CONTINUOUS PORTFOLIO OPTIMIZATION (SENTIMENT ANALYSIS BASED)

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PRESENTATION OUTLINE

- Introduction
  - Problem formulation and techniques for finding solution
- Methodology & Results
  - Implementation of financial engineering techniques and analysis of results
- Discussion
  - Major contributions and difficulties encountered
- Conclusions
- References

INTRODUCTION

- This project is geared at portfolio diversification to include stocks and cryptocurrency
- Sentiment analysis as a tool for predicting cryptocurrency price is explored
- Capital Asset pricing model is utilized to qualify and rank stocks from a wide pool
  - $E[R_i - R_f] = \beta_i E[R_M - R_f]$ - Traditional CAPM model
  - $(R_i - R_f)_t = \bar{\alpha} + \beta_i (R_M - R_f)_t$ - Time series modification
- Crypto currency adopted for analyses are Bitcoin and Dogecoin
- Portfolio optimization implemented using Markowitz portfolio theory, with the central aim of maximizing returns while minimizing risks
  - $SR_i = (ER_i - R_f)/\sigma_i$ - Sharpe Ratio

METHODOLOGY & RESULTS - CAPM

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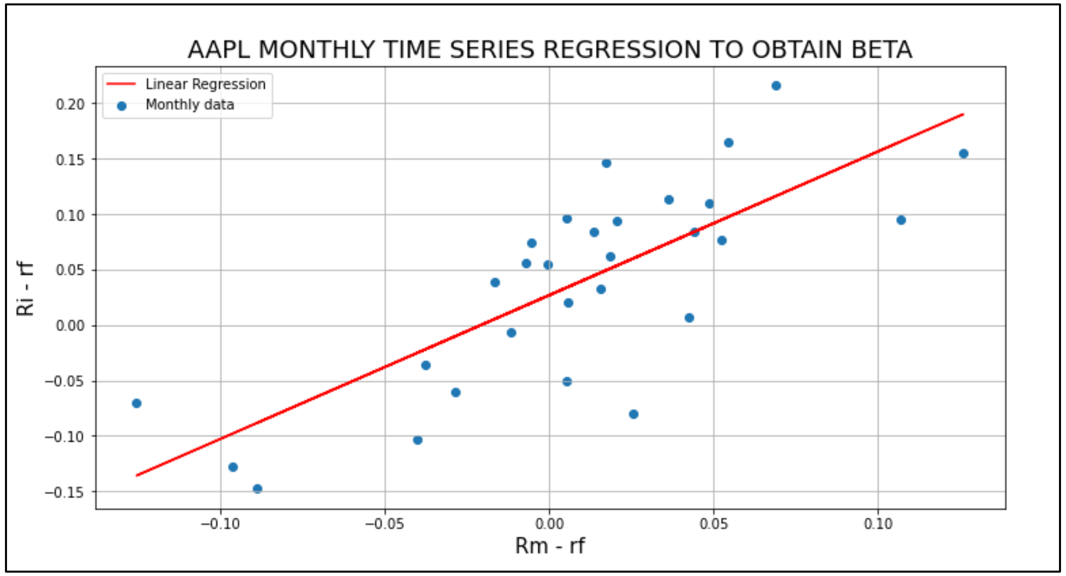

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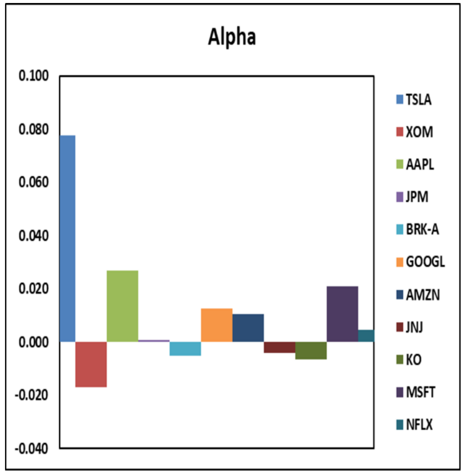
Key Notes

- Time series regression was done using modified CAPM to obtain Beta and Alpha values
- Time frame of study between Jan 1 2019 to June 30 2021 (30-months)
- Stock price data pulled from yahoo finance and all analysis done using Python scripts
- Market rate/return assumed to be S&P 500.
- Risk free rate assumed to be 3-month treasury bill historical return

CAPM STOCK RANKING



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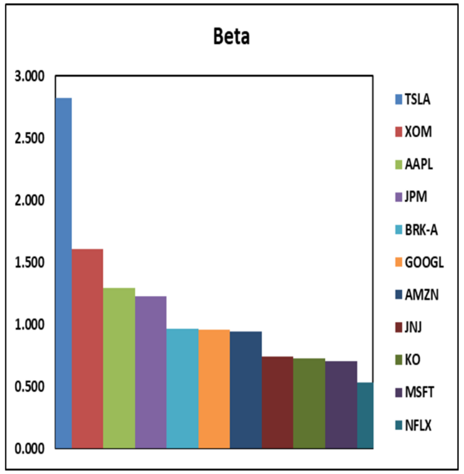

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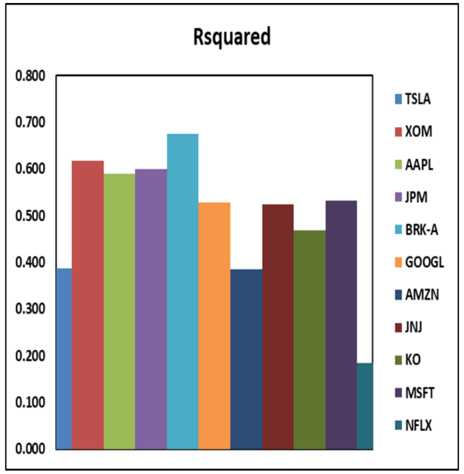

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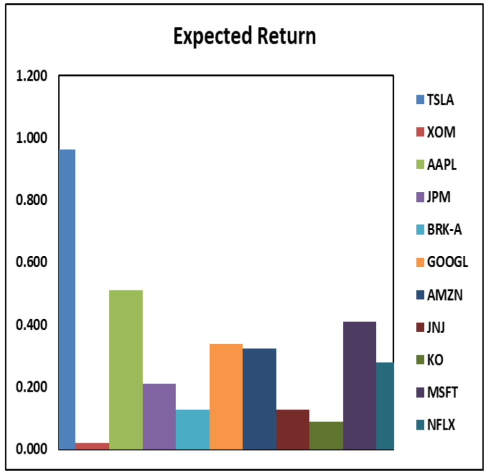

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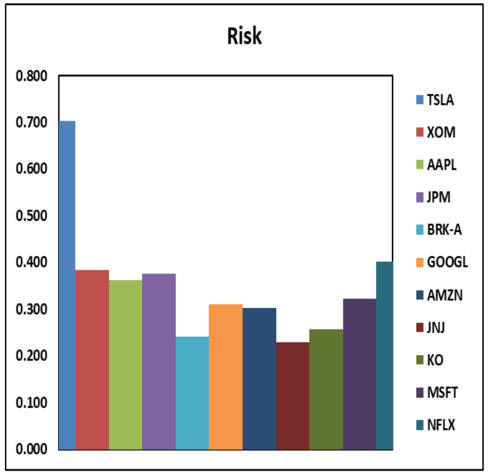

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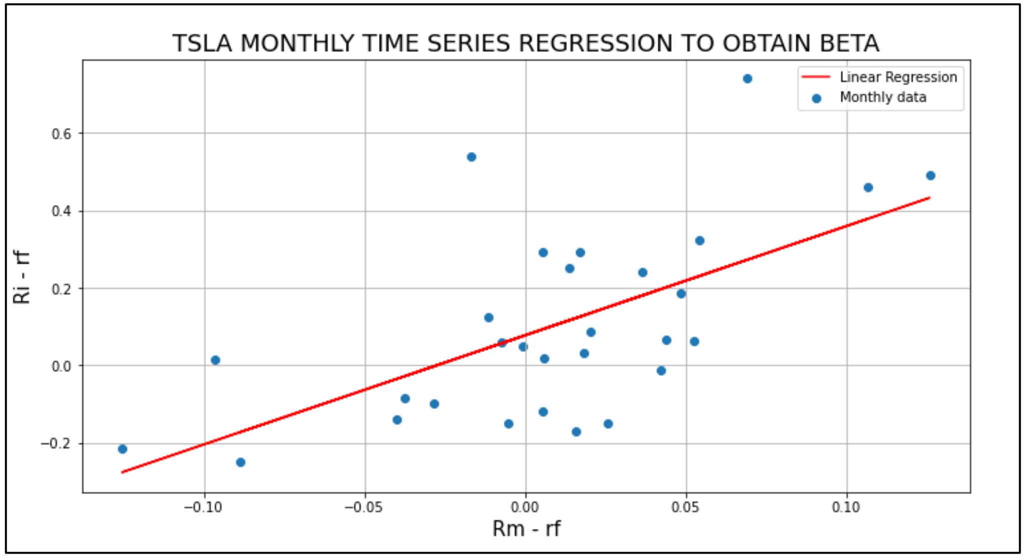
Ranking Methodology

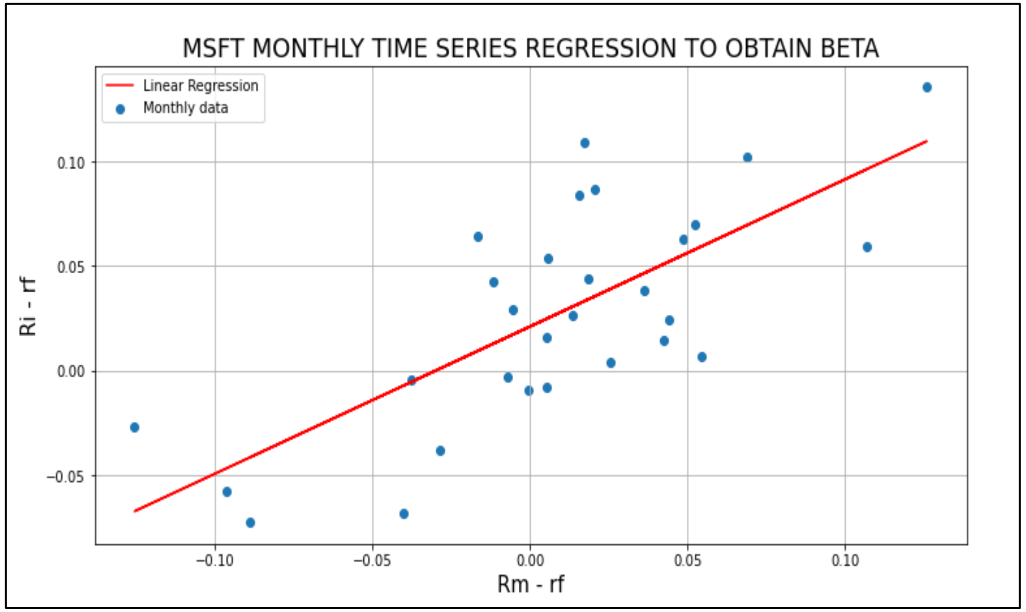
- Consider Alpha, Beta, Expected Return and Risk as qualifiers
- Rank each of the qualifiers as follows:
  - ➢ Alpha, Beta & Expected Return: Highest to Lowest (rank 1-11)
  - ➢ Risk: Lowest to Highest (rank 1-11)
- Sum all qualifiers scores and rank stocks based on this total score. Least score is the highest rank.

Stock	Alpha	Beta	Rsquared	Expected Return	Risk
TSLA	0.078	2.820	0.386	0.963	0.703
XOM	-0.017	1.609	0.617	0.019	0.383
AAPL	0.027	1.296	0.589	0.509	0.361
JPM	0.001	1.226	0.600	0.209	0.377
BRK-A	-0.005	0.967	0.676	0.127	0.240
GOOGL	0.012	0.959	0.528	0.338	0.311
AMZN	0.010	0.942	0.385	0.324	0.302
JNJ	-0.004	0.738	0.524	0.127	0.229
KO	-0.007	0.728	0.469	0.088	0.256
MSFT	0.021	0.704	0.532	0.409	0.322
NFLX	0.004	0.531	0.184	0.277	0.402

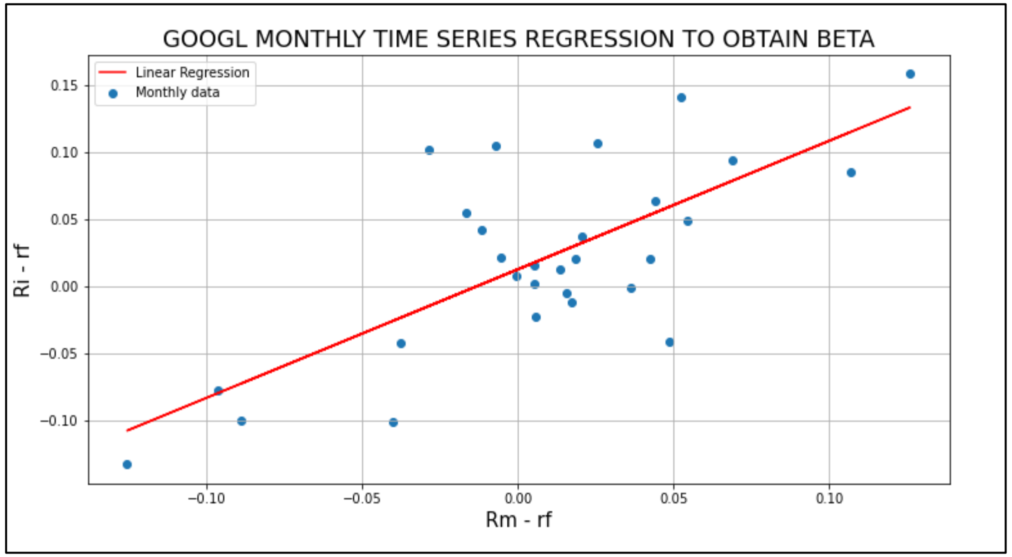
Stock	Alpha	Beta	Expected Return	Risk	TOTAL SCORE	RANK
AAPL	2	3	2	7	14	1
TSLA	1	1	1	11	14	2
GOOGL	4	6	4	5	19	3
AMZN	5	7	5	4	21	7
MSFT	3	10	3	6	22	5
BRK-A	9	5	9	2	25	4
JNJ	8	8	8	1	25	8
JPM	7	4	7	8	26	6
KO	10	9	10	3	32	10
XOM	11	2	11	9	33	9
NFLX	6	11	6	10	33	11

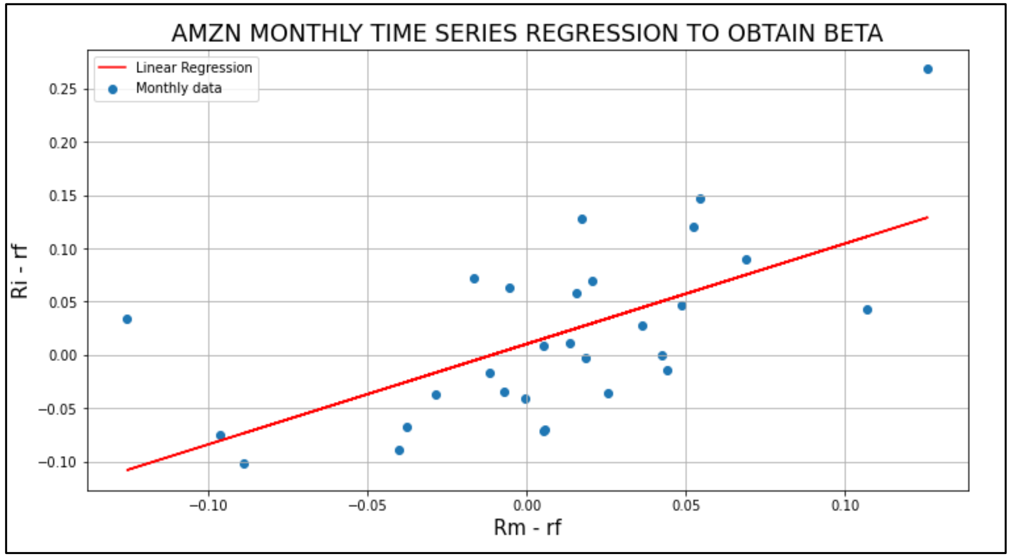
CAPM RESULTS FOR TESLA & MICROSOFT



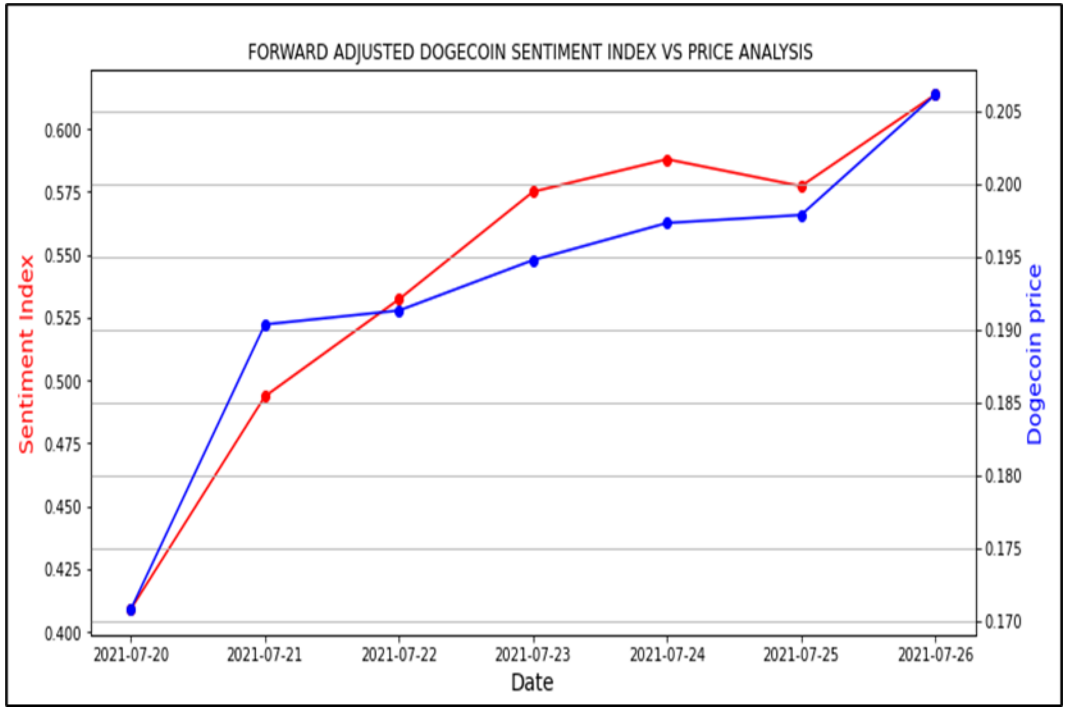


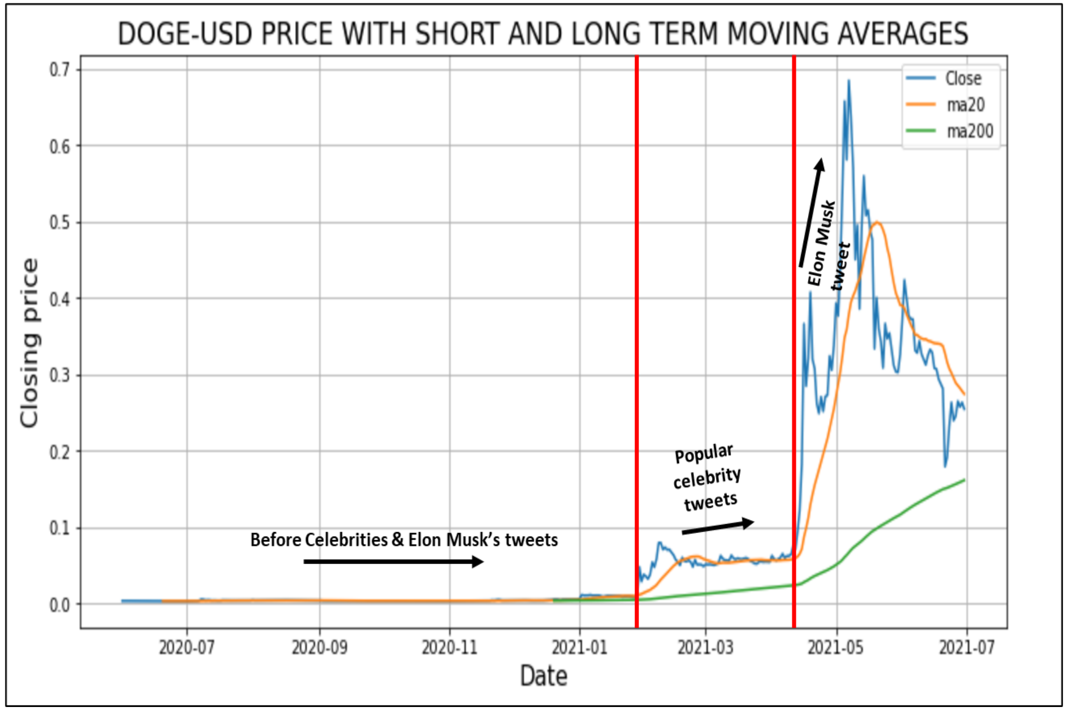
CAPM RESULTS FOR ALPHABET & AMAZON





SENTIMENT ANALYSIS - DOGECOIN

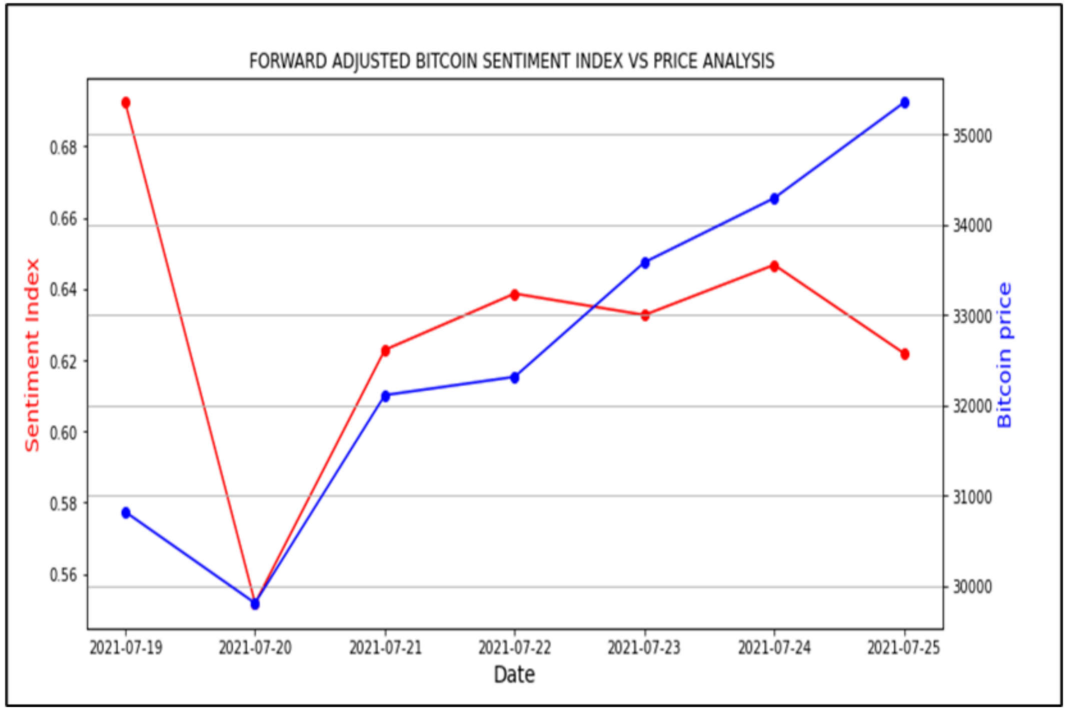


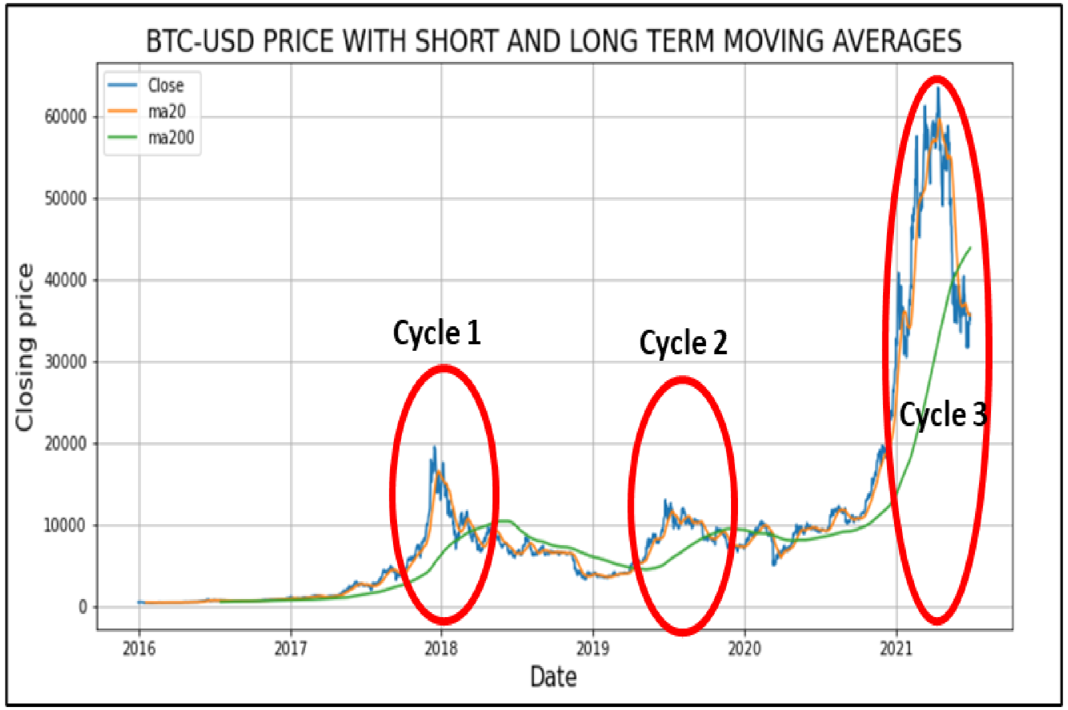


Key Notes

- Dogecoin price exhibits strong positive correlation with twitter sentiments
- Historical data illustrates influence of statements by popular figures on price. Elon Musk's tweet on the 04/14/2021 caused a buying frenzy and sharp price hike
- Analysis suggests Dogecoin price is a function of mere speculation

SENTIMENT ANALYSIS - BITCOIN

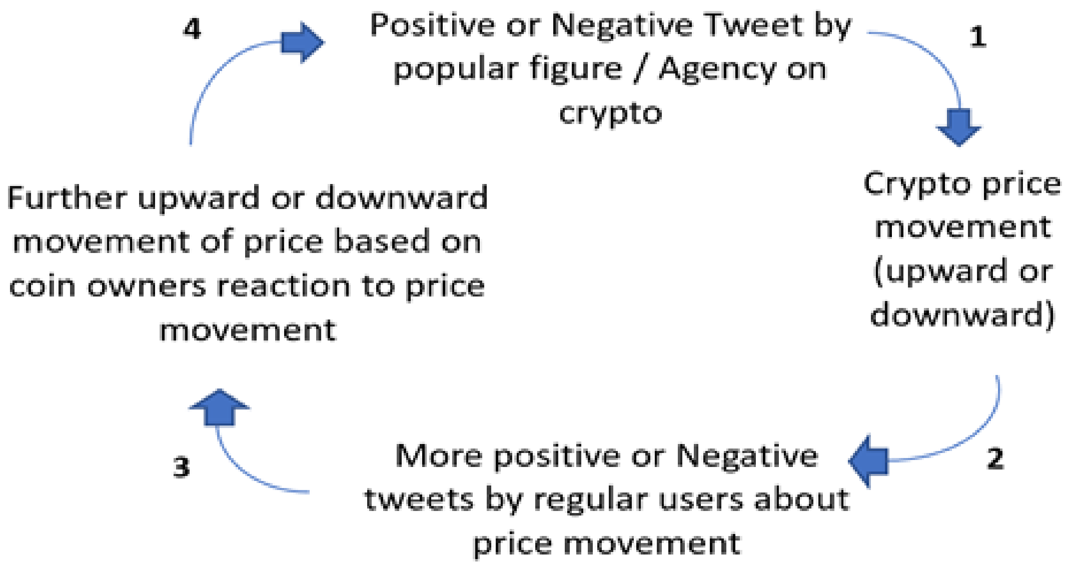




Key Notes

- Bitcoin price shows a lower degree of correlation with twitter sentiments
- Due to Bitcoin being in use for much longer, and limited coin circulation (demand and supply), its adoption by central banks and companies as a payment alternative also drives price movement in addition to speculation
- In the past 5 years, Bitcoin has experienced 3 cycles of rise and fall, each being linked to adoption. The most recent cycle in 2021 was partly due to a brief adoption and regress by Tesla as a payment alternative

IMPLICIT NATURE OF CRYPTO PRICE AND TWITTER SENTIMENTS



<u>Key Notes</u>

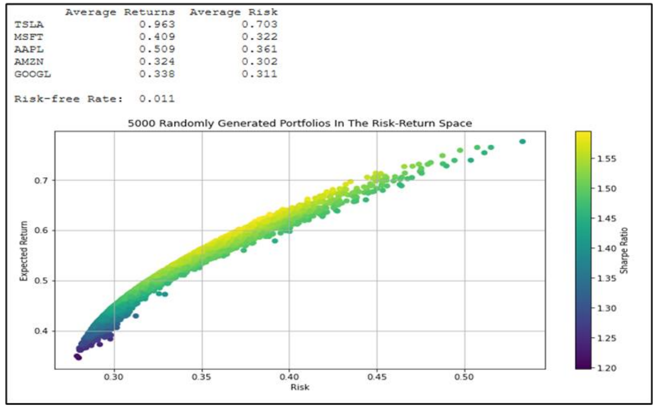
- Due to the implicit nature of cryptocurrency price and twitter sentiments, one must take advantage of a very short time window between 1-2 and 2-3 to extract twitter sentiments and trade coin based on forecast

- This time window typically lies between 1 minute to 1 hour

- To take advantage of this time window requires near real time monitoring of twitter sentiments

PORTFOLIO OPTIMIZATION – STOCK ONLY

30 months



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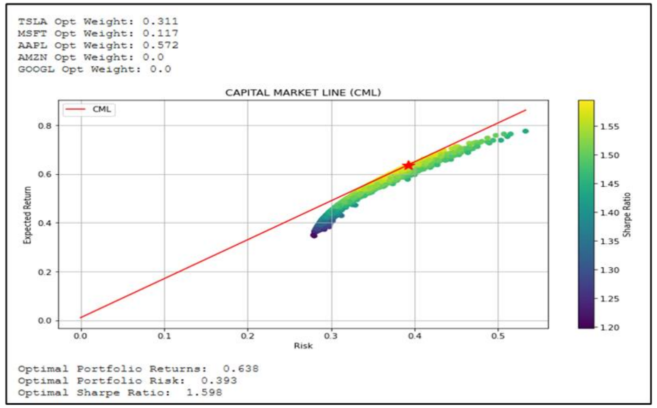

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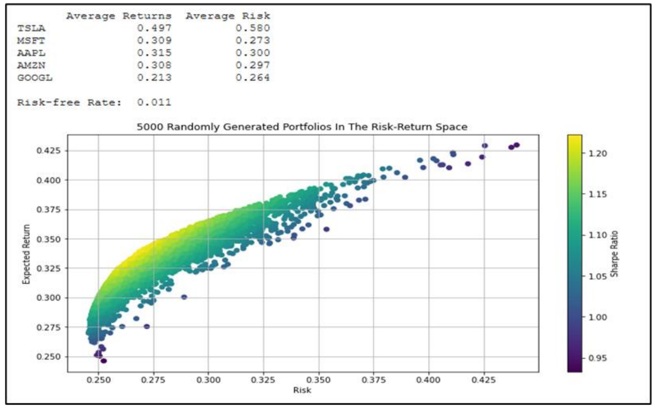
66 months



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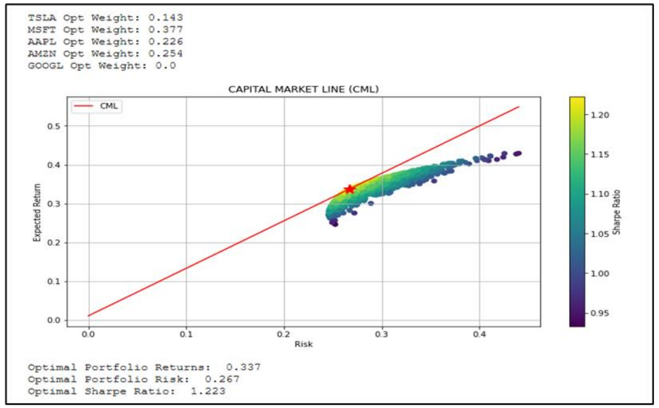


(b)

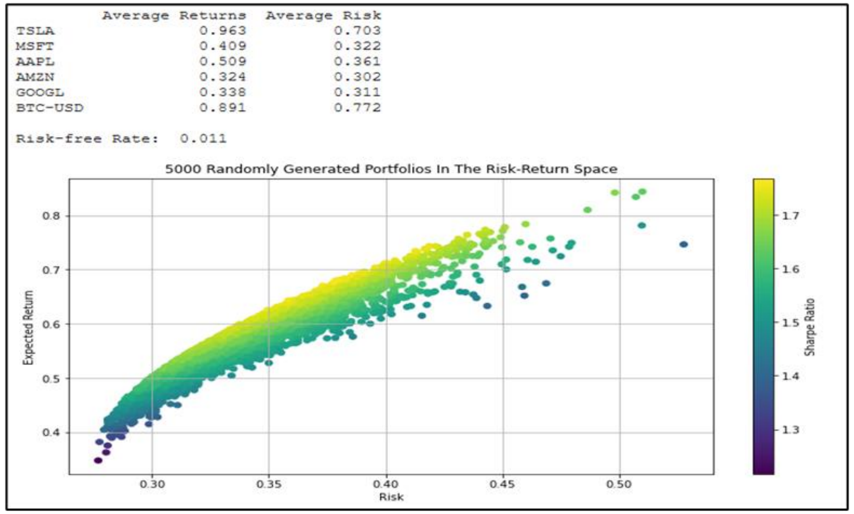
Red line depicts the central market line (CML) drawn on the efficient frontier for the maximized Sharpe ratio portfolio

Key Notes

- 3 different cases were considered for portfolio optimization:
  - ➢ Stocks only
  - ➢ Stocks + Bitcoin
  - ➢ Stocks + Bitcoin + Dogecoin
- For each case, the risk return space was generated using Monte-Carlo like simulation of portfolio risk and return
- Each simulation had different weights generated randomly assigned to each stock.
- The risk-return space clearly depicts the efficient frontier
- The Capital Market Line (CML) was drawn to tangent to the efficient frontier at the point of maximum Sharpe ration
- The risk-free rate intercept obtained from US 3-month treasury bill return rates.

PORTFOLIO OPTIMIZATION – STOCK + BTC

30 months



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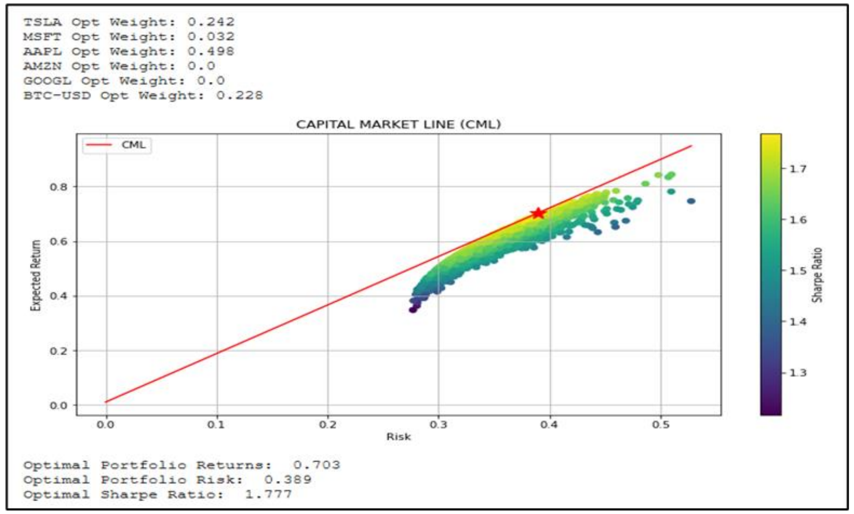

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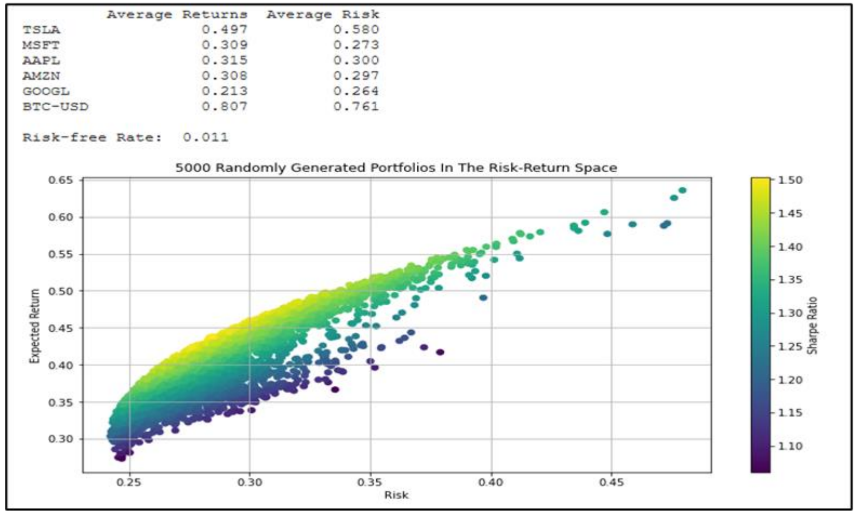
66 months



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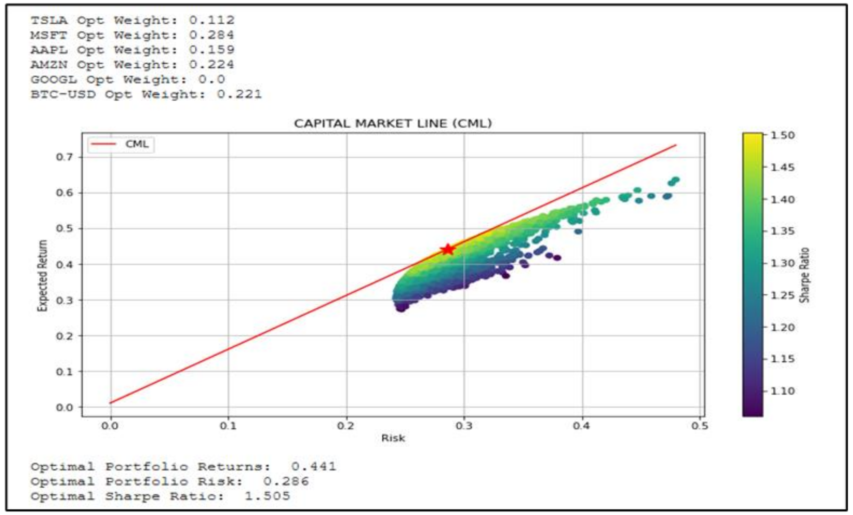

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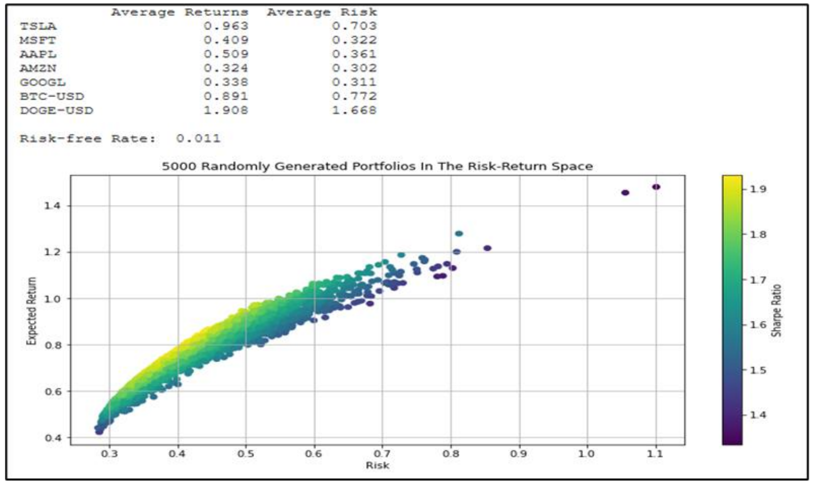
Red line depicts the central market line (CML) drawn on the efficient frontier for the maximized Sharpe ratio portfolio

PORTFOLIO OPTIMIZATION – STOCK + 2 CRYPTO

30 months



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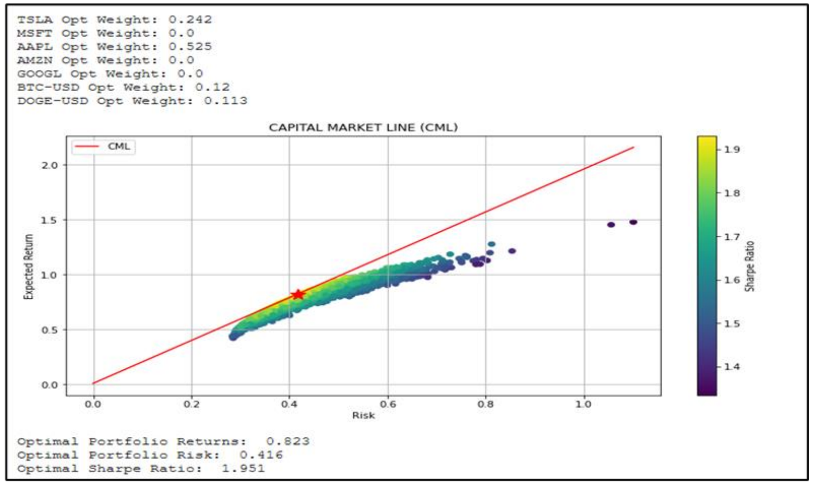

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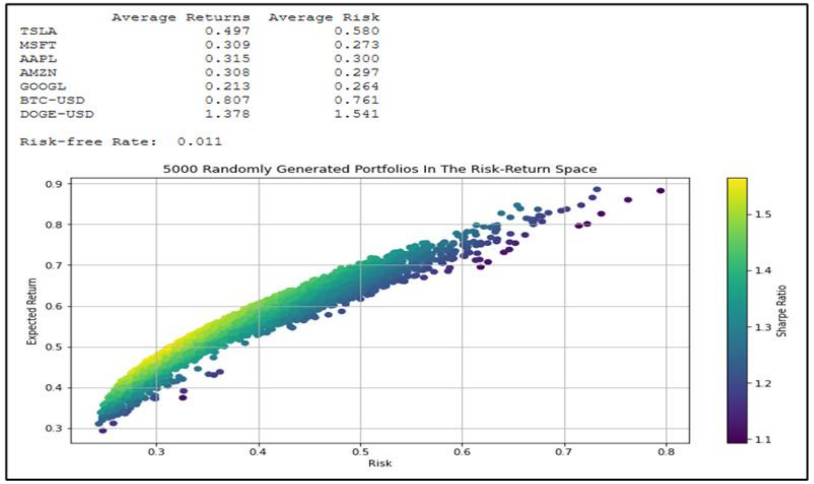
66 months



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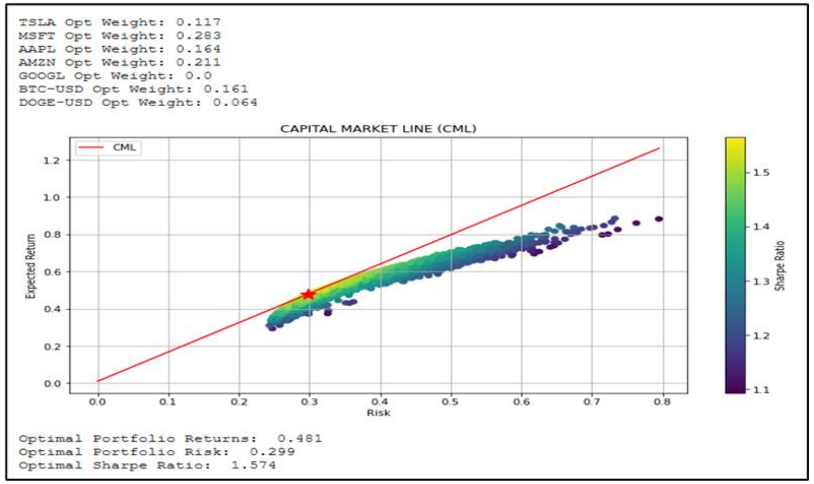
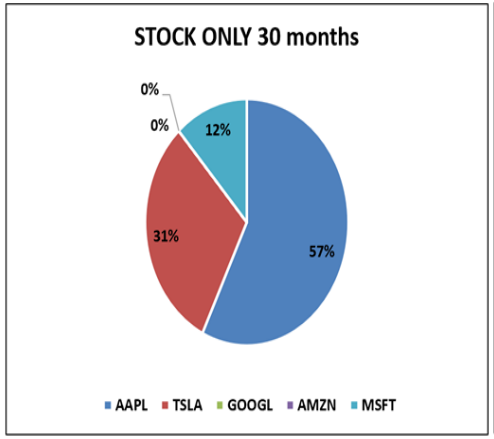
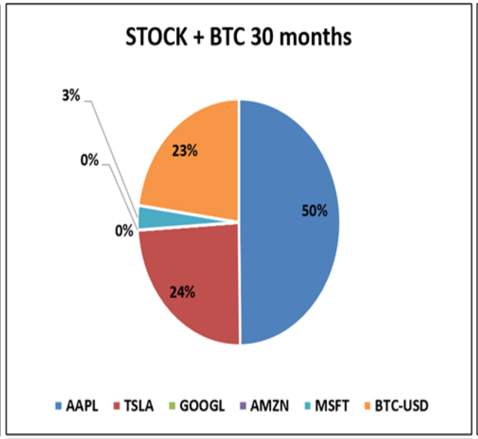


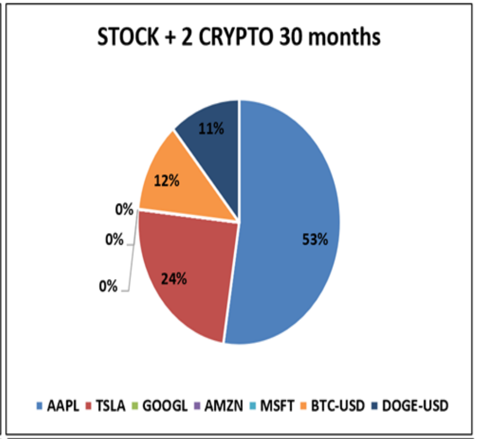
(b)

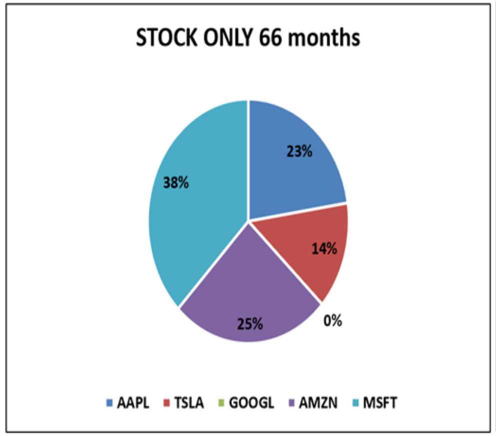
Red line depicts the central market line (CML) drawn on the efficient frontier for the maximized Sharpe ratio portfolio

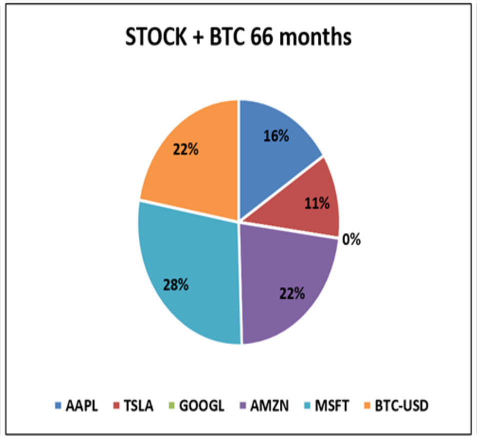
PORTFOLIO WEIGHTS ANALYSIS

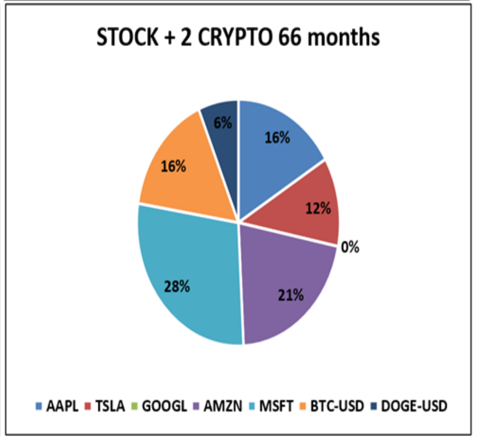












Key Notes

- In all cases, the weight assigned to Alphabet Corp (GOOGL) is 0%
- This indicates that the ranking done prior to portfolio optimization does not represent all the stocks that must be invested in to achieve optimal portfolio
- Time horizon also impacts the weights attached as seen with Amazon stocks
- Apple stock takes major share of investors wealth and is consistent with its first place ranking

PORTFOLIO OPTIMIZATION – RESULTS SUMMARY

STOCK ONLY PORTFOLIO		
	Weights	
Stock	30 months	66 months
AAPL	57%	23%
TSLA	31%	14%
GOOGL	0%	0%
AMZN	0%	25%
MSFT	12%	38%
TOTAL	**100%**	**100%**

Risk free Rate	1%	1%
Expected Return	64%	34%
Risk	39%	27%
Sharpe Ratio	1.598	1.223

(a)

STOCK + BTC PORTFOLIO		
	Weights	
Stock	30 months	66 months
AAPL	50%	16%
TSLA	24%	11%
GOOGL	0%	0%
AMZN	0%	22%
MSFT	3%	28%
BTC-USD	23%	22%
TOTAL	**100%**	**100%**

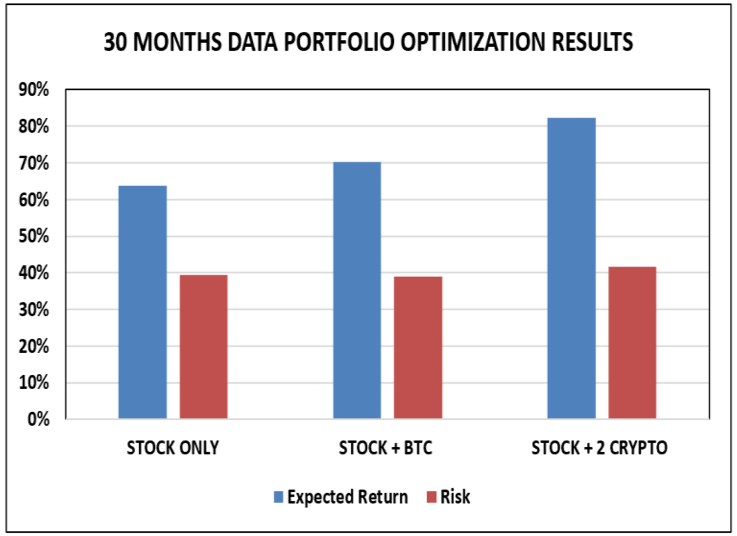
Risk free Rate	1%	1%
Expected Return	70%	44%
Risk	39%	29%
Sharpe Ratio	1.777	1.505

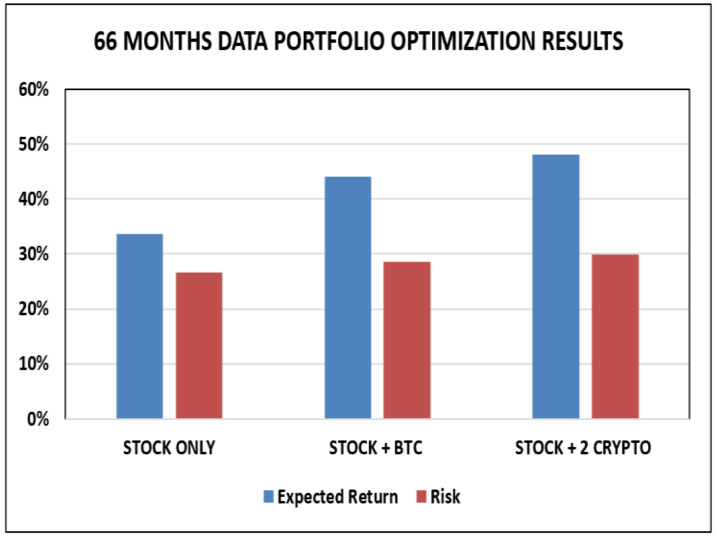
(b)

STOCK + 2 CRYPTO PORTFOLIO		
	Weights	
Stock	30 months	66 months
AAPL	53%	16%
TSLA	24%	12%
GOOGL	0%	0%
AMZN	0%	21%
MSFT	0%	28%
BTC-USD	12%	16%
DOGE-USD	11%	6%
TOTAL	**1**	**1**

Risk free Rate	1%	1%
Expected Return	82%	48%
Risk	42%	30%
Sharpe Ratio	1.951	1.574

(c)





Key Notes

- Depending on time horizon considered for study, the expected portfolio return and risk varies
- Average portfolio return for the 30-month period is between 64-82%
- Average portfolio return for the 66-month period is between 34-48%
- Addition of cryptocurrencies to portfolio bolsters portfolio earnings by between 6-18% while only increasing risk by a maximum of 3%

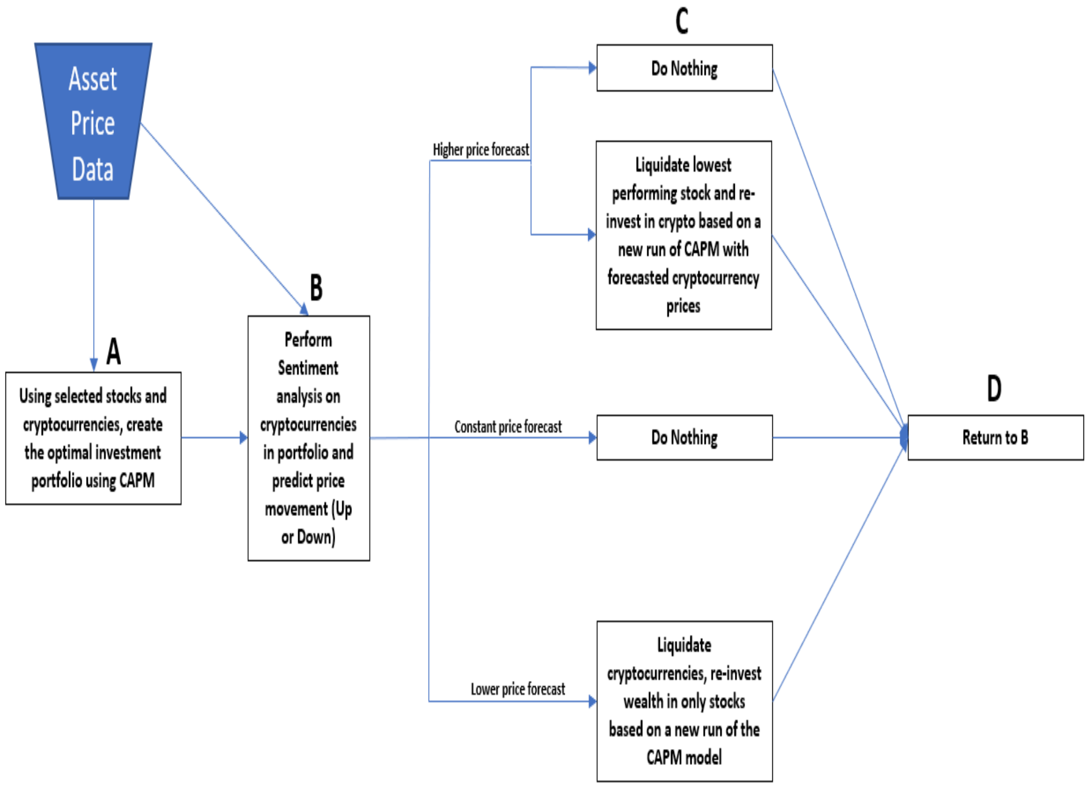
DISCUSSION

Difficulties Encountered

- Major difficulty encountered in this study was the inability to perform the real time optimization as depicted in the algorithm flow chart. This was due to restrictions by the twitter free API

- However, a sample of the algorithm by analysing 100 tweets per minute for 3 iterations is presented to show proof of concept

- Price prediction for Bitcoin requires other data sources including news reports on use regulation and business payment solution adoption



Major Contributions

- The code for the continuous optimization, automated CAPM, sentiment analysis and portfolio optimization is all available open source on GitHub here

CONCLUSIONS

- Utilizing CAPM and Markowitz portfolio theory, we demonstrated that adding cryptocurrency to investment portfolio yields greater returns with minimal increase in risk
- Dogecoin price was observed to have strong correlation with twitter sentiments but price prediction can only be done with near real time data (due to implicit nature)
- Bitcoin price prediction requires more information than twitter sentiments to predict price
- Algorithm for continuous portfolio optimization developed and is available open-source.

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