581	1219	0.323624	0.31752

Table A23. Summary statistics for the OLS linear regression models for IOTA Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
IOTA_hour1	29487	0.204314	0	NaN	NaN	NaN
IOTA_hour2	29483	0.204032	4	0.000282	242.86765	1.32E-205
IOTA_hour3	29482	0.201787	1	0.002245	7728.53876	0.00E+00
IOTA_hour4	29483	0.181257	-1	0.02053	-70672.8398	NaN
IOTA_hour5	29481	0.180328	2	0.000929	1598.77512	0.00E+00
IOTA_day1	1225	0.000411	28256	0.179916	21.918949	0.00E+00
IOTA_day2	1221	0.000408	4	0.000003	2.606966	3.43E-02
IOTA_day3	1220	0.000394	1	0.000014	49.425964	3.42E-12
IOTA_day4	1221	0.000368	-1	0.000026	-90.21679	NaN
IOTA_day5	1219	0.000354	2	0.000014	23.537008	9.34E-11

Table A24. ANOVA statistics for the OLS linear regression models for IOTA Cryptocurrency

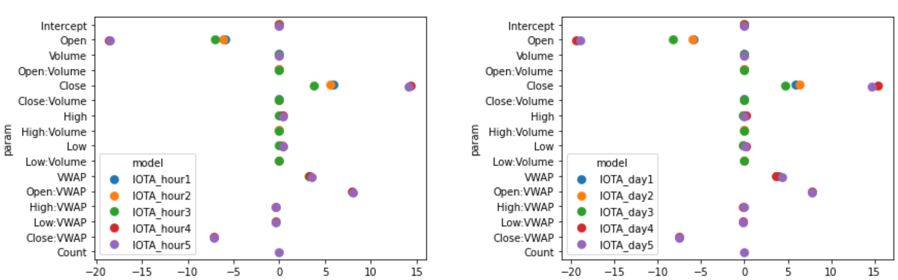

Figure A12. Plot of estimates and parameters for OLS linear regression models for IOTA Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
maker_hour1	7.16E-222	-94531.2675	-94487.1284	11568	0.085701	0.085306
maker_hour2	1.96E-224	-94556.1573	-94482.5921	11564	0.088295	0.087586
maker_hour3	3.59E-225	-94562.5017	-94481.58	11563	0.088952	0.088165
maker_hour4	6.18E-199	-94437.8457	-94364.2806	11564	0.078928	0.078211
maker_hour5	1.24E-217	-94530.2861	-94442.0079	11562	0.086571	0.085702
maker_day1	1.02E-01	-4157.77355	-4131.23407	610	0.014924	0.006849
maker_day2	2.35E-01	-4152.2733	-4108.04083	606	0.018913	0.004342
maker_day3	1.23E-01	-4153.94438	-4105.28867	605	0.024742	0.008622
maker_day4	3.62E-02	-4158.61391	-4114.38144	606	0.02896	0.014538
maker_day5	5.80E-02	-4155.92713	-4102.84816	604	0.031028	0.013381

Table A25. Summary statistics for the OLS linear regression models for Maker Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
maker_hour1	11568	0.192059	0	NaN	NaN	NaN
maker_hour2	11564	0.191514	4	0.000545	2.019357	0.088858
maker_hour3	11563	0.191376	1	0.000138	2.045658	0.152668
maker_hour4	11564	0.193482	-1	-0.002106	31.209443	NaN
maker_hour5	11562	0.191877	2	0.001605	11.89749	0.000007
maker_day1	610	0.04143	10952	0.150446	0.203594	1
maker_day2	606	0.041263	4	0.000168	0.621686	0.64719
maker_day3	605	0.041017	1	0.000245	3.633731	0.057093
maker_day4	606	0.04084	-1	0.000177	-2.628802	NaN
maker_day5	604	0.040753	2	0.000087	0.644504	0.525283

Table A26. ANOVA statistics for the OLS linear regression models for Maker Cryptocurrency

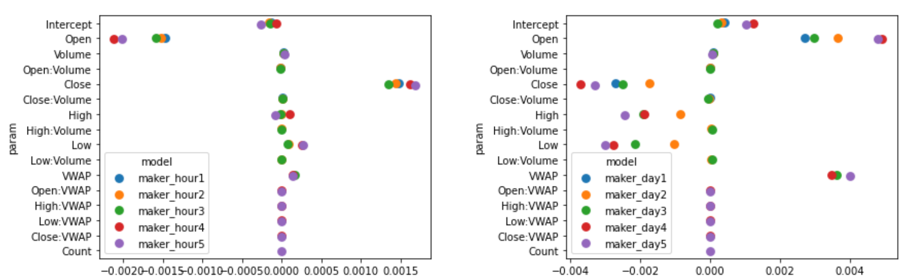

Figure A13. Plot of estimates and parameters for OLS linear regression models for Maker Cryptocurrency

	F-pvalues	AIC	BIC	Residuals	R-Squared	R-Squared Adj
dogecoin_hour1	0.00E+00	-185731.742	-185683.922	21371	0.178181	0.177988
dogecoin_hour2	0.00E+00	-185830.561	-185750.86	21367	0.182277	0.181932
dogecoin_hour3	0.00E+00	-185832.015	-185744.344	21366	0.182409	0.182026
dogecoin_hour4	0.00E+00	-185044.614	-184964.913	21367	0.151653	0.151296
dogecoin_hour5	0.00E+00	-185386.594	-185290.953	21365	0.165273	0.164843
dogecoin_day1	1.88E-88	-10487.8753	-10459.1077	887	0.376342	0.372826
dogecoin_day2	1.05E-94	-10527.8175	-10479.8716	883	0.408941	0.402916
dogecoin_day3	2.41E-94	-10528.4976	-10475.7572	882	0.410712	0.404031
dogecoin_day4	2.46E-55	-10341.5874	-10293.6415	883	0.271884	0.264463
dogecoin_day5	1.03E-78	-10456.6291	-10399.094	881	0.362754	0.354798

Table A27. Summary statistics for the OLS linear regression models for Dogecoin Cryptocurrency

	df_resid	ssr	df_diff	ss_diff	F	Pr(>F)
dogecoin_hour1	21371	0.210818	0	NaN	NaN	NaN
dogecoin_hour2	21367	0.209767	4	0.001051	553.515583	0.00E+00
dogecoin_hour3	21366	0.209734	1	0.000034	71.397358	3.10E-17
dogecoin_hour4	21367	0.217623	-1	-0.00789	16623.6429	NaN
dogecoin_hour5	21365	0.214129	2	0.003494	3680.73098	0.00E+00
dogecoin_day1	887	0.000409	20478	0.21372	21.989851	0.00E+00
dogecoin_day2	883	0.000388	4	0.000021	11.267225	6.40E-09
dogecoin_day3	882	0.000387	1	0.000001	2.448775	1.18E-01
dogecoin_day4	883	0.000478	-1	-0.000091	191.93169	NaN
dogecoin_day5	881	0.000418	2	0.00006	62.8148	3.15E-26

Table A28. ANOVA statistics for the OLS linear regression models for Dogecoin Cryptocurrency

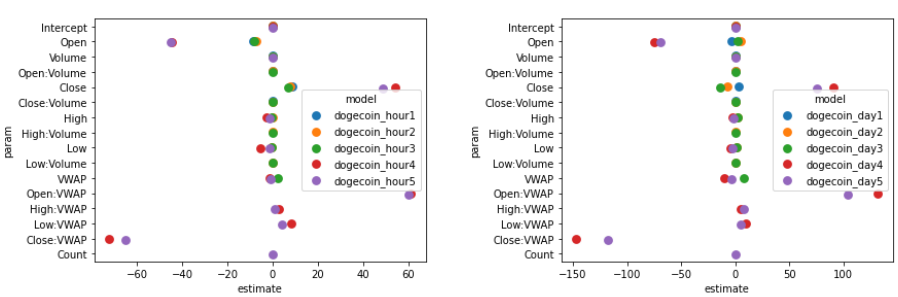

Figure A13. Plot of estimates and parameters for OLS linear regression models for Dogecoin Cryptocurrency