A Portfolio Approach to Investing in Crypto Currencies

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Introduction

The crypto-space has been fast evolving ever since the first bitcoin was mined in 2009. Hundreds of other cryptocurrencies have come up since then. The collective market capitalization of all cryptocurrencies has gone up from $ 1.4 billion (May 2013) to about $ 330 billion currently. With new cryptocurrencies coming up, the share of bitcoin in the total market cap (of all cryptocurrencies) has gone down over the years from more than 90% (April 2013) to less than 50% at present. However, in absolute amount, bitcoin's market-cap has shot up from $ 0.5 billion to about $ 130 billion in the same period.

The views on cryptocurrencies are deeply polarized, to say the least. On the one hand, there are those who believe this is the best thing to happen in technology (after internet). On the other end of the spectrum, people believe this is all hype and speculation as cryptocurrencies are "inherently worthless". In order to judge whether it is reasonable to consider cryptocurrencies as a new alternative asset class, we assess it on the following parameters: source of value, correlation with traditional asset classes, regulatory approval and existing (as well as potential) use cases.

To begin with, unlike fiat currencies, most cryptocurrencies are limited in supply. e.g. supply of bitcoin is capped at 21 million with a timeline spread till 2140. Till now, about 17 million have already been mined. With every passing day, mining of new bitcoins is going to become increasingly tougher, requiring even more computing power, as the cumulative supply-curve gets flattened. This relative scarcity is potentially a huge source of value for the cryptocurrencies. In that sense, it's comparable to a commodity like gold: no inherent cash flows and limited in supply.

Secondly, cryptocurrencies have so far had weak relationships with established asset classes, according to some recent studies. e.g. "Cryptocurrencies as an asset class? An empirical assessment." by Daniele Bianchi (University of Warwick). Bitcoin, in particular, has had consistently low correlations with other asset classes like equities, bonds, US Dollar, real estate and commodities (gold, oil). Such correlations, (on both, rolling bases as well as average over a period), have been found to fluctuate within a range of -0.5 to +0.3. In a recent study by Chris Burniske and Jack Tatar, "portfolios with even a small percentage exposure to bitcoin, are likely to be rewarded for taking on this risk with higher beneficial Sharpe Ratios than even the FANG stocks". So, if diversification is what an investor is looking for, cryptocurrencies are difficult to ignore.

The use-cases of cryptocurrencies are primarily based on the two concepts of blockchain and smart contracts. Blockchain is a distributed ledger technology (DLT) i.e. an immutable, transparent, decentralized record (ledger) spread over thousands of computers across the globe. It can store data on transactions, land-ownership, intellectual property and much more. The key idea is to dis-intermediate. e.g. direct money transfers across borders, thereby substantially reducing time and costs involved.

The term "smart" implies self-executing feature of the programming code, based on well-defined milestones to be achieved at specific stages of the contract. At each one of those stages, the code will decide whether to execute that part of the contract, only on the basis of whether the necessary pre-conditions for that stage, have been fulfilled. Smart contract can be used to exchange not just money, but also stocks, property or anything else, without the need of a lawyer, notary, broker or any other service provider. A trusted legal entity (government or a company) needs to first tokenize (or digitize) the physical assets (e.g. real estate) in a transparent and secure manner, so that the buyer can trace their purchase of those assets back to the same legal entity. And once that happens, we no longer need a trusted third party (lawyer/notary) to modify and authorize any change in the entire chain of ownership of the asset. Some blockchain networks are compatible with smart contracts (e.g. Ethereum), while others are not (e.g. bitcoin).

Since the blocks (in block-chain) are heavily encrypted, verifying the authenticity of transactions becomes like a complex puzzle that only powerful computing devices can solve. This process of solving such complicated puzzles on these blocks and thereafter adding them to the public blockchain (the ledger) is what 'mining' is all about. 'Miners' are the nodes (computer devices) which verify the transactions, thereby ensuring that they are genuine. In return, they get to 'mine' the cryptocurrency (e.g. bitcoin), in a manner such that their remuneration is in accordance with their contribution. Whenever a set of new transactions is broadcast across the network, miners check it and verify its correctness. When majority of the network acknowledges it as correct, that same block is included in the latest chain and all the miners in the network will eventually migrate to the new chain.

Decentralization rests on the principle of accurately generating consensus (i.e. validation of transactions). Different blockchains use different methods to do so. The most commonly used and a secure one is Proof of Work (PoW) where miners do it through "hashing" (using computer power to win a race to solve a difficult mathematical formula) in order to mine (unlock) the reward. PoW relies heavily on computing power to outsmart other nodes (i.e. to be the first one to solve the puzzle) and processing also takes a lot of time.

Another much cheaper and much more energy-efficient method of validation, is Proof of Stake (PoS), where heavy computing equipment is not required, and any device connected to the internet will suffice. All a miner needs to do, is to prove that she has a "stake" in the blockchain network. e.g. owning tokens beyond a certain value. It allocates responsibility to maintain the public ledger to one of the participant nodes, in proportion to the number of virtual currency tokens held by it. Though miners are chosen at random, those with an older stake have an increasingly higher chance of being chosen. Proof of Importance (PoI) is similar to PoS, but it also takes into account other factors in giving nodes an advantage in mining blocks. e.g. With NEM, nodes are rewarded for their productivity in the network, which includes not just their balance, but their number and value of transactions as well, among other 'reputation' factors.

The huge benefit of decentralization is completely getting rid of the operational single-point-of-failure problem. Since there is no single central server prone to hacking and malfunctioning, in a decentralized network, even if a few nodes (computers) get disconnected, others will chip in and get the job done. So, neither internal fraud nor external hacking of a few systems will work because other nodes will not validate the change in ("mutation" of) records.

Within the financial services sector, blockchain use cases can be accessing capital (e.g. issuing bonds), trade execution and post-trade services (clearing & settlement, KYC, proxy voting). Benefits for the latter are particularly significant for un-cleared OTC derivatives: automation of computations, real-time calculation and maintenance of margins and management of collateral, because of reduction in need for reconciliations, litigations and capital requirements.

Many established players across the spectrum are already in the process of leveraging the potential gains based on this new platform. e.g. Citi and CME are using blockchain to reduce costs of back-office functions and speed up margin funding times. IBM is developing DLT based solutions for derivatives' processing. ASX (Australia) is experimenting with use of blockchain for maintaining records of shareholdings and clearing and settlement of equities transactions. LSE is working with IBM to issue private shares of Italian SMEs. CME has already launched bitcoin futures contracts. Bolsa de Madrid is developing a blockchain based customer identification network.

Regulatory authorities in many countries have adopted the sandbox approach where fintech start-ups are experimenting – under the umbrella of the regulator herself - with new disruptive models which can have huge implications for the financial services. The regulatory landscape on cryptocurrencies is currently in a flux, as it is evolving rapidly. It varies from one territorial jurisdiction to another. For the objectives of this study, it is important to keep in mind that every single announcement on the regulatory front, seems to have an impact on the prices of the crypto-assets.

In the US, SEC has indicated that companies which raise money through the sale of digital assets must adhere to federal securities laws, while Commodity Futures Trading Commission says bitcoin is a commodity. EU has expressed concern over the risks of money laundering and financing of illegal activities through virtual exchanges. Estonia's attempt to create a state-backed crypto-currency "Estcoin" was rejected as "no EU member-state can introduce its own currency". In China, crypto-exchanges are illegal and ICOs are banned. But crypto-activity has carried on through alternative channels like mining. The ban came in 2017 and as a result, the huge trading volumes have primarily moved to Japan (biggest market for bitcoin) where bitcoin is legal tender and crypto-exchanges are legal but they need to register with the regulator. In South Korea, crypto-exchanges are legal and need to be registered with the regulator, but use of anonymous bank accounts for trading, is prohibited. Also, trading in bitcoin futures is banned. In India, crypto-exchanges are legal and unregulated, but customers are not allowed to trade on them through their bank accounts.

In Singapore, crypto-exchanges are legal but are likely to fall under the regulatory purview. Singapore has emerged as a hub for ICOs. It is positioning itself as crypto-friendly. Switzerland is one of the most crypto-friendly countries in the world. The town of Zug has been nicknamed "Crypto Valley" and is the base for blockchain companies like Ethereum and Cardano. In Canada, 3iQ has launched a crypto-asset fund which will invest directly in bitcoin, ether and Litecoin.

Infrastructure & Regulation

Let us briefly consider the different ways of buying cryptocurrencies (especially bitcoin). How easy or cumbersome is it, to start trading in bitcoin? Can a person trade without an exchange? Are there any security risks involved?

Bitcoin can be bought on exchanges, or directly from others (wanting to sell) via marketplaces. Buyer can pay in a variety of ways e.g. hard cash (fiat currency), credit/debit cards, wire transfer or even with other cryptocurrencies, depending on the platform used, who the seller is and what location we are talking about. Irrespective of the method used, it is necessary to have a wallet to store the cryptocurrency. The wallet could be online (e.g. on an exchange or on a drive in the cloud storage) or offline (e.g. in an external computer hard drive or printed on a paper). The online and offline wallets are called and "hot" and "cold" wallets respectively. In either case, the key issue boils down to keeping the key and the password hidden from others, since that is the only gateway to access the wallet. Ledger (Nano) and Trezor are among the two most popular hardware wallets. These are basically physical USB drives that must be plugged into your computer with a pin code that you create, to access your cryptocurrency. Both of them allow you to store Bitcoin, Bitcoin Cash, Ethereum, Ripple and most other common cryptocurrencies.

If the cryptocurrencies are bought through an exchange, they generate a wallet for the buyer. The cryptocurrencies inside such an (online) wallet can be subsequently moved to an offline one, if the buyer wishes to do so. Another way to buy bitcoin is through online platforms like *LocalBitcoins* which help in connecting the buyer to a seller in that particular location. The transaction takes place offline in that case. In the US, there are retail outlets where one can exchange cash for bitcoin. *Coinatmradar* helps in finding the nearest 'bitcoin ATM' in a location: Buyer inserts the fiat currency, holds the wallet's QR code up to a screen, and the corresponding amount of bitcoin is credited to that wallet.

Due to regulatory clampdown regarding Know Your Customer (KYC) and Anti Money laundering (AML) concerns, one usually needs a verified identification document, especially if indulging in a big-ticket size transaction.

At present, almost the entire trading volume in cryptocurrencies is routed through centralized exchanges. This goes against the very purpose of having a decentralized digital asset. It also makes the process prone to hacking as exchanges are the weakest link in an otherwise secure blockchain network. The hacking incidents so far (Mt. Gox – Japan; BitGrail - Italy; Bitfinex – Hong Kong; NiceHash – Slovenia; CoinCheck - Japan) have shown that exchanges can and have been hacked. An estimated one out of every 16 bitcoins, has been stolen. Though exchanges claim to move their records offline into cold storage and implement the 2 Factor Authentication (2FA), there is still a risk in keeping your cryptocurrency online as a number of wallets have been hacked and your security is dependent on the security of the exchange.

Decentralized Exchanges (DEX) imply that there is no single party which controls the data, and orders are matched and executed through smart contracts. Some people believe that DEX is the way forward for solving the above-mentioned problems inherent in a centralized exchange model. Waves DEX is already handling about $ 6 million of daily trading volume, while others are being developed and tested. A DEX will typically charge little or no fee, have a transparent code and will be more secure since the user controls his/her wallets.

Selection of Investment universe

The conventional and time-tested way is to select about 15 different assets, to get reasonably high benefit of diversification and to collect as many data points as possible, to capture all aspects of the return distribution. However, the challenge in case of cryptocurrencies is that an overwhelmingly large number of them have come up rather recently. If we try to increase the number of assets in the portfolio, we end up having many of them having very few data points (e.g. daily price data, volume etc.). On the other hand, if we try to include only those assets which have sufficient data points going back (let's say) 5 years, we are left with only a handful of them. So, the challenge is to strike the right balance for dealing with this inherent trade-off. We set a threshold of 1000 data points, this also allowed us to include Ethereum - the largest cryptocurrency after bitcoin, in terms of market capitalization - in our portfolio.

Another factor considered for selection of crypto- investment universe, is market-capitalization. Portfolio will require re-balancing at regular intervals, based on objectives and constraints of optimization. Therefore, it is better to stick to those assets having a higher market-cap as they have higher liquidity. i.e. more options to buy/sell, when required.

An important thing to be kept in mind here, is the fact that unlike conventional equity or fixed income markets, trading of cryptocurrencies happens on a continuous 24 * 7 basis. No markets closing. No weekends. No OHLC data format. Different exchanges often give different historical price data as there is no concept of "end of trading session". So, we procured the required data from www.coinmarketcap.com which is one of the respected websites.

Is there any inherent difference in the different, famous cryptocurrencies? Or are they all just 'more of the same'? If there are some key fundamental differences in the underlying assets, their usage, limitations or potential risks (security; regulation), in that case, these factors need to be taken into consideration, not only while forming the portfolio composition, but also for asset allocation within the portfolio.

Brief description of each of the 8 cryptocurrencies in our portfolio:

Bitcoin (BTC): Out of the total supply of 21 million, 17 million of have already been mined. Blocks (in blockchain) store data e.g. transactions and validation of transactions is done by algorithms. It is meant for transactions between individuals i.e. to completely bypass the role of intermediaries (banks). Each transaction can be traced all the way back to its miner/origination. Transaction costs vary and can be as high as $25 per transaction. This payments' technology, though decentralized, ends up relying heavily on centralized exchanges e.g. Coinbase, Bitstamp etc. as that is where most of the transactions happen at the moment. However, this may change, going forward, as other ways of buying bitcoin become more popular or the exchanges themselves become decentralized.

Litecoin (LTC): The transactions on the blockchain are validated at a frequency ('block-time') of every 2.5 minutes i.e. 4 times that of BTC (10 minutes). Transaction costs are low but since the transactions are traceable, the network is not very private. So, it's good for relatively small payments where privacy is less of a concern. LTC is the first cryptocurrency to use the Script algorithm which is a lot more flexible to adapt to new technologies. Liquidity is high and LTC can be bought on the Coinbase exchange. Charlie Lee (the founder) sold most of his LTC coins in January 2018. It has been perceived as the key person himself no longer having skin in the game, and hence, a red flag. However, he has argued that he did it because he was often accused of manipulating the price of LTC and that this was his way of avoiding the conflict of interest.

Ripple (XRP): It's the native currency of the Ripple platform. It seeks to eliminate reliance on centralized exchanges. Validation (e.g. of transactions) is required by at least 80% of nodes (validators which are selected by stakeholders themselves). All XRP tokens have already been issued/mined and 60% of them are currently owned by the parent company Ripple. It's been designed for FOR money transfer between banks, rather than to replace banks. The 2 main advantages for legacy banks, are regarding international payments: instant transfer of money and low transaction fee. XRP acts as a bridge currency between the fiat currencies. Since the legacy banks are tightly regulated, the Ripple gateways can freeze users' funds, if required. Exception: if the money is in the form of XRP itself. XRP has a very fast adoption rate in Japan. Examples of mainstream financial institutions using XRP, are from across the world: Santander, Standard Chartered, ATB Financial (Canada), YES Bank (India). However, it is not clear how many global banks would trust and use a cryptocurrency - more than half of which is owned by a private company - for payments between each other. e.g. A large banking group like Santander is using XRP, primarily for internal payments within the group. Ripple has been recently hit by a lawsuit in the US, alleging that it raised hundreds of millions of dollars through unregistered sales of its XRP tokens. XRP can be bought on the exchanges like Bitstamp, Kraken and Coinone.

Monero (XRM): It is one of the most popular 'privacy coins', apart from Zcash and Dash. It is also the most private and secure among the privacy coins. The 2 most important features are un-traceability and un-linkability. i.e. Transactions are not linked with the public address, as 1-time stealth addresses are created for each transaction. And each transaction is routed through different nodes, to mix things up and make the network impossible to trace. Result: complete anonymity of sender, receiver, amount and location of the money transfer. The technology is blockchain-analysis resistant i.e. Information stored on the blockchain, is deliberately obfuscated. XRM has huge potential in terms of regaining control over (and optional monetization of) our personal data, because of the feature of complete anonymity. However, at the same time, it is very prone to misuse e.g. money-laundering. The underlying blockchain has no limit on its block-size (which determines number of transactions per second). Transaction costs are very high and can even be double that of BTC. XRM can be bought on exchanges like Bitfinex, Binance, Poloniex, Kraken and Changelly.

Ether (ETH): Ethereum was split into 2 separate blockchains: the new separate version became Ethereum (ETH) while the original one continued as Ethereum Classic (ETC). The underlying generalized blockchain has built-in programming languages (solidity, serpent and LLL). Blocks store not only the transaction data, but also smart contracts i.e. transactions can not only be executed and tracked, but also programmed. Ethereum has been specifically designed for (smart contracts based) decentralized applications (dApps) which are transparent, trustworthy, cryptographically secure e.g. managing records and contracts, social networking which allows users to control their own data, trading under-utilized computational resources (CPU; hard drive space), online voting and distributed governance. It has a facility for peer-to-peer messaging, unlike SWIFT which is an old, one-way method. Examples of ETH already being used, include

Barclays (trading of derivatives) and CME (launch of two new Ethereum price benchmarks). Five rural banks in Philippines have started a financial inclusion project on a pilot basis, for real-time retail payments system based on ETF blockchain. It's called 'Project i2i' – island-to-island, institution-to-institution, and individual-to-individual. ETH lost almost all its value in in single day (June 21st, 2017), before bouncing back. It can be bought on the Coinbase exchange.

Dash: It is one of the three main 'privacy coins'. However, the underlying network is perceived to be not as safe (private) as Monero. So, Dash remains prone to hacking and government interference. The block size is currently 2 MB, but there are plans to increase it all the way up to 400 MB. It has a very fast speed network. The ultimate goal is of mass-adoption by billions of users. Examples of companies using Dash include VISA, Misconduct Wine (Canada) and Shakepay.

NEM (XEM): It uses a centralized blockchain which is similar to Dash. Blocks complete (refresh) every 60 seconds. Transaction fee to send money, is very low. e.g. $ 0.15 to send $ 1000. This makes it very useful for small purchases. All the coins have already been distributed. i.e. supply is fixed. We can only buy from someone or 'harvest' (mine) it ourselves. The nodes which process the transactions, get the 'harvest' in terms of transaction fee. Its blockchain network is the first one to be based on Proof of Importance (PoI). It is based on 'skin in the game' principle: Those having maximum coins, get maximum votes. At present, about 10000 NEM coins are needed to become a 'harvester' and about 3 million of them to become a 'super node'. It takes 100 times less electricity to make an NEM payment, than it does to make a bitcoin payment. It contains an inbuilt messaging system, for which one needs to pay a tiny fee. It takes less than 60 seconds for the payment confirmation to show up in a wallet. The network can process up to 3000 transactions per second, in comparison to less than 10 for bitcoin. NEM is 2nd largest cryptocurrency used in Japan. It is 100% traceable, just like bitcoin. i.e. The focus is on ease of use, speed and scalability, rather than privacy. It has been built as a competitor to companies like VISA and PayPal. It can be traded on exchanges like Binance, Poloniex and Changelly.

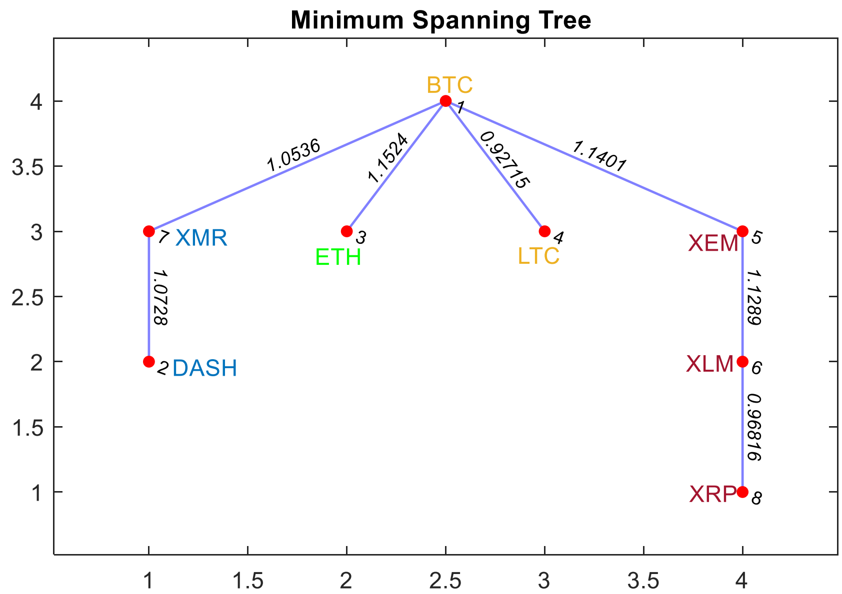
Stellar (XLM): It is to be used primarily for currency interchange. Transaction time is between 2-5 seconds and transaction (base) fee is very low. Hence, it is very useful for transfer of small-size payments. All tokens have already been pre-mined and circulating supply is half that of XRP. Users' funds cannot be frozen, unlike Ripple. Use cases include IBM, Keybase and Deloitte (building CBS). XLM is sometimes called "Ripple for the people" and "Ripple without banks".

To summarize, cryptocurrencies can be classified into 4 to 5 different baskets. The important criteria for such a classification could be potential use cases of the cryptocurrency and consensus mechanism used by the underlying blockchain network. Monero and Dash clearly fall into the category of 'privacy' coins. They are likely to remain prone to regulatory headwinds. e.g. Japanese Financial Security Agency (FSA) recently announced that from June 2018 onwards, there will be an outright ban on "all cryptocurrencies that provide a sufficient degree of anonymity to its end users". This description fits Monero and Dash perfectly well, and regulators in other countries may follow suit. XRP and Stellar have been designed primarily as 'payment' crypto-currencies, each having its own respective consensus algorithm. ETH, best positioned for applications based on smart contracts, consists of a sui generis category, also because of its expected shift from PoW to PoS as the consensus mechanism, in near future. Bitcoin and Litecoin can be clubbed together, both using the PoW consensus mechanism. Litecoin has been forked from BTC and is perceived as the one better suited for new technologies, besides having a faster network and higher supply limit of coins. LTC has been designed to be easier to mine and cheaper to transact than bitcoin, in the hope that these features could make it a cryptocurrency used for real-world use (e.g. to pay for buying other goods) in the future. XEM has got mixed traits. While it is the only one in our cryptocurrency basket to use the PoI consensus mechanism, XEM network also allows individuals and businesses to store data or information securely. i.e. what is stored there is kept protected, without tampering. So, it has an element of privacy too. But because of scalability and high speed of its transactions, XEM often ends up getting compared with payment coins like XRP and Stellar.

We attempt to visualize the correlation matrix of the 8 selected crypto currencies via the minimum spanning tree (MST) approach. First, we convert the correlation matrix C, an 8 × 8 matrix into an 8×8 distance matrix, D with the following equation;

$$D_{ij} = \sqrt{2(1 - C_{ij})}$$

This converts the correlation coefficient of two securities into a distance metric with values between 0 and 2. To confirm our understanding, we calculate 90 day rolling correlation and distance matrices, and then average the pair-wise elements as shown in Graph 1. The distance matrix is used to construct the minimum spanning tree (using MATLAB's Tree object), which is a graph of connected nodes (each security - N) with only (N – 1) edges and the sum of all the edges is the lowest possible. MST is a reduced and visual representation of the correlation matrix. In the graph below there are 8 nodes (cryptos) and 7 edges (blue lines) highlighted by their distance coefficients with their **nearest respective nodes**. BTC is the node with the maximum no. of edges indicating its importance or centrality within this basket. The branches nicely tie in with our qualitative classification earlier. The shortest distance (high correlation) pairs 1) BTC and LTC, 2) XLM and XRP, both LTC and XLM were forked from BTC and XRP respectively and have similar protocols or use cases. Visualizing the correlation matrix can help discover relationships between the cryptos, providing useful information to an investor.



Initial Correlation Matrix calculated via returns from 23/8/15 – 9/5/2018
Blue – Privacy Coins; Green – Smart contracts; Yellow – Store of Value; Red - Payments

We recognize the following key risks or drivers of crypto currencies: the technology is extremely young, and unlike typical early stage investments like VC or PE, these assets are marked to market. Communication and information flow is particularly viral & sentiment driven given the integration with social media. There aren't any widely used valuation frameworks or standardized data sets to perform fundamental analysis either. Regulatory paranoia remains rampant as nations evolve their frameworks, with negatively perceived announcements creating market contagion. Participation is largely retail, sometimes with minimal understanding of the underlying technology, leading to mass herd like or trend following behaviour. Also, the infrastructure around cryptos can be challenging. We believe with time and as the technology matures, some of these challenges would ease.

Modern Portfolio Theory & Efficient Frontier

Noted economist, Harry Markowitz received a Nobel Prize for his pioneering theoretical contributions to financial economics and corporate finance. His innovative work established the underpinnings for Modern Portfolio Theory (MPT) —an investment framework for the selection and construction of investment portfolios based on the maximization of risk adjusted returns. The framework provides a mathematical solution to identify the best return portfolio given a target risk level or vice-versa. Markowitz was the first to quantify risk (as standard deviation) and showed precisely how the risk of the portfolio was less than the risk of its components.

The key driver pertaining to the risk of an asset is not the risk of each asset in isolation, but the contribution of each asset to the risk of the overall portfolio. Weakly correlated assets will produce greater portfolio diversification. Consider a portfolio with **n** different assets where asset number **i** with a weight of **x(i)** will give the return **r(i)** and let **S** be the co-variance matrix, a **n x n** matrix. Then portfolio moments can be defined by;

Equation (1) – Portfolio Return;

$$\sum_{i=1}^{n} x_i \, E(r_i)$$

Equation (2) – Portfolio Variance;

$$\sigma(p)^2 = x^T S x$$

Equation (3) – Subject to weights;

$$\sum_{i=1}^{n} x_i = 1$$

We can also calculate risk contribution per asset. Marginal contribution to risk (MCR) gives the change in volatility of the portfolio induced by a small increase in the weight of a specific asset. Total risk contributions (TRC) is MCR times the weight of an asset. The total risk of a portfolio is then the sum of all the total risk contributions [11]. Risk contributions are important to understand the sources of risk in a portfolio. For example, we take two equal weighted portfolios 1) consisting of BTC and ETH and 2) XLM and XRP, then decompose risk contributions per crypto as shown below. We notice strongly correlated pairs like XLM and XRP have more equal risk contributions when compared to BTC and ETH which have relatively weaker correlations.

Equation (4) – Risk Contribution per asset

1. $MCR(i) = \frac{Sx_i}{\sigma(p)}$

2. $TCR(i) = MCR(i) * \; x(i)$

3. $Risk\ Contributions(i) = \frac{TCR_i}{\sigma(p)}$

Sample Data	BTC	ETH	XLM	XRP
Equal Weight Portfolio	50.0%	50.0%	50.0%	50.0%
Risk Contributions	30.5%	69.5%	53.7%	46.3%

Various portfolios are possible however, a rational investor would always prefer to choose a portfolio with the highest return for a given level of risk. Such a portfolio could be categorized as "efficient" and when different "efficient" portfolios are plotted on a risk / return scale, an **efficient frontier** emerges. It is on this frontier; the investor would find the portfolio with the best return given a level of risk. Sharpe Ratio of a portfolio is defined by the excess returns of the portfolio divided by volatility of the portfolio. The portfolio with the highest Sharpe Ratio in that sense is the most desirable portfolio on the frontier.

An investor can combine a risk-free asset with the highest Sharpe portfolio to reach a desired portfolio with a specified return target level by either borrowing to allocate over (or under) 100% to “market portfolio” (Max Sharpe Portfolio) if the target return is higher (or lower) than the expected return of the market portfolio. The Capital Market Line (CML) is a linear function between risk and return for various combination of portfolios consisting of the risk-free asset and the highest Sharpe portfolio (also referred to as the Market Portfolio). This function can be expressed by the following equation;

Equation (5)

$$E(R_p) = R_f + \frac{E(R_m) - R_f}{\sigma(R_{m)}} \sigma(R_p)$$

This assumes an investor can borrow or lend at the risk-free rate and the risk-free rate has zero volatility. When this is possible, the CML is the new efficient frontier. However, in real-life constraints may apply and this may not be strictly possible. MPT still provides a useful analytical framework for portfolio selection and with the help of computational finance techniques, one can optimize portfolios and construct efficient frontiers efficiently.

Crypto Portfolio Framework

We apply MPT framework to a basket of crypto currencies to construct efficient frontiers and target certain portfolios for selection using MATLAB’s portfolio object which allows for constrained portfolio optimizations. We focus on 1) Minimum Variance Portfolios, 2) Maximum Sharpe Portfolio and 3) Momentum (Max Return) Portfolios. As noted earlier, crypto correlations with traditional assets is low and therefore extracting diversification benefits through a portfolio framework may yield additional benefits. We however only analyse 100% crypto portfolios to better understand the asset class. One could always take this crypto portfolio and add it to a larger portfolio consisting of other assets, reapplying the same framework.

We use average pair-wise 90 day rolling correlations to identify changes in the correlation structure. As shown in Graph 1. the pair wise correlation ranges from 0.3 to 0.8, steadily increasing with time. Frequent re-estimation of the co-variance matrix is advised to account for changing correlations. Another key consideration is the correlation spikes during negative market returns, essentially diminishing benefits of a portfolio exactly when an investor needs it.

Crypto currencies may have long term value but currently are extremely volatile and the crash risk remains persistent. The return distributions have had large drawdowns and spikes in short periods of time. To understand the risk return profile, we study two ratios (in addition to Sharpe & Sortino Ratio); 1) Tooth to Tail Ratio [30] - defined as the ratio of the 5th percentile of returns to 95th percentile of returns (compares the best vs worst daily returns), 2) Omega Ratio [5] - defined as the probability weighted ratio of returns above and below a threshold return which in this case is zero. For all the cryptos in the portfolio, these ratios are above one making them attractive distributions to own as an investor.

The approach we take, looks at minimum variance portfolios, simulated frontiers and short-term risk managed momentum portfolios. A minimum variance portfolio (MVP) is the portfolio which lies on the efficient frontier with the least risk. A risk averse investor's portfolio selection will be the MVP. Under the conditions of equal expected returns for all assets in the universe, minimum variance portfolio weights will converge with the Max Sharpe portfolio weights. For an unconstrained portfolio optimization, the MVP weights can be estimated by;

Equation (6) - Merton

$$MVP\ weights\ =\ \frac{\{1,..,1\}S^{-1}}{\{1,..,1\}S^{-1}\ \begin{pmatrix} 1 \\ m \\ 1 \end{pmatrix}}$$

Within MATLAB's portfolio object we use a quadratic function (as a solver) for portfolio optimizations and construct the efficient frontier (without risk-free asset) and each of the three portfolio types. The key inputs being mean returns and co-variance matrix estimated from sample data of 8 crypto currencies. We verify the convergence of MATLAB's portfolio object's minimum variance portfolio (unconstrained) weights with the weights derived from equation (6).

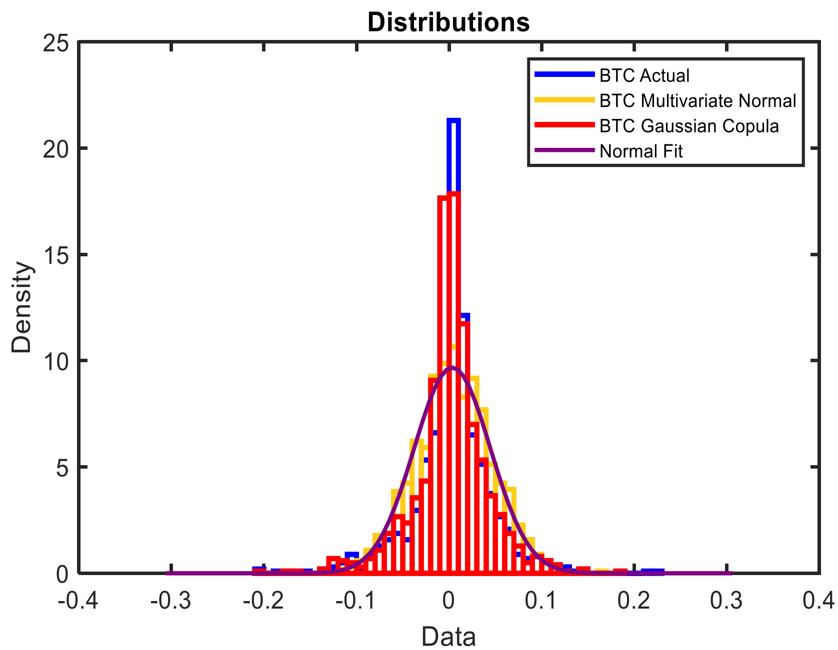
Next step is to formalize constraints for the portfolio optimization. Whilst constrained frontiers will be lower and to the right of unconstrained frontiers, constraints are a critical decision a portfolio manager makes. To ensure practicality, diversification and other qualitative beliefs, robust constraints need to be formed. Basis our assessment of the individual crypto currencies, we set the maximum weight of BTC at 100%, maximum weight per security (other than bitcoin) to 30%, a minimum weight per security of 0% and sum of all weights to 100%. We construct long-only portfolios to reflect the practical difficulties of short selling.

The efficient frontier is efficient if and only if the inputs of mean vector, μ, and a covariance matrix, Σ are correct. The difficulty is to accurately estimate these inputs thereby limiting the use case of a classic portfolio optimization. The crypto currency market is relatively young, and the technology underlying is fast evolving, increasing the estimation error and uncertainty of these inputs. To better represent this uncertainty, we construct simulated frontiers which average many future outcomes based on the sample inputs.

It is well documented, that stock returns do not follow a normal distribution and as per Kolmogorov-Smirnov test, the selected crypto currencies are not normally distributed either. Therefore, one could apply distributions such as Student T or other non-normal distributions for the simulation. We however limit ourselves to only construct one frontier with original data returns from (2015 – 2018) and two resampled frontiers using; 1) Multi variate normal distribution, 2) Gaussian copula to generate correlated simulated returns. Both the distributions are parameterized with a mean vector μ, and a covariance matrix Σ only. Multi variate normal is a distribution for random vectors of correlated variables, each element of which has a univariate normal distribution. Copulas are functions that describe dependencies among variables and provide a way to create distributions. Using a Gaussian copula, we generate correlated samples and convert them to their original scale via MATLAB's inverse cumulative distribution function. (Appendix)

We note the following; 1) As shown in Graph 2, the distribution of simulated returns (BTC) using the copula framework are a better fit to the original distribution when compared to the multivariate normal distribution. The simulated distribution has fatter tails and longer peaks which closely resemble the actual distribution. 2) As shown in Graph 3, we check for the dependency structure between ETH and BTC. The copula framework again provides a better fit and, a stronger occurrence of tail dependence between the currencies. This is important as empirically, correlations have risen during extreme market events, the Copula framework in this regard maybe considered a better distribution to use for frontier simulations.

Graph 2.



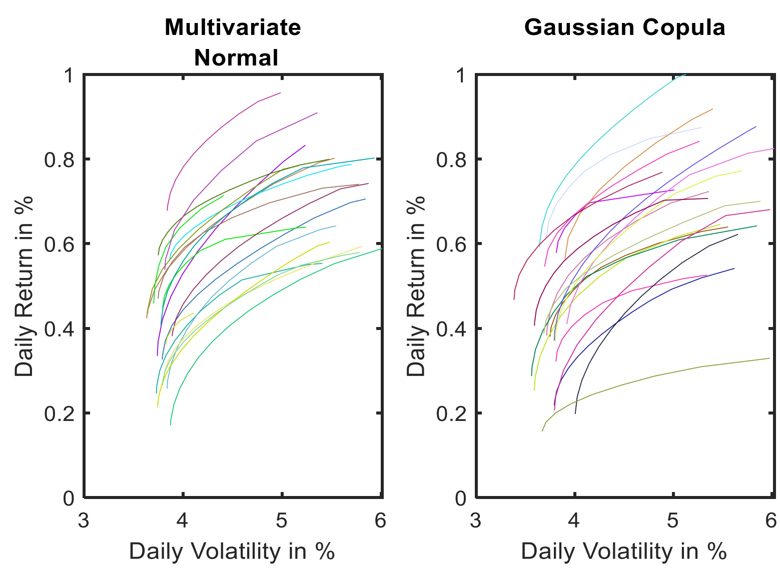
Simulating Efficient Frontiers

We calculate mean returns and co-variance matrix of the original sample data (sample data from 2015 – 2018), then using the MATLAB in-built function **'mvnrnd' and 'copularnd',** we generate two set of correlated returns of the individual assets per distribution. Using these simulated returns, we construct efficient frontiers (with 20 portfolios) and repeat this process for **20** simulations. For each portfolio specified by a target return on the simulated frontiers, the corresponding assets weights are averaged. For example, the minimum variance portfolio would be the average of the portfolio weights of all the simulated minimum variance portfolios (i.e. 20 simulations). These averaged weights per portfolio are then used to redraw the efficient frontier by using the original means and co-variance matrix.

Graph (3) shows the parameter uncertainty inherent in the portfolio optimization and portfolio selection with the varied simulated frontiers generated from a given co-variance matrix and mean return vector. Simulating many frontiers and then averaging the weights to recreate the simulated frontiers as shown in Graph (4) accounts for this uncertainty. While we have performed only 20 simulations for this academic study, a larger number of simulations will be more robust in a practical environment.

```
  for i = 1:nSim % 20 Simulations
    SimRets = mvnrnd(wmean,wcov,length(wreturns)); % Simulating Returns using Multivariate
    wmeani = mean(SimRets);
    Sigmai = cov(SimRets);
    Rs = linspace(max(min(wmeani),0), max(wmeani),Nports); % Lowest (L) to Higher (L) Return
    P1 = setAssetMoments(P1, wmeani, Sigmai);
    for m = 1:length(Rs)
    dwgt = estimateFrontierByReturn(P1, Rs(m)); % Estimating portfolios from L to H return
    [drsk, dret] = estimatePortMoments(P1, dwgt);
    Drsk(i,m) = drsk; % Storing Risk, Return and Weights per portfolio on the frontier
    Dret(i,m) = dret;
    Dwgt(i,m,:) = dwgt;
    end
  end
% Averaging Weights to construct resampled frontier
wRes = reshape(mean(Dwgt),Nports,noa);
for i = 1:Nports
  SigR(i)   = sqrt(wRes(i,:)*wcov*wRes(i,:)'); % Original Co-Variance Matrix
  MuR(i)    = wmean*wRes(i,:)';            % Original Mean Estimates
end
```

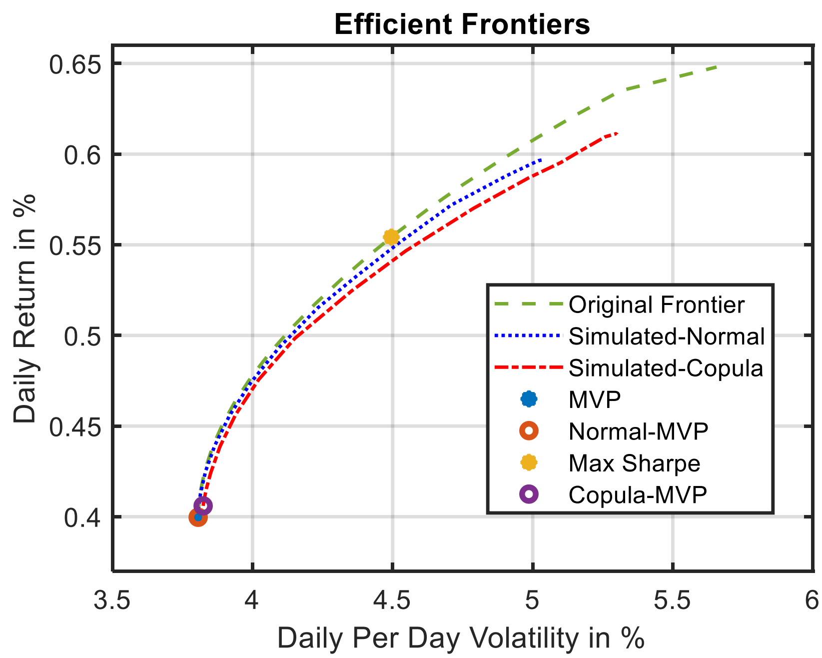
Graph 3. – Simulated Frontiers



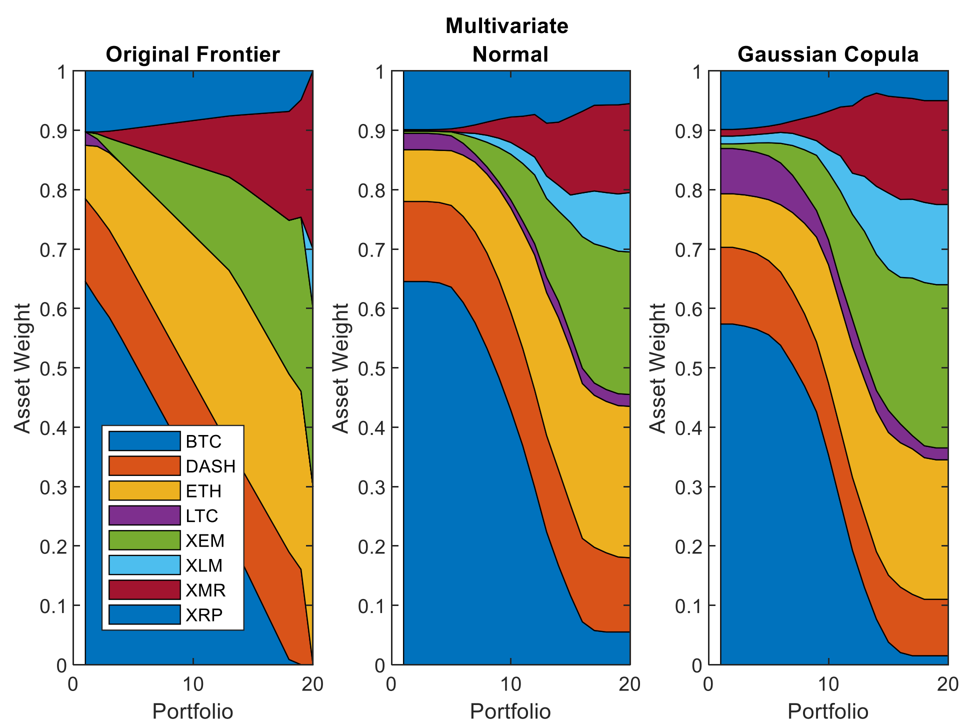
The simulated frontiers (Graph 4) lie below the original frontier, this is expected as we average the weights of the simulated frontiers and then apply original risk and return estimates. For the given estimates, we already know the efficient frontier (original frontier), therefore any other weights will be less efficient. While this is an in-sample assessment only, we can see in Graph (5) that portfolio weights are more diverse in the simulated frontiers when compared to the original frontier. Comparing the minimum variance portfolios of the various frontiers and max Sharpe portfolio as shown in Table 1, there are meaningful differences in the weights of the assets, the original MVP allocates to only five of the eight assets with the largest weight in BTC of 64.5%.

Gaussian Copula Simulated MVP allocates to all assets with the largest weight in BTC of 58.2%. Simulated MVP's have a higher standard deviation as well.

Graph 4- Main Frontiers



Graph 5. - Weights of each asset across 20 portfolios (low to high risk) for each frontier



So far, our key variables for the portfolio optimization were mean and co-variance matrix, we now use a similar methodology to extract momentum factors returns by replacing mean estimates with factor scores for each security.

Crypto Systematic Strategy

MPT framework assumes the markets are efficient, however Fama-French (1992) [2] in their work designed a three-factor model to describe stock returns. The factors are 1) Market Risk, 2) Size (small companies vs large companies) and 3) Value (Low P/B vs High P/B). Numerous studies have shown that these factors do exist and are in direct contrast to the efficient market hypothesis. An extension to the Fama-French model is the Carhart (1997) [3] four factor model, which includes the additional factor 4) Momentum (Winners vs Losers).

Momentum is described as the tendency for the asset price to continue rising if it is going up and to continue declining if it is going down. We apply the momentum factor to our portfolio to construct a strategy which could systematically harvest the momentum factor premium in the crypto currency markets.

To calculate the momentum scores, we calculate the rolling 15-day returns of the all assets in the universe and the cross-sectional mean and standard deviation of those returns. We apply the below equation (7) to calculate the momentum score for each security. Assets which have a higher return than the average return of the universe, will get a higher momentum score and correspondingly higher weight allocations in the portfolio, subject to the constraints mentioned above.

Equation (7)

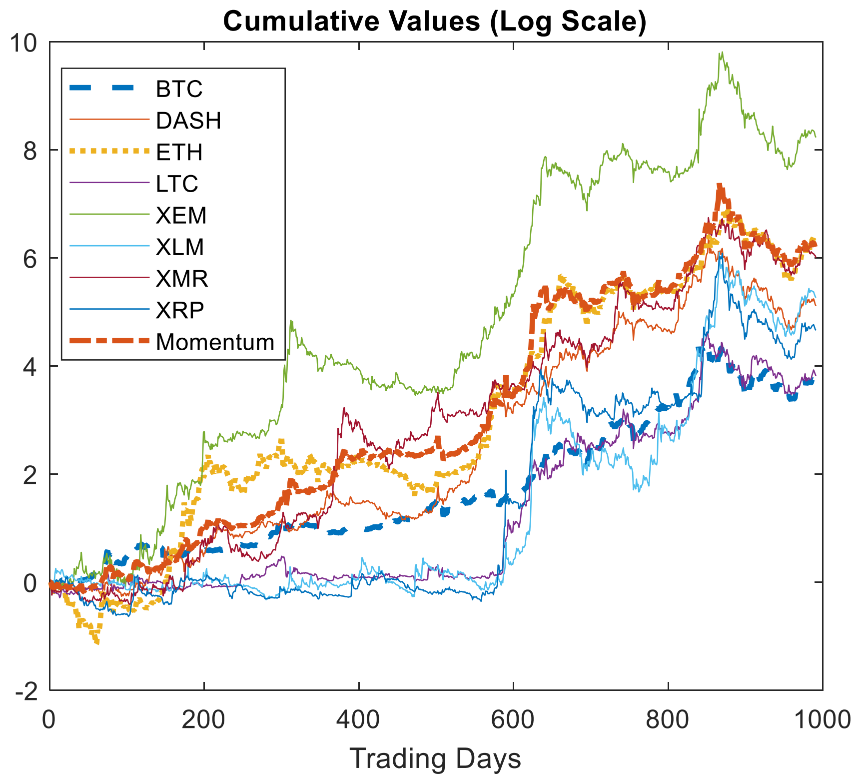
$$Momentum\ Score\ (x_i) = \frac{(r_i) - Avg(r_{i..n}^{n})}{\sigma_{i..n}}$$

We perform a back-test on a long only momentum portfolio using rolling portfolio optimizations. Taking data from Sep 2015 to May 2018, we calculate 15-day rolling momentum scores of each asset as per **Equation (7)** and corresponding rolling co-variance matrices. Thereafter we run a portfolio optimization at time **t**, which solves for the appropriate portfolio weights which maximize the portfolio momentum score. These weights are then invested from **t to t+15 days**.

Replacing asset mean estimates with asset momentum scores, converts the mean-variance frontier to a score-variance frontier, where we can derive a portfolio in relation with its momentum score and portfolio variance. The portfolio is rebalanced every **t+15 days** basis new estimates of the momentum scores. While our back-test does not include transaction costs, which may be significant, we use a shorter-term momentum measure and rebalancing frequency to reflect the high volatility and correlation spikes persistent in the crypto currency markets.

As per our back-tests, the momentum portfolio as shown in Table 2, has better risk adjusted returns, with a Sharpe ratio of 2.04 vs BTC 1.73 and ETH 1.75. However, the drawdown of 78% is larger vs BTC 66% and ETH 73%. Graph 6 shows the cumulative values of the universe selection and momentum portfolio.

Graph 6.



As we have allowed BTC an upper weight of 100%, whenever the 15-day trailing return exceeds the average return of whole basket, the portfolio increases allocation to BTC; the higher the excess return of Bitcoin vs others, larger the weight in the portfolio. This essentially anchors the portfolio to BTC during negative returns. One way of looking at it is, an investor wants to hold a diversified portfolio of cryptos if BTC returns are below the basket average, however if in the event of sustained market contagion (expecting BTC to outperform), wants to only own BTC. (Please refer Graph 12)

Instead of targeting the Max Sharpe portfolio during the portfolio optimization procedure, we optimized for maximum momentum score (which is the maximum return portfolio on the frontier). While this provides full exposure to the momentum factor weighted by the co-variance matrix, the level of risk can vary drastically in the crypto space and momentum factor is often associated with large drawdowns and crash risk, because of which we choose to scale the daily exposure (dollar value) to the momentum portfolio daily targeting a risk level.

We first calculate the total risk of the momentum factor using a rolling 15-day window and estimate Beta co-efficient of the momentum factor with BTC ("market") by regressing momentum factor returns with BTC returns. We then decompose the total risk into "market risk" and "specific risk" via the below equation;

Equation (8)

$$\sigma_p{}^2 = \beta^2\, BTC\ Variance + Specific\ Variance$$

As shown in Graph 8, the decomposed risk estimates appear to have no clear relationship with the portfolio with BTC. Momentum factor return's beta to BTC returns varies over time, ranging from 0.8 to -1.0. It's rolling total risk varies from 2.0% to as high as 14% per day.

Equation (9)

$$Scaled\ Weights = \frac{Target\ \sigma}{Trailing\ \sigma}$$

Using total risk as the risk estimate, equation (9) effectively reduces the exposure below one if the trailing risk estimate is greater than the target risk chosen. However, if the trailing risk estimate is smaller than the target risk, the exposure as will be over one, implying a levered exposure. For comparability with the unscaled momentum factor, scaled momentum maximum weights are capped at 100%. This allows to study the effect of scaling purely on the downside. Target risk of 3.5% per day is chosen which is closer to the volatility of the minimum variance portfolio as shown in Graph 4. The scaled weights are re-estimated daily altering the exposure to the portfolio; these weights are multiplied by next day returns to calculate Total Risk Scaled portfolio (Graph 7).

The scaled weights range from 100% to 20%, averaging close to 70% over the whole back-test (please refer Graph 11). Scaling the exposure via this method reduces the drawdown of the scaled momentum portfolio to 56% from 78% and improves the Sharpe ratio to 2.56 from 2.08 when compared to unscaled momentum portfolio, however a significant amount of absolute upside has been lost (please refer Table 3). An investor depending on his preferences and risk appetite can choose a more aggressive or defensive target risk level. Also, some crypto exchanges provide margin trading, therefore one could un-cap the maximum weights and employ leverage when trailing risk estimate is lower than the target risk.

We also scale the momentum by the individual risk estimates arrived in Equation (8). As there appears to be no consistent relationship of the momentum factor with BTC (which we use as Market reference) the decomposed risk estimates are not stable. Total risk estimate provides the best improvement to risk adjusted return over decomposed risk estimates as shown in Table 3.

Conclusion

We provide a framework for portfolio construction and selection of a basket of crypto currencies. The main considerations we have addressed are 1) Universe Selection (qualitative assessment) 2) Simulating Frontiers (parameter uncertainty) and 3) Behavioural factors reflected by the momentum portfolio.

Universe selection is arguably the most important consideration when building portfolios. Identifying the right crypto currencies includes understanding three broad concepts, 1) protocols or consensus mechanism, 2) economics and governance (which dictates how the different stakeholders interact with each other), 3) Adoption rates and use cases. Our chosen basket of 8 crypto currencies are amongst the 15 largest cryptos with a combined market capitalization of USD

258 billion at the time of writing. We attempted to classify them into 1) Store of value, 2) Payments, 3) Smart contracts (Platform) and 4) Privacy coins. The correlation structure among the selected universe decides the diversification benefit, the main reason why an investor would choose a portfolio approach.

Simulating frontiers, we believe, accounts for the inherent uncertainty in estimating parameters. Choosing the right distribution matters: we find Gaussian copula a better fit to the original data due to fatter tails and stronger tail dependence between currencies during extreme events. While the simulated frontiers are below the original frontier indicating less return (or utility), it accounts for the possibility of the original parameters, mean and co-variance being wrong and tries to manage this by averaging many simulated future outcomes. This framework provides a far more stable method to construct frontiers and leads to better diversified portfolios. On the frontier, an investor may choose a portfolio subject to his preference and utility.

We build a short-term momentum factor portfolio and test a method to scale the exposure by its trailing volatility. This improves the risk adjusted returns of the momentum portfolio, indicating momentum risk has some predictability power. Both the momentum portfolios have superior Omega & Tooth to Tail ratios when compared to individual cryptos. As the crypto markets are volatile and one should expect tail events due to the reasons highlighted earlier, the scaled momentum factor is a useful tool for an investor to manage that risk. Our assessment of BTC (others may consider ETH) as a “safe haven” among the universe selected may be wrong, however in the event it proves to be correct, we expect BTC to preform like other safe havens (i.e. outperform on the downside), the portfolio can allocate up to 100% in BTC thereby adding a second defensive mechanism.

The momentum portfolios are based entirely on price action, an investor could incorporate sentiment data (google trends, tweet analysis) to boost the information value during the optimization process to better reflect the behavioural heuristics within crypto markets. As valuation frameworks evolve and the data features of the various crypto currencies become easily available other tilts like size (market cap weighted scores) or value (transactions on chain / use cases) could be used to build factor portfolios using this framework.

It is important to note, that crypto currencies could all go to zero for various reasons: there remains a high risk of catastrophic failure. However, the return distributions are positively skewed with omega ratios (over 130%) and tooth to tail ratios (over 1.0) which indicate the magnitude and probability of positive returns is greater than negative returns (please refer table 2). For some investors, the question may not be whether to invest or not but rather how much to allocate, to which cryptos and how to build a framework for managing risk. Whether an investor wants to allocate and hold for the long term or capitalize on the trading opportunities present, a portfolio optimization framework would be extremely valuable to create efficient and diversified portfolios.

Bibliography

1. Dynamic asset trees and portfolio analysis - J.-P. Onnela1, A. Chakraborti1, K. Kaski1, and J. Kertesz

2. Common risk factors in the returns on stocks and bonds (1992) Eugene F. Fama and Kenneth R. French

3. On Persistence in Mutual Fund Performance Mark M. Carhart The Journal of Finance, Vol. 52, No. 1. (Mar 1997), pp. 57-82.

4. Momentum has its moments (Nov 2014) – Pedro Barroso and Pedro Santa Clara

5. An Introduction to Omega® - (2002) – Con Keating and William F. Shadwick

6. Estimation Error and Portfolio Optimization: A Resampling Soluiton – Richard Michaud and Robert Michaud

7. Optimization with Non-Normal Resampling by Noah Kraut (New Frontier Advisors' Newsletter September 2004)

8. Portfolio selection with higher moments - CAMPBELL R. HARVEY, JOHN C. LIECHTY, MERRILL W. LIECHTY and PETER MULLER

9. Minimum Variance: Exposing the "magic" (2011) – Global Markets Research (Deutsche Bank)

10. Generalized Risk-Based Investing – Emmanuel Jurezenko, Thierry Michel and Jerome Teiletche

11. On the properties of equally-weghted risk contributions portfolio (2009) – Sebastier Maillard, Thierry Roncalli and Jerome Teiletche

12. Facts and Fantasies About Factor Investing (2014) - Zelia Cazalet and Thierry Roncalli

13. Portfolio Optimization for Student T and skewed t returns (2008) – Wenbo Hu and Alec N Kercehval

14. Expected Utility Asset Allocation – FAJ – William F. Sharpe

15. Portfolio Selection - Harry Markowitz (The Journal of Finance, Vol. 7, No. 1. (Mar 1952), pp. 77-91)

16. Markowitz's "Portfolio Selection" – A fifty year retrospective (2002) – Mark Rubinstein

17. A SIMPLIFIED PERSPECTIVE OF THE MARKOWITZ PORTFOLIO THEORY - Myles E. Mangram, SMC University, Switzerland (GLOBAL JOURNAL OF BUSINESS RESEARCH ♦ VOLUME 7 ♦ NUMBER 1 ♦ 2013)

18. Modeling Non-normality Using Multivariate t: Implications for Asset Pricing Raymond Kan and Guofu Zhoul (2016)

19. Managing Risk Exposures using the Risk Budgeting Approach (2012) - Benjamin Bruder and Thierry Roncalli

20. Contrarian Factor Timing is Deceptively Difficult (2017) CLIFFORD ASNESS, SWATI CHANDRA, ANTTI ILMANEN, AND RONEN ISRAEL

21. A SIMPLE DIVERSIFIED PORTFOLIO STRATEGY (JOIM 2014) - Bernd Hanke and Garrett Quigleya

22. Momentum Strategies Across Asset Classes, Risk Factor Approach to Trend Following (2015) – Marko Kolanovic PhD and Zhen Wei, PhD (J.P. Morgan)

23. https://ch.mathworks.com/help/finance/portfolio.html?s_tid=doc_ta

24. https://ch.mathworks.com/help/stats/copulas-generate-correlated-samples.html

25. https://ch.mathworks.com/help/stats/multivariate-normal-distribution.html

26. https://ch.mathworks.com/help/stats/copularnd.html

27. https://ch.mathworks.com/help/matlab/ref/graph.html?s_tid=doc_ta

28. https://ch.mathworks.com/help/matlab/ref/graph.minspantree.html?s_tid=doc_ta

29. BARRA – Risk Model Handbook – Version 3 (E3)

30. https://en.wikipedia.org/wiki/Tooth-to-tail_ratio

31. https://www.cnbc.com/2018/03/27/a-complete-guide-to-cyprocurrency-regulations-around-the-world.html

32. https://hackernoon.com/an-introduction-to-cryptocurrency-wallets-288629d879a4

33. https://www.newswire.ca/news-releases/3iq-corp-announces-global-cryptoasset-fund-to-invest-in-multiple-cryptoassets-671283804.html

34. http://www.businessinsider.com/cme-group-ethereum-ether-reference-rate-ether-real-time-index-2018-5

35. http://www.businessinsider.fr/us/jpmorgan-ask-oliver-harris-to-explore-cryptocurrency-strategy-2018-5

36. https://www.bloomberg.com/news/articles/2018-05-04/ripple-hit-with-class-action-suit-over-never-ending-ico

37. https://www.cnbc.com/2018/05/15/amazon-is-moving-into-blockchain-with-a-new-partnership.html

38. http://bitmalta.com/blockchain-consensus/

39. https://unhashed.com/cryptocurrency-coin-guides/blockchain-consensus-mechanisms/

40. https://hackernoon.com/an-overview-of-cryptocurrency-consensus-algorithms-9d744289378f

41. https://en.wikipedia.org/wiki/Proof-of-stake

42. https://en.wikipedia.org/wiki/NEM_(cryptocurrency)

43. https://www.newgenapps.com/blog/8-blockchain-consensus-mechanisms-and-benefits

44. https://ripple.com/use-cases/banks/

45. https://coinmarketcap.com/charts/

46. https://www.statista.com/statistics/730782/cryptocurrencies-market-capitalization/

47. https://cointelegraph.com/news/so-is-there-a-correlation-between-bitcoin-and-stock-market-yes-but-no

48. https://cointelegraph.com/news/cryptocurrencies-as-portfolio-diversification-systematic-hedge-with-excellent-risk-reward-profile

49. https://medium.com/@etiennebr/the-birth-of-a-new-asset-class-crypto-assets-part-ii-institutional-investors-are-coming-fe99fb94957b

50. https://www.bloomberg.com/graphics/2018-bitcoin-investment/

51. https://www.thestreet.com/story/14427758/1/considering-bitcoin-and-cryptoassets-as-an-alternative-asset-class.html

52. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3077685

53. https://medium.com/@Jernfrost/what-is-a-smart-contract-and-why-do-we-need-them-7d92f2131f03

54. https://www.forbes.com/sites/jasonevangelho/2018/03/13/mining-101-what-exactly-is-cryptocurrency-mining/#6af73acaa83a

55. https://www.coindesk.com/information/how-can-i-buy-bitcoins/

56. http://fortune.com/2018/01/03/bitcoin-buy-how-to-cryptocurrency/

57. https://hackernoon.com/how-to-buy-bitcoin-and-trade-cryptocurrencies-a-step-by-step-guide-7e64faecfa3f

58. https://www.cnet.com/how-to/buying-and-selling-bitcoin-explained/

59. https://www.coindesk.com/bitcoin-brokers-trade-millions-without-exchange/

60. https://www.coindesk.com/future-crypto-exchanges-decentralization-coming/

61. https://www.coindesk.com/information/how-to-store-your-bitcoins/

62. https://www.coindesk.com/japan-wake-call-get-ready-defend-privacy-coins/

63. https://www.stocksgazette.com/2018/01/21/ripple-xrp-vs-nem-xem-which-one-is-better/

64. https://www.cnbc.com/2017/12/20/litecoin-founder-charlie-lee-sells-his-holdings-in-the-cryptocurrency.html

65. https://techcrunch.com/2017/12/20/litecoin-charlie-lee-conflict-of-interest/?guccounter=1

66. https://www.ccn.com/philippines-banks-to-pilot-ethereum-based-blockchain-for-retail-payments/

Table 1.

Weights	MVP Constrained	MVN MVP	Copula MVP	Max Sharpe Portfolio	Max Return Portfolio
Daily Return	0.399%	0.402%	0.404%	0.554%	0.648%
Daily Volatility	3.804%	3.806%	3.818%	4.495%	5.656%
BTC	64.5%	63.4%	58.2%	22.3%	0.0%
DASH	13.9%	14.1%	13.5%	15.1%	0.0%
ETH	9.0%	9.0%	8.9%	29.4%	30.0%
LTC	2.3%	2.6%	6.4%	0.0%	0.0%
XEM	0.0%	0.1%	0.4%	15.5%	30.0%
XLM	0.0%	0.3%	1.2%	0.0%	10.0%
XMR	0.0%	0.6%	0.7%	10.1%	30.0%
XRP	10.3%	9.9%	10.7%	7.6%	0.0%

- *Portfolio moments and weights per asset for the minimum variance portfolio on the original and simulated frontiers. [Date Range: August 2015 – May 2018] (Only 20 simulations)*

Table 2.

23/8/15 - 9/5/2018	BTC	DASH	ETH	LTC	XEM	XLM	XMR	XRP	Long Only Momentum
Cumulative Return	3908%	16459%	54455%	4448%	374316%	19209%	40283%	10441%	47737%
CAGR	282%	540%	887%	300%	1887%	577%	785%	443%	841%
Volatility	78%	117%	131%	114%	182%	170%	141%	152%	110%
Rolling Avg Returns	*482%*	*2022%*	*2417%*	*1376%*	*5643%*	*3954%*	*1897%*	*4372%*	*2447%*
Rolling Volatility	*439%*	*2500%*	*2732%*	*1891%*	*7704%*	*7033%*	*858%*	*7738%*	*2339%*
Skewness	*- 0.2*	*0.9*	*0.3*	*1.4*	*1.9*	*2.0*	*1.1*	*3.0*	*- 0.1*
Kurtosis	*7.6*	*8.9*	*6.2*	*16.0*	*18.3*	*17.2*	*10.2*	*40.9*	*13.5*
Sharpe Ratio	*1.73*	*1.59*	*1.75*	*1.22*	*1.64*	*1.13*	*1.55*	*1.11*	*2.04*
Sortino Ratio	*2.53*	*2.63*	*2.80*	*2.05*	*2.92*	*2.00*	*2.59*	*2.07*	*3.07*
Omega Ratio	*1.32*	*1.28*	*1.31*	*1.25*	*1.31*	*1.22*	*1.27*	*1.26*	*1.42*
Tooth to Tail Ratio	*1.0*	*1.3*	*1.4*	*1.2*	*1.2*	*1.2*	*1.2*	*1.4*	*1.2*
Daily VaR @ 99%	*-12%*	*-16%*	*-18%*	*-15%*	*-23%*	*-22%*	*-19%*	*-16%*	*-17%*
Max DD	-66%	-82%	-73%	-68%	-89%	-83%	-68%	-86%	-78%
Correlation with BTC	100%	41%	34%	57%	34%	31%	43%	25%	51%
Correlation with ETH	34%	34%	100%	33%	24%	24%	34%	20%	43%

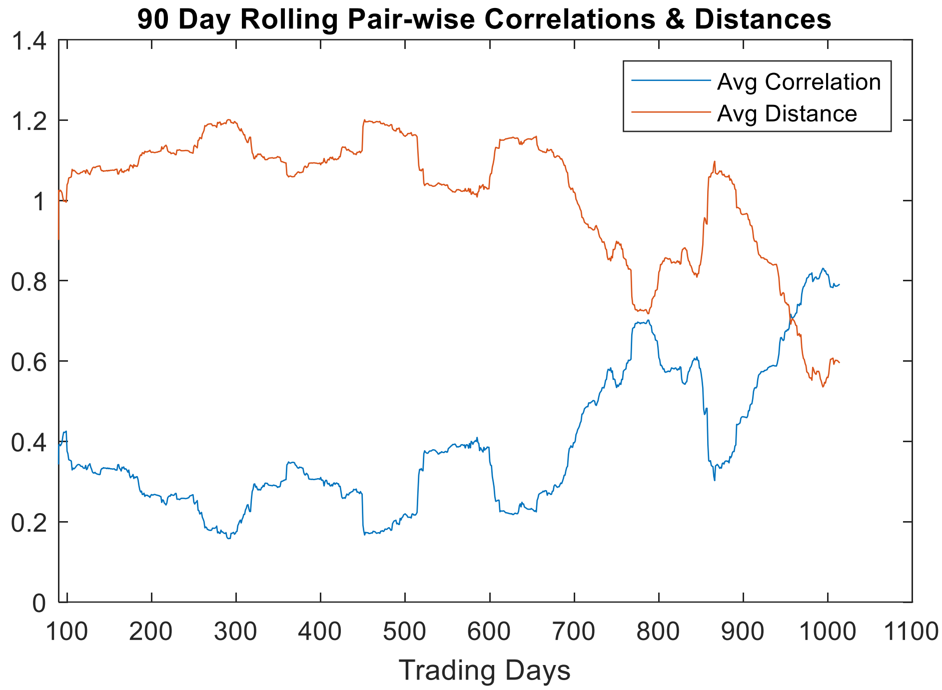
Table 3.

07/09/15 - 9/5/2018	BTC	Momentum	Total Risk	Specific Risk	Market (BTC) Risk
Cumulative Return	3750%	49461%	12878%	14592%	31115%
CAGR	284%	887%	502%	530%	732%
Volatility	78%	110%	70%	85%	97%
Rolling Avg Returns	*490%*	*2490%*	*882%*	*1035%*	*1881%*
Rolling Volatility	*441%*	*2351%*	*466%*	*638%*	*1518%*
Skewness	*- 0.2*	*- 0.1*	*0.1*	*- 0.3*	*- 0.2*
Kurtosis	*7.5*	*13.4*	*7.5*	*8.5*	*17.9*
Sharpe Ratio	*1.73*	*2.08*	*2.56*	*2.16*	*2.18*
Sortino Ratio	*2.53*	*3.12*	*4.03*	*3.23*	*3.29*
Omega Ratio	*1.32*	*1.43*	*1.51*	*1.42*	*1.47*
Tooth to Tail Ratio	*1.0*	*1.2*	*1.4*	*1.2*	*1.4*
Daily VaR @ 99%	*-12%*	*-17%*	*-11%*	*-13%*	*-16%*
Max DD	-66%	-78%	-56%	-66%	-72%
Correlation with BTC	100%	51%	50%	58%	44%
Correlation with ETH	100%	51%	50%	58%	44%

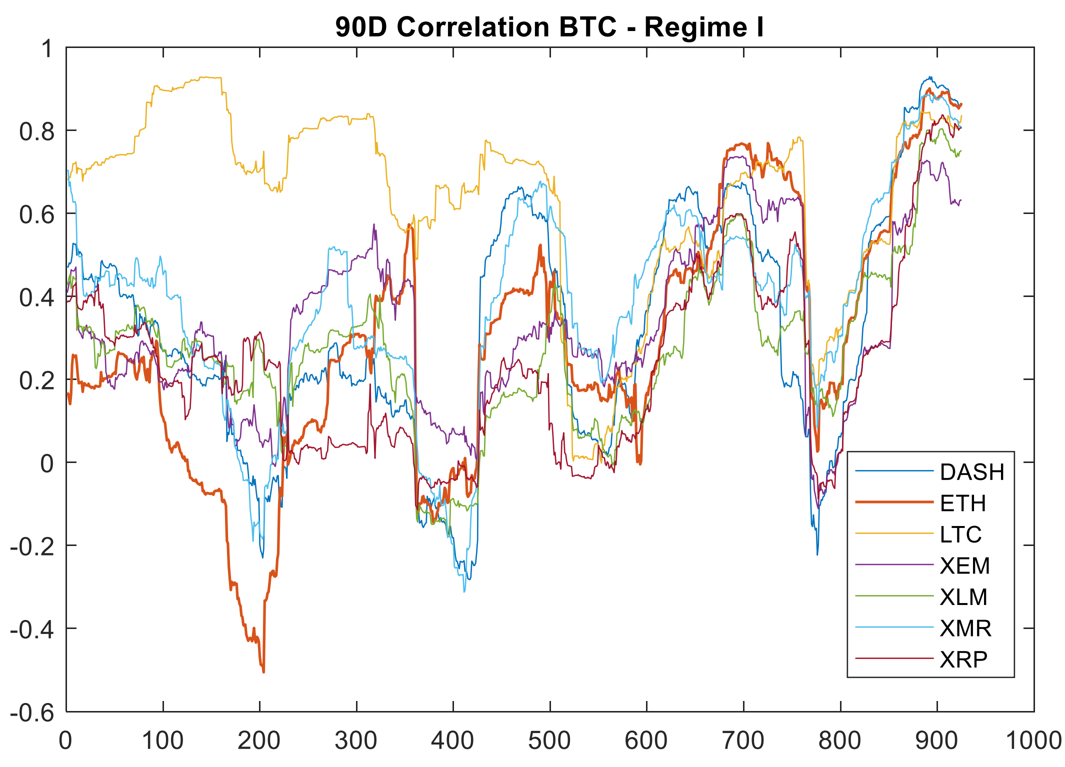
Notes:

1. *Risk free rate is assumed to be zero for the risk ratios.*
2. *Tail Ratio is defined as the ratio of the 5th percentile of returns and 95th percentile of returns, compares the best returns vs the worst returns (daily)*
3. *Omega Ratio is defined as the probability weighted ratio of returns above and below a threshold return which in this case is zero.*

Graph 1



Graph 9



- *90 day rolling correlations of crypto currencies with BTC.*

Graph 13 – Distance Matrix [Date Range: 23/8/2015 – 09/05/2018]

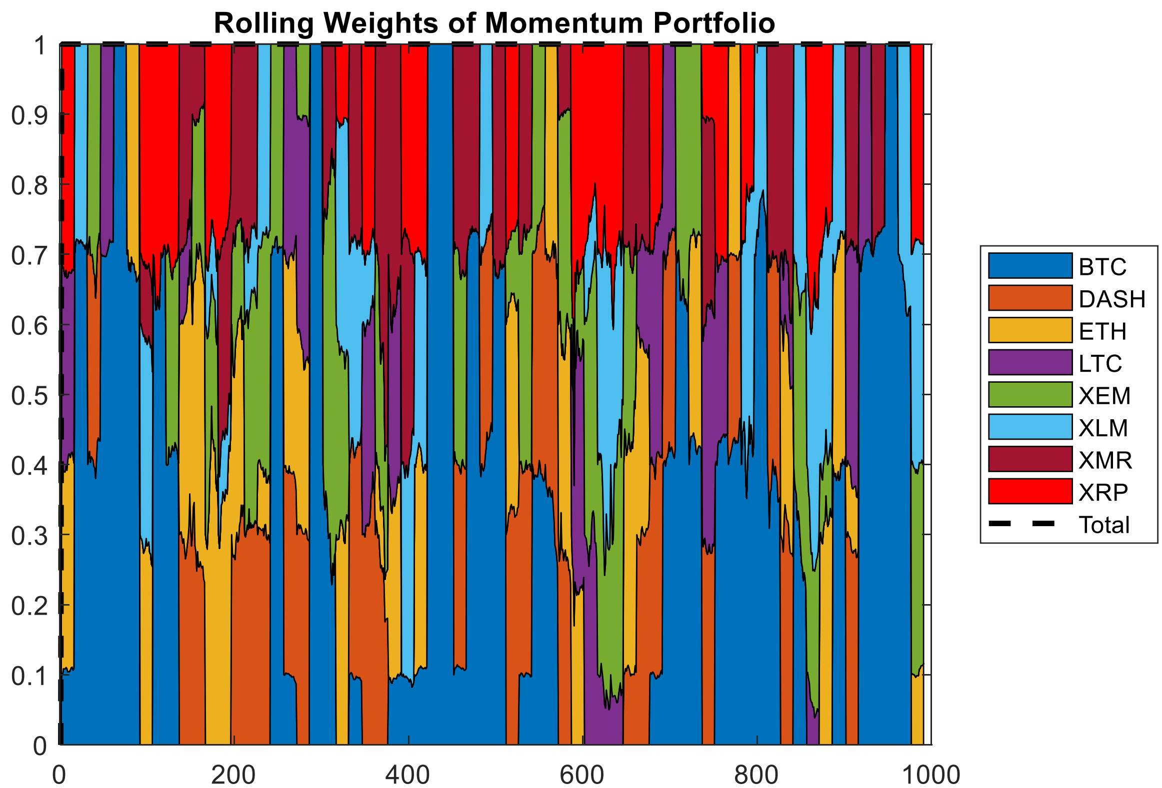
- *Higher Distance coefficients equate to lower correlation*

Graph 14 – Correlation Matrix

1. BTC; 2. DASH; 3. ETH; 4.LTC; 5.XEM; 6.XLM; 7.XMR; 8.XRP

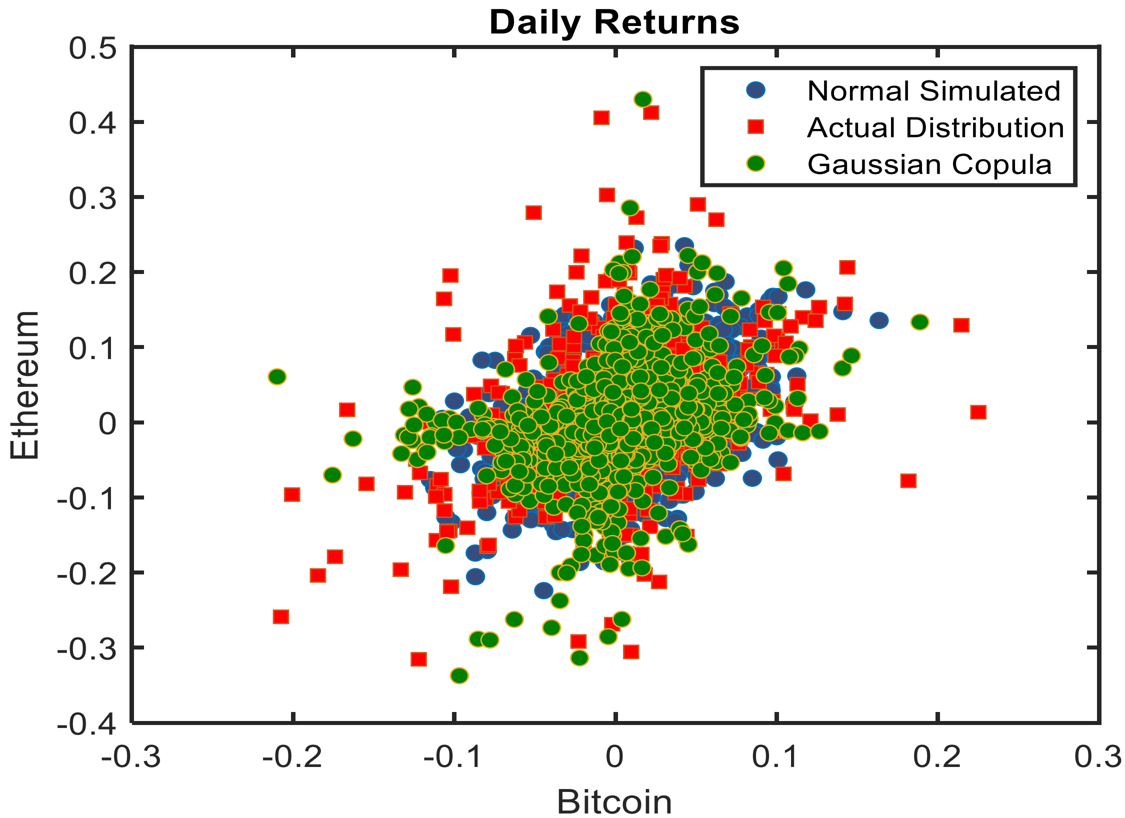
Graph 12

-



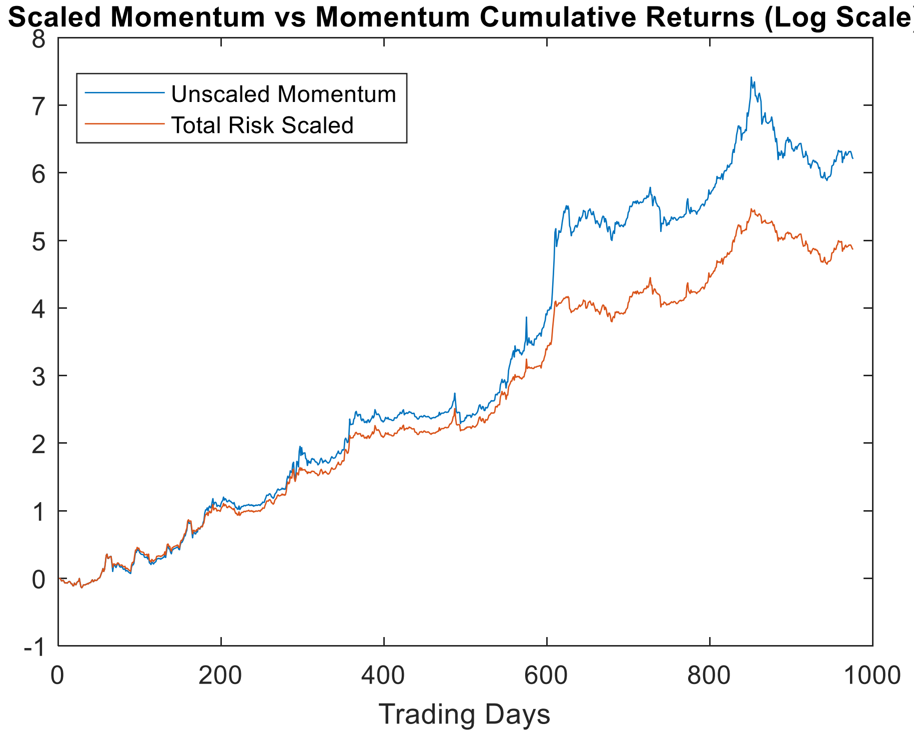
- *Daily weights of individual cryptocurrencies in the momentum portfolio from 23/8/2015 till 9/5/2018 in total close to 1000 trading days. There have been a few instances where BTC has had a weight of 100%.*

Graph 3



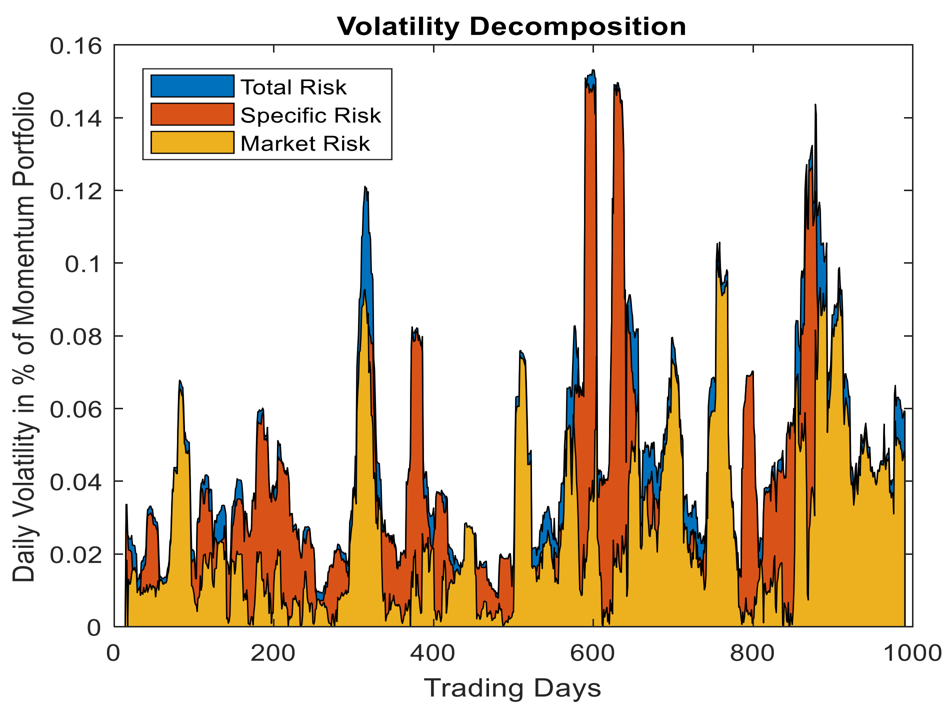
- *A sample draw of simulated returns of Bitcoin and Ethereum. Extreme Returns appear to be more strongly correlated in the actual and Gaussian copula distributions.*

Graph 7.



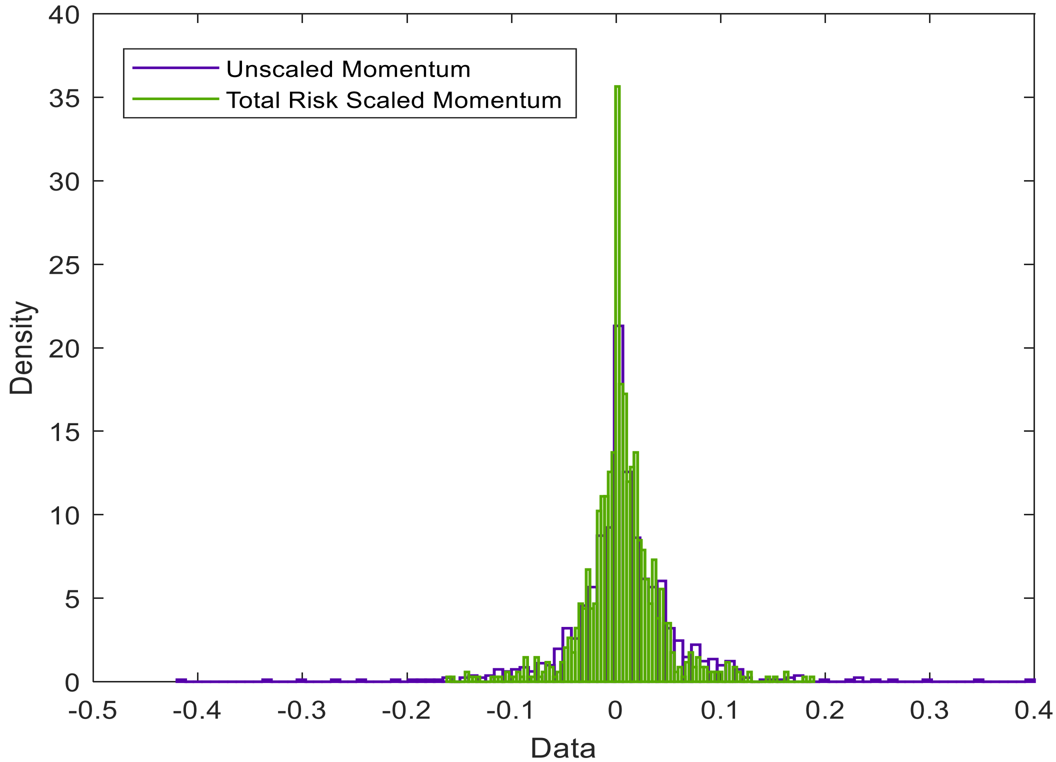
- *Risk scaled portfolio has a superior Sharpe Ratio and lower drawdowns in the back-test.*

Graph 8



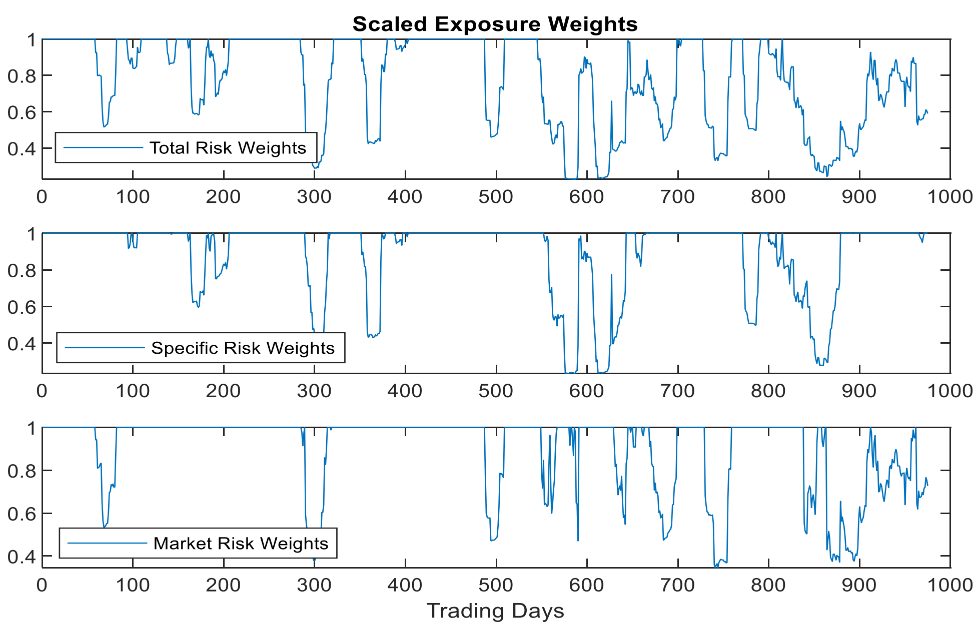
- *15 day rolling volatility of the momentum factor and decomposed market and specific risks as per Equation 8. 15 day rolling total volatility varies from 2% to 14% per day.*

Graph 10



- *Return distributions of the scaled momentum vs unscaled momentum. Not surprisingly, the scaled portfolio has thinner tails as the exposure varies between 20% and 100%.*

Graph 11



Appendix I – MATLAB Code for Calculations

```
clear
clc
```

Portfolio Optimization & Efficient Frontier Resampling

Version 1 - June 2018 - Uday Vikram Gates

```
short   = 0; % 1 = Shorting Allowed
x       = short; % For backtest function
go_1    = 1;% GVMP Unconstrained
go_2    = 0;% Efficient Portfolio with CML / Tangent Line
go_6    = 1;% Resampling Frontiers - Normal
go_6a   = 1; % Resampling Frontiers - Gaussian Copula
go_500  = 1; % Plotting T Frontier
go_10   = 1;% Plotting Frontiers (Main)
go_999  = 0; % Backtest Initialization (Check port function for parameters)
```

Initialization of Global Variables

```
load('crypto1.mat')
load('AssetList.mat')
load('constraints.mat')
AssetList   = AssetList';
CashMean    = 0.0;
nsam        = 15; % Rolling Window
noa         = 8;  % No.of Assets
nSim        = 20; %No. of Simulations for Resampling
Nports      = 20; %No. of Portfolio on Frontier
Target_ret  = 100; % Max Return or Score
Target_risk = 0.0; % Min Vol
if short == 1 % Shorting Allowed (Market Neutral)
    ub      = 0.30; % Upper Bound
    lb      = -ub; % Lower Bound
    lbudget = 0; % Lower Budget
    ubudget = 0; % Upper Budget
elseif short == 0 % Shorting Not Allowed
    lb      = 0.0; % Lower Bound
    ub      = 0.30; % Upper Bound
    lbudget = 1; % Lower Budget
    ubudget = 1; % Upper Budget
end
BuyCost     = 0.00000;
SellCost    = 0.00000;
timeframe   = 'd';
```

Initial Variable Set-up

```
if timeframe == 'm'
t = 12;
elseif timeframe == 'w'
t = 52;
```

```
elseif timeframe =='d'
t = 365;
end
wreturns = price2ret(input);
% Checking for Normality - Kolmorgov - Smirnoff Test
for n = 1:noa
    h(:,n) = kstest(wreturns(:,n));
end
wmean    = mean(wreturns);
wcov     = cov(wreturns,1);
cor      = corrcov(wcov);
wstd     = std(wreturns);
```

Global Minimum Variance Portfolio (Unconstrained) - Merton

```
if go_1 == 1
S        = cov(wreturns);
m        = mean(wreturns)';
%Calculation of GMV-weights
iota     = ones(size(S,1),1);
wts11    = (inv(S)*iota)/(iota'*inv(S)*iota);
gvmpmean = m'*wts11;
gvmpstd  = sqrt(wts11'*S*wts11);
end
```

Adding Parameters & Constraints - Portfolio Object

```
P1              = Portfolio;
P1              = Portfolio('AssetList', AssetList, 'RiskFreeRate', CashMean);
P1              = setSolver(P1, 'quadprog'); %P1 = setSolver(P1, 'lcprog');
P1.NumAssets    = noa;
P1.LowerBudget  = lbudget; % Min Exposure
P1.UpperBudget  = ubudget; % Max Exposure
P1              = setOneWayTurnover(P1, 1, 1, 0); % Long Only Portfolios
% Individual Constraints
P1.LowerBound   = [0,0,0,0,0,0,0,0];
P1.UpperBound   = [1,0.3,0.3,0.3,0.3,0.3,0.3,0.3];
% Input Variables in Optimizer
n   = size(input);
P1  = setAssetMoments(P1, wmean, wcov);
```

Efficient Frontier with Tangent Line

```
if go_2 == 1
P1      = setBudget(P1, 0, 1);
qwgt    = estimateFrontier(P1, Nports);
[qrsk, qret] = estimatePortMoments(P1, qwgt);
end
```

Frontier with Constraints - Gross

```
pwgt         = estimateFrontier(P1,Nports);
[prsk, pret] = estimatePortMoments(P1, pwgt);
```

Efficient Frontier with Transaction Costs - Net

```
P1           = setCosts(P1, BuyCost, SellCost);
qwgt         = estimateFrontier(P1, Nports);
[qrsk, qret] = estimatePortMoments(P1, qwgt);
qwgt         = qwgt'; % In the same format as wRes
```

Target Portfolios - Max Sharpe, Risk or Return

```
awgt         = estimateFrontierByRisk(P1, Target_risk);
[arsk, aret] = estimatePortMoments(P1, awgt);
bwgt         = estimateMaxSharpeRatio(P1);
[brsk, bret] = estimatePortMoments(P1, bwgt);
cwgt         = estimateFrontierByReturn(P1, Target_ret);
[crsk, cret] = estimatePortMoments(P1, cwgt);
```

Resampling Frontier with Constraints - Multivariate Normal

```
if go_6 == 1
    for i = 1:nSim % 20 Simulations
        SimRets = mvnrnd(wmean,wcov,length(wreturns)); % Simulating Returns using Multivariate
        wmeani  = mean(SimRets);
        Sigmai  = cov(SimRets);
        Rs = linspace(max(min(wmeani),0), max(wmeani),Nports); % Lowest (L) to Higher (L) Return
        P1 = setAssetMoments(P1, wmeani, Sigmai);
        for m = 1:length(Rs)
        dwgt = estimateFrontierByReturn(P1, Rs(m)); % Estimating portfolios from L to H return
        [drsk, dret] = estimatePortMoments(P1, dwgt);
        Drsk(i,m) = drsk; % Storing Risk, Return and Weights per portfolio on the frontier
        Dret(i,m) = dret;
        Dwgt(i,m,:) = dwgt;
        end
    end
% Averaging Weights to construct resampled frontier
wRes = reshape(mean(Dwgt),Nports,noa);
for i = 1:Nports
    SigR(i)   = sqrt(wRes(i,:)*wcov*wRes(i,:)'); % Original Co-Variance Matrix
    MuR(i)    = wmean*wRes(i,:)';                % Original Mean Estimates
end
Re_wts = wRes';
Re_portfolios = [MuR;SigR;Re_wts];
% Choosen Resampled Portfolio - MVP
Re_wts = Re_portfolios(3:end,1);
end
```

Resampling Frontier with Constraints - Gaussian Copula

```
if go_6a == 1
    %[rho] = copulafit('Gaussian',wreturns);
    for i = 1:nSim
        if go_500 == 1
            r_G = copularnd('Gaussian',cor,length(wreturns));
            for o = 1:noa
            SimRetsx(:,o) = ksdensity(wreturns(:,o),r_G(:,o),'function','icdf'); % Converting to
returns
            end
        end
        wmeanix = mean(SimRetsx);
        Sigmaix = cov(SimRetsx);
        Rsx = linspace(max(min(wmeanix),0), max(wmeanix),Nports);
        P1 = setCosts(P1, BuyCost, SellCost);
        P1 = setAssetMoments(P1, wmeanix, Sigmaix);
        for m = 1:length(Rsx)
        dwgtx = estimateFrontierByReturn(P1, Rsx(m));
        [drskx, dretx] = estimatePortMoments(P1, dwgtx);
        Drskx(i,m) = drskx;
        Dretx(i,m) = dretx;
        Dwgtx(i,m,:) = dwgtx;
        end
    end
% Averaging Weights to construct resampled frontier
wResx = reshape(mean(Dwgtx),Nports,noa);
for i = 1:Nports
    SigRx(i)    = sqrt(wResx(i,:)*wcov*wResx(i,:)');
    MuRx(i)     = wmean*wResx(i,:)';
end
Re_wtsx = wResx';
Re_portfoliosx = [MuRx;SigRx;Re_wtsx];
% Choosen Resampled Portfolio - Lowest Return on Efficient Frontier and SR
Re_wtsx = Re_portfoliosx(3:end,1);
end
```

Adding all Portfolios in Matrix (MERTON GVMP - TARGET - SHARPE)

```
out_ret = [gvmpmean,aret,bret,cret];
out_rsk = [gvmpstd,arsk,brsk,crsk];
out_wts = [wts11,awgt,bwgt,cwgt];
out     = [out_ret;out_rsk;out_wts];
% Adding Resampled (GVMP & MAX SHARPE) Portfolios to Output
out = [out,Re_portfolios(:,1),Re_portfoliosx(:,1)]; % Manual Identification
% risk contributions
risk_mctr = (wcov*awgt)./(arsk);
risk_tctr = risk_mctr.*awgt;
% percentage risk contribution
Risk_Cont = risk_tctr./arsk;
```

All Portfolio Weights - Comparing Resampled GVMP to Sample GVMP

```
port_wts = out(3:end,:);% Excluding Merton GVMP
figure(10)
subplot(1,3,1)
bar(port_wts(:,2)); % GVMP Sample Set
subplot(1,3,2)
bar(port_wts(:,6)); % GVMP MVN Simulated
subplot(1,3,3)
bar(port_wts(:,7)); % GVMP Gaussian Copula Simulated
hold on
```

Distribution & Correlation Analysis

```
    BTC_Act     = wreturns(:,1); % Original Distribution
    BTC_Normal  = SimRets(:,1);  % Multivariate Normal Simulation
    BTC_T       = SimRetsx(:,1); % Gaussian Copula Simulation
    ETH_Act     = wreturns(:,3);
    ETH_Normal  = SimRets(:,3);
    ETH_T       = SimRetsx(:,3);
    figure(10001)
    createFit(BTC_Act,BTC_Normal,BTC_T);
    set(gca,'Box','on','LineWidth', 1.5, 'FontSize',12')
    title('Distributions')
    figure(10000)
    createprobfit(BTC_Act,BTC_Normal,BTC_T);
    set(gca,'Box','on','LineWidth', 1.5, 'FontSize',12')
    title('Probability Plots')
% Correlation Comparisions
    figure(333)
scatter(BTC_Normal,ETH_Normal,'DisplayName','Normal Simulated',...
    'MarkerFaceColor',[0.203921571373940 0.301960796117783 0.494117647409439]);
hold on
scatter(BTC_Act,ETH_Act,'DisplayName','Actual Distribution',...
    'MarkerFaceColor',[1 0 0],...
    'Marker','square');
hold on
scatter(BTC_T,ETH_T,'DisplayName','Gaussian Copula',...
    'MarkerFaceColor',[0 0.498039215803146 0]);
hold on
set(gca,'Box','on','LineWidth', 1.5, 'FontSize',12')
legend('Normal Simulated','Actual Distribution','Gaussian Copula')
ylabel('Ethereum')
xlabel('Bitcoin')
title('Daily Returns')
```

Plotting Frontiers

```
if go_10 == 1
figure(1)
subplot(1,3,1)
area(qwgt)
```

```
title('Markowitz Weights');
set(get(gcf,'Children'),'YLim',[0 1]);
xlabel('Portfolio')
ylabel('Asset Weight')
subplot(1,3,2)
area(wRes)
title('Resampled Weights - Normal');
set(get(gcf,'Children'),'YLim',[0 1]);
xlabel('Portfolio')
ylabel('Asset Weight')
if go_500 == 1
    subplot(1,3,3)
    area(wResx)
    title('Resampled Weights - Gaussian Copula');
    set(get(gcf,'Children'),'YLim',[0 1]);
    xlabel('Portfolio')
    ylabel('Asset Weight')
end

figure(2)
subplot(1,2,1)
for k = 1:nSim
    color = rand(1,3);
    plot(Drsk(k,:)*100,Dret(k,:)*100,'Color',color)
    hold on
end
set(gca,'Box','on','LineWidth', 1.5, 'FontSize',12')
title('Resampled Frontiers - Normal')
ylabel('Daily Return in %')
xlabel('Daily Volatility in %')
subplot(1,2,2)
for u = 1:nSim
    color = rand(1,3);
    plot(Drskx(u,:)*100,Dretx(u,:)*100,'Color',color)
    hold on
end
set(gca,'Box','on','LineWidth', 1.5, 'FontSize',12')
title('Resampled Frontiers - Gaussian Copula')
ylabel('Daily Return in %')
xlabel('Daily Volatility in %')

figure(20)
hold on
plot(prsk*100,pret*100,'m','LineWidth',1.5) % Gross
hold on
%plot(qrsk*100,qret*100,'r--','LineWidth',1.5) % Net
%hold on
plot(SigR*100,MuR*100,'b','LineWidth',1.5) % Resampled Normal
hold on
if go_500 == 1
    plot(SigRx*100,MuRx*100,'r','LineWidth',1.5) % Resampled G Copula
    hold on
end
    scatter(arsk*100, aret*100)% Target Risk
```

```
    hold on
    scatter(SigR(1,1)*100, MuR(1,1)*100)% Resampled MVN GVMP
    hold on
    scatter(brsk*100, bret*100)% Max Sharpe Portfolio
    hold on
    scatter(SigRx(1,1)*100, MuRx(1,1)*100)% Resampled Copula GVMP
    hold on
set(gca,'Box','on','LineWidth', 1.5, 'FontSize',12')
grid on
ylabel('Daily Return in %')
if go_500 == 1
legend('Original Frontier','Simulated-Normal','Simulated-Copula','MVP','Normal-MVP','Max
Sharpe','Copula-MVP')
    else if go_500 == 0
legend('Gross','Resampled','GVMP','Merton-GVMP','Resampled-GVMP','Max Sharpe','Risk Parity')
    end
title('Mean-Variance Efficient Frontier')
xlabel('Daily Volatility in %')
end
end
```

Score/Strategy Developer within Efficient Frontier Framework & Backtester

```
clear
clc
```

```
load('crypto1.mat')
load('AssetList.mat')
load('constraints.mat')
AssetList = AssetList';
CashMean  = 0.0;
input     = input(1:end,:);
nsam      = 15; % Rolling Window for Rebalancing
roll      = 15; % Rolling Window for Score
noa       = 8;
wts       = [];
score     = [];
nSim      = 20; %No. of Simulations for Resampling
Nports    = 100; %No. of Portfolio on Frontier
Target_ret   = 100; % Max Return or Score
Target_risk  = 0.0; % Min Vol
short     = 1;
x         = short;
if short == 1 % Shorting Allowed (Market Neutral)
    ub      = 0.35; % Upper Bound
    lb      = -ub; % Lower Bound
    lbudget = 1; % Lower Budget
    ubudget = 1; % Upper Budget
elseif short == 0 % Shorting Not Allowed
    lb      = 0.0; % Lower Bound
    ub      = 0.35; % Upper Bound
    lbudget = 1; % Lower Budget
    ubudget = 1; % Upper Budget
```

```
end
BuyCost      = 0.00000;
SellCost     = 0.00000;
timeframe    = 'd';
```

Return & Score Calculations

```
wreturns = price2ret(input);
wcov     = cov(wreturns);
for i = 1:length(input)-roll
   ret(i+roll,:)        = (input(i+roll,:)./input(i,:))-1;
   stdd(i+roll,:)       = std(wreturns(i:i+roll-1,:));
   retrisk(i+roll,:)    = ret(i+roll,:)./stdd(i+roll,:);
   avg_ret(i+roll,:)    = mean(ret(i+roll,:));
   avg_std(i+roll,:)    = std(ret(i+roll,:));
   avgretrisk(i+roll,:) = avg_ret(i+roll,:)/avg_std(i+roll,:);
   t_score(i+roll,:)    = ((ret(i+roll,:)- avg_ret(i+roll,:))./avg_std(i+roll,1));
end
```

Adding Parameters & Constraints - Portfolio Object

```
wmean = (score(end,:)); % or m_score or mean(wreturns)
P1              = Portfolio;
P1              = Portfolio('AssetList', AssetList, 'RiskFreeRate', CashMean);
P1              = setSolver(P1, 'quadprog'); %P1 = setSolver(P1, 'lcprog');
P1.NumAssets    = noa;
P1.LowerBudget = lbudget; % Min Exposure
P1.UpperBudget = ubudget; % Max Exposure
P1              = setOneWayTurnover(P1, 1, 1, 0);
% Individual Constraints
P1.LowerBound  = [0,0,0,0,0,0,0,0];
P1.UpperBound  = [1.0,0.3,0.3,0.3,0.3,0.3,0.3,0.3];
n   = size(input);
P1  = setAssetMoments(P1, wmean, wcov);
qwgt           = estimateFrontier(P1, Nports);
[qrsk, qret]   = estimatePortMoments(P1, qwgt);
```

Target Portfolios - Max Sharpe, Risk or Return

```
awgt         = estimateFrontierByRisk(P1, Target_risk);
[arsk, aret] = estimatePortMoments(P1, awgt);
bwgt         = estimateMaxSharpeRatio(P1);
[brsk, bret] = estimatePortMoments(P1, bwgt);
cwgt         = estimateFrontierByReturn(P1, Target_ret);
[crsk, cret] = estimatePortMoments(P1, cwgt);
```

Plotting Frontiers & Portfolios

```
figure(20)
hold on
subplot(1,3,1)
```

```
plot(qrsk*100,qret*100,'r--','LineWidth',1.5) % Net
hold on
    scatter(brsk*100, bret*100)%, {sprintf('Sharpe')})
    hold on
    scatter(crsk*100, cret*100)%, {sprintf('Max Return')})
    hold on
set(gca,'Box','on','LineWidth', 1.5, 'FontSize',12')
grid on
legend('Score Frontier','Max Efficient Score','Max Score')
title('Score-Variance Efficient Frontier')
xlabel('Daily Volatility in %')
subplot(1,3,2)
bar(cwgt);
hold on
set(gca,'Box','on','LineWidth', 1.5, 'FontSize',12')
grid on
title('Max Score Weights')
subplot(1,3,3)
bar(bwgt);
set(gca,'Box','on','LineWidth', 1.5, 'FontSize',12')
grid on
title('Efficient Score Weights')
xlabel('Weights %')
```

Backtesting

```
score = score;
[pr_output,wtsx,f_index,tree,f_cv,char,B_wts,beta] =
s_1(input,wts,timeframe,noa,nsam,score,AssetList,x);
bm1 = pr_output(:,1);
bm2 = pr_output(:,3);
rollwts(B_wts(:,1:noa),x);
ts_cv = pr_output(:,end);
```

Plotting Cumulative Values

```
figure100 = figure;
axes1 = axes('Parent',figure100);
hold(axes1,'on');
plot1 = plot(log(pr_output(:,1:9)),'Parent',axes1);
set(plot1(1),'LineWidth',2);
set(plot1(3),'LineWidth',2);
set(plot1(end),'LineWidth',2);
box(axes1,'on');
```

Asset Moments - Portfolio + Assets

```
[char,beta,z1,areturns,cv,cor,wreturns] = rrprofile1(pr_output,timeframe,bm1,bm2);
```

Volatility Targeting - Benchmark Returns, Unscaled & Scaled Portfolios

```
Tgt_vol = 0.035; % Target Vol per T (Day)
window  = 15;
ports   = [pr_output(:,1),pr_output(:,end)];
[A_1,t_wts,m_beta] = reg_func(ports,Tgt_vol,window);% t_wts for scaling last portfolio or live
portfolio
```

Asset Moments - Scaled Portfolio + Assets

```
bm1r = A_1(:,1);
bm2r = A_1(:,1);
[char_scale] = rrprofile1(A_1,timeframe,bm1r,bm2r);
```

function [A_1,t_wts,m_beta] = reg_func(input,x,nsam)

Scaling Momentum Portfolios

```
    mkt_returns = price2ret(input(1:end,1)); % Benchmark Returns
    wreturns    = price2ret(input(1:end,2)); % Strategy Returns

% Initializing Variables
mkt_returns = [ones(size(mkt_returns)),mkt_returns]; % Adding Ones in Col. 1
[t,noa]     = size(wreturns);
nsam        = nsam; % Rolling Window
tgt_vol     = x; % Set Target Volatility Per Day
% Rolling Returns & Vol of Momentum Factor Returns
%t_ret = input(nsam:end,:)./input(1:end-(nsam-1),:)-1; % NSAM rolling window returns
for j = 1:noa
for i = nsam:t
    t_var(i,j)   = (var(wreturns(i-(nsam-1):i,j))); % Total Variance
    mkt_var(i,j) = (var(mkt_returns(i-(nsam-1):i,j+1))); % Market Variance
    z(i,j)       = (corr(wreturns(i-(nsam-1):i,j),mkt_returns(i-(nsam-1):i,j+1)));% Correlation
    m_beta(i,j)  = z(i,j).*(sqrt(t_var(i,j))./sqrt(mkt_var(i,j))); % Beta Calculation I
    m_betay(i,j) = regress(wreturns(i-(nsam-1):i,j),mkt_returns(i-(nsam-1):i,j+1)); % Beta
Calculation II
    m_var(i,j)   = (m_beta(i,j)^2*mkt_var(i,j)); % Market Variance (Momentum)
    s_var(i,j)   = t_var(i,j) - m_var(i,j); % Specific Variance
end
% Scaled Momentum Returns(One day lagged momentum returns * vol adjustment)
t_wts(:,j) = (tgt_vol./sqrt(t_var(nsam:end-1,j))); % Total Risk Scaled Weights
m_wts(:,j) = (tgt_vol./sqrt(m_var(nsam:end-1,j))); % Market Risk Scaled Weights
s_wts(:,j) = (tgt_vol./sqrt(s_var(nsam:end-1,j))); % Specific Risk Scaled Weights

% Initialize Max & Min Weights - Leverage
max = 1.0; % Max Exposure
min = 0.0; % Min Exposure
    t_wts(t_wts(:,:)>=max) = max;
    m_wts(m_wts(:,:)>=max) = max;
    s_wts(s_wts(:,:)>=max) = max;
    t_wts(t_wts(:,:)<=min) = min;
    m_wts(m_wts(:,:)<=min) = min;
    s_wts(s_wts(:,:)<=min) = min;
```

```
t_scaled(:,j) = t_wts(:,j).*wreturns(nsam+1:end,j); %Total Risk Scaled Returns
m_scaled(:,j) = m_wts(:,j).*wreturns(nsam+1:end,j); %Market Risk Scaled Returns
s_scaled(:,j) = s_wts(:,j).*wreturns(nsam+1:end,j); %Specific Risk Scaled Returns

cv(:,j)     = (ret2price(wreturns(nsam+1:end,j))); % Unscaled Momentum Cumulative Returns
cv_mkt(:,j) = (ret2price(mkt_returns(nsam+1:end,j+1))); % Market Excess Cumulative Returns
t_prc(:,j)  = (ret2price(t_scaled(:,j))); % Scaled by total risk cumulative returns
m_prc(:,j)  = (ret2price(m_scaled(:,j))); % Scaled by market risk cumulative returns
s_prc(:,j)  = (ret2price(s_scaled(:,j))); % Scaled by specific risk cumulative returns
end

b = [m_beta,m_betay(:,:)]; % Beta Check

% Plottings
    figure (1) % Volatility
    area(sqrt(t_var),'DisplayName','Total Risk');hold on;
    area(sqrt(s_var),'DisplayName','Specific Risk');
    area(sqrt(m_var),'DisplayName','Market Risk');hold off;
    legend('show')

    figure (2) % Scaled Weights
    subplot(3,1,1);plot(t_wts,'DisplayName','Total Risk Weights');hold on;
    legend('show')
    subplot(3,1,2);plot(s_wts,'DisplayName','Specific Risk Weights');
    legend('show')
    subplot(3,1,3);plot(m_wts,'DisplayName','Market Risk Weights');hold off;
    legend('show')

    figure(3) % Distribution of Returns
    pd1 = createFit2(wreturns,t_scaled,s_scaled,m_scaled);

    figure(4) % Cumulative Returns
    plot(log(cv),'DisplayName','Unscaled Momentum');hold on;
    %plot(log(s_prc),'DisplayName','Specific Risk');
    hold on;plot(log(t_prc),'DisplayName','Total Risk Scaled');
    %plot(log(m_prc),'DisplayName','Market Risk');
    %plot(log(cv_mkt),'DisplayName','BTC Returns');hold off;
    legend('show')
    A_1 = [cv_mkt(:,1),cv(:,1),t_prc(:,1),s_prc(:,1),m_prc(:,1)]; % Single Asset

    end
```

Asset Moments & Time Series Analysis

```
function [char,beta,z1,areturns,cv,cor,wreturns,mean_corr] =
rrprofile1(input,timeframe,benchmark1,benchmark2)
 if timeframe == 'm'
t = 12;
elseif timeframe == 'w'
t = 52;
elseif timeframe =='d'
t = 360;
end
```

```
n = size(input);
noa = n(1,2);
load('assetmoments.mat')
% Weekly data points to normalize all markets points
wreturns  = price2ret(input);
wmean     = mean(wreturns);
bmarkret1 = price2ret(benchmark1);
bmarkret2 = price2ret(benchmark2);
% Normalizing Values to 100;
cv      = ret2price(wreturns);
wcov    = cov(wreturns);
cor     = corrcov(wcov);
wstd    = std(wreturns)*sqrt(t); % Annualized Vol
wstd_n  = std(wreturns);
skew    = (skewness(wreturns));
kurt    = (kurtosis(wreturns));
% CAGR Return
pv   = 1;
time = length(cv);
cagr = ((cv(end,:)/pv).^(t/time)) - 1;
cret = cv(end,:)./pv-1;

% 1Y Rolling Returns
if n(:,1)>t
    areturns = cv(t:end,:)./cv(1:end-(t-1),:)-1;
    amean    = mean(areturns(1:end,:));
    astd     = std(areturns(1:end,:));
    amax     = max(areturns(1:end,:));
    amin     = min(areturns(1:end,:));
end

% Return to Risk
sr      = (sharpe(wreturns,0)*sqrt(t));
sort    = (wmean - 0)./ sqrt(lpm(wreturns, 0, 2))*sqrt(t);
Omega   = lpm(-wreturns, -0, 1) ./ lpm(wreturns, 0, 1);

% Pre allocate to VaR
% VAR Historical Basis Original Data Frequency - Daily / Weekly
for i = 1:noa
    wVaR_Hist(1,i) = computeHistoricalVaR(wreturns(:,i),[0.99]);
    Tail(1,i)      = computeHistoricalVaR(wreturns(:,i),[0.05])./-
computeHistoricalVaR(wreturns(:,i),[0.95]);
    aVaR_Hist(1,i) = computeHistoricalVaR(areturns(:,i),[0.99]);
    [MaxDD(:,i), MaxDDIndex(:,i)] = maxdrawdown(input(:,i));
end
MaxDD = MaxDD.*-1;
DD_p  = (MaxDDIndex(2,:) - MaxDDIndex(1,:))./t;

% Correlation with two benchmarks
nassets     = size(wreturns(1,1:end)); % finding no. of assets in input
for i       = 1:nassets(1,2)
corr1       = corrcoef(wreturns(1:end,i),bmarkret1(1:end,1));
wcorr1(i)   = corr1(1,2);
end
```

```
for i        = 1:nassets(1,2)
corr2        = corrcoef(wreturns(1:end,i),bmarkret2(1:end,1));
wcorr2(i)    = corr2(1,2);
end

% Output
char =
[cret;cagr;wstd;amean;astd;skew;kurt;sr;sort;Omega;Tail;wVaR_Hist;MaxDD;DD_p;MaxDDIndex;wcorr1;wc
orr2];

% Rolling Correlations
 n_corr = size(wreturns(1:end,:));
 z = zeros(n_corr);
 t = 90;
 for i = t:n_corr
z(i,:) = (corr(wreturns(i-(t-1):i,1:end),bmarkret1(i-(t-1):i,1)));
vol1(i,:) = std(wreturns(i-(t-1):i,1:end));
vol2(i,:) = std(bmarkret1(i-(t-1):i,1:end));
mean_corr(i,:) = mean(mean(corr(wreturns(i-(t-1):i,1:end))));
 end
 z1   = z(t:end,:);
 vol1 = vol1(t:end,:);
 vol2 = vol2(t:end,:);
 beta = z1(1:end,:).*(vol1(1:end,:)./vol2(1:end,:));
('XRP')
end
```

Graph Theory & Minimum Spanning Tree (Correlation to Distance)

```
clear
clc

load('crypto1.mat')
load('AssetList.mat')
%load('index.mat')
noa = size(input);
noa = noa(1,2);
```

Correlation & Distance Matrix

```
input = input(1:end,:);
r = price2ret(input);
sectorCorr = corr(r(:,:));
tx          = heatmap(sectorCorr);
sectorDist = sqrt(2*(1-sectorCorr));
figure (3)
heatmap(sectorDist);
sectorDist = (sectorDist + sectorDist.')/2;
```

Minimum Spanning Tree

```
G = graph(sectorDist);
T = minspantree(G);
%T.Nodes.Name = AssetList';
plot(T);
edgeWeights = T.Edges.Weight;
edgeWidths  = 3*edgeWeights/max(edgeWeights);
incidence   = centrality(T, 'degree');
closeness   = centrality(T, 'closeness', 'Cost', edgeWeights);
betweenness = centrality(T, 'betweenness', 'Cost', edgeWeights);
x = 0;
```

Rolling Correlations, Mean Correlation, Mean Distance & Central Node Ranks

```
wreturns = price2ret(input);
 n_corr = size(wreturns(1:end,:));
 z = zeros(n_corr);
 t = 90;
 for i = t:n_corr
     sCorr      = corr(wreturns(i-(t-1):i,1:end));
mean_corr(i,:) = mean(mean(corr(wreturns(i-(t-1):i,1:end))));
     Dist       = sqrt(2*1-sCorr);
mean_dist(i,:) = mean(mean(sqrt(2*(1-sCorr))));
     Dist       = (Dist + Dist.')/2;
     G          = graph(Dist);
     T          = minspantree(G);
     edgeWeights = T.Edges.Weight;
     edgeWidths  = 3*edgeWeights/max(edgeWeights);
 end
 plot(mean_corr)
 hold on
 plot(mean_dist)
 hold off
```

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Consolidated price data for the 8 cryptocurrencies in the portfolio:

https://drive.google.com/file/d/1EBqwz9MUPivyix3cb7zu1ObWVml1OVls/view?usp=sharing

Python notebook/code used to retrieve price data from https://coinmarketcap.com:

https://drive.google.com/open?id=1SCQWwWWrRL4Qd4Ae-UeMGTUUjTS6AiqZ