Final Report
IEORE4524 Analytics in Practice
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P020: Cognitive Analytics

Introduction

Our stakeholder for this project is an entrepreneur and investor that has recently shifted his focus to the emerging world cryptocurrencies and blockchain technology. In order to keep his anonymity we will leave his name out of our report. Our initial meeting with him was focused on research and educating ourselves on the wide ranging topics of the crypto world and defining the problem statement for our project. Much of our early work was done on Dune Analytics as we wanted to understand some of the dominant coins, different types of crypto and metrics such as Market Capitalization, Funding Rates, Exchanges Flows, On-balance Volume and others.

After our initial research and understanding our stakeholder's interest in emerging cryptocurrencies we collectively decided to focus on Solana and Polygon. Solana is an open-source blockchain project based in Geneva, Switzerland. It was first released in 2018[1]. Like Bitcoin and Ethereum, Solana is not built upon other blockchains. It serves as an underlying blockchain (Layer 1) which other blockchains (layer 2) can base on[2]. Solana's native coin trades under the ticker SOL. Polygon is a layer 2 blockchain that was developed to provide a solution to the scalability and development issues of Layer 1 blockchains, such as Ethereum. [3] Solana's native coin trades under the ticker MATIC. For further information on Polygon and Solana see Phase 3 Report. Although our initial scope of cryotos focused on Polygon and Solana as the project went out our stakeholder suggested that we also include Ethereum and Bitcoin as these two cryptos tend to be first movers in the crypto ecosystem.

Early in our analysis and research we recognized that there existed a contradictory relationship between the blockchain technology itself and the pricing of the blockchain's cryptocurrency. As a result we shifted our focus on the potential relationship between traditional financial markets and crypto currencies. With this in mind we hoped to understand if traditional asset classes explain the variation in the cryptocurrency market. Separately we wanted to build off of that and understand the idiosyncratic risk that pertains to crypto currencies, as we do not expect that

[1] Solana Documentation, https://docs.solana.com/introduction
[2] Layer1 vs Layer 2
https://medium.com/the-capital/layer-1-vs-layer-2-what-you-need-to-know-about-different-blockchain-layer-solutions-69f91904ce40
[3] https://www.coinbase.com/learn/crypto-basics/what-is-polygon

traditional assets will be able to explain most of the risk. A resource that our stakeholder had provided us with the article *Risk Analysis of Crypto Assets*[4], released by Two Sigma's Markets & Economy group. This article served as a useful blueprint for our analysis.

Data Analysis

To analyze the 'health' of these two cryptocurrencies Solana and Polygon we first conducted exploratory data analysis using Dune[5]. Dune is a platform that allows users to explore, create and share crypto data and dashboards. In order to work in Dune we needed to leverage SQL as this is the query language used by the platform. After a few weeks of exploratory data analysis we found that Dune was inadequate for our needs as the data was not clean and the queries took over 20 minutes to run even a small query. Although we faced a hard stop with Dune, we were able to build a few useful analysis and dashboards to visualize and better understand Solana and Polygon. See appendix 34 for dashboard results.

Methodology

In order to understand if traditional asset classes explain the variation in the cryptocurrency market we start by using the Linear Regressions. As we will see in the *Results section* in each of our regression models there still exists an unexplained risk. To analyze this unexplained risk we use Principal Component Analysis. This will allow us to look at the risk that is idiosyncratic to cryptocurrencies.

Linear Regression

We developed six different linear regression models per cryptocurrency, totalling out to 24 across Bitcoin (BTC), Ethereum (ETH), Polygon (MATIC) and Solana (SOL). See below for the six linear regression models:

1. Cryptocurrencies's relationship to the **overall** market over the **past 3 years**
2. Cryptocurrencies's relationship to the **equity** markets over the **past 3 years**
3. Cryptocurrencies's relationship to the **equity** markets in **crypto bull-run**
4. Cryptocurrencies's relationship to the **equity** markets in **crypto winter**
5. Cryptocurrencies's relationship to the **overall** markets in **crypto bull-run**
6. Cryptocurrencies's relationship to the **overall** markets in **crypto winter**

[4] https://www.twosigma.com/articles/risk-analysis-of-crypto-assets/
[5] https://dune.com/browse/dashboards

We define time periods for the *bull-run market* and *crypto winter based* on the guidance given to us by our stakeholder for this project. A bull-run is a period of time when, on average, the price of an asset (in this case crypto), rises continuously.[6] A *crypto winter* is the inverse. The bull market goes from January 1, 2020 to December 31, 2021 and the crypto winter time frame is January 1, 2022 until present. Next we selected proxies that would serve as representatives for the traditional financial markets (i.e. the independent variable for the overall markets vs cryptocurrency). Each proxy represented an asset class and was used as an independent variable. Each cryptocurrency (BTC, ETH, MATIC and SOL) is then used as the dependent variable.

The above regression models were built sequentially. We first analyzed the results of cryptos against the overall markets and then used those findings to develop additional hypotheses around the specific relationship of equites to cryptos and how cryptos compare to other asset classes in times of strong markets and times of down markets.

When selecting proxies, we wanted to be sure that we were able to find the optimal proxies to represent equities, bonds, credit, currencies, commodities, and other crypto currencies. To select proper proxies, we took a bifurcated approach. First, we leveraged the T*wo Sigma Factor Lens*[7] risk model. Separate from Two Sigma's risk model we also did our own research to find global indices and other assets. Through this two layered approach we felt that we had constructed a well-rounded list of proxies to serve as our independent variables. Please see below for a breakdown of each proxy and the asset class it represents:

- Equities:
    - Global Equity: iShares MSCI ACWI ETF (Ticker: ACWI)
    - Emerging Markets: MSCI Emerging Markets NTR Index (Ticker: MMN=F)
- Bonds:
    - Corporate Treasury Bonds: Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity (Ticker: BAA10Y)
    - Global Bonds: Templeton Global Bond Fund (Ticker: TPINX)
- Commodities
    - SPDR Gold Trust Index (Ticker: GLD)

[6] https://www.investopedia.com/terms/b/bullmarket.asp#:~:text=A%20bull%20market%20is%20a,two%20declines%20of%2020%25%20each.
[7] https://www.twosigma.com/articles/thematic-research-introducing-the-two-sigma-factor-lens/

- Crude Oil Futures (Ticker: CL=F)

- Market Volatility: Chicago Board Options Exchange's CBOE Volatility Index (Ticker: VIX)
- Credit: Fidelity Global Credit Fund (Ticker: FGBFX)
- Cryptocurrency: Ethereum USD (Ticker: ETH-USD)
- Currencies: US Dollar/USDX - Index - Cash (Ticker: DX-Y.NYB), MSCI Intl Emerging Market Currency Historical Data[8]

For a subset of our regression models we focus strictly on the equity markets relationship to cryptocurrencies. The motivation for doing so is discussed later in the *Results* section. To do so we developed a list of equity proxies that covered the broad categories of sub-asset classes in the equities markets. See below for equity proxies:

- Large Cap Blend: Vanguard Total Stock Market Index Fund (VTSMX)
- Global Equities: iShares MSCI ACWI ETF (ACWI)
- Mid Cap Growth: Invesco S&P MidCap 400 Pure Growth ETF (RFG)
- Small Cap Blend: SPDR S&P 600 Small Cap ETF (SLY)
- Small Cap Growth: iShares S&P Small-Cap 600 Growth ETF (IJT)
- Foreign Large Value: WisdomTree International Equity Fund (DWM)
- Emerging Markets: WisdomTree Emerging Markets High Dividend Fund (DEM)
- U.S. Tech: Nasdaq (^IXIC)
- U.S. Industrials: Dow Jones (^DJI)

Regression Models 1, 5-6: Cryptocurrencies relationship to the ***overall*** *market with varying time frames*

$$y(CRYPTOCURRENCY) = \beta_0 + \beta_1(ETH) + \beta_2(ACWI) + \beta_3(MMN = F) + \beta_4(VIX) + \beta_5(GOLD) + \beta_6(OIL) + \beta_7(DXY) + \beta_8(FGBFX) + \beta_9(TPINX) + \beta_{10}(BAA10Y) + \beta_{11}(EM\ Currency) + \varepsilon$$

Regression Model 2 -4: Cryptocurrencies relationship to the ***equity*** *market with varying time frames*

$$y(CRYPTOCURRENCY) = \beta_0 + \beta_1(VTSMX) + \beta_2(ACWI) + \beta_3(RFG) + \beta_4(SLY) + \beta_5$$

[8] https://www.investing.com/indices/msci-intl-em-currency-historical-data

$$(IJT) + \beta_6(DWM) + \beta_7(DEM) + \beta_8(Nasdaq) + \beta_9(DowJones) + \varepsilon$$

Principal Component Analysis (PCA)

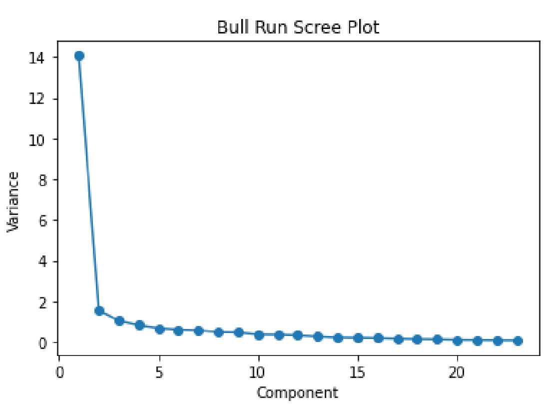
Due to the large number of variables that are not significant in the linear regression model, we decided to use PCA to analyze common drivers of price changes in cryptos.

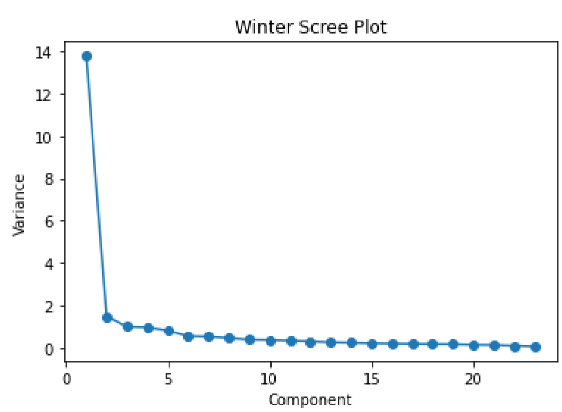
In order to use a diverse portfolio, we included major cryptos as well as cryptos of Defi, NFT and Metaverse in our PCA. Since some of them belong to more than one category, the cryptos are not listed in categories. Moreover, we included gold and USD as standards to see how cryptos move relatively. Please find the coins we used listed as follows:

Bitcoin (BTC), Solana(SOL), Polygon(Matic), Ethereum (ETH), XRP(XRP), Dogecoin(DOGE), Cardano(AdA), TRON(TRX), Litecoin (LTC), Uniswap(UNI), Avalanche (AVAX), Chainlink (LINK), Internet Computer (ICP), Apecoin (APE), Decentraland (MANA), Theta Network (THETA), Stacks (STX), Polkadot (DOT), Sushi swap (SUSHI), Gold (GLD), USD (DX-Y.NYB)

We anticipated that the crypto market performs differently during the bull run vs the winter. Therefore, to analyze the drivers during different periods, we separated the data according to bull run and winter to run PCA separately.

To choose an appropriate number of factors to use, we created scree-plots for both time periods. Then, we chose the elbow accordingly and used 2 factors for our PCA (see Figure 1 and 2).





```
get_summary(bull_pca)
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	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	...	PC14	PC15	PC16	PC17	PC18	PC19	PC20	PC21	PC22	PC23
Sum of Squared Loadings	14.08	1.54	1.05	0.82	0.67	0.60	0.56	0.49	0.47	0.36	...	0.22	0.21	0.19	0.16	0.14	0.13	0.10	0.10	0.09	0.08
Proportion of Variance Explained	0.61	0.07	0.05	0.04	0.03	0.03	0.02	0.02	0.02	0.02	...	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00
Cumulative Proportion	0.61	0.68	0.72	0.76	0.79	0.82	0.84	0.86	0.88	0.90	...	0.95	0.96	0.97	0.97	0.98	0.98	0.99	0.99	1.00	1.00

```
get_summary(winter_pca)
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	...	PC14	PC15	PC16	PC17	PC18	PC19	PC20	PC21	PC22	PC23
Sum of Squared Loadings	13.78	1.49	1.01	0.98	0.82	0.55	0.53	0.47	0.39	0.37	...	0.24	0.22	0.20	0.19	0.18	0.18	0.15	0.14	0.1	0.08
Proportion of Variance Explained	0.60	0.06	0.04	0.04	0.04	0.02	0.02	0.02	0.02	0.02	...	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.0	0.00
Cumulative Proportion	0.60	0.66	0.71	0.75	0.79	0.81	0.83	0.85	0.87	0.89	...	0.94	0.95	0.96	0.96	0.97	0.98	0.99	0.99	1.0	1.00

Figure 1, Figure 2 : Bull Run and Winter Scree-Plots

Results

Linear Regression Results

In this section we will focus on the models that yielded the most important findings and leave the remaining analysis in the appendix for a reference point. After running regressions with the overall market as the set of dependent variables we found that very few of our variables were significant and the average R^2 value was ~ 15% with a slightly lower Adjusted R^2. Across all initial models our proxy for the global equity market (iShares MSCI ACWI ETF, ticker ACWI, was the only consistently significant variable with a p-value of 0.003 for Bitcoin, 0.004 for Polygon, 0.005 for Solana and 0.014 for Ethereum. After seeing that equities explained most of the variation in each of the cryptocurrencies we developed our second hypothesis and regression model that focused strictly on sub-asset classes of the equities market.

In the second model, where the selected cryptocurrency is the dependent variable and equities are the dependent variable, we found that *Foreign Large Value (proxy DWM)* and the *Nasdaq* were statistically significant across all models aside from the Solana model in which the Nasdaq yields a p-value of 0.095 (see Appendix 28). Additionally, we see a slight increase in the R^2 for Bitcoin, which the model accounts for ~20% of the variation in Bitcoin, however, for the other models the the R^2 stays similar to regression with all asset classes.

In the next models we add a second layer of variation. In models 3 through 6 we adjust the time periods to zero-in on the *crypto winter* and *bull market*. In model 3 we regress cryptos against equites during the *bull market* period (2020 to end of 2021). Across all models and especially for Solana we see a decrease in the R^2, but the same variables stay statistically significant (i.e. *Foreign Large Value (proxy DWM)* and the *Nasdaq*). In model 4 we regress cryptos against equites during the *crypto winter* period (2022 to present). Across all models we see a large increase in the R^2 values, with an average R^2 around 24.7%. but the same variables stay statistically significant (i.e. *Foreign Large Value (proxy DWM)* and the *Nasdaq*) for most models, aside from Solana where *Foreign Large Value* is not significant. In model 4 Bitcoin regressed against equities has the highest R^2 compared to model 4 for Ethereum, Solnana and Polygon. Bitcoin's model 4 has an R^2 of about 28.7% and Adjusted-R^2 of 27.4%. When looking at the beta's for this model we see that as Bitcoin return's decrease by 0.0002 Foreign Large Value has a positive beta of 1.1286 and the Nasdaq has a positive beta of 2.2424.

In models 5 and 6 keep the theme of controlling for *crypto winter* and *bull-run* market, however in these cases we revert back to the overall market regression. In model 5 we regress cryptos against the overall market (using proxies from model 1) during the *bull market* period (2020 to end of 2021). In model 5 we see a relatively low R^2 across each crypto's regression. The Solana model does not reveal any significant relationships between traditional asset classes and SOL. However, we do see something interesting in model 5 for Bitcoin and Ethereum. We see a relationship between the US Dollar and MATIC/BTC. In the BTC model we see that in the period of 2020-2021 as USD goes down by 1.59% Bitcoin rises very slightly, which indicates an inverse relationship between USD and Bitcoin. In the Polygon model 5 we see similar results but with an even stronger beta. We see that as USD decreases by 4.48% MATIC rises very slightly. This is likely because individuals may look at crypto as an alternative currency and during times of a crypto bull-run investors may see their crypto currencies as a better alternative or possible hedge to depreciation in USD. Additionally for model 5 we see that the Bitcoin and Ethereum models each have a significant relationship with VIX, which measures volatility. In both models the VIX has a negative beta value while BTC and ETH have a positive or close to zero beta (see Appendices 16 and 17).

In our final model, model 6 we regress cryptos against the overall market (using proxies from model 2) during the *crypto winter* period (2022 to present). In model 6 we across all models we see the highest R^2 with an average R^2 of 28.7%. Across all models for model 6 we see that

ACWI is the only statistically significant variable with an average p-value of 0.002. These results are expected and are in line with what we saw in model 1.

Our analysis reveals that in recent periods of a crypto downturn our model 6 is able to explain about 28% of variation in crypto asset returns (ETH, SOL, BTC and MATIC as the proxies for crypto assets). Over this same time period our models show that the equity market explains about 24% of the variation in crypto asset returns. Given that the model with the overall market (all asset classes) has only one statistically significant variable and that variable is a proxy for global equity markets we believe that there may be slight overfitting in the model with each crypto asset regressed against the overall market. In model 4, which explains on average 24% of the variation in ETH, SOL, MATIC and BTC we saw that Nasdaq and Foreign Large Value were the most statistically significant variables. Nasdaq has the strongest relationship to each crypto asset, we believe this may be due to the fact that Nasdaq, being composed of largely traded tech companies, tend to be a leading indicator for the markets. This can be seen in months such as May/June 2022 and October 2022 (see Figure 1), where we see Bitcoin trading in a similar pattern to the Nasdaq, but slightly after the Nasdaq does.

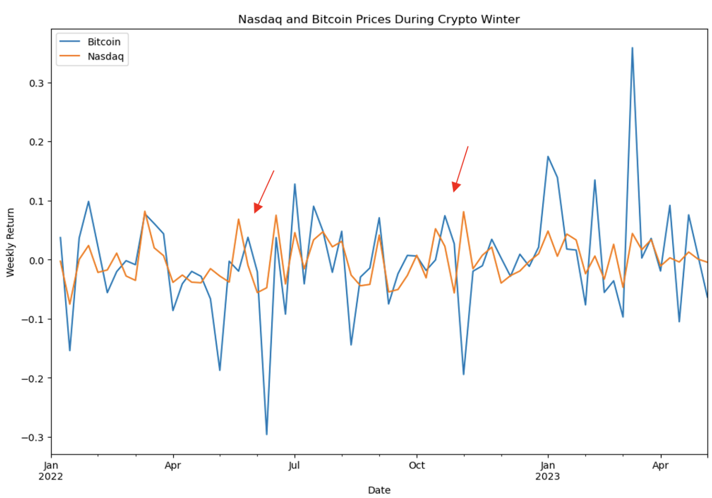

Figure 3: Nasdaq and Bitcoin during crypto winter

However, this is not totally consistent for equities and crypto as we see in the graph of Bitcoin and the equity markets for 2022 there are many instances where Bitcoin moves inversely to specific equities. This is illustrated in months November 2022 and January 2023 (see figure 2). This is likely because Bitcoin and other cryptos are often thought of as a speculative investment. As discussed previously our models in which equities and/or other traditional asset classes accounted for the most variation in the crypto market was during periods of the crypto winter.

Coincidentally the crypto winter falls from 2022 to present which is also a time in which cryptos have become more heavily adopted. Therefore it is hard to argue that the increase in the R^2 is likely because of the crypto winter when it could also be that the cryptocurrencies are becoming more widely traded and therefore have a stronger relationship with the overall market.

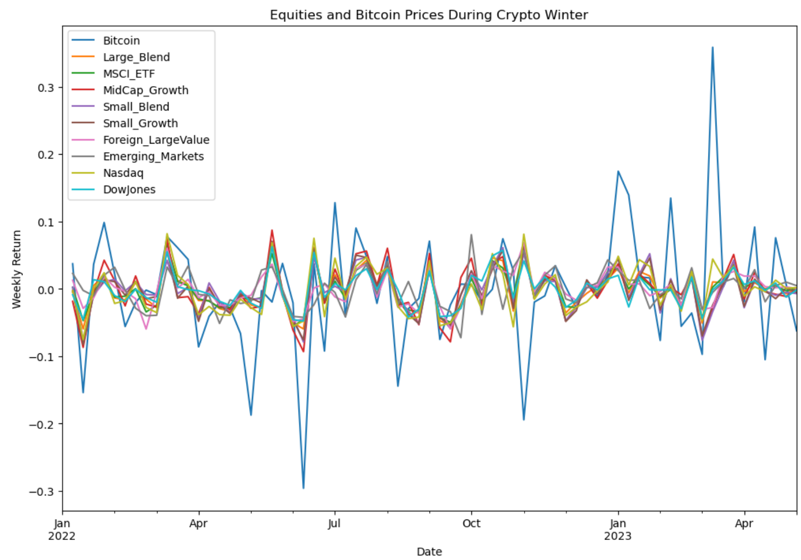

Figure 4: Bitcoin and Equities (2020-2021)

PCA Results

Factor 1: We can see that factor 1 is positively correlated with all cryptos and the magnitude of correlation does not vary greatly between crypto winter and bull run (see figure 6: Bull run and figure 7: Winter). Therefore, the first factor is less dependent on short-term market trends and more related to the fundamental characteristics of cryptocurrencies or long-run macroeconomic trends. Such factors include technological development and public acceptance of crypto and Defi. In “Risk Analysis of Crypto Assets”[9] by Two Sigma, they listed a similar factor as the Market Beta. In our analysis, factor 1 has similar properties as the leading factor in the analysis by Two Sigma.

Factor 2: Given the large positive correlation between USD price and factor 2 as well as the large negative correlation between gold price and factor 2, it is reasonable to suggest that factor 2 captures fluctuations in USD strength. Since crypto prices are measured in USD, changes in

[9] Two Sigma, Risk Analysis of Crypto Assets: https://www.twosigma.com/articles/risk-analysis-of-crypto-assets/

the prices of USD will influence the prices of cryptos.

In general, we did not see a major difference in behavior of driving factors during the bull run and the crypto winter (see figure 6 and figure 7). This suggests that the common drivers of crypto prices are largely unrelated with the short-term fluctuations of the crypto market and more related to some long-term factors such as development in technology and public acceptance of crypto and Defi.

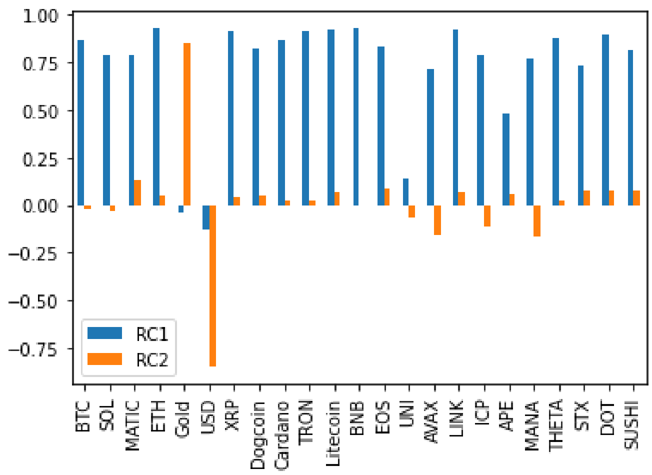

Figure 6: Bull run (Data from 2021/5/10-2021/12/31) [10]

```
bullpca2
```

	RC1	RC2	communalities
BTC	0.872	-0.022	0.760
SOL	0.784	-0.030	0.615
MATIC	0.788	0.132	0.639
ETH	0.928	0.046	0.864
Gold	-0.041	0.849	0.722
USD	-0.130	-0.850	0.739
XRP	0.911	0.045	0.831
Dogcoin	0.822	0.052	0.678
Cardano	0.872	0.027	0.761
TRON	0.915	0.024	0.837
Litecoin	0.919	0.064	0.849
BNB	0.929	-0.006	0.863
EOS	0.835	0.085	0.705
UNI	0.139	-0.066	0.024
AVAX	0.712	-0.155	0.531
LINK	0.924	0.067	0.859
ICP	0.785	-0.108	0.628
APE	0.485	0.063	0.240
MANA	0.773	-0.164	0.624
THETA	0.879	0.020	0.773
STX	0.736	0.074	0.547
DOT	0.893	0.074	0.803
SUSHI	0.813	0.079	0.667

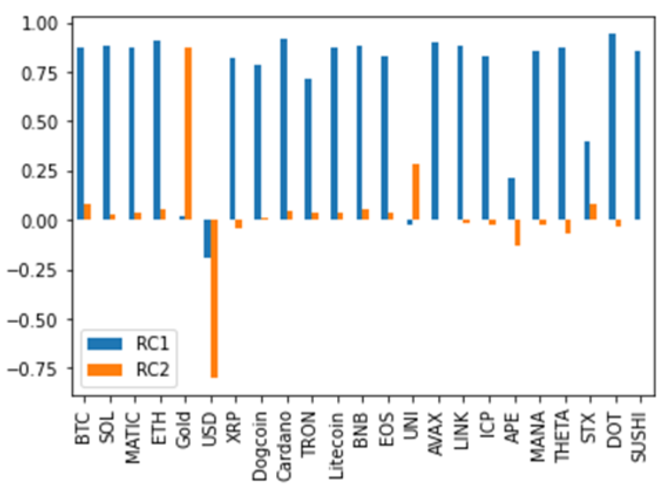

Figure 7: Winter (Data from 2022/1/3-2023/5/9)

	RC1	RC2	communalities
BTC	0.878	0.084	0.777
SOL	0.885	0.031	0.785
MATIC	0.873	0.041	0.764
ETH	0.909	0.056	0.830
Gold	0.024	0.872	0.761
USD	-0.188	-0.799	0.674
XRP	0.824	-0.044	0.681
Dogcoin	0.784	0.009	0.614
Cardano	0.915	0.046	0.839
TRON	0.717	0.039	0.516
Litecoin	0.875	0.041	0.767
BNB	0.884	0.051	0.785
EOS	0.829	0.041	0.689
UNI	-0.023	0.282	0.080
AVAX	0.898	-0.002	0.807
LINK	0.884	-0.014	0.782
ICP	0.827	-0.023	0.684
APE	0.212	-0.127	0.061
MANA	0.859	-0.026	0.738
THETA	0.870	-0.071	0.762
STX	0.402	0.081	0.168
DOT	0.941	-0.037	0.887
SUSHI	0.859	0.005	0.737

[10] Earliest Data available for all cryptos starts from 2021/5/10.

Conclusion

In conclusion our linear regression models had a higher R^2 during the crypto winter as opposed to broader time periods or a crypto bull market. On average equities were the only statistically significant variables across all models. Although our models had R^2 values ranging from 20-31%, whereas Two Sigma's model, that regressed Bitcoin to the rest of the market, has an R^2 of ~9%. Cryptocurrencies still have high volatility and we believe that much of the risk in cryptos is still idiosyncratic to cryptocurrencies, however we do see that as time goes on more of the variation in cryptocurrencies returns related to the overall market.

As future analysis we believe our regression models should incorporate additional techniques such as ridge and lasso methods to mitigate any multicollinearity. Most importantly we believe that future analysis should focus on signals and metrics specific to cryptocurrencies and blockchain transactions. Lastly, from a technical implementation standpoint two of our proxies are based on csv files that need to be uploaded daily, in order to ensure a user friendly and efficient program we would suggest finding new proxies or API's that will allow the user to take this manual step out of the regression analysis.

In the PCA models, we used 2 factors to explain common drivers of cryptos. The first factor was a long-term common driver that is unrelated to short-term fluctuations (e.g. technological development, public acceptance of Crypto and Defi). The second factor was related to USD price changes. There was no significant difference in behavior of driving factors during the bull run and the crypto winter. Therefore, we concluded that the common drivers of cryptos were more related to long term factors such as technological development and public acceptance of crypto instead of short-term fluctuations. Finally, please see our Github link in appendix 35 for access to the code and READ ME files.

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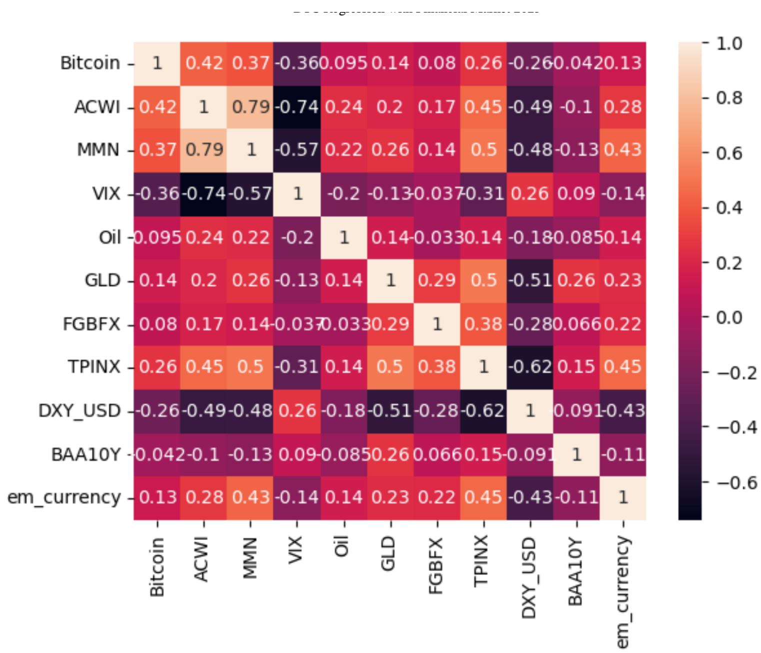
Appendix

Appendix 1: Bitcoin Correlation to Market Proxies



Appendix 2: Model 1 Results - Bitcoin and Overall market (2020-2023)

BTC Regression with Financial Market 2023

OLS Regression Results

Dep. Variable:	Bitcoin	**R-squared:**	0.191
Model:	OLS	**Adj. R-squared:**	0.180
Method:	Least Squares	**F-statistic:**	16.57
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	4.58e-27
Time:	16:08:24	**Log-Likelihood:**	1373.1
No. Observations:	712	**AIC:**	-2724.
Df Residuals:	701	**BIC:**	-2674.
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0014	0.001	1.044	0.297	-0.001	0.004
ACWI	0.7397	0.249	2.975	0.003	0.252	1.228
MMN	0.2721	0.186	1.461	0.144	-0.094	0.638
VIX	-0.0621	0.026	-2.364	0.018	-0.114	-0.011
GLD	0.0703	0.175	0.401	0.689	-0.274	0.415
Oil	-0.0272	0.054	-0.503	0.615	-0.134	0.079
DXY_USD	-0.4599	0.426	-1.080	0.280	-1.296	0.376
FGBFX	-0.0887	0.437	-0.203	0.839	-0.948	0.770
TPINX	0.5771	0.471	1.225	0.221	-0.348	1.502
BAA10Y	-0.0249	0.043	-0.579	0.563	-0.109	0.060
em_currency	-0.5791	0.641	-0.903	0.367	-1.838	0.680

Omnibus:	63.804	**Durbin-Watson:**	2.021
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	244.541
Skew:	0.324	**Prob(JB):**	7.92e-54
Kurtosis:	5.797	**Cond. No.**	500.

Appendix 3: Model 2 Results - Bitcoin and Equity Markets (2020-2023)

OLS Regression Results

Dep. Variable:	Bitcoin	**R-squared:**	0.196
Model:	OLS	**Adj. R-squared:**	0.190
Method:	Least Squares	**F-statistic:**	32.95
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	4.09e-52
Time:	16:08:27	**Log-Likelihood:**	2432.4
No. Observations:	1223	**AIC:**	-4845.
Df Residuals:	1213	**BIC:**	-4794.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0016	0.001	1.648	0.100	-0.000	0.003
Large_Blend	-0.9796	0.980	-0.999	0.318	-2.903	0.944
MSCI_ETF	-1.6004	0.843	-1.899	0.058	-3.254	0.053
MidCap_Growth	-0.2738	0.214	-1.282	0.200	-0.693	0.145
Small_Blend	0.2859	0.321	0.891	0.373	-0.343	0.915
Small_Growth	0.3718	0.378	0.983	0.326	-0.370	1.114
Foreign_LargeValue	1.2569	0.330	3.812	0.000	0.610	1.904
Emerging_Markets	0.2300	0.181	1.269	0.205	-0.126	0.586
Nasdaq	1.9936	0.367	5.427	0.000	1.273	2.714
DowJones	-0.2131	0.433	-0.492	0.623	-1.062	0.636

Omnibus:	130.440	**Durbin-Watson:**	2.059
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	981.058
Skew:	-0.115	**Prob(JB):**	9.24e-214
Kurtosis:	7.382	**Cond. No.**	1.25e+03

Appendix 4: Model 3 Results - Bitcoin and Equity Markets (2020-2021)

OLS Regression Results

Dep. Variable:	Bitcoin	**R-squared:**	0.167
Model:	OLS	**Adj. R-squared:**	0.157
Method:	Least Squares	**F-statistic:**	16.04
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	4.28e-24
Time:	16:08:29	**Log-Likelihood:**	1377.5
No. Observations:	728	**AIC:**	-2735.
Df Residuals:	718	**BIC:**	-2689.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.0029	0.001	2.106	0.036	0.000	0.006
Large_Blend	-0.5522	1.312	-0.421	0.674	-3.128	2.023
MSCI_ETF	-2.0952	1.096	-1.912	0.056	-4.246	0.056
MidCap_Growth	-0.6436	0.299	-2.149	0.032	-1.232	-0.056
Small_Blend	0.2725	0.395	0.690	0.490	-0.502	1.047
Small_Growth	0.6125	0.470	1.304	0.193	-0.310	1.535
Foreign_LargeValue	1.3664	0.443	3.087	0.002	0.497	2.235
Emerging_Markets	0.4477	0.266	1.684	0.093	-0.074	0.970
Nasdaq	1.9971	0.485	4.120	0.000	1.045	2.949
DowJones	-0.3562	0.616	-0.579	0.563	-1.565	0.852

Omnibus:	74.101	**Durbin-Watson:**	2.108
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	419.065
Skew:	-0.220	**Prob(JB):**	1.00e-91
Kurtosis:	6.691	**Cond. No.**	1.16e+03

Appendix 5: Model 4 Results - Bitcoin and Equity Markets (2022-2023)

BTC Regression with Financial Market 2023

OLS Regression Results

Dep. Variable:	Bitcoin	**R-squared:**	0.287
Model:	OLS	**Adj. R-squared:**	0.274
Method:	Least Squares	**F-statistic:**	21.56
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	1.00e-30
Time:	16:08:33	**Log-Likelihood:**	1078.4
No. Observations:	491	**AIC:**	-2137.
Df Residuals:	481	**BIC:**	-2095.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.0002	0.001	-0.186	0.852	-0.003	0.002
Large_Blend	-1.8292	1.500	-1.219	0.223	-4.777	1.119
MSCI_ETF	-1.1745	1.426	-0.824	0.410	-3.976	1.627
MidCap_Growth	0.5832	0.324	1.800	0.072	-0.053	1.220
Small_Blend	0.0727	0.698	0.104	0.917	-1.298	1.444
Small_Growth	-0.3230	0.777	-0.416	0.678	-1.849	1.203
Foreign_LargeValue	1.1287	0.522	2.163	0.031	0.103	2.154
Emerging_Markets	0.0027	0.250	0.011	0.991	-0.488	0.493
Nasdaq	2.2437	0.597	3.759	0.000	1.071	3.417
DowJones	0.2605	0.641	0.406	0.685	-0.999	1.520

Omnibus:	57.438	**Durbin-Watson:**	1.945
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	349.967
Skew:	0.241	**Prob(JB):**	1.01e-76
Kurtosis:	7.108	**Cond. No.**	1.52e+03

Appendix 6: Model 5 Results Bitcoin and Overall Market (2020-2021)

OLS Regression Results

Dep. Variable:	Bitcoin	**R-squared:**	0.137
Model:	OLS	**Adj. R-squared:**	0.115
Method:	Least Squares	**F-statistic:**	6.056
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	1.46e-08
Time:	16:08:38	**Log-Likelihood:**	723.46
No. Observations:	392	**AIC:**	-1425.
Df Residuals:	381	**BIC:**	-1381.
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0037	0.002	1.828	0.068	-0.000	0.008
ACWI	0.2297	0.478	0.480	0.631	-0.711	1.170
MMN	0.1839	0.295	0.624	0.533	-0.395	0.763
VIX	-0.1067	0.039	-2.703	0.007	-0.184	-0.029
GLD	-0.1250	0.257	-0.486	0.627	-0.631	0.381
Oil	-0.1322	0.096	-1.380	0.168	-0.321	0.056
DXY_USD	-1.5973	0.761	-2.098	0.037	-3.094	-0.100
FGBFX	-0.4852	1.031	-0.471	0.638	-2.512	1.542
TPINX	1.1103	0.949	1.170	0.243	-0.756	2.976
BAA10Y	-0.1620	0.094	-1.717	0.087	-0.348	0.023
em_currency	-0.1104	1.081	-0.102	0.919	-2.236	2.016

Omnibus:	23.536	**Durbin-Watson:**	2.081
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	63.541
Skew:	0.203	**Prob(JB):**	1.59e-14
Kurtosis:	4.930	**Cond. No.**	598.

Appendix 7: Bitcoin Model 6 Results Bitcoin and Overall Market (2022-2023)

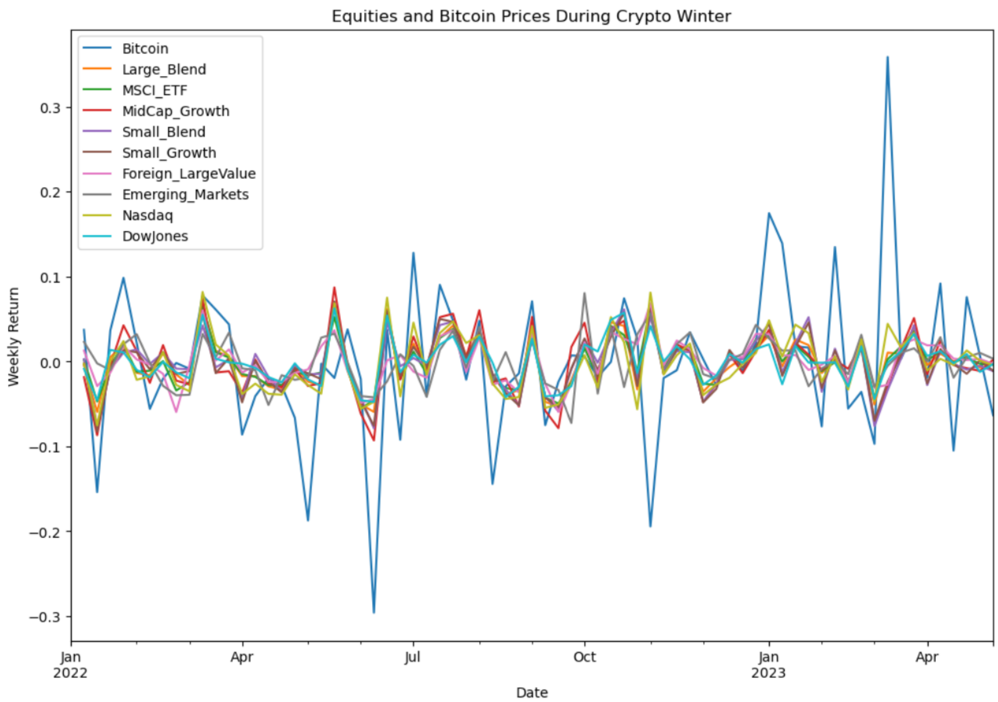
OLS Regression Results

Dep. Variable:	Bitcoin	**R-squared:**	0.316
Model:	OLS	**Adj. R-squared:**	0.294
Method:	Least Squares	**F-statistic:**	14.30
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	8.07e-21
Time:	16:08:39	**Log-Likelihood:**	668.23
No. Observations:	320	**AIC:**	-1314.
Df Residuals:	309	**BIC:**	-1273.
Df Model:	10		
Covariance Type:	nonrobust		

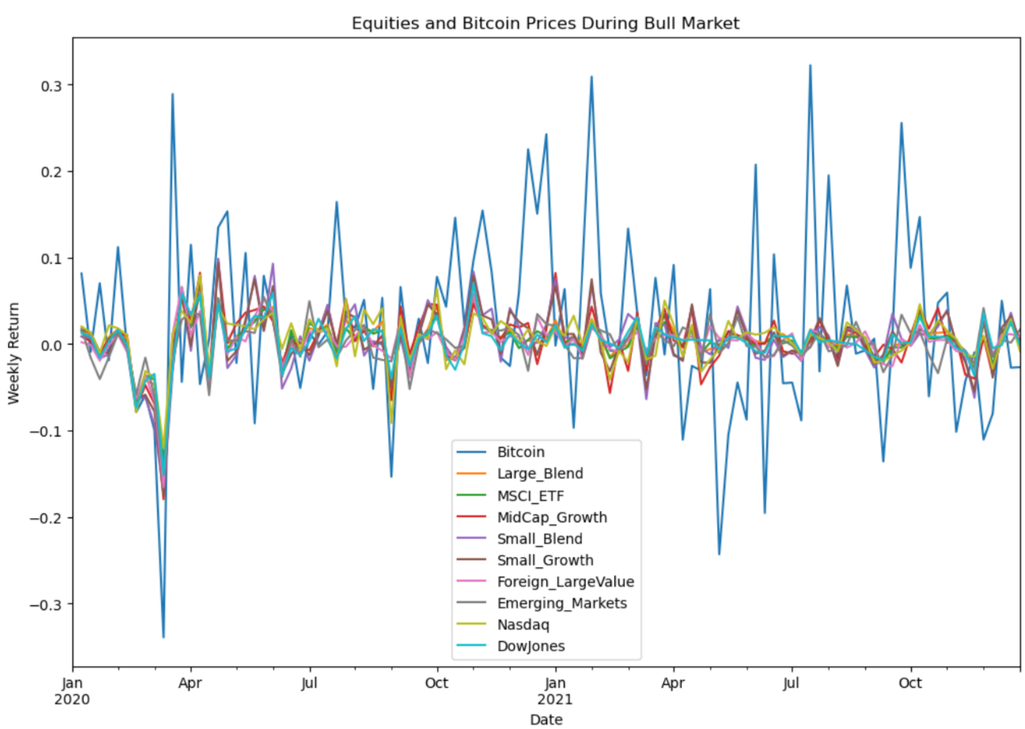
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.0010	0.002	-0.589	0.556	-0.004	0.002
ACWI	1.0052	0.288	3.485	0.001	0.438	1.573
MMN	0.4383	0.232	1.888	0.060	-0.018	0.895
VIX	-0.0310	0.041	-0.755	0.451	-0.112	0.050
GLD	0.1970	0.263	0.748	0.455	-0.321	0.715
Oil	0.0360	0.063	0.567	0.571	-0.089	0.161
DXY_USD	0.1321	0.470	0.281	0.779	-0.792	1.056
FGBFX	-0.0952	0.443	-0.215	0.830	-0.968	0.777
TPINX	0.2151	0.583	0.369	0.712	-0.931	1.361
BAA10Y	0.0274	0.045	0.608	0.544	-0.061	0.116
em_currency	-0.7342	0.754	-0.974	0.331	-2.218	0.750

Omnibus:	43.760	**Durbin-Watson:**	1.866
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	220.397
Skew:	0.391	**Prob(JB):**	1.39e-48
Kurtosis:	6.990	**Cond. No.**	471.

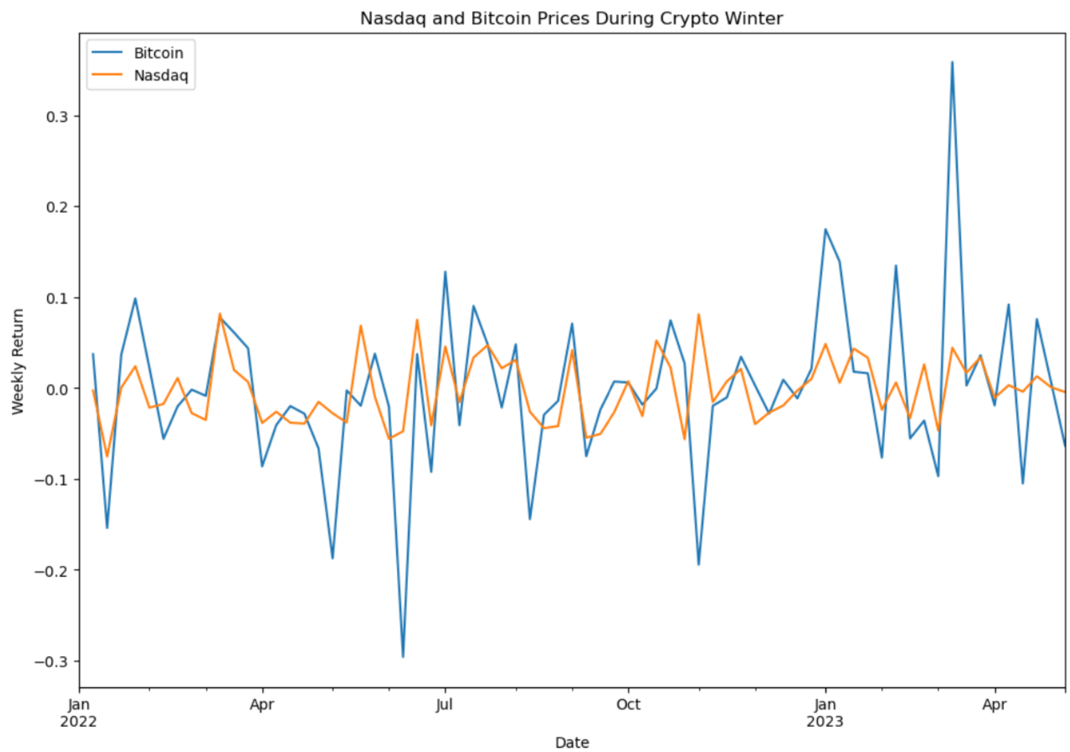
Appendix 8: Bitcoin and Equity Market (2022-2023)



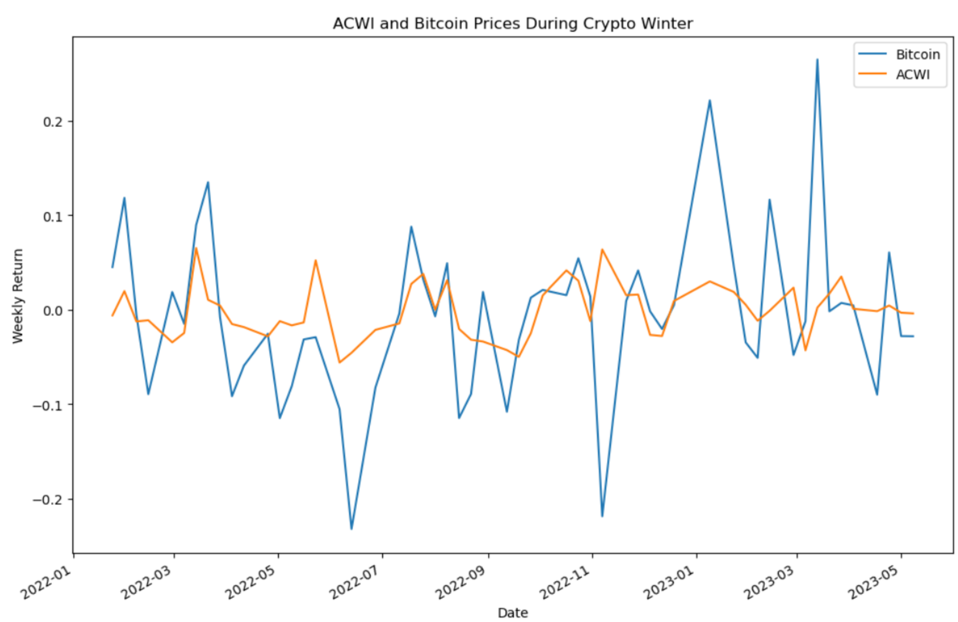
Appendix 9: Bitcoin and Equity Market (2020-2021)



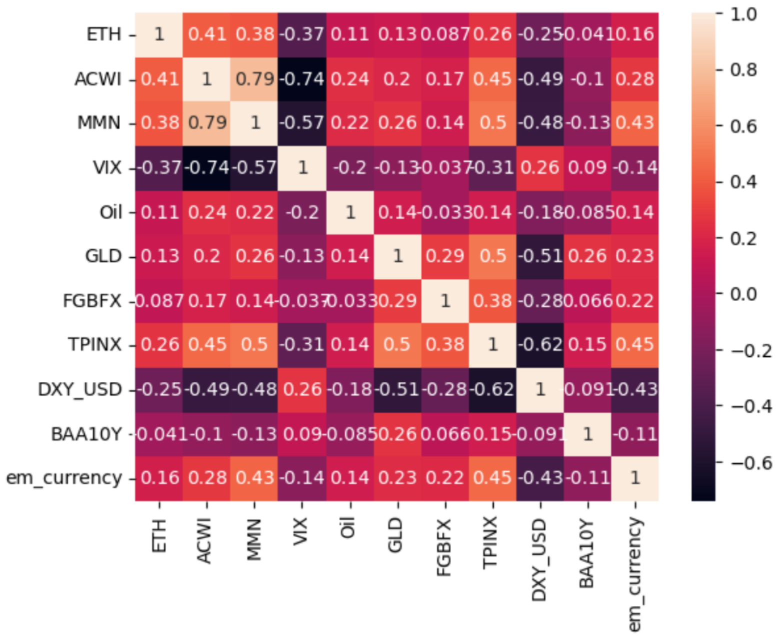
Appendix 10: Bitcoin and Nasdaq (2022-2023)



Appendix 11: Bitcoin and ACWI (2022-2023)



Appendix 12: Ethereum and Overall Market Correlation



Appendix 13: Model 1 Results- Ethereum and Overall Market (2020-2023)

ETH Regression with Financial Market 2023

OLS Regression Results

Dep. Variable:	ETH	**R-squared:**	0.189
Model:	OLS	**Adj. R-squared:**	0.177
Method:	Least Squares	**F-statistic:**	16.29
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	1.35e-26
Time:	16:10:18	**Log-Likelihood:**	1197.0
No. Observations:	712	**AIC:**	-2372.
Df Residuals:	701	**BIC:**	-2322.
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0018	0.002	1.062	0.289	-0.002	0.005
ACWI	0.6814	0.318	2.140	0.033	0.056	1.307
MMN	0.4603	0.239	1.930	0.054	-0.008	0.929
VIX	-0.1013	0.034	-3.012	0.003	-0.167	-0.035
GLD	0.0088	0.225	0.039	0.969	-0.432	0.450
Oil	-0.0052	0.069	-0.075	0.940	-0.141	0.131
DXY_USD	-0.4361	0.545	-0.800	0.424	-1.507	0.634
FGBFX	0.0971	0.560	0.173	0.862	-1.003	1.197
TPINX	0.6651	0.603	1.102	0.271	-0.520	1.850
BAA10Y	-0.0129	0.055	-0.235	0.814	-0.121	0.095
em_currency	-0.0056	0.821	-0.007	0.995	-1.618	1.607

Omnibus:	69.478	**Durbin-Watson:**	2.100
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	385.926
Skew:	-0.189	**Prob(JB):**	1.57e-84
Kurtosis:	6.587	**Cond. No.**	500.

Appendix 14: Model 2 Results - Ethereum and Equity Market (2020-2023)

OLS Regression Results

Dep. Variable:	ETH	**R-squared:**	0.166
Model:	OLS	**Adj. R-squared:**	0.162
Method:	Least Squares	**F-statistic:**	34.65
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	3.05e-44
Time:	16:10:25	**Log-Likelihood:**	2073.2
No. Observations:	1223	**AIC:**	-4130.
Df Residuals:	1215	**BIC:**	-4089.
Df Model:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.0031	0.001	2.394	0.017	0.001	0.006
MSCI_ETF	-2.6754	0.734	-3.647	0.000	-4.115	-1.236
MidCap_Growth	-0.1668	0.276	-0.604	0.546	-0.709	0.375
Small_Blend	0.0108	0.408	0.026	0.979	-0.790	0.812
Small_Growth	0.3502	0.505	0.694	0.488	-0.640	1.341
Foreign_LargeValue	1.5753	0.411	3.829	0.000	0.768	2.382
Emerging_Markets	0.3103	0.230	1.351	0.177	-0.140	0.761
Nasdaq	1.9943	0.332	6.003	0.000	1.342	2.646

Omnibus:	129.079	**Durbin-Watson:**	2.125
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	983.943
Skew:	-0.074	**Prob(JB):**	2.19e-214
Kurtosis:	7.392	**Cond. No.**	663.

Appendix 15: Model 3 Results- Ethereum and Equity Market (2020-2021)

ETH Regression with Financial Market 2023

OLS Regression Results

Dep. Variable:	ETH	**R-squared:**	0.135
Model:	OLS	**Adj. R-squared:**	0.124
Method:	Least Squares	**F-statistic:**	12.42
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	2.02e-18
Time:	16:10:27	**Log-Likelihood:**	1160.7
No. Observations:	728	**AIC:**	-2301.
Df Residuals:	718	**BIC:**	-2256.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.0054	0.002	2.947	0.003	0.002	0.009
Large_Blend	-0.9568	1.767	-0.542	0.588	-4.425	2.512
MSCI_ETF	-2.1873	1.476	-1.482	0.139	-5.084	0.710
MidCap_Growth	-0.6128	0.403	-1.519	0.129	-1.405	0.179
Small_Blend	0.1944	0.532	0.366	0.715	-0.849	1.238
Small_Growth	0.6226	0.633	0.984	0.325	-0.619	1.865
Foreign_LargeValue	1.6320	0.596	2.737	0.006	0.461	2.802
Emerging_Markets	0.3772	0.358	1.054	0.292	-0.326	1.080
Nasdaq	2.2800	0.653	3.493	0.001	0.998	3.562
DowJones	-0.0345	0.829	-0.042	0.967	-1.662	1.593

Omnibus:	75.671	**Durbin-Watson:**	2.165
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	488.814
Skew:	-0.141	**Prob(JB):**	7.17e-107
Kurtosis:	7.004	**Cond. No.**	1.16e+03

Appendix 16: Model 4 Results- Ethereum and Equity Market (2022-2023)

ETH Regression with Financial Market 2023

OLS Regression Results

Dep. Variable:	ETH	**R-squared:**	0.277
Model:	OLS	**Adj. R-squared:**	0.263
Method:	Least Squares	**F-statistic:**	20.45
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	3.16e-29
Time:	16:10:29	**Log-Likelihood:**	943.96
No. Observations:	491	**AIC:**	-1868.
Df Residuals:	481	**BIC:**	-1826.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-0.0001	0.002	-0.066	0.947	-0.003	0.003
Large_Blend	-1.6426	1.973	-0.833	0.405	-5.519	2.234
MSCI_ETF	1.3596	1.875	0.725	0.469	-2.324	5.043
MidCap_Growth	0.8030	0.426	1.885	0.060	-0.034	1.640
Small_Blend	-0.3171	0.917	-0.346	0.730	-2.120	1.486
Small_Growth	-0.2937	1.021	-0.288	0.774	-2.300	1.713
Foreign_LargeValue	0.4460	0.686	0.650	0.516	-0.902	1.794
Emerging_Markets	-0.0522	0.328	-0.159	0.874	-0.697	0.593
Nasdaq	1.5657	0.785	1.995	0.047	0.023	3.108
DowJones	-0.6005	0.843	-0.712	0.477	-2.257	1.056

Omnibus:	41.364	**Durbin-Watson:**	2.055
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	198.406
Skew:	0.049	**Prob(JB):**	8.25e-44
Kurtosis:	6.113	**Cond. No.**	1.52e+03

Appendix 17: Model 5 Results- Ethereum and Overall Market (2020-2021)

OLS Regression Results

Dep. Variable:	ETH	**R-squared:**	0.191
Model:	OLS	**Adj. R-squared:**	0.134
Method:	Least Squares	**F-statistic:**	3.367
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	0.000573
Time:	16:10:29	**Log-Likelihood:**	299.19
No. Observations:	154	**AIC:**	-576.4
Df Residuals:	143	**BIC:**	-543.0
Df Model:	10		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.0037	0.003	1.184	0.238	-0.003	0.010
ACWI	-0.2626	0.594	-0.442	0.659	-1.436	0.911
MMN	-0.2463	0.445	-0.553	0.581	-1.127	0.634
VIX	-0.2008	0.065	-3.078	0.003	-0.330	-0.072
GLD	0.5174	0.342	1.515	0.132	-0.158	1.193
Oil	-0.0749	0.127	-0.590	0.556	-0.326	0.176
DXY_USD	-1.6704	1.088	-1.535	0.127	-3.821	0.480
FGBFX	1.1237	1.868	0.602	0.548	-2.568	4.816
TPINX	-0.9850	1.546	-0.637	0.525	-4.041	2.071
BAA10Y	0.0100	0.149	0.067	0.946	-0.284	0.304
em_currency	1.1189	1.433	0.781	0.436	-1.714	3.952

Omnibus:	2.503	**Durbin-Watson:**	2.144
Prob(Omnibus):	0.286	**Jarque-Bera (JB):**	2.067
Skew:	0.194	**Prob(JB):**	0.356
Kurtosis:	3.414	**Cond. No.**	680.

Appendix 18: Model 6 Results- Ethereum and Overall Market (2022-2023)

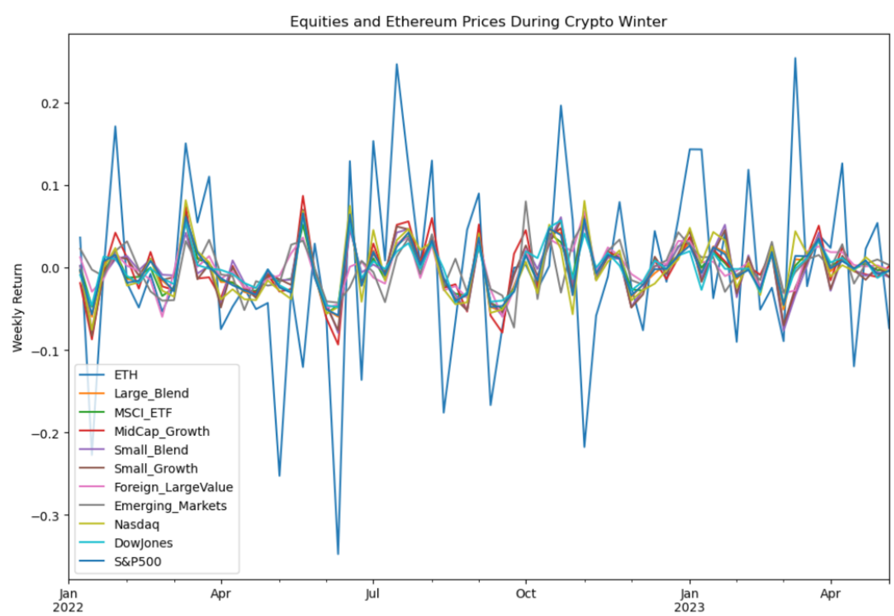
OLS Regression Results

Dep. Variable:	ETH	**R-squared:**	0.330
Model:	OLS	**Adj. R-squared:**	0.308
Method:	Least Squares	**F-statistic:**	15.22
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	4.20e-22
Time:	16:10:31	**Log-Likelihood:**	591.76
No. Observations:	320	**AIC:**	-1162.
Df Residuals:	309	**BIC:**	-1120.
Df Model:	10		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-0.0005	0.002	-0.247	0.805	-0.005	0.004
ACWI	1.1518	0.366	3.144	0.002	0.431	1.873
MMN	0.7183	0.295	2.437	0.015	0.138	1.298
VIX	-0.0639	0.052	-1.227	0.221	-0.166	0.039
GLD	0.0793	0.335	0.237	0.813	-0.579	0.738
Oil	0.1035	0.081	1.285	0.200	-0.055	0.262
DXY_USD	0.4604	0.597	0.772	0.441	-0.713	1.634
FGBFX	-0.0715	0.563	-0.127	0.899	-1.180	1.037
TPINX	0.1087	0.740	0.147	0.883	-1.347	1.564
BAA10Y	0.0278	0.057	0.486	0.627	-0.085	0.140
em_currency	-0.0579	0.958	-0.060	0.952	-1.942	1.827

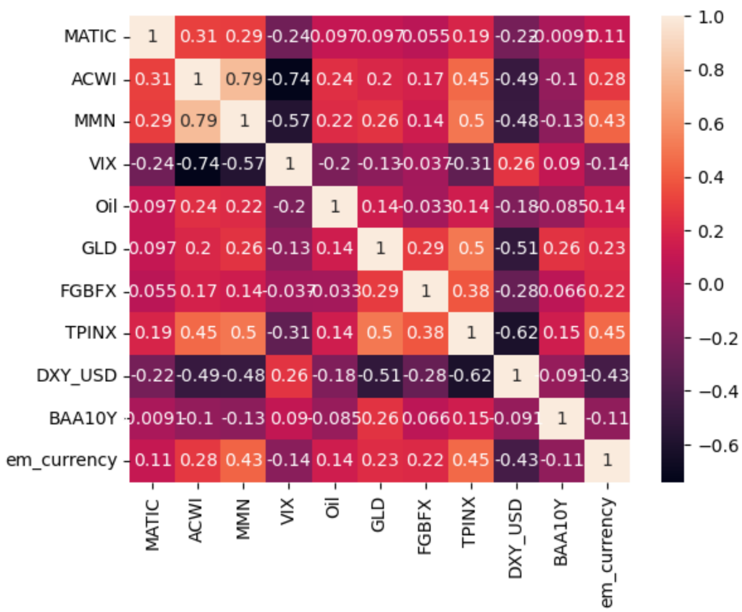
Omnibus:	27.937	**Durbin-Watson:**	1.880
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	122.009
Skew:	-0.023	**Prob(JB):**	3.21e-27
Kurtosis:	6.025	**Cond. No.**	471.

Appendix 19: Ethereum and Market (2022-2023)



Appendix 20: Model and Overall Market correlation

MATIC Regression with Financial Market 2023



Appendix 20: Model 1 Results- Polygon and Overall Market (2020-2023)

OLS Regression Results

Dep. Variable:	MATIC	**R-squared:**	0.109
Model:	OLS	**Adj. R-squared:**	0.096
Method:	Least Squares	**F-statistic:**	8.580
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	2.67e-13
Time:	16:13:09	**Log-Likelihood:**	775.25
No. Observations:	712	**AIC:**	-1528.
Df Residuals:	701	**BIC:**	-1478.
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0088	0.003	2.835	0.005	0.003	0.015
ACWI	0.9793	0.576	1.701	0.089	-0.151	2.110
MMN	0.9005	0.431	2.088	0.037	0.054	1.747
VIX	-0.0554	0.061	-0.911	0.362	-0.175	0.064
GLD	-0.1836	0.406	-0.452	0.651	-0.981	0.614
Oil	0.0588	0.125	0.469	0.639	-0.187	0.305
DXY_USD	-1.6974	0.986	-1.722	0.086	-3.633	0.238
FGBFX	-0.1635	1.013	-0.161	0.872	-2.153	1.826
TPINX	0.3651	1.091	0.335	0.738	-1.777	2.507
BAA10Y	0.0472	0.100	0.474	0.636	-0.148	0.243
em_currency	-1.1055	1.485	-0.744	0.457	-4.022	1.810

Omnibus:	345.534	**Durbin-Watson:**	1.991
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3314.309
Skew:	1.949	**Prob(JB):**	0.00
Kurtosis:	12.825	**Cond. No.**	500.

Appendix 21: Model 2 Results - Polygon and Equity Market (2020-2023)

OLS Regression Results

Dep. Variable:	MATIC	**R-squared:**	0.137
Model:	OLS	**Adj. R-squared:**	0.130
Method:	Least Squares	**F-statistic:**	21.30
Date:	Tue, 09 May 2023	**Prob (F-statistic):**	1.07e-33
Time:	18:53:51	**Log-Likelihood:**	1485.7
No. Observations:	1222	**AIC:**	-2951.
Df Residuals:	1212	**BIC:**	-2900.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0059	0.002	2.867	0.004	0.002	0.010
Large_Blend	-2.7657	2.124	-1.302	0.193	-6.933	1.401
MSCI_ETF	-2.1401	1.826	-1.172	0.241	-5.722	1.442
MidCap_Growth	-0.8089	0.464	-1.745	0.081	-1.718	0.101
Small_Blend	-0.3088	0.695	-0.444	0.657	-1.672	1.054
Small_Growth	2.0544	0.820	2.506	0.012	0.446	3.663
Foreign_LargeValue	1.9961	0.714	2.794	0.005	0.595	3.397
Emerging_Markets	0.7120	0.393	1.814	0.070	-0.058	1.482
Nasdaq	3.3621	0.796	4.225	0.000	1.801	4.923
DowJones	-0.2561	0.938	-0.273	0.785	-2.096	1.584

Omnibus:	529.098	**Durbin-Watson:**	2.059
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	6022.037
Skew:	1.686	**Prob(JB):**	0.00
Kurtosis:	13.339	**Cond. No.**	1.25e+03

Appendix 22: Model 3 Results- Polygon and Equity Market (2020-2021)

OLS Regression Results

Dep. Variable:	MATIC	**R-squared:**	0.120
Model:	OLS	**Adj. R-squared:**	0.109
Method:	Least Squares	**F-statistic:**	10.93
Date:	Tue, 09 May 2023	**Prob (F-statistic):**	4.86e-16
Time:	18:53:52	**Log-Likelihood:**	782.05
No. Observations:	728	**AIC:**	-1544.
Df Residuals:	718	**BIC:**	-1498.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0101	0.003	3.262	0.001	0.004	0.016
Large_Blend	-3.2118	2.972	-1.081	0.280	-9.047	2.624
MSCI_ETF	-3.1798	2.483	-1.281	0.201	-8.054	1.694
MidCap_Growth	-1.2076	0.679	-1.780	0.076	-2.540	0.124
Small_Blend	-0.1737	0.894	-0.194	0.846	-1.930	1.582
Small_Growth	2.3552	1.064	2.213	0.027	0.266	4.444
Foreign_LargeValue	2.4448	1.003	2.437	0.015	0.476	4.414
Emerging_Markets	1.1141	0.602	1.850	0.065	-0.068	2.296
Nasdaq	3.8038	1.098	3.463	0.001	1.648	5.960
DowJones	-0.1445	1.395	-0.104	0.917	-2.883	2.594

Omnibus:	305.941	**Durbin-Watson:**	2.078
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2571.586
Skew:	1.669	**Prob(JB):**	0.00
Kurtosis:	11.581	**Cond. No.**	1.16e+03

Appendix 23: Model 4 Results- Polygon and Equity Market (2022-2023)

OLS Regression Results

Dep. Variable:	MATIC	**R-squared:**	0.223
Model:	OLS	**Adj. R-squared:**	0.208
Method:	Least Squares	**F-statistic:**	15.30
Date:	Tue, 09 May 2023	**Prob (F-statistic):**	5.34e-22
Time:	18:53:55	**Log-Likelihood:**	770.68
No. Observations:	490	**AIC:**	-1521.
Df Residuals:	480	**BIC:**	-1479.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0002	0.002	0.075	0.940	-0.004	0.005
Large_Blend	-0.6864	2.799	-0.245	0.806	-6.187	4.814
MSCI_ETF	-0.8866	2.660	-0.333	0.739	-6.113	4.340
MidCap_Growth	0.2062	0.608	0.339	0.735	-0.988	1.400
Small_Blend	-1.8824	1.302	-1.446	0.149	-4.441	0.676
Small_Growth	1.6505	1.452	1.137	0.256	-1.202	4.504
Foreign_LargeValue	1.3333	0.974	1.369	0.171	-0.580	3.246
Emerging_Markets	0.2503	0.465	0.538	0.591	-0.664	1.165
Nasdaq	2.1967	1.114	1.972	0.049	0.008	4.386
DowJones	-0.4732	1.197	-0.395	0.693	-2.824	1.878

Omnibus:	84.787	**Durbin-Watson:**	2.080
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	434.358
Skew:	0.634	**Prob(JB):**	4.79e-95
Kurtosis:	7.435	**Cond. No.**	1.52e+03

Appendix 24: Model 5 Results- Polygon and Overall Market (2020-2021)

OLS Regression Results

Dep. Variable:	MATIC	**R-squared:**	0.078
Model:	OLS	**Adj. R-squared:**	0.057
Method:	Least Squares	**F-statistic:**	3.611
Date:	Tue, 09 May 2023	**Prob (F-statistic):**	0.000245
Time:	18:53:58	**Log-Likelihood:**	361.43
No. Observations:	392	**AIC:**	-702.9
Df Residuals:	382	**BIC:**	-663.2
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0164	0.005	3.199	0.001	0.006	0.026
ACWI	0.2030	1.203	0.169	0.866	-2.163	2.569
MMN	0.8212	0.717	1.145	0.253	-0.589	2.231
VIX	-0.0930	0.098	-0.951	0.342	-0.285	0.099
GLD	-0.5917	0.647	-0.915	0.361	-1.864	0.680
Oil	0.0306	0.240	0.127	0.899	-0.442	0.503
DXY_USD	-4.4843	1.881	-2.384	0.018	-8.182	-0.787
FGBFX	-2.3171	2.587	-0.896	0.371	-7.403	2.769
TPINX	2.4954	2.340	1.066	0.287	-2.106	7.097
BAA10Y	0.0812	0.234	0.347	0.729	-0.380	0.542

Omnibus:	173.925	**Durbin-Watson:**	2.032
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1062.176
Skew:	1.791	**Prob(JB):**	2.25e-231
Kurtosis:	10.225	**Cond. No.**	555.

Appendix 25: Model 6 Results- Polygon and Overall Market (2022-2023)

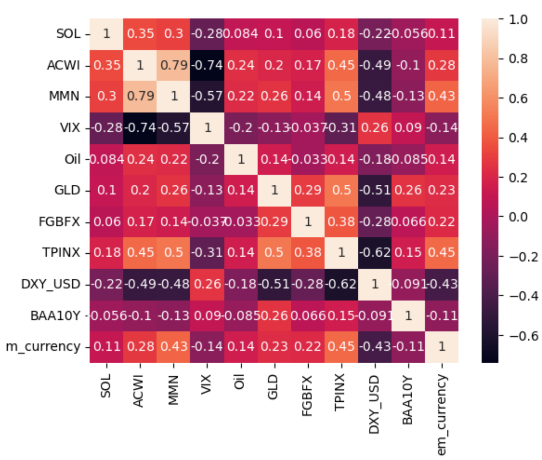
OLS Regression Results

Dep. Variable:	MATIC	**R-squared:**	0.246
Model:	OLS	**Adj. R-squared:**	0.222
Method:	Least Squares	**F-statistic:**	10.10
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	1.05e-14
Time:	12:31:54	**Log-Likelihood:**	469.91
No. Observations:	320	**AIC:**	-917.8
Df Residuals:	309	**BIC:**	-876.4
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0013	0.003	0.416	0.678	-0.005	0.008
ACWI	1.5742	0.536	2.936	0.004	0.519	2.629
MMN	0.8490	0.431	1.968	0.050	0.000	1.698
VIX	-0.0179	0.076	-0.235	0.814	-0.168	0.132
GLD	0.1480	0.490	0.302	0.763	-0.815	1.111
Oil	0.0382	0.118	0.324	0.746	-0.194	0.270
DXY_USD	-0.0541	0.873	-0.062	0.951	-1.772	1.664
FGBFX	0.4053	0.824	0.492	0.623	-1.216	2.027
TPINX	-0.0517	1.083	-0.048	0.962	-2.182	2.079
BAA10Y	0.0304	0.084	0.364	0.716	-0.134	0.195
em_currency	-1.1442	1.402	-0.816	0.415	-3.902	1.614

Omnibus:	61.684	**Durbin-Watson:**	1.890
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	295.447
Skew:	0.690	**Prob(JB):**	6.99e-65
Kurtosis:	7.500	**Cond. No.**	471.

Appendix 26: Solana and Overall Market Correlation



Appendix 27: Model 1 Results- Solana and Overall Market (2020-2023)

OLS Regression Results

Dep. Variable:	SOL	**R-squared:**	0.127
Model:	OLS	**Adj. R-squared:**	0.115
Method:	Least Squares	**F-statistic:**	10.21
Date:	Tue, 09 May 2023	**Prob (F-statistic):**	3.60e-16
Time:	18:52:38	**Log-Likelihood:**	831.47
No. Observations:	712	**AIC:**	-1641.
Df Residuals:	701	**BIC:**	-1591.
Df Model:	10		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.0037	0.003	1.279	0.201	-0.002	0.009
ACWI	1.5073	0.532	2.833	0.005	0.463	2.552
MMN	0.4370	0.399	1.097	0.273	-0.345	1.220
VIX	-0.0686	0.056	-1.220	0.223	-0.179	0.042
GLD	0.1131	0.375	0.301	0.763	-0.624	0.850
Oil	-0.0304	0.116	-0.263	0.793	-0.258	0.197
DXY_USD	-1.2746	0.911	-1.399	0.162	-3.063	0.514
FGBFX	-0.1282	0.936	-0.137	0.891	-1.966	1.710
TPINX	0.0170	1.008	0.017	0.987	-1.963	1.997
BAA10Y	-0.0790	0.092	-0.858	0.391	-0.260	0.102
em_currency	-0.7595	1.372	-0.553	0.580	-3.454	1.935

Omnibus:	107.175	**Durbin-Watson:**	2.037
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	724.481
Skew:	0.458	**Prob(JB):**	4.80e-158
Kurtosis:	7.856	**Cond. No.**	500.

Appendix 28: Model 2 Results - Solana and Equity Market (2020-2023)

OLS Regression Results

Dep. Variable:	SOL	**R-squared:**	0.091
Model:	OLS	**Adj. R-squared:**	0.084
Method:	Least Squares	**F-statistic:**	12.36
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	8.11e-19
Time:	15:46:30	**Log-Likelihood:**	1337.2
No. Observations:	1123	**AIC:**	-2654.
Df Residuals:	1113	**BIC:**	-2604.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.0049	0.002	2.220	0.027	0.001	0.009
Large_Blend	1.2267	2.522	0.486	0.627	-3.722	6.175
MSCI_ETF	-1.3782	2.353	-0.586	0.558	-5.995	3.239
MidCap_Growth	-1.2010	0.537	-2.238	0.025	-2.254	-0.148
Small_Blend	-0.8785	1.111	-0.791	0.429	-3.058	1.301
Small_Growth	1.4418	1.267	1.138	0.255	-1.044	3.928
Foreign_LargeValue	1.7676	0.887	1.992	0.047	0.026	3.509
Emerging_Markets	0.3244	0.466	0.697	0.486	-0.589	1.238
Nasdaq	1.6608	0.995	1.669	0.095	-0.291	3.613
DowJones	-0.7360	1.113	-0.661	0.509	-2.920	1.448

Omnibus:	151.426	**Durbin-Watson:**	2.054
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	890.605
Skew:	0.457	**Prob(JB):**	4.05e-194
Kurtosis:	7.266	**Cond. No.**	1.41e+03

Appendix 29: Model 3 Results- Solana and Equity Market (2020-2021)

OLS Regression Results

Dep. Variable:	SOL	**R-squared:**	0.059
Model:	OLS	**Adj. R-squared:**	0.045
Method:	Least Squares	**F-statistic:**	4.308
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	1.88e-05
Time:	15:46:25	**Log-Likelihood:**	659.43
No. Observations:	629	**AIC:**	-1299.
Df Residuals:	619	**BIC:**	-1254.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	0.0104	0.003	3.017	0.003	0.004	0.017
Large_Blend	4.3734	3.789	1.154	0.249	-3.067	11.814
MSCI_ETF	-3.7957	3.484	-1.090	0.276	-10.637	3.045
MidCap_Growth	-2.2124	0.838	-2.641	0.008	-3.858	-0.567
Small_Blend	-1.8444	1.657	-1.113	0.266	-5.098	1.409
Small_Growth	2.5750	1.858	1.386	0.166	-1.074	6.224
Foreign_LargeValue	2.6221	1.354	1.936	0.053	-0.038	5.282
Emerging_Markets	0.8577	0.767	1.118	0.264	-0.649	2.364
Nasdaq	1.1176	1.489	0.751	0.453	-1.806	4.041
DowJones	-1.2752	1.745	-0.731	0.465	-4.702	2.152

Omnibus:	61.957	**Durbin-Watson:**	2.106
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	187.346
Skew:	0.457	**Prob(JB):**	2.08e-41
Kurtosis:	5.513	**Cond. No.**	1.36e+03

Appendix 30: Model 4 Results- Solana and Equity Market (2022-2023)

OLS Regression Results

Dep. Variable:	SOL	**R-squared:**	0.198
Model:	OLS	**Adj. R-squared:**	0.183
Method:	Least Squares	**F-statistic:**	13.22
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	5.79e-19
Time:	15:46:21	**Log-Likelihood:**	732.14
No. Observations:	491	**AIC:**	-1444.
Df Residuals:	481	**BIC:**	-1402.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.0017	0.002	-0.700	0.484	-0.007	0.003
Large_Blend	-4.0652	3.037	-1.339	0.181	-10.032	1.902
MSCI_ETF	1.4827	2.886	0.514	0.608	-4.188	7.153
MidCap_Growth	0.5429	0.656	0.828	0.408	-0.746	1.832
Small_Blend	0.1777	1.412	0.126	0.900	-2.597	2.953
Small_Growth	-0.3482	1.572	-0.222	0.825	-3.437	2.741
Foreign_LargeValue	0.8787	1.056	0.832	0.406	-1.197	2.955
Emerging_Markets	-0.2583	0.505	-0.511	0.609	-1.251	0.734
Nasdaq	2.9885	1.208	2.473	0.014	0.614	5.363
DowJones	0.2488	1.298	0.192	0.848	-2.301	2.798

Omnibus:	87.079	**Durbin-Watson:**	1.976
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1233.905
Skew:	-0.191	**Prob(JB):**	1.15e-268
Kurtosis:	10.757	**Cond. No.**	1.52e+03

Appendix 31: Model 5 Results- Solana and Overall Market (2020-2021)

OLS Regression Results

Dep. Variable:	SOL	**R-squared:**	0.080
Model:	OLS	**Adj. R-squared:**	0.058
Method:	Least Squares	**F-statistic:**	3.684
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	0.000193
Time:	15:46:11	**Log-Likelihood:**	400.85
No. Observations:	392	**AIC:**	-781.7
Df Residuals:	382	**BIC:**	-742.0
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.0110	0.005	2.368	0.018	0.002	0.020
ACWI	0.9963	1.088	0.916	0.360	-1.143	3.136
MMN	0.2544	0.649	0.392	0.695	-1.021	1.530
VIX	-0.1374	0.088	-1.554	0.121	-0.311	0.036
GLD	-0.0892	0.585	-0.152	0.879	-1.239	1.061
Oil	-0.1932	0.217	-0.889	0.375	-0.621	0.234
DXY_USD	-2.7359	1.701	-1.609	0.109	-6.080	0.608
FGBFX	0.1532	2.339	0.065	0.948	-4.447	4.753
TPINX	0.0742	2.116	0.035	0.972	-4.087	4.235
BAA10Y	-0.1942	0.212	-0.916	0.360	-0.611	0.223

Omnibus:	56.214	**Durbin-Watson:**	2.101
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	216.235
Skew:	0.562	**Prob(JB):**	1.11e-47
Kurtosis:	6.460	**Cond. No.**	555.

Appendix 32: Model 6 Results- Solana and Overall Market (2022-2023)

OLS Regression Results

Dep. Variable:	SOL	**R-squared:**	0.258
Model:	OLS	**Adj. R-squared:**	0.234
Method:	Least Squares	**F-statistic:**	10.76
Date:	Wed, 10 May 2023	**Prob (F-statistic):**	1.08e-15
Time:	15:46:07	**Log-Likelihood:**	469.48
No. Observations:	320	**AIC:**	-917.0
Df Residuals:	309	**BIC:**	-875.5
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.0049	0.003	-1.535	0.126	-0.011	0.001
ACWI	1.6950	0.537	3.158	0.002	0.639	2.751
MMN	0.7169	0.432	1.660	0.098	-0.133	1.567
VIX	0.0041	0.076	0.054	0.957	-0.146	0.154
GLD	-0.0492	0.490	-0.100	0.920	-1.014	0.915
Oil	0.0518	0.118	0.439	0.661	-0.180	0.284
DXY_USD	-0.5702	0.874	-0.652	0.515	-2.290	1.150
FGBFX	-0.4477	0.825	-0.542	0.588	-2.072	1.176
TPINX	0.6137	1.084	0.566	0.572	-1.519	2.747
BAA10Y	-0.0167	0.084	-0.200	0.842	-0.182	0.148
em_currency	-2.0339	1.403	-1.449	0.148	-4.795	0.728

Appendix 33.

A list of variables from CSV files

Liquidity Index

ICE BofA High Yield US Emerging Markets Liquid Corporate Plus Index Option-Adjusted Spread

https://fred.stlouisfed.org/series/BAMLEMHYHYLCRPIUSOAS

BAMLEMHYHYLCRPIUSOAS.csv

Credit Spread

Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity

High yield - treasury

https://fred.stlouisfed.org/series/BAA10Y

BAA10Y.csv

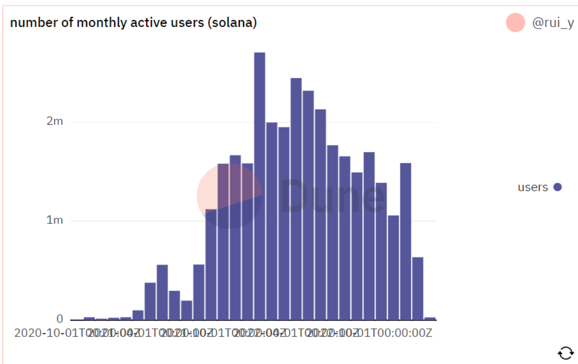
EM Currency

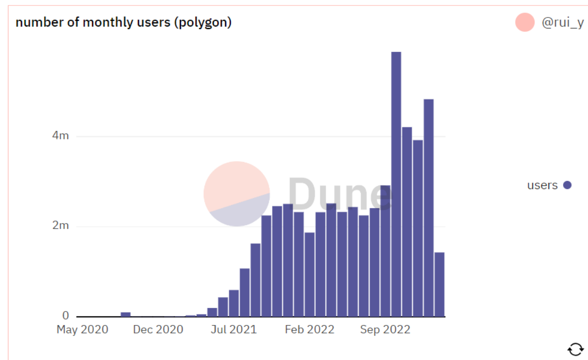
MSCI Intl Emerging Market Currency (MIEM00000CUS)

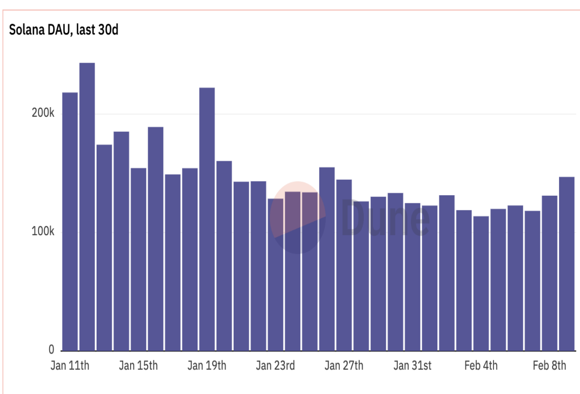
https://www.investing.com/indices/msci-intl-em-currency-historical-data

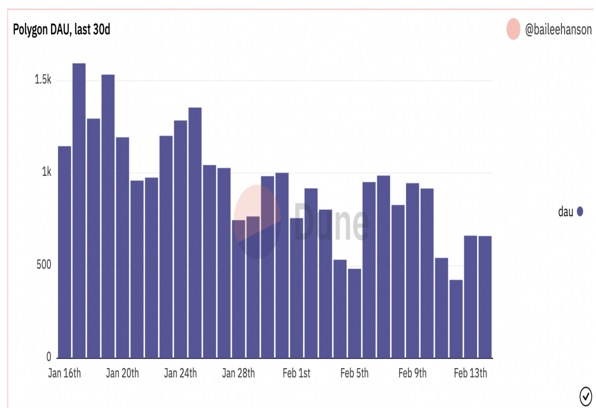
MSCI Intl Emerging Market Currency Historical Data.csv

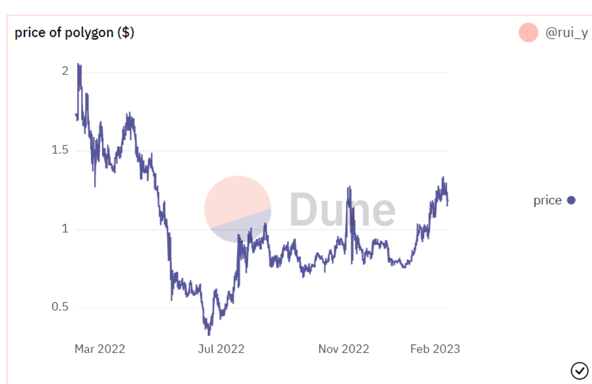
Appendix 34

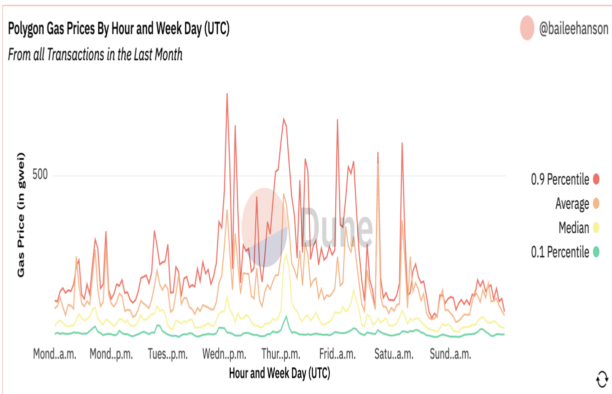


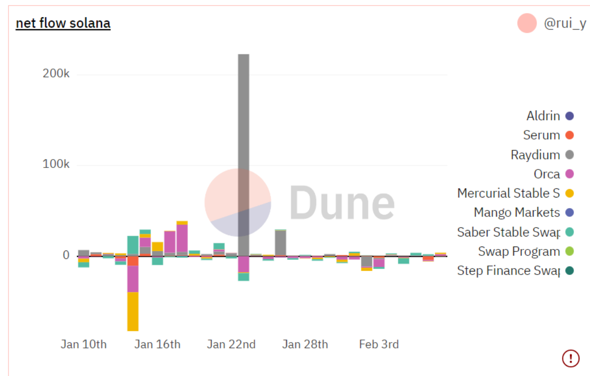












Appendix 35

Github Link:https://github.com/ruiy2/Analytics-in-Practice-Crypto-Project/tree/main