Cryptocurrency as a Gamble, Hedging Instrument, or Store of Value

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ABSTRACT

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Since the launch of Bitcoin in 2008, cryptocurrencies have garnered a lot of attention in the financial world. This paper analyzes whether cryptocurrencies can be used as a hedging instrument or a store of value, or whether they are just highly volatile assets with gamble-like traits. To investigate this, I compare cryptocurrencies to lottery-like investments in the CRSP universe and find that the two major cryptocurrencies, bitcoin and ether, possess high idiosyncratic volatility and idiosyncratic skewness. This implies cryptocurrencies have lottery-like behavior and activities on these networks could be motivated by speculative behavior of investors. To examine hedging instrument traits of cryptocurrencies, I perform a spanning-test to determine if adding cryptocurrencies to the market portfolio reduces risk. The addition of cryptocurrencies to a traditional asset portfolio with assets such as S&P500 stocks, Gold, Silver, Real Estate, and commodities, is found to reduce portfolio risk, but expose investors to significantly high tail-risk due to the cryptocurrency's intrinsic skewness. Adding cryptocurrencies shifts the portfolio frontier significantly to the left, but this better risk-return ratio is offset by exposure to high volatility of the test asset class. From the viewpoint of a store of value, cryptocurrencies may not possess characteristics like the store of value component in gold, but the results are weak and inadequate to draw any strong conclusions. Overall, the analysis seems to suggest that even though cryptocurrencies are not likely to possess attributes of a store of value, they offer diversification benefits to investors at the cost of exposure to larger potential losses.

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3. Introduction

Since the invention of Bitcoin (Nakamoto 2008), cryptocurrencies have gained increasing interest in the world of finance. Bitcoin was introduced as a decentralized peer to peer payment system that can be used to transfer money anonymously between two parties. This system uses the concept of cryptography and decentralization to create an immutable ledger that is always publicly available and arguably anonymous. This technology was later known as the 'blockchain', and it gave rise to an era of a whole new class of assets. Following Bitcoin (BTC), many other cryptocurrencies, referred to as 'altcoins', were introduced. Of these many altcoins, Ether (ETH) is one of the most popular cryptocurrencies and it runs on the Ethereum blockchain.

Although Bitcoin was created with the intention of establishing a completely decentralized and anonymous system of payments, it also gave birth to a highly volatile and speculative investment opportunity for investors. Unlike stocks and commodities, cryptocurrencies do not have any tangible assets backing their value. The value of cryptocurrencies fluctuate based on their demand and supply in the market. In some cases, like Bitcoin, the supply may be capped at a pre-defined value, whereas in other cases, like Ether, the supply may be unlimited but increasing at a controlled rate. The returns from the two cryptocurrencies have, thus far, significantly outperformed other traditional asset classes. *Figure 1* shows the returns on one dollar invested in various asset classes. The holding period returns depicted in *Table 2* show that the cryptocurrencies have provided returns many folds higher compared to other assets. For instance, a dollar invested in BTC or ETH each in 2015 would have realized returns of +42.3% or +276.1% until December 2020, as compared to just 0.81% for the S&P500. Considering these staggering returns, it is no wonder that an increasing number of investors are attracted to add cryptocurrencies to their portfolios. Yet, a continuous introduction of new cryptocurrencies raises questions whether this class is truly safe and reliable. It is therefore very important to analyze the behaviour of this asset class and fully understand what investors are investing in.

Despite not having any tangible assets or governments backing their value, cryptocurrencies are seen as a digital currency with potential to replace traditional forms of money. The year-wise holding period returns for BTC and ETH *(Table1)* show large variations across different timeframes. BTC realized exceptionally high returns in 2013, 2017 and 2020, but had negative returns in 2014 and 2018. Similarly, ETH observed high positive returns in 2016, 2017 and 2020, but experienced negative returns in 2018-2019. While volatile in terms of returns, the prices of these cryptocurrencies have significantly increased since their launch. This poses questions on whether such a volatile asset has the capacity to store value like money does? Is the volume of trade on these networks for transactional purposes or is it just speculative behaviour of investors? Is cryptocurrency just a gamble or has merit as an investment? In the light of these questions, I attempt to address some of these matters from the perspective of an investor.

Cryptocurrencies are highly volatile and have not existed for a long period of time in the history of financial assets. While cryptocurrencies are different from traditional forms of investments, they are actively traded by retail traders on exchanges specially designed for cryptocurrency trading. Although the blockchain technology has fueled a lot of innovation in the cryptocurrency and finance world, it is not clear whether cryptocurrencies are a prudent investment or just a highly speculative and volatile asset. In this study I consider two of the most popular and widely held cryptocurrencies (bitcoin and ether) to analyze whether the asset class has gamble like characteristics. I study these two cryptocurrencies in particular not only because of their instant recognition in the space, but also because they have a long price history and are among the most capitalized and liquid of cryptocurrencies.

To classify as lottery-like, I use the classification constructed by Kumar (2009) as a base and modify the methodology to be applicable to cryptocurrencies. As most accepted gambles are low price and have low probability of high gains, Kumar defines lottery-like stocks to have low prices and high idiosyncratic volatility and skewness. Adopting this logic, I compare the volatility and skewness of BTC and ETH to the complete CRSP universe of equities to determine whether cryptocurrencies exhibit lottery-like behaviour.

Moreover, as BTC and ETH are highly volatile, they possess the potential to be traded for profit. The low correlations (*Table 2*) of BTC and ETH with traditional assets make them a desirable asset class for investors. Using the modern portfolio theory, I create an optimally weighted portfolio of traditional assets like S&P500, Gold, Silver, Real Estate (NAREIT index), and other commodities (SPGSC Index); and test whether adding cryptocurrencies to this portfolio provides any diversification benefits, an important consideration for any investor contemplating adding an asset. I construct the portfolio frontier with traditional investments and assess whether adding cryptocurrencies (test asset) moves the fronter in a favorable direction and provides a better risk-return tradeoff.

In addition to assessing the diversification benefits of cryptocurrencies, I analyze other risks associated with adding cryptocurrencies to an investor portfolio. It might be the case that inclusion of cryptocurrencies into a portfolio simultaneously improves risk performance in one dimension while still worsening it in another. To explore this aspect, I conduct a Value at Risk (VaR) analysis using BTC, ETH, S&P500 and the traditional asset portfolio. Complementing the VaR analysis, I fit a three parameter Weibull distribution to the cryptocurrency returns and the benchmark S&P500 returns. I plot these stacked over one another to visually interpret the tail risks involved with cryptocurrencies.

The results for the lottery-like analysis show that BTC and ETH exhibit higher volatility and skewness than the 50th percentile of the CRSP universe for most of the sample. This implies that cryptocurrencies show gamble-like properties most of the time and is suggestive of the idea that majority activity on these networks is speculative. The portfolio analysis shows that adding the test asset to the traditional asset portfolio offers diversification benefits to investors. This is validated by the results from the mean-variance spanning test of the test asset class on the benchmark of S&P500. The examination of the tail-risk associated with cryptocurrencies reveals that this asset class has higher probability of larger losses compared to traditional assets. This high Value at Risk is visually observable in the fat-tails of ETH and BTC gross returns in *Figure 3*, when compared to Weibull-fit for S&P500.

Another possible purpose of cryptocurrencies isn't as an investment vehicle at all, but rather as money. A good form of money should serve three functions: a store of value, a unit of account and a medium of exchange. In addition to these, money should be durable, portable, uniform, divisible, limited in supply and acceptable. Historically, society has moved from the exchanging goods in the barter system to using government issued fiat money to conduct business. While this transition from barter to fiat saw many forms of money in between, such as cowry shells, precious metal coins, and gold backed paper money, some people now argue that bitcoin has the potential to replace the current forms.

Intuitively, bitcoin and ether have some characteristics that make them a desirable form of money. The supply of bitcoin is capped at 21 million, and ether's supply can only increase at a controlled rate. This characteristic is similar to the limited (or slowly growing) supply feature of gold and seems to offer an advantage over fiat currencies, which can be printed at the will of centralized authorities like the government. Mining gold requires heavy infrastructure and power costs. Analogously, mining cryptocurrencies consumes a lot of electricity, thus slowing supply growth. Both bitcoin and gold seem to derive their value from scarcity and difficulty of extraction (Dyhrberg 2016). Cryptocurrencies possess other desirable traits as a currency: they are digital, they are highly durable, portable, and divisible. Theoretically, as long as an internet exists, each cryptocurrency and its owning wallet can be determined from the blockchain. Cryptocurrencies can be transferred at high speeds from one party to another making them very portable. Moreover, each bitcoin or ether can be divided into small fractions up to 1×10^{-8} BTC or 1×10^{-18} ETH, respectively. These characteristics arguable grant cryptocurrencies the potential to be a unit of account, just like existing fiat currencies. In terms of liquidity, both gold and bitcoin are considered highly liquid and have a fair number of market participants willing to buy and sell the asset[1].

On the other hand, unlike gold, cryptocurrencies do not have any intrinsic value due to the absence of any tangible element backing them. However, this is the same for fiat currencies as their value is derived from trust in the central banks and the taxable economy backing them. Moreover, due to the relatively short existence of cryptocurrencies, bitcoin and ether are not presently widely accepted as modes of payment like fiat currencies are. Gold and fiat currencies are trusted by the society as a medium of exchange due to their long history and acceptance. To be accepted as modes of payment, majority of the people would have to trust and accept the use of cryptocurrencies. Traditionally, gold has also been accepted as a store of value and investors resort to gold in times of economic turmoil. Bitcoin and ether may possess similar characteristics as they are seen as an alternative to traditional investments by some. Similar to gold, BTC and ETH have very low correlations with

[1] https://ca.sports.yahoo.com/news/bitcoin-vs-gold-buy-175037032.html

traditional assets. This makes BTC and ETH potentially attractive to investors looking for safe havens and alternate investments to store their wealth.

Of all cryptocurrencies, BTC in specific has been compared to gold in terms of store of value. The current study tries to touch upon this aspect by decomposing the returns from cryptocurrencies and gold into sub-components and compares the store of value element in the returns of both classes. Exploiting the similar consumption patterns of gold and platinum, I isolate the store of value component in gold returns. Similarly, I isolate the potential store of value component from cryptocurrencies by removing market sentiment or hysteria from the returns by using 'memecoins'. Memecoins are a sub-section of altcoins which are created as a joke and often have no deflationary mechanisms[2]. Since these coins are not accepted as legal tender anywhere at the date of this thesis, they seemingly must derive their value from social media and online community sentiments which feed speculation. As I will later demonstrate, analyzing the store of value component of both cryptocurrencies (BTC and ETH) and gold, the results weakly suggest that cryptocurrencies do not have a store of value component to them. However, as these results are limited, this might be an area for improvement of methodology and be the focus of future studies.

The rest of this thesis follows the following sequence: Section IV talks about the literature on cryptocurrencies, gambling, mean-variance portfolio analysis, Value at Risk and store of values, Section V shows the data and methodology, Section VI discusses the results and finding, and Section VII states the conclusion.

[2] A deflationary mechanism is a set of instructions that controls the supply of a currency to prevent inflation in prices of goods and services. For BTC, the supply cap of 21 million bitcoins and halving of miner rewards tends to make bitcoin scarce and deflationary. For ETH, a certain percentage of ETH is burned annually to control the supply. Future upgrades with Ethereum 2.0 propose to lower the issuance rate for ether, thereby contributing to its scarcity. (https://coinmarketcap.com/alexandria/glossary/deflation, https://www.coindesk.com/tech/2021/10/27/the-evolution-of-ethereums-monetary-policy/)

4. Literature Review

Nakamoto (2008), introduced the concept of a peer-to-peer electronic payment system that works without the interference of a third-party financial institution. The introduced system uses several individual nodes that verify a transaction, while also preventing double-spending. The said system works on the concept of hash-based proof of work, where several nodes, called miners, solve a complex mathematical problem to validate a block of transactions on the network. So long as fifty-one percent of the mining power is not coordinated towards manipulating the verified chain of the transactions (blockchain), the primary chain, recording all past transactions, maintains its integrity and cannot be defrauded. The chain is publicly available and is under constant observation by miners and users on the network.

This first blockchain cryptocurrency, introduced by Nakamoto, is called Bitcoin. Following the nomenclature in the sphere of cryptocurrencies, Bitcoin with a capital 'B' refers to the blockchain network and bitcoin with a lower case 'b' refers to a unit of the currency. By design, the circulation of bitcoin (BTC) is capped at 21 million bitcoins. Unlike any other currency, no central authority like a bank or a financial institution is able to increase the supply of bitcoins, thereby creating scarcity. To enter the network, anyone can generate a pair of private and public keys without providing any personal details and buy, sell, and transfer bitcoins. Attributed to the anonymity Bitcoin provides, bitcoins were initially used for purchasing illicit goods on websites like SilkRoad and for online gambling (Böhme et al. 2015). In addition to providing anonymity, the decentralization of verification power to miners prevents concentration of power to any single entity, and steers clear of the need of any financial intermediary to authenticate transactions. Such a mechanism has some drawbacks as well. A person using bitcoin is not just exposed to the volatility in the currency market, but also faces the problem of irreversibility of transactions. Due to the absence of a financial intermediary, bitcoins sent to a wrong account cannot be retrieved back and belong to the receiver[3].

[3] In September 2021, a popular cryptocurrency platform mistakenly transferred approximately $89 million worth of cryptocurrency to users because of a bug in the routine update. Due to the absence of an intermediary or a

Unlike Bitcoin, which is only intended to facilitate a substitute for cash, the Ethereum network provides additional services on their blockchain, such as 'smart contracts', that enable users to undertake more complex transactions than simple transfer of currency. Ether (ETH), the currency on the Ethereum blockchain, is an altcoin (alternative coin) that claims to build on Bitcoin and provide a programmable blockchain. Ethereum provides many other services and products like decentralized finance, non-fungible tokens (NFTs) and other decentralized apps (Dapps). Moreover, the Ether is not the only cryptocurrency on the Ethereum blockchain. The blockchain allows for anyone to create an asset on the network. These are known as 'tokens'. (www.ethereum.org).

Sovbetov (2018) finds that the S&P500 has a weak, but positive and statistically significant coefficient with both BTC and ETH prices in the long run. Contrary to the reported long-run relationship, the short-run relationship is insignificant for ether and negative for bitcoin. These results from the study indicate ETH and BTC may offer diversification benefits to the market portfolio. Meanwhile, Jareño et al. (2020) report a positive and statistically significant relationship between bitcoin and gold prices. They also report that volatility in the stock market has a statistically significant negative impact on BTC returns. Additionally, these authors suggest that BTC returns are more responsive to extreme market trends and may act as a safe-haven asset in times of economic turmoil. Aforementioned results are reinforced by the findings by Mariana, Ekaputra, and Husodo (2021), who state that both ETH and BTC act as a safe haven during an economic turmoil in the short horizon. They use the COVID-19 outbreak as a natural experiment and indicate that ETH may be a better safe-haven than BTC. The results show that the cryptocurrencies have a positive relationship with gold and a negative relationship with S&P500 during 7-day, 10-day and 14-day windows post the pandemic announcement date.

From a clinical point of view, Granero et al. (2012) state that people gambling in the stock market have similar traits like pathological gamblers. Though stock market gamblers have less disruptive behaviours, the study claims that stock market gambling is the most accepted form of gambling. Delfabbro et al. (2021) show that people with high problem

recourse mechanism, the founder of the platform had to resort to requesting and persuading the users to return the money through social media. While some of the money was returned, the community had divided opinions on who the money should belong to, the platform or the recipients. (www.cbsnews.com) gambling scores (intensity to gamble) are more likely to engage in cryptocurrency trading. In the cryptocurrency market pre 2016, Conlon and McGee (2020) find that 32% of the price changes in BTC can be explained by the volume of gambling transactions made on the Bitcoin network. They show that risk-loving sentiment, proxied by gambling transactions, explains 10% of BTC returns over their complete sample from 2013 to 2018. The effect is documented to be stronger pre-2016 and disappears in the last two years of their sample period. In light of these previous findings, I try to determine whether cryptocurrencies exhibit gambling-stock-like characteristics, using methods laid out in existing finance literature.

Kumar, Nguyen, and Putnins (2020) find that there is an estimated 3.5 times gambling in the stock market than there is in traditional gambling casinos and lotteries in terms of dollar value. They also estimate that 14% to 18% of the stock market volume is gambling motivated, The activity of gambling and taking on risk in expectation of rewards is inherent in human psychology. Kumar (2009) defines the concept of lottery-type stocks in his study and identifies characteristics that make an asset attractive to gamblers. He shows that stocks with high idiosyncratic volatility, high idiosyncratic skewness and low-price act like lotteries and exhibit gamble-like behaviour. Assets with high idiosyncratic volatility and idiosyncratic skewness imply a possibility of extreme returns with high perceived probabilities, just like any other gamble. In addition to these two factors, low price is another characteristic of lottery-type stocks because they emulate the low negative expected returns of cheap bets.

Brière, Oosterlinck, and Szafarz (2015) show that holding small amounts of bitcoin in can dramatically improve the risk-return trade-off of diversified portfolios. As in this study, they also consider a variety of asset classes and analyze the risk-return of bitcoin from a portfolio risk standpoint. Guesmi et al. (2019) find that short positions in the Bitcoin market can be used to hedge risk against all financial assets. Using a VARMA (1,1)-DCC-GJR-GARCH approach, they also suggest that when bitcoin is added to a portfolio with gold, oil and equity, the portfolio risk (variance) significantly reduces. Extending this finding on bitcoin, the results imply diversification capabilities of cryptocurrencies in general. Frazzini and Pedersen (2014) describe an approach where betting against beta produces high risk adjusted returns and Sharpe ratios. They propose a strategy where overweighting low beta assets and underweighting high beta assets to achieve an overall beta of one produces a significantly positive alpha. This betting against beta portfolio also yields a higher Sharpe ratio when compared to a portfolio with only high beta assets.

Financial markets are subject to high risk and the conventional measures of risk, like the standard deviation, are inadequate indicators of the risk involved (Mandelbrot et al. 2005). To have a better understanding of risk involved, additional measures like the VaR (Value at Risk) are used to estimate the expected loss at given threshold or probability. VaR is a more suitable instrument to measure the down-side risk exposure of an investment (Goorbergh and Vlaar 1999). Historical VaR is one such measure that represent expected loss at a given probability using historical data. VaR is also calculated using the normal distribution, however, recent literature prefers the Weibull distribution to visualize tail-risk (Chen and Gerlach 2013). However, researchers have shown that VaR is not a coherent measure of risk as it does not satisfy the subadditivity property (Artzner et al. 1999, Basak and Shapiro 2001). To overcome this, some researchers have proposed the Conditional Value at Risk (CVaR) approach and it may be a preferred approach over VaR (VAR'S, M. L. 2012). CVaR is computed as the average value of all returns falling below a specified confidence lever of VaR level (Chen et al 2009). Silahli et al. (2021) show that the two-tailed Weibull distribution is a better fit to series with extreme volatility and skewness when compared to the normal distribution. Using the Weibull distribution is a better method to estimate the Value at Risk for portfolios with high volatility.

Kubát (2015) compares bitcoin to traditional definitions of money and states that it does not meet the defined criteria to be referred to as money. The author states that stability of value is an important feature of money. If the value of an asset is not stable, storing it to make purchases in the future is not feasible. Their results show that bitcoin is more volatile than currencies, gold, and shares, and cannot function as a store of value. They conclude that Bitcoin, at most, is a payment network that may be replaced by more efficient payment systems introduced by financial institutions. Gold and silver have been historically used as monetary metals, but that is not always the case for platinum (Patrick, 2001). Gold has two traits, one a store of value and the other a consumption good. The author argues that platinum is more of a consumption good, with its prices being affected by industrial sectors rather than the sentiment of holders. As per the WPIC Platinum Quarterly Q2 2021 report[4], the demand of platinum is derived majorly by its uses in the automobile, jewellery, chemical, and other industries. Approximately only 7% of platinum's total demand is for investment purposes. Platinum is a precious metal similar to gold and has similar uses as gold in consumption but is rarely considered a store of value (Duc Huynh, Burggraf, and Wang 2020). Huang and Kilic (2019) point out that the Gold-Platinum ratio is insulated from consumption shocks and proves to be an important economic state variable. On the contrary, Diaz (2016) states that platinum may have qualities of a safe harbour investment.

As no cryptocurrency can be consumed, being only a digital ledger of accounts, we cannot analyze this asset in the same way. Thus, we try to partition cryptocurrencies not on the basis of investment and consumption but rather on investment and (hysterical) speculation, or gambling motive. To decompose this, we make use of the presence of select cryptocurrencies that were created as a joke or gag. In fact, many of these coins do not even have a deflationary mechanism and without any central authority backing the fact that they have a non-zero price can hardly be attributed to any fundamental value. These coins are often called memecoins, and Dogecoin (*DOGE*) is one such popular memecoin that was introduced as a satire to Bitcoin (Chohan 2017). The value of memecoins is believed to be derived from the hype (what we will refer to as hysteria) in the market and '*fear of missing out*' in the mind of investors (https://academy.binance.com/en/articles/what-are-meme-coins). These coins have high risk involved and their prices are often derived from social media sentiment and community speculation. I use the memecoin returns as a proxy for market frenzy and isolate the potential store of value component in bitcoin using these returns in this study.

[4] https://platinuminvestment.com/files/165890/WPIC_PR_PQ_Q2_2021_20210909.pdf

5. Data and Methodology

I collect daily stock process from the Center for Research in Security Prices (CRSP) database and use the entire CRSP universe for my sample period of 2013 to 2020. I use FactSet database to collect the BTC and ETH prices for their respective sample periods of 2013-2020 and 2015-2020. I collect the prices for S&P500 (SP500), Real Estate index (NAREIT), Commodities Index (SPGSCI), Gold (NYGOLD FDS), and Silver (SLVR FDS) from the FactSet database as well. The S&P500 acts as representative of the equities asset class and NAREIT as a proxy for the performance of the real-estate sector in the economy. The SPGSCI is used to indicate the returns from investment in commodities. Gold is used to proxy for a store of value and Silver for industrial metals. The Fama-French 5 Factors and the momentum factor data is collected from the Fama-French website. As the risk-free rate (R_f) from the Fama-French website is available as a one-month treasury bill rate, I convert it to a daily rate by taking the 30th root of each percentile value plus one and deducting one. For the store of value analysis specifically, I collect the daily prices for Platinum from FactSet and Dogecoin prices from www.coingecko.com. Since the cryptocurrency market is an ongoing continuous market, but the alternative class markets only have data available for five days a week, I use only the dates where the data for S&P500 is available. Once all the data is aligned to a common date index, I convert the daily prices to daily returns and use them for the analysis.

Next, to calculate the annual and full sample holding period returns (HPR) for by using the following methodology:

$$HPR = \left(\prod_{i=m}^{n} (1 + r_i) \right) - 1$$

Where r_i is the daily return for the sample period from m to n. The results of this calculation are shown in *Table 1*. The methodology for the rest of the paper is defined into five sections: Gamble-like behaviour, Portfolio Diversification, Spanning test, Tail-Risk analysis, and Store of Value.

5.1. Gamble-like Behaviour

The three-component filter described by Kumar (2009) considers idiosyncratic skewness (*ISKEW*), idiosyncratic volatility (*IVOL*) and price (*PRICE*) to categorize a stock as a lottery-type stock (LTS). The price component of the filter seems to be valid when analyzing stock prices because a stock needs to be bought in units of one. Since cryptocurrencies can be bought in fractions up to 8 decimal places for bitcoin (Satoshi) and up to 18 decimal places for ether (Wei), the price component of the filter may not be valid for this asset class. The average of the 50^{th} percentile price for the CRSP universe in the last year of the sample period is approximately $21. It follows that, for a Satoshi or Wei to not be in the lower the 50^{th} percentile price level, the price for one bitcoin and one ether would have to surpass $2.1 billion and $21 quintillion respectively. As of the time of this study, these values seem improbable in the near future. Therefore, for cryptocurrencies, the price component is irrelevant as at the current market rates.

Thus, a tradeable unit of Satoshi or Wei will always be flagged in our sample as lottery-like since they will fall in the lowest 50^{th} percentile of the CRSP universe and a full unit of BTC and ETH will likewise never be flagged as lottery-like at current prices. To work around this situation, I propose a modification to Kumar's filter to suit the current situation. I consider two approaches: either the cryptocurrencies can always be flagged lottery-like in the price component as they can readily be bought in fractional quantities, or the price component can be dropped overall. In the former case where cryptocurrency prices are always flagged as lottery-like, it leads to an asymmetric comparison between stocks and cryptocurrencies. Therefore, I test whether the price component can be dropped, and the same filter can be applied across all assets. To test this, I run Kumar's analysis on the CRSP universe for his sample period of 1991 to 1996 with (a.) Three components (*IVOL, ISKEW* and *PRICE*) and (b.) Two components (*IVOL* and *ISKEW*). For each stock in the three-component analysis, a stock is categorized as a LTS when it falls in the top (highest) 50^{th} percentile of *IVOL* and *ISKEW* each, and the lowest 50^{th} percentile of *PRICE* in the whole CRSP universe for a particular date *t*. Similarly, for the two-component filter, a stock is categorized as a LTS when it falls in the top 50^{th} percentile of *IVOL* and *ISKEW* each.

Following Kumar's approach, *ISKEW* for each asset (stock or cryptocurrency) i is calculated as the skewness of the residuals of excess asset returns regressed on the excess market return and square of the excess market return. This approach is adopted from Harvey and Siddique (2000) and can be mathematically represented as:

$$R_i = \alpha + \beta_1(R_m - R_f) + \beta_2(R_m - R_f)^2 + \varepsilon$$

Where R_i is the return for stock i, and $(R_m - R_f)$ is the market risk premium. *ISKEW* is calculated as the third moment (skewness) of the residuals (ε) with a rolling window of last 120 days.

IVOL is calculated as the standard deviation of the residuals of the four-factor model on asset returns. The calculations for time *t* use a rolling window of 120 days before *t*, i.e., from *t-120* to *t-1*. The mathematic representation for these equations is as below:

$$R_i = \alpha + \beta_1(R_m - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 MOM + \varepsilon$$

Where R_i is the return for stock i, $(R_m - R_f)$ is the market risk premium, SMB is the excess returns of small-cap companies over large-cap companies, HML is excess returns of value stocks over growth-stocks and MOM is the momentum factor. *IVOL* on day *t* is the sample standard deviation of $\varepsilon_{t-120} to\ \varepsilon_{t-1}$.

Next, I compare the time series data of each stock in the three-component LTS filter that have non-zero standard deviation with the time-series of the same stock in the two-component filter. I choose the non-zero standard deviations stocks because correlations between two time-series where either one has zero standard deviation cannot be calculated. After calculating the correlations for all these series respectively, I calculate the average correlation between the two-component and three-component filters to judge whether the price filter can be dropped without appreciable impact.

Upon conducting this analysis, I find that the results for the two-component and the three-component filter are highly correlated (*Table 2*). This suggests that using a price filter does not significantly change the results obtained from the three-component filter. The high correlation between the LTS flags from both filters provides adequate comfort that dropping the price component from the original filter, as defined by Kumar, will not distort the results.

On obtaining a high median correlation of 0.87 as shown in *Table 3*, I run the two-component filter on more recent data of the CRSP universe with ETH and BTC prices added to the dataset and check whether the cryptocurrencies are classified as lottery-type. The sample period for the analysis for ETH is August 2015- December 2021 and for BTC is October 2013 to December 2021. To check whether the two-component filter is valid for this sample period, I use the same methodology to compare the correlation between two-component and three-component LTS classifications and obtain a high median correlation of 0.93. This high correlation strengthens the confidence to use the two-component filter in the current time period as well.

5.2. Portfolio Diversification

After checking for gamble-like behaviour, I look for the correlation between traditional assets and cryptocurrencies by calculating correlation matrix *Table 2*. In addition to the correlation with traditional assets, I regress the BTC and ETH returns on the Fama-French 5 factors individually in order to understand whether traditional factors influence the test asset class.

Next, I check whether adding cryptocurrencies to an investor portfolio provides any diversification benefits. To understand this, I construct the Markovitz portfolio frontier using a portfolio for traditional asset classes. The assets in consideration for the traditional asset frontier include S&P500 index for the equities, NAREIT index for real estate, SPGSCI for commodities, NYGOLD for Gold and SLVR for Silver.

To construct the frontier, I plot the annualized standard deviation (σ) of a portfolio for an annualized expected return $E(r_p)$. The standard deviation of a portfolio for a given expected return is calculated as

$$\sigma_p^2 \equiv \mathbf{w}^{\top}.\ \mathbf{V}.\ \mathbf{w}$$

Where $\boldsymbol{V}$ is the covariance matrix of all assets in consideration and $\mathbf{w}$ is the vector of optimal weights for a given $E(r_p)$. $\mathbf{w}$ for each portfolio with expected return $E(r_p)$ is

$$\mathbf{w} = \mathbf{g} + \mathbf{h}\,.E(r_p)$$

and,

$$\mathbf{g} = \frac{1}{D}[\mathrm{B}(\mathbf{V}^{-1}.\mathbf{1}) - \mathrm{A}(\mathbf{V}^{-1}.\bar{\mathbf{r}})] \ ,$$

$$\mathbf{h} = \frac{1}{D}[C(\mathbf{V}^{-1}.\bar{\mathbf{r}}) - A(\mathbf{V}^{-1}.\mathbf{1})] \ ,$$

$$A = \bar{\mathbf{r}}^{\top} \cdot \boldsymbol{V}^{-1} \cdot \mathbf{1}$$

$$B = \bar{\mathbf{r}}^{\top} \cdot \boldsymbol{V}^{-1} \cdot \bar{\mathbf{r}}$$

$$C = \mathbf{1}^{\top} \cdot \boldsymbol{V}^{-1} \cdot \mathbf{1}$$

$$D = BC - A2$$

Upon constructing the portfolio frontier using the above equations for traditional assets, I add BTC returns to the set of assets plot the frontier for the same expected returns. Next, I plot the frontier by adding only the ETH returns to the set of traditional assets. Finally, I add both ETH and BTC returns to my set of traditional assets and plot the newly obtained frontier. The results for this are shown in *Figure 2a*. In addition to the mean-variance portfolio frontier, I construct a mean-semivariance frontier to evaluate the downside risk associated with the assets. To construct the mean-semivariance frontier (*Figure 2b*), I replace the variance-covariance (**$\boldsymbol{V}$**) matrix with the semi-covariance matrix in the above equations. The semi-covariance matrix is calculated by considering all the returns below a benchmark return (*B*) of zero where the pairwise co-semivariance is calculated as:

$$\boldsymbol{\Sigma_{i,j}} = E\{min[(R_i - B_i), 0] \cdot min\big[\big(R_j - B_j\big), 0\big]\}$$

Where $\boldsymbol{\Sigma_{i,j}}$ is the co-semivariace between asset i and asset j and R_i is the return on asset i.

5.3. Spanning Test

Upon obtaining the visual results for the with and without cryptocurrency portfolios, I conduct a spanning test to infer whether the diversification benefits are statistically significant. Using the methodology of Nguyen and Switzer (2019), I test whether adding cryptocurrencies shift the portfolio frontier when compared to the benchmark S&P500 Index. To test the hypothesis, I use four return series: (a) BTC, (b) ETH (c)Optimally weighted portfolio of ETH and BTC and (d) S&P500. Here (d) is the benchmark portfolio and each of (a), (b), and (c) are test assets.

First, I regress the each of the test asset returns individually on benchmark portfolio returns after subtracting the risk-free rate from all asset returns. This is represented by the following equation:

$$R_{TestAsset-Rf} = \alpha + \beta\, R_{S\&P500-Rf}$$

Where $R_{TestAsset-Rf}$ is the series of returns from the test asset, minus the risk-free rate of return and $R_{S\&P500-Rf}$ is the returns from S&P500, minus the risk-free rate of return. Next, I conduct a Wald test on each of the obtained regression results to test the hypothesis

$$H_0\colon \alpha = 0,\ \ \beta = 1$$

If the null hypothesis is rejected, the test asset returns do not span the benchmark asset returns and investors can obtain diversification benefits from adding the test assets to their portfolio. In case H_0 is not rejected, the test asset returns span the benchmark asset returns and investors cannot obtain statistically significant diversification benefits. The results of the spanning test are shown in *Table 6*.

5.4. Tail Risk Analysis

The above analysis on diversification does not consider the tail risk involved when looking at portfolio frontiers. Even though adding new asset the portfolio may shift the portfolio frontier to the left, the portfolio frontier analysis does not consider risk dimensions other than the standard deviation (Mandelbrot et al. 2005). Considering this, it is important to assess the impact of tail risk, or Value at Risk, in order to comprehend the probable consequences of adding assets to the portfolio.

To visually understand the fat-tail risk component, I fit a three-parameter Weibull distribution to the daily gross returns from BTC, ETH and S&P500. The S&P500 provides a fair estimate of the commonly accepted risk in the financial markets. As shown by Silahli et al.

(2021), the Weibull distribution is better fit in the cryptocurrency segment when compared to the traditional normal distribution as it allows to capture extreme volatility, skewness and fat-tails. The results for the three-parameter Weibull fit are shown in *Figure 3*.

In order to statistically assess the tail risk, I analyze the returns from BTC, ETH, S&P500, the optimally weighted traditional asset portfolio, optimally weighted traditional assets with BTC portfolio, optimally weighted traditional assets with ETH portfolio, and optimally weighted traditional assets with BTC and ETH portfolio. First, I calculate the annualized expected return and annualized standard deviation of each of the sets of returns. Next, I calculate the skewness and kurtosis for these return series. After calculating these raw statistics, I conduct a Jarque-Bera test for normality on the log of gross daily returns for each portfolio in consideration. To quantitatively measure the tail risk involved in each portfolio, I calculate the average historical VaR at 95% and 99% levels of confidence (CI). The VaR is calculate as:

$$AverageHistoricalVaR_{CI} = \frac{\sum_{i=a}^{b} VaR_{i,CI}}{b - a + 1}$$

Where, a is the starting year of the sample period, b is the ending year of the sample period and $VaR_{i,CI}$ is the $(1 - CI)^{th}$ percentile of the series of daily returns for year i. These results in addition to the Sharpe ratio of the optimally weighted portfolios are reported in *Table 5*. A high VaR would imply a probability of a larger loss at the daily returns level and may not be desirable, whereas a low VaR would imply the probability of a smaller loss at the daily returns level. A low VaR is usually preferred over a high VaR from an investors' perspective. CVaR is calculated as the average of all the returns below a corresponding level of VaR. The area under the left tails of the Weibull distribution are a visual representation of the value at risk. The greater the area under the tail up to some point X, the higher the probability of a return of X or below. A slimmer left tail would indicate a lower VaR, i.e., a lesser probability of an adverse return, and is preferred over a fat-tail. It's conceivable that some distributions, especially those that are not approximately normal, may have modest variance while still posing substantial VaR. Thus we use this second measure to confirm or contest the apparent risk benefits the spanning test provided.

5.5. Store of Value Analysis

Bitcoin has been frequently compared with gold for reasons such as hedging capabilities and store of value (Duc Huynh, Burggraf, and Wang 2020; Dyhrberg 2016). As there is no defined test for a store of value, I attempt to compare the cryptocurrencies (ETH and BTC) to gold from a store of value perspective. Gold is considered a store of value; however, it is also a commodity used for consumption (mostly jewellery). So, the demand and prices for gold can be decomposed into two parts: a) Store of value, and b) General consumption. My motive is to compare the store of value component reflected in gold prices to the potential store of value component in BTC and ETH. As shown by some studies (Duc Huynh, Burggraf, and Wang 2020; Huang and Kilic 2019; Patrick 2001), platinum is a commodity that has similar characteristics to gold when compared based on consumption in the economy.

Contrary to the common belief that gold prices rise in times of economic turmoil, studies have shown that gold prices fall (Duc Huynh, Burggraf, and Wang 2020; Huang and Kilic 2019), but at a lower rate than commodities like platinum. In times of economic turmoil, the consumption of commodities like gold and platinum reduces due to their procyclical nature. Since gold is not just used for consumption, the demand/price of gold falls at a lower rate due to countercyclical properties of its store of value component (Huang and Kilic 2019). In a world where gold and platinum are only used for consumption, the returns from the two metals should increase and decrease at the same rates. This implies that the difference in the changes of returns from gold and platinum should be because of the store of value component of gold. Using this logic, when gold returns are regressed on platinum returns, the residuals of this regression should capture the store of value component of gold (*GOLD_SOV*). This regression can be expressed as:

$$R_{GOLD} = \alpha + \beta R_{PLATINUM} + \varepsilon_{GOLD\_SOV}$$

Where, R_{GOLD} are the returns from gold, $R_{PLATINUM}$ are the returns from platinum and ε is the error term that captures *GOLD_SOV*.

Next to check whether cryptocurrencies (ETH and BTC) have a store of value component, I decompose their price/demand into two parts: a) Potential Store of Value (*SOV*) and b) Market sentiment or hysteria. To separate the market hysteria component in cryptocurrency (ETH and BTC) returns, I leverage the concept 'memecoins' in the cryptocurrency market. Dogecoin (*DOGE*) is one such memecoin that was created as a 'joke currency' for leisure and has no deflationary characteristics like BTC (Chohan 2017). Since *DOGE* is not designed to be a store of value, its gains and loses value based on sudden spikes or decline in investor attention in the cryptocurrency market. Using this logic as basis for separating market hysteria from the potential store of value component in cryptocurrencies, I define the following regression:

$$R_{CRYPTO_i} = \alpha + \beta R_{DOGE} + \varepsilon_{CRYPTO\_SOV_i}$$

Where, R_{CRYPTO_i} are represents the returns from cryptocurrency $CRYPTO_i$ (either BTC or ETH), R_{DOGE} represents the returns from Dogecoin and $\varepsilon_{CRYPTO\_SOV_i}$ represents the store of value component in the returns from the $CRYPTO_i$.

On obtaining the store of value component of gold (ε_{GOLD_SOV}) and the potential store of value component of the cryptocurrencies ($\varepsilon_{CRYPTO\_SOV_i}$), I check whether the two are related or not. To do so, I regress $\varepsilon_{CRYPTO\_SOV_i}$ on ε_{GOLD_SOV}. This can be mathematically represented as:

$$\varepsilon_{CRYPTO\_SOV_i} = \alpha + \beta\, \varepsilon_{GOLD\_SOV} + \Psi$$

Where, β represent the magnitude of the relationship between the store of value component of cryptocurrency *i* and gold, and Ψ is the error term. If β turns out to be significant with a high R-square, we can say that the variation store of value component is related to the store of value component in the cryptocurrency market. This would be emphasised if $\varepsilon_{CRYPTO\_SOV_i}$ and ε_{GOLD_SOV} have a high correlation between them. The results of the above are shown in *Table 7*.

I use Dogecoin for my main analysis, due to unavailability of data for other memecoins in the cryptocurrency market. As a robustness check to ensure my results are not driven by an arbitrary selection of memecoin, I also conduct an analysis using the same methodology, but by replacing Dogecoin with an equally weighted portfolio of top ten memecoins by market capitalization. This analysis is not included in the main analysis due to availability of a limited number of observations outside the sample period in consideration. However, even with the limited sample, the results are qualitatively consistent, if not statistically significant, with the findings of using Dogecoin in isolation. The results for this analysis are shown in *Appendix A*.

6. Results and Findings

By Conducting Kumar's Analysis (Kumar 2009) with the three-component filter system and the modified two component system on Kumar's original sample (1991-1996), I find that that dropping the *PRICE* component does not significantly impact the results. This is indicated by a high median correlation of 0.87, a high mean correlation of 0.791 and a third quartile of 1. These descriptive statistics suggest that the distribution of correlations between the two-component and three-component LTS stocks is negatively skewed, and majority of the correlations are above the accepted norm of 0.7. These results imply that using a two-component LTS mechanism does not provide vastly different results. On conducting the same analysis on the current sample period (2013-2020), I obtain similar results showing a median correlation of 0.92, a mean correlation of 0.71 and a third quartile of 1, implying a negatively skewed distribution with majority correlations greater than 0.7. These results provide reasonable comfort to drop the price component and conduct the analysis with he two-component filter. Doing this provides a way to compare cryptocurrencies and equities in the CRSP universe using a symmetric filter. This is important as it allows me to compare both asset classes with the same methodology and avoids the problem of unintentional biases in the process.

After confirming that using the two-component filter does not distort the results of the LTS analysis, I find that BTC and ETH show lottery-like characteristics based on *IVOL* and *ISKEW*. BTC is flagged as lottery-like approximately 51% of the days in the sample, whereas ETH is flagged as LTS for 76% of the sample. These results suggest that trading activity for cryptocurrencies may be motivated by gambling and not by fundamentals. Extending the findings of Kumar (2009), it is safe to say that cryptocurrencies seem to be complementary to state-lotteries and may have similar clienteles. These results are consistent with the findings of Conlon and McGee (2020), who find that gambling related transactions on the Bitcoin blockchain have a considerable impact on the prices of BTC. Recalling findings of Delfabbro et al. (2021), people with higher propensity to gamble are more likely to engage in cryptocurrency trading intensifies our results and suggests significant speculation in the cryptocurrency market. This analysis strongly suggests that cryptocurrencies have traits of a speculative asset and a noticeable portion of changes in the prices may be due to gamble-like behavior of investors.

Other than suggesting gamble-like behaviour of cryptocurrencies, the LTS analysis results imply that BTC and ETH may be uncorrelated with the stock market and perhaps other traditional assets. Negative or no correlation with traditional assets is a desirable trait for an asset from the diversification point of view. Looking at the correlation of 0.10 between BTC and S&P500, it is evident that they have little or no correlation. BTC also has low correlation with other traditional assets such as real estate (0.08), commodities (0.03), gold (0.1) and silver (0.04). Similarly, ETH has low correlations with S&P500 (0.13) and other traditional assets like real estate (0.1), commodities (0.07), gold (0.1) and silver (0.05). Moreover, the Fama-French 5 factor analysis shows that cryptocurrencies are not significantly related to any of the 5 factors except *MKT-Rf*. The coefficient of *MKT-Rf* is statistically significant, but seem to have a low economic significance because of the small magnitude of 0.004 for BTC and 0.008 for ETH. These low correlations and weak coefficients with other assets/factors may make the cryptocurrency asset class a desirable element to diversify risks. Investors may also be able to obtain potential hedging benefits due to these low correlations.

Just as gold offers diversification benefits to investors because of its negative/low correlation with S&P500 (-0.02 for 2013-2020, and 0.009 for 2015-2020), it is reasonable to test whether BTC or ETH may have the same impact. Moreover, like BTC and ETH, Gold has negligible or no relationship with the Fama-French 5 factors. These traits imply that BTC and ETH may possess potential to diversify risks that existing assets classes are exposed to. Taking these elements into consideration, I speculate that holding cryptocurrencies may be beneficial as cryptocurrencies may not be affected by shocks or changes in traditional economic factors, whereas traditional assets are highly related to such factors. The low correlations of cryptocurrencies with traditional assets hint towards the possibility that the fundamental factors causing movements in traditional assets do not significantly contribute to the day-to-day fluctuations in cryptocurrencies.

As shown in *Figure 2a*, adding BTC and/or ETH to a portfolio with only traditional assets indeed shifts the portfolio frontier significantly to the left. Adding only one of the cryptocurrencies to the traditional asset portfolio diversifies some amount of risk, however, adding both BTC and ETH moves the frontier even further to the left implying greater diversification. Assuming the S&P500 as a benchmark for usually accepted levels of risk, the S&P500 provides an annual expected return of 12.54% at 17.59% level of risk (annualized standard deviation). An optimally weighted portfolio with traditional assets, i.e., Equity (S&P500), Real-Estate (NAREIT), Commodities (SPGSCI), Gold (NYGOLD) and Silver (SLVR FDS), provides approximately 19.6% expected return for the same level of risk. When BTC is added to this traditional portfolio it provides an approximate 27.7% expected return for the same standard deviation, i.e., an 8% increase over the traditional assets. Adding only ETH to the traditional portfolio leads to an annual expected return of approximately 29.3% at the same level of risk. This return is 9.7% more than the traditional assets portfolio return. When both BTC and ETH are added to the traditional set of assets, they provide approximately 31.90% expected annual return; 12.3% greater than the optimally weighted traditional portfolio and 19.36% greater than the S&P500.

One possible consideration is that crypto may provide asymmetric diversification opportunities to standard assets. That is, their inclusion may have more or less impact on the upside risk (exceeding mean expectations) than on the downside risk. To analyze this possibility, I compute the contribution of cryptocurrency inclusion on portfolio semivariance. On comparing the mean-variance frontier with the mean-semivariance frontier (*Figure 2b*), it is evident that the mean-semivariance lies further to the left and provides a better risk-return trade off. When only gauging the down-side risk using semivariance, the portfolios provide even higher expected returns at the same levels of risk compared to the mean-variance frontier. Consistent with my findings using the full variance measure, this analysis suggests that using portfolio weights suggested by the mean-semivariance frontier an investor can minimize the downside risk and reap better returns. I conclude that the efficient frontier is reliably expanded by the inclusion of crypto if one restricts themselves to defining risk as functions of the second moment.

Even though the diversification benefits seem economically significant, their statistical significance is emphasised by the Wald Test results. The p-value of <0.001

indicates that the cryptocurrency returns are not spanned by the S&P500 returns, and the null hypothesis is rejected. The results show that adding either or both the cryptocurrencies to the portfolio significantly diversify the risk in terms of standard deviation at conventional levels of significance. Based on this analysis, a risk averse investor would prefer the traditional portfolio with both ETH and BTC as it provides the highest expected return for a given level of risk. Only based on these findings, a rational investor would choose to have the cryptocurrencies in their portfolio as it significantly diversifies portfolio risk. This is consistent with existing studies like Guesmi et al. (2019), where they find that adding BTC to a portfolio of traditional assets such as gold, oil and equity considerably reduces the overall portfolio risk. The results are solidified by the findings of Brière, Oosterlinck, and Szafarz (2015), who state that although BTC adds high risk to the portfolio, holders are compensated by the low correlation with other existing asset classes. Although these studies only consider BTC, my analysis shows that ETH also provides diversification of risk, even more than BTC.

Another interesting observation can be derived from the regression results in *Table 6*. The regression of the test assets on the market index (*S&P500*) is the essentially the Capital Asset Pricing Model (CAPM). The results for the CAPM regression show that all the three test assets have a positive alpha and a beta lower than one. This implies a long position in cryptocurrencies could be used to bet against beta (BAB). As described by Frazzini and Pedersen (2014), holding long leveraged positions in low beta assets and short positions high beta assets with allocation in accordance with the BAB factor can produce high risk adjusted returns. Holding a long position in cryptocurrencies of a BAB portfolio may add positively to the alpha while it may also contribute to reduce the overall beta to one.

However, as stated previously, standard deviation is not a complete measure of risk (Mandelbrot et al. 2005; Goorbergh and Vlaar 1999). To understand whether adding cryptocurrencies to the portfolio actually reduces risk, it is essential to look at the tail risk that comes with them. Looking at the expected loss at a given level of probability is an important risk measure as it informs investors of the worst-case scenario. An investor who is aware the VaR would better understand the level of exposure they have to volatility of the asset market. In visual terms, it is evident in *Figure 3* that the gross returns for BTC and ETH have fatter left and right tails compared to the S&P500. This indicates that although the probability of having higher returns is more for cryptocurrencies when compared to S&P500, the probability of losses is also high. On checking for normality by conducting the Jarque-Bera test on $log(1 + r)$ for all portfolios in consideration, none qualify as normally distributed, therefore a Weibull three parameter distribution is a better choice to depict the probability density function of these returns.

The only BTC portfolio has an annual expected return of 89.89% at a standard deviation of 70.75%, producing a Sharpe ratio of 1.26. The only ETH portfolio has an annual expected return of 162.17% at a standard deviation of 110.11%, producing a Sharpe ratio of 1.466. Although ETH has a higher Sharpe ratio than BTC, it also much riskier than BTC in terms of variance in the returns. On the other hand, the S&P500 has a considerably low standard deviation of 17.59% and provides an expected return of 12.54% with a Sharpe ratio of 0.671. The standard deviations clearly show that holding BTC or ETH individually exposes an investor to at least 4x the risk of S&P500. This finding is re-enforced by looking at the 95% VaR for these portfolios. Based on the average historical VaR, the minimum daily loss at 5% probability for ETH and BTC is 9.2% and 6.7 percent, whereas it is only 1.5% for the S&P500. Looking at the minimum possible loss at 1% probability (99% VaR), the results amplify the riskiness of cryptocurrencies with a possible 13.9% daily loss for ETH and 12.3% for BTC. This value is only 2.8% for the S&P500.

It has been noted that VaR may not be an ideal measure of extreme left tail risk. Some have suggested that CvaR is a better metric for this application (Chen et al 2009; VAR'S, M. L. 2012). Thus, I also consider the CVaRs for these assets. The 95% (99%) CVar for BTC and ETH is -10.4% (-14.9%) and -12.9% (-19.1%) respectively, where it is only -2.3% (-3.4%) for the S&P500. Once again, as with traditional VaR, my findings clearly imply that cryptocurrencies expose an investor to a much higher tail risk than traditional equities. Even though cryptocurrencies are uncorrelated with traditional assets, they have a large probability of a greater loss when compared in terms of Value at Risk.

However, since investors usually hold more than one asset class in their portfolio, I now look at the risk levels for optimally weighted traditional asset portfolios with and without cryptocurrencies. The traditional asset portfolio has an annual expected return of 10.51% and a standard deviation of 13.02%, producing a Sharpe ratio of 0.75. Adding BTC to the traditional assets portfolio increases the expected return to 27.98%, while also making it riskier by moving the standard deviation up to 19.79%, producing a Sharpe ratio of 1.377. When ETH is added to the traditional portfolio, it further increases the expected return and standard deviation to 34.34% and 20.57% respectively with a Sharpe ratio of 1.633. Adding both ETH and BTC to the traditional asset portfolio provides a better Sharpe ratio and expected return of 1.842 and 47.88% respectively, while also increasing the standard deviation to 25.59%. This again implies that high expected returns from cryptocurrencies come at a cost of exposure to high volatility. These findings are emphasised by the 95% (99%) VaR for Traditional assets + BTC at 1.9% (3.4%), Traditional assets + ETH at 1.8% (2.6%), Traditional assets + BTC and ETH at 2.2% (3.8%). When no cryptocurrency is added to the portfolio, the 95% (99%) VaR stands at 1.1% (1.8%) for only traditional assets. These results suggest that an investor invested in cryptocurrencies faces the risk of approximately double the loss at the same probability/confidence level. Moreover, the portfolios with cryptocurrencies have CVaRs of higher magnitude, implying that the average loss within the left tails is higher and there is increased tail risk involved.

It is evident from these results that even though BTC and ETH seem to diversify risk on the portfolio frontier, they allow for huge exposures to tail-risks. An investor holding the optimally weighted traditional portfolio has a 5% (1%) chance of losing 1.1% (1.8%) of their investment in a day. Adding BTC, ETH, or BTC and ETH together increases this risk to 1.9% (3.4%), 1.8% (2.6%) or 2.2% (3.8%) respectively. This suggests that despite cryptocurrencies reducing portfolio risk as measured by standard deviation, they simultaneously expose the investor to the high kurtosis, inherent to the cryptocurrency market. Adding small amounts of cryptocurrencies to a portfolio may be beneficial, while adding unreasonable quantities may add risk that outweighs the benefit of diversification.

From the store of value perspective, the preliminary results seem to show a significant beta for both BTC and ETH. A one percent increase in the $GOLD\_SOV$ component leads to a 2.9% increase in the BTC_SOV component at statistical significance level of 0.05. Similarly, a one percent increase in the $GOLD\_SOV$ component leads to a 6.6% increase in the ETH_SOV component at statistical significance level of 0.01. These results look promising prima-facie, but are heavily undermined by the extremely low adjusted R-Squared values of 0.002 for BTC_SOV and 0.005 for ETH_SOV. The importance of the low R-squared value is further emphasised by the low correlations between the $GOLD\_SOV$ component and the $CRYPTO_i\_SOV$ component (0.05 for BTC and 0.07 for ETH). The results, combined, imply that the SOV component of gold does not explain much of the variations in SOV component of cryptocurrencies. The model does not have much explanatory power and indicates that cryptocurrencies may not possess a store of value component, at least as measured by this simple approach. The significant coefficients may be due to few observations of large magnitudes, such as in times of crisis. This is consistent with (Dwita Mariana, Ekaputra, and Husodo 2021) who state that BTC and ETH show negative correlation with the S&P500 during the COVID-19 pandemic in the short run, but are highly volatile when compared to gold and equities.

The methodology used for the store of value analysis, however, has a few limitations. First, there is no consensus in the literature about platinum not being a store of value and only a consumption good (Diaz 2016; Huang and Kilic 2019). If metals like platinum possess attributes of a safe-harbour investment, then this makes it difficult to extract the store of value component from gold returns. In such a situation, the store of value component captured by the residuals of the model used will not suffice as they would capture some other quality that is intrinsic to gold, but not platinum. Second, DOGE is a relatively unexplored cryptocurrency and could have prominence outside the 'joke currency' aspect. There is a possibility that DOGE returns capture factors other than market hysteria, and this could undermine the reliability of the potential store of value component recorded in the residuals of the model. To work around this, I conduct a brief analysis (*Appendix A*) using an equally weighted portfolio of top ten memecoins as a proxy for market hysteria. The results from this analysis are consistent with the results of the main store of value analysis and indicate no relationship between *GOLD_SOV and*

CRYPTO_SOV; however, the analysis using the memecoin portfolio has only 57 days of data available and should be interpreted with caution because of the short sample size. These challenges may be explored in a future study, particularly as the data history lengthens, but are outside the scope of this one.

7. Conclusion

This study analyzes how cryptocurrencies behave relative to other widely adopted asset classes. I look at cryptocurrencies from three aspects, a.) a gamble, b.) a hedging instrument and c.) a store of value.

By modifying the lottery-type stock filter defined by Kumar (2009), I look at the idiosyncratic volatility and idiosyncratic skewness of cryptocurrencies and compare them to the same measures for stocks in the CRSP universe. The results show that cryptocurrencies tend to fall in the category of a gamble for most of the sample period. This conveys that a considerable portion of the activity on the cryptocurrency market may be motivated by speculative intentions of investors. These findings are consistent with what Conlon and McGee (2020) find in their study, where they look at the relationship between bitcoin prices and the dollar volume of transactions directed to and from a gambling service accepting bitcoin. These findings are also corroborated by Delfabbro et al. (2021), who show, from a clinical standpoint, that people who gamble engage intensively in cryptocurrency trading. The current study provides complementing results to both studies from a school of though established in the financial literature.

Cryptocurrency's high returns and low correlation with traditional assets make them an apparently attractive asset class to investors. Using the mechanisms defined by the modern portfolio theory, bitcoin and ether seem to significantly diversify portfolio risk of an optimally weighted traditional asset portfolio. The inclusion of cryptocurrencies moves the portfolio frontier to the left, providing a better risk return trade-off and Sharpe ratio. The spanning test examining diversification benefits of BTC and ETH with the benchmark S&P500 further support these results. These results are also in agreement with the findings of Brière, Oosterlinck, and Szafarz (2015) and Guesmi et al. (2019). However, the increased expected return and lower standard deviation benefits by adding cryptocurrencies come at a cost of increased exposure to tail risk. Upon conducting a VaR analysis, and considering the kurtosis of the estimated return distributions, my results strongly suggest that adding cryptocurrencies to traditional asset portfolios might increase the probability of larger losses. When compared to holding the S&P500, holding cryptocurrencies expose the investor to a possibility of at least four times higher daily loss. As such, cryptocurrencies may have a hidden risk factor that explains their outsized returns much as other bubbles have, in retrospect, offered high returns for improbable but staggering losses. Adding cryptocurrencies to a portfolio does seem to reduce the portfolio standard deviation, however it exposes investors to high tail-risk, therefore, investors should exercise caution while allocating funds to this volatile asset class.

The store of value aspect of cryptocurrencies is explored by defining a preliminary approach. Exploiting the shared procyclical characteristics of platinum and gold, I isolate the store of value component in gold returns. On comparing this *GOLD_SOV* component with the potential store of value component in cryptocurrencies, I find that *GOLD_SOV* does not hold substantial explanatory power over the potential *SOV* component in cryptocurrencies. The results weakly imply that cryptocurrencies may not have characteristics of a store of value. This methodology, however, may be refined in the future studies due to the challenges described previously.

Table 1: Holding period return calculations for assets considered

This table shows the calculation of the holding period returns (HPR) for cryptocurrencies - ether (ETH) and bitcoin (BTC), lottery type stocks (Other LTS), risk-free treasury bills (RF), the Standard and Poor's 500 equity index (SP500), National Association of Real Estate Investment Trusts Index (NAREIT), S&P Commodity Index (SPGSCI), Gold (NYGOLD FDS), and Silver (SLVR FDS). The RF data is obtained from the Fama-French website as a one-month treasury bill rate. For the HPR calculation, this monthly rate is converted to the daily rate by taking the 30th root as ($\sqrt[30]{(1+r_f} - 1$). The HPR for the Other LTS stocks is calculated as the mean HPR for stocks whose LTS status as per the two-component filter is highly correlated with bitcoin's two-component LTS status (stocks in the top decile of LTS correlation with BTC.). *Panel A* shows the annual holding period return for each year in the sample period. *Panel B* shows the holding period return for the full sample period[1] for both BTC and ETH.

Holding Period	ETH	BTC	Other LTS	RF	SP500	NAREIT	SPGSCI	NYGOLD FDS	SLVR FDS
Panel A:	*Yearly Holding Period Return*								
Oct-2013 - Dec 2013	-	7.372	0.043	0.000	0.090	-0.032	0.004	-0.065	-0.101
Jan 2014 - Dec 2014	-	-0.657	0.053	0.000	0.114	0.256	-0.339	-0.015	-0.181
Jan 2015 - Dec 2015	0.567	0.045	-0.026	0.000	-0.007	-0.007	-0.255	-0.104	-0.135
Jan 2016 - Dec 2016	6.016	0.568	0.044	0.000	0.095	0.038	0.278	0.085	0.175
Jan 2017 - Dec 2017	42.846	13.715	0.090	0.000	0.194	-0.002	0.111	0.136	0.038
Jan 2018 - Dec 2018	-0.840	-0.776	-0.125	0.001	-0.062	-0.076	-0.154	-0.021	-0.083
Jan 2019 - Dec 2019	-0.349	0.326	0.339	0.001	0.289	0.195	0.165	0.189	0.167
Jan 2020 - Dec 2020	4.513	4.336	0.629	0.000	0.163	-0.131	-0.061	0.246	0.468
Panel B:	*Full Sample Holding Period Return*								
Oct-2013 - Dec 2020	-	108.856	0.556	0.002	1.216	0.200	-0.350	0.472	0.221
Jan 2015 - Dec 2020	276.081	42.390	0.957	0.002	0.808	0.016	0.121	0.730	0.796

Note: The HPR in the first year is for the time period of October 2013 to December 2013 because of the availability of bitcoin price data. [1]The sample period for bitcoin is October 2013 to December 2020, and for ether is from 2015 to 2020.

Table 2: Correlations for traditional asset classes

This table reports the Person correlation coefficient matrix of the daily returns for all the asset classes. The returns data for all assets (ETH, BTC, SP500, NAREIT, SPGSCI, NYGOLD FDS, SLVR FDS) except RF is collected from the FactSet database. The data for RF is collected from the Fama-French website. *Panel A* shows the correlations for the complete sample period for bitcoin, from 2013 to 2020. *Panel B* shows the correlations for the complete sample period for ether, from 2015 to 2020.

	ETH	**BTC**	**RF**	**SP500**	**NAREIT**	**SPGSCI**	**NYGOLD FDS**	**SLVR FDS**
Panel A:				**2013 - 2020**				
BTC	-	1.000	-	-	-	-	-	-
RF	-	-0.030	1.000	-	-	-	-	-
SP500	-	0.101	-0.020	1.000	-	-	-	-
NAREIT	-	0.084	-0.018	0.715	1.000	-	-	-
SPGSCI	-	0.039	-0.016	0.372	0.236	1.000	-	-
NYGOLD FDS	-	0.101	0.014	-0.017	0.083	0.118	1.000	-
SLVR FDS	-	0.048	-0.015	0.118	0.145	0.100	0.338	1.000
Panel B:				**2015 - 2020**				
ETH	1.000	-	-	-	-	-	-	-
BTC	0.340	1.000	-	-	-	-	-	-
RF	-0.079	-0.044	1.000	-	-	-	-	-
SP500	0.126	0.104	-0.025	1.000	-	-	-	-
NAREIT	0.096	0.092	-0.016	0.733	1.000	-	-	-
SPGSCI	0.070	0.052	-0.047	0.403	0.277	1.000	-	-
NYGOLD FDS	0.101	0.135	-0.005	0.009	0.086	0.103	1.000	-
SLVR FDS	0.045	0.068	-0.043	0.153	0.170	0.121	0.352	1.000

Table 3: Descriptive statistics of correlation between two-component and three-component filter LTS. This table shows the descriptive statistics of the distribution of correlations between lottery-type stock (LTS) signals from Kumar's three-component filter and the modified two-component filter. All stocks in the CRSP universe are considered for this analysis. The table reports the calculations for two sample periods, 1991-1996, which is Kumar's (2009) original sample period, and 2013-2021, which is the sample period used throughout this study. The three-component filter flags a stock as an LTS when the stock lies in the top 50th percentile of both idiosyncratic skewness and idiosyncratic volatility; and is in the lowest 50th percentile of prices in the CRSP universe on a given day. On the other hand, the modified two-component filter flags a stock as an LTS when the stock lies in the top 50th percentile of idiosyncratic skewness and idiosyncratic volatility in the CRSP universe on a given day. For each of the sample periods, a daily series of dummy variables is calculated showing whether the three-component filter flags a stock as an LTS. Then, the same time series is calculated for all the stocks using the modified two-component filter. For all the stocks that switched between LTS and Non-LTS during the sample period (i.e., stocks with non-zero standard deviation of LTS flags), correlations between the two-component and three-component filter results are calculated. The descriptive statistics of this series of correlations obtained are reported below.

Sample Period	Count	Mean	Standard Deviation	Min	25%	50%	75%	Max
1991-1996 (Kumar's Sample Period)	7954	0.791	0.251	0.020	0.682	0.870	1.000	1.000
2013-2021 (Current Sample Period)	6689	0.809	0.259	0.018	0.707	0.927	1.000	1.000

Table 4: Fama French 5 Factor Model

This table shows the results for the Fama French Model applied to bitcoin (BTC), ether (ETH), S&P500, gold (NYGOLD FDS) and silver (SLVR FDS). The data for the Fama-French factors is sourced from their website and the data for other assets is sourced from the FactSet database. Mkt-Rf is the market factor minus the one-month treasury bill rate. SMB is the Small minus big factor representing the size effect. HML is the high minus low factor calculated by subtracting returns on growth portfolios from returns on value portfolios. RMW is the Robust minus weak factor proxying the profitability of firms and CMA is the Conservative minus aggressive factor representing investment strategies.

Dependent Variable:	**BTC**			**ETH**			**S&P500**			**NYGOLD FDS**			**SLVR FDS**		
Variable	**Beta**	**Std. Error**	**P>|t|**	**Beta**	**Std. Error**	**P>|t|**	**Beta**	**Std. Error**	**P>|t|**	**Beta**	**Std. Error**	**P>|t|**	**Beta**	**Std. Error**	**P>|t|**
Constant	0.003	0.001	0.002	0.006	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.279	0.000	0.000	0.722
Mkt-RF	0.004	0.001	0.000	0.008	0.002	0.000	0.010	0.000	0.000	0.000	0.000	0.510	0.002	0.000	0.000
SMB	0.004	0.002	0.049	0.003	0.003	0.329	-0.001	0.000	0.000	0.001	0.000	0.007	0.001	0.001	0.492
HML	-0.002	0.002	0.182	-0.004	0.003	0.182	0.000	0.000	0.000	-0.002	0.000	0.000	0.000	0.001	0.504
RMW	0.005	0.003	0.079	0.006	0.005	0.261	0.001	0.000	0.000	0.000	0.001	0.885	0.001	0.001	0.365
CMA	0.000	0.004	0.991	0.004	0.006	0.556	0.000	0.000	0.000	0.004	0.001	0.000	0.001	0.001	0.737
N	1826			1360			1826			1826			1836		
R-Squared	0.014			0.018			0.998			0.022			0.015		
Adjusted R-Squared	0.011			0.015			0.998			0.019			0.012		
F-Statistic	5.244			5.086			163100.000			8.198			5.458		
F-Test p-value	0.0001			0.00013			0.00000			0.00000			0.00005		

Table 5: Value at Risk (VaR) and Jarque Bera Analysis

This table reports the annualized standard deviation, expected return, skewness and kurtosis of returns (r) from optimally weighted portfolios. In addition to these statistics, the table shows results for the Jarque Bera test for normality conducted on log\left(1+r\right) for the daily returns from optimally weighted portfolios. The 95% and 99% VaR is calculated using historical returns from the optimally weighted portfolios. The Historical VaR is calculated as the average of individual VaRs for each yar in the sample period. For portfolios with only one asset, all funds are allocated to the asset (weight = 1). Conditional VaR (CVaR) is calculated as the average of all the values less than the VaR level indicated. The set of traditional assets comprises of SP500 (equities), NAREIT (Real Estate), SPGSCI (Commodities), NYGOLD FDS (Gold), and SLVR FDS (Silver).

Optimally Weighted Portfolio	**Time Period**	**Expected Return**	**Standard Deviation (Annualized)**	**Skewness (Annualized)**	**Kurtosis**	**Jarque Bera (Statistic)**	**Jarque Bera (p-value)**	**VAR 95% (Daily Returns)**	**CVAR 95% (Daily Returns)**	**VAR 99% (Daily Returns)**	**CVAR 99% (Daily Returns)**	**Sharpe Ratio**
BTC	2013-2020	89.89%	70.75%	0.285	7.331	4183.010	0.000	-0.067	-0.104	-0.123	-0.149	1.260
ETH	2015-2020	162.17%	110.11%	1.378	8.906	2343.442	0.000	-0.092	-0.129	-0.139	-0.191	1.466
SP500	2013-2020	12.54%	17.59%	-0.681	20.615	37653.159	0.000	-0.015	-0.023	-0.028	-0.034	0.671
Traditional Assets	2013-2020	10.51%	13.02%	-0.825	27.270	65006.019	0.000	-0.011	-0.016	-0.018	-0.024	0.751
Traditional Assets + BTC	2013-2020	27.98%	19.79%	-0.355	9.665	8892.689	0.000	-0.019	-0.029	-0.034	-0.042	1.377
Traditional Assets + ETH	2015-2020	34.34%	20.57%	0.305	8.544	4605.650	0.000	-0.018	-0.028	-0.026	-0.041	1.633
Traditional Assets + ETH and BTC	2015-2020	47.88%	25.59%	-0.174	6.348	3202.008	0.000	-0.022	-0.037	-0.038	-0.058	1.842

Table 6: Spanning Test for Cryptocurrencies

This exhibit shows the spanning test result with the S&P500 index as benchmark and cryptocurrencies as the test asset. The dependent variable (or the test asset) for of the columns is bitcoin returns (BTC), ether returns (ETH), and bitcoin and ether optimally weighted portfolio returns (BTC&ETH) minus the risk-free rate for each. The independent variable (benchmark asset) is the S&P500 minus the risk-free rate. The risk-free rate is the Fama-French one-month treasury bill rate converted to the daily rate. The top panel shows the results for the ordinary-least square regression. The lower panel show the results for the Wald test with the null hypothesis ($\alpha = 0,$ $and\ \beta = 1$) stating that the test asset spans the benchmark asset, resulting in no diversification benefits for the investor.

Dependent Variable:		**BTC**			**ETH**			**BTC&ETH (Optimally Weighted Portfolio)**	
Variable	**Beta**	**Std. Error**	**P>|t|**	**Beta**	**Std. Error**	**P>|t|**	**Beta**	**Std. Error**	**P>|t|**
Constant	0.003	0.001	0.001	0.006	0.002	0.001	0.004	0.001	0.000
SP500-RF	0.405	0.094	0.000	0.719	0.154	0.000	0.500	0.095	0.000
N	1826			1360			1360		
R-Squared	0.010			0.016			0.020		
Adjusted R-Squared	0.010			0.015			0.019		
F-Statistic	18.675			21.848			27.534		
F-Test p-value	0.0000			0.0000			0.0000		

Wald Test									
Null Hypothesis:		α=0, β=1			α=0, β=1			α=0, β=1	
Test Statistic	**Value**	**df**	**Prob**	**Value**	**Df**	**Prob**	**Value**	**df**	**Prob**
F-statistic	24.54889	(2, 1824)	0.0000	6.700048	(2, 1358)	0.0013	20.50332	(2, 1358)	0.0000
Chi-square	49.09779	2	0.0000	13.40010	2	0.0012	41.00665	2	0.0000

Table 7: Store of Value (SOV) Component analysis

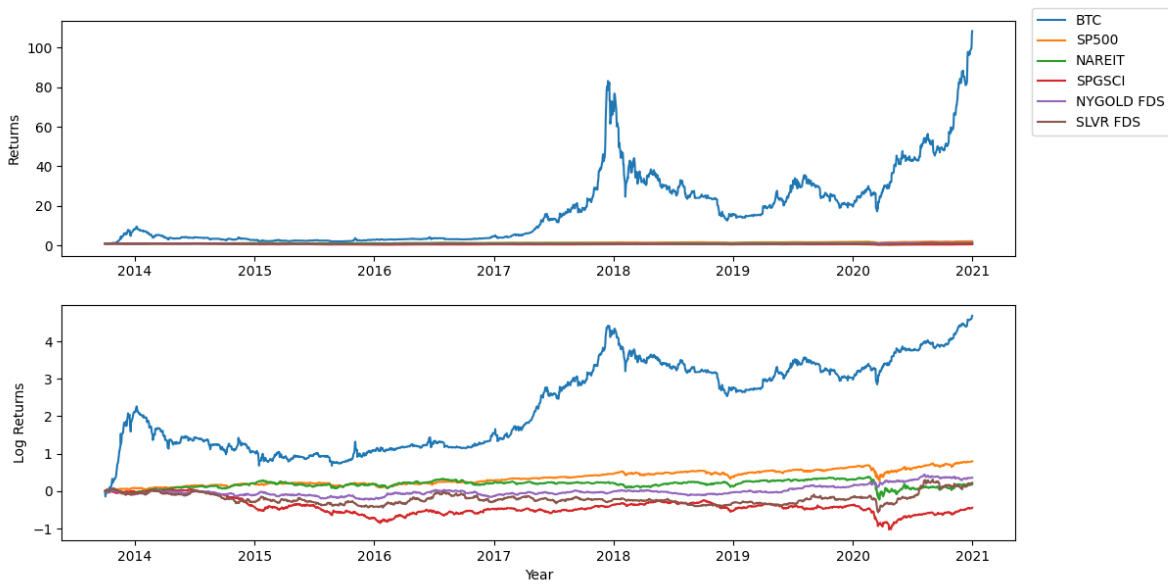
This table reports the results for the regression of the potential store of value component in cryptocurrency returns (BTC_SOV for bitcoin and ETH_SOV for ether) on the store of value component in gold returns (Gold_SOV). The cryptocurrency SOV component is the series of residuals obtained by regressing the cryptocurrency returns on memecoin returns (Dogecoin). The Gold_SOV component is obtained by regressing gold returns on platinum returns, thereby isolating the counter-cyclical component in the residuals. This series of counter cyclical component is used as the GOL_SOV. The table also reports the Pearson correlation coefficient between the dependent and independent variable.

Dependent Variable:	**BTC_SOV**			**ETH_SOV**		
Variable	**Beta**	**Std. Error**	**P>|t|**	**Beta**	**Std. Error**	**P>|t|**
Constant	0.000	0.001	1.000	0.000	0.002	1.000
Gold_SOV	0.290	0.131	0.027	0.659	0.241	0.006
Sample period	2013-2020			2015-2020		
Correlation Coefficient (Gold_SOV)	0.052			0.074		
N	1772			1360		
R-Squared	0.003			0.005		
Adjusted R-Squared	0.002			0.005		
F-Statistic	4.879			7.489		
F-Test p-value	0.0273			0.00629		

Figure 1: Cumulative returns

This figure shows the cumulative returns from traditional assets and cryptocurrencies. Panel A shows the returns for bitcoin and traditional assets for the sample period from 2012 to 2020. Panel B shows returns for ether, bitcoin and traditional assets from 2015 to 2020. The top portion of each panel shows the raw cumulative returns calculated as compounded daily return for each day t as $R_i = \prod_{i=1}^{t}(1 + r_i)$, where $r_i = (return\ on\ day\ t)/r_1$. The bottom half of each panel shows the $log(R_i)$ plotted for each day in the sample period.

Panel A: Bitcoin Sample Period (2013 –2020)



Panel B: Ethereum Sample Period (2015 –2020)

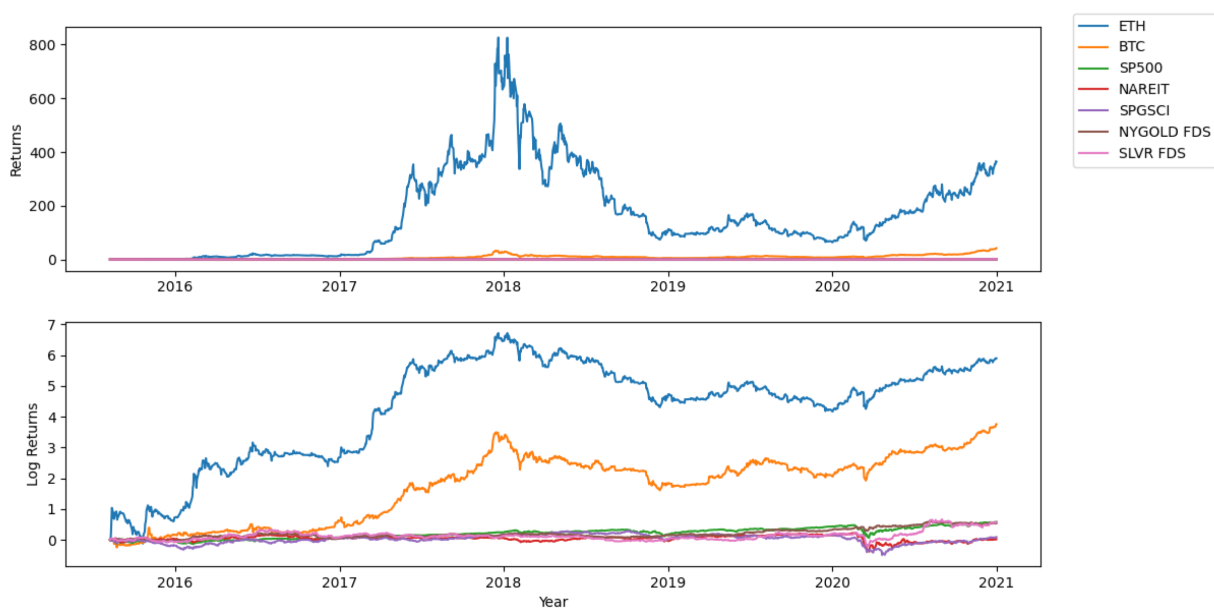
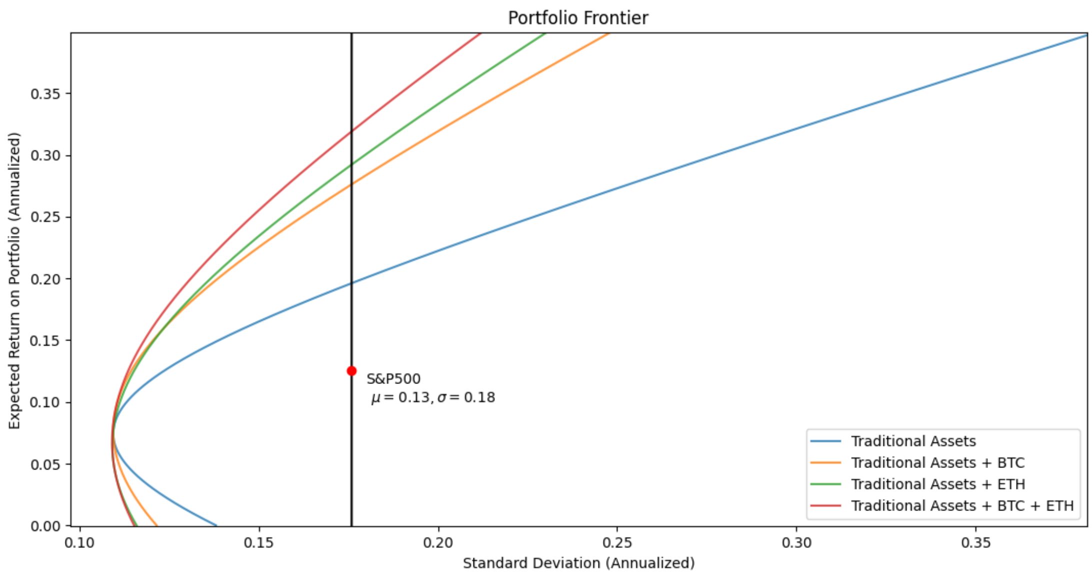


Figure 2: Portfolio Frontier

This figure shows the portfolio frontier of optimally weighted portfolios with and without cryptocurrencies. The frontiers represent a risk return trade-off where risk is represented on as standard deviation and semi-standard deviation; and return is represented as the annualized expected return on the portfolio. The risk-return of S&P500 is plotted to show usually accepted levels of risk for the corresponding return. A risk-averse investor would always prefer the highest return for a given level of risk.

a. Mean-Variance Frontier



b. Semi-variance Frontier

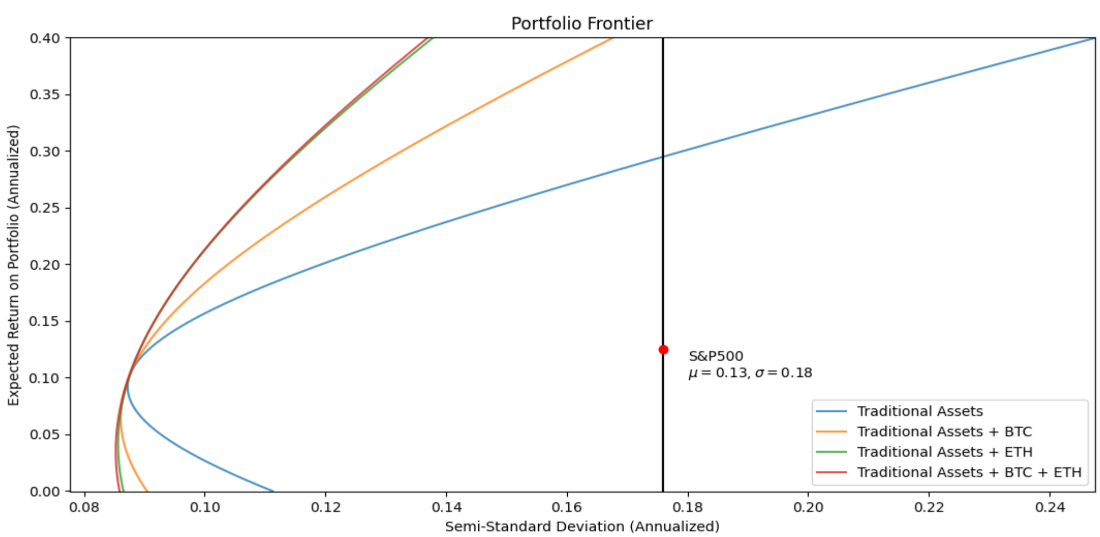
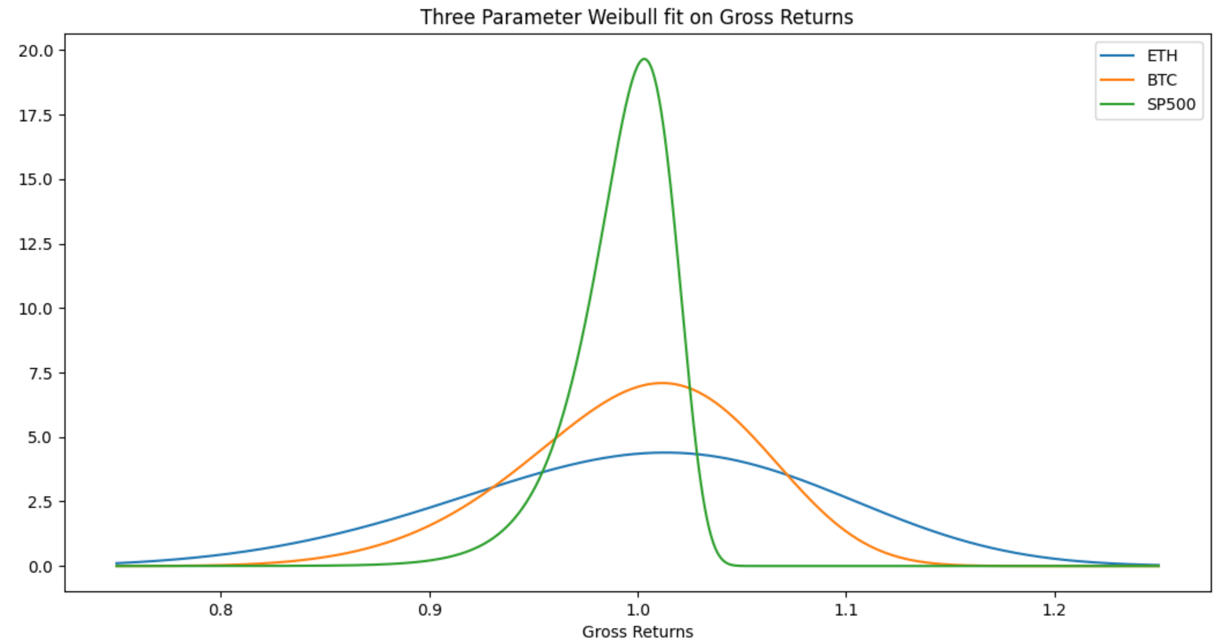


Figure 3: Asset Returns under a three-parameter Weibull distribution

This figure shows a three-parameter Weibull cumulative distribution function of returns on ether (ETH), bitcoin (BTC) and S&P500 (SP00) individually. The Weibull distribution is fit on gross returns $(1 + r)$ for the complete sample period of each asset. The sample period for BTC and SP500 is from 2013 to 2020 and the sample period for ETH is 2015 to 2020. The gross return values below 1 imply negative returns, whereas values grater than 1 show positive returns.



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9. Appendix

9.1. Appendix A: Store of Value Analysis using an equally weighted portfolio of Memecoins

Table A: This table reports the results for the regression of the potential store of value component in cryptocurrency returns (BTC_SOV for bitcoin and ETH_SOV for ether) on the store of value component in gold returns (Gold_SOV). The cryptocurrency SOV component is the series of residuals obtained by regressing the cryptocurrency returns on returns from an equally weighted portfolio of top ten memecoins* based on market capitalization. The Gold_SOV component is obtained by regressing gold returns on platinum returns, thereby isolating the counter-cyclical component in the residuals. This series of counter cyclical component is used as the GOL_SOV. The table also reports the Pearson correlation coefficient between the dependent and independent variable.

Dependent Variable:	**BTC_SOV**			**ETH_SOV**		
Variable	**Beta**	**Std. Error**	**P>|t|**	**Beta**	**Std. Error**	**P>|t|**
Constant	0.000	0.005	1.000	0.000	0.005	1.000
Gold_SOV	-0.159	0.620	0.799	-0.721	0.684	0.296
Sample period	Oct 2021 - Dec 2021			Oct 2021 - Dec 2021		
Correlation Coefficient (Gold_SOV)	-0.034			-0.141		
N	57			57		
R-Squared	0.001			0.020		
Adjusted R-Squared	-0.017			0.002		
F-Statistic	0.065			1.111		
F-Test p-value	0.7990			0.29600		

* The tokens included in this portfolio are the top ten memecoins based on market capitalization on www.coingecko.com as of December 2021. These coins are namely: Dogecoin, Shiba Inu, Magic Internet Money, Spell Token, Dogelon Mars, Baby Doge Coin, Samoyedcoin, Hoge Finance, CateCoin, and DogeGF.

The above results show that the *GOLD_SOV* component does not hold any explanatory power over the Potential *CRYPTO_SOV* components for Bitcoin and Ethereum. The results reveal neither the R-squared values nor the coefficients (-0.16 for BTC and -0.72 for ETH) are significant. This lack of a relationship between the two variables of interest is emphasized by the low correlation coefficients for both the cryptocurrencies. The sample period for this analysis is only 57 observations due the non-availability of memecoin price data, and these results should be considered with caution.