

Cryptocurrency: A New Investment Opportunity?

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Abstract

Bitcoin was the first cryptocurrency using blockchain and has been the market leader since the first bitcoin was mined in 2009. After the birth of bitcoin in the Genesis Block, more than 1000 altcoins and crypto-tokens have been created with at least 919 trading actively on unregulated or registered exchanges. This entire class of cryptocurrencies and tokens has been classified by some tax authorities as having the same status as commodities. If cryptocurrency is viewed in the same class as commodities, how different it is in terms of its risk and return structure? This paper sets out to help the readers to understand cryptocurrencies, and to explore the risk and return characteristics using a portfolio of cryptocurrency represented by the CRyptocurrency Index (CRIX). Substantial discussions are centred on bitcoin and its close variants. Some questions are raised about the potential of cryptocurrencies as an investment class. Results show that the correlations between the cryptocurrencies and traditional assets are low, and incorporation of CRIX index will improve the performance of the portfolio that consists mainly of mainstream assets. Sentiment analysis also indicates the CRIX index has a relatively high Sharpe ratio. While we may view the results with care, a new form of financing for cryptocurrency and blockchain start-ups is born. The disruption brought about by bitcoin may be felt beyond payments through what is known as Initial Crypto-Token Offering (ICO) or Initial Token Sales (ITS).

JEL Classification: G02, G10, G11, G12

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1 Introduction

The invention of bitcoin, along with its ingenious adoption of blockchain in 2009, has spurred the emergence of other altcoins using similar cryptography technology but employing different algorithms. Many of these altcoins were invented for different purposes or to address the pain points of bitcoin such as the high usage of energy caused by its Proof of Work consensus algorithm or the limit of coin supply to 21 million among others. As network effect weighs in, the prices of bitcoin and its variants have also risen in tandem. These innovations and perceived investment potential have led to the rapid growth of the number of altcoins and market size of cryptocurrency. According to CoinMarketCap , there are close to 787 cryptocurrencies currently trading around the world with a combined market capitalisation by circulating supply of US\$102.6 Billion and US\$1.9 Trillion by total supply as at end of June 2017. The price of bitcoin surged to US\$3,018.54 on 11 June, 2017. Many have argued that despite the payment utility, bitcoin and cryptocurrencies have no intrinsic value and may be a perfect vehicle for forming a bubble.

Even for those who believe that there is intrinsic value, when prices of cryptocurrencies are rising, there will be doubts about the prices running ahead of its value. Technologists will argue that its value is higher than Linus and lower than Internet - both are facilitators rather than an asset class that is worth much. Finance traditionalists will argue that it is just another form of value transfer that raises fund globally using cryptography and creates little value beyond that. To put it into perspective, with US\$40 billion and US\$100 billion market capitalisation for bitcoin and total cryptocurrency respectively, this investable class is minute compared to the size of US\$66.8 trillion and US\$48.2 trillion for listed equity and Gold respectively. Cryptocurrency is a subset of the class of digital currency (Lee [2015]) but it has become an important type of digital currency. Unlike other digital currencies that can be centrally issued, circulated within a community or geographical location, or tied to fiat currency or organisation issuing them, cryptocurrency has very different characteristics. The blockchain technology used by cryptocurrency such as bitcoin is an open distributed ledger that record transactions. It solves the double-spending problem and does not require a trusted third party. The decentralization allows

the blockchain technology to have increased capacity, better security, and faster settlement. Some of these features are at the top of the list of shortcomings that traditional financial systems need to improve on. As a result, blockchains and cryptocurrencies have become one of the most pressing topics in the financial industries. In this paper, we focus on the diversification role of cryptocurrencies and explore the possibility that it may generate new investment opportunities based on historical data.

We first evaluate the co-movement between traditional asset class and CRIX by studying their correlation coefficients. Results suggest a very low correlation between CRIX and traditional assets. This suggests that based on historical data, cryptocurrency as an asset class, would have been a good diversifier in a traditional portfolio. We then further conduct multivariate Dynamic Conditional Correlation (DCC) model to examine the dynamic co-movement as a robustness check. Consistent with our expectations, cryptocurrencies were considered a potentially better portfolio diversifier under DCC setting with the largest DCC of 0.24, a value between CRIX and Gold. Next, we investigate whether an inclusion of cryptocurrencies in a traditional portfolio will lead to additional benefits in terms of risk adjusted returns. Our empirical results show that CRIX not only expands the efficient frontier of an initial portfolio consisting of only traditional assets, but provides additional utility to investors, as evidenced by the spanning test in Table 9. However, it seems that cryptocurrencies may not lead to a large improvement in the utility of a mean-variance investor. There are various explanations. First, the current sample period of CRIX is too short to fully explore the investment opportunity of cryptocurrencies. Indeed, by using historical returns of bitcoin from 2010, we find a significant improvement for mean-variance investors with $P < 0.01$. Second, over the sample period, cryptocurrency market is too volatile with a daily maximum drawdown of 22%. Hence, it is important for investors to understand the return-risk structure of cryptocurrencies before investment commitment. In the paper, we conjecture that the high volatility of cryptocurrency is driven mainly by investor sentiment rather than an improvement in fundamentals. We are not arguing that there are no fundamentals, but rather, there has not been any meaningful interpretation using traditional fundamental analysis. It

is either that the old economy framework is not suitable for a new technology such as cryptocurrency, or that immeasurable fundamentals are proxied by sentiments of those who know more than the market.

We then propose an investor sentiment measure based on the past average returns for the cryptocurrency market. Our measure of investor sentiment reveals strong return reversal on the next trading day, suggesting rational investors explore the benefit of sentiment induced mispricing. To further explore the sentiment effect, we start by the Fama-MacBeth regression to examine the cross-sectional premium of investor sentiment using top 100 cryptocurrencies that are components of CRIX. After controlling trading volume and lagged return, Fama-MacBeth result suggests that for a certain cryptocurrency with 1% investor sentiment in excess of the average cryptocurrency sentiment, it tends to have 0.38% lower future return compared to the entire cryptocurrency portfolio. As a result, we identify potential profits from using daily trading strategies based on the investor sentiment. The strategy that buys low sentiment and sell high sentiment cryptocurrencies generates an annualized return of 12.39 with a Sharpe Ratio of 8.21. We also conduct two analyses to assess the robustness of our findings. Our sentiment strategy survives after assuming reasonable transaction costs from 1 bps to 10 bps per trade. The result is not sensitive to the selection of formation period of investor sentiment. The average annualized return remains more than 11 times with a T value larger than 15. Overall, our results provide some evidence of cryptocurrencies being a potential candidate as a new vehicle of investment opportunity.

The rest of the paper is organized as follows. Section 2 introduces the background of cryptocurrency market. Section 3 explains data, key variables and methodologies used in this paper. Section 4 presents empirical results on diversification role of cryptocurrencies and Section 5 explains sentiment impact on the cryptocurrency market with robustness check. Section 6 concludes.

2 Cryptocurrency

2.1 From centralization to decentralization

The major drawbacks of traditional fiat currency payment system are higher transaction fees with longer settlement period. These have led people to alternative currencies that allow for shorter peer-to-peer processing time without intermediaries, resulting in a thriving market for digital currencies that have lower settlement risk. Prior to the creation of cryptocurrencies, there were many other types of digital currencies. An notable example is a digital currency created by an institution and transacted on a platform. Such currencies can be loyalty points created by companies or digital coins created by Internet-based platforms. The institutions or legal entities control the creation, transaction, bookkeeping, verification of the digital currencies. In other words, these platform-based digital currencies are centralized. Notable example are the loyalty points of e-commerce companies like Rakuten and iHerb. These points function like cash on the platform. Q-coin introduced by the Chinese social platform Tencent can be bought using the fiat currency, Renminbi, and can be used to buy services at Tencent; World of Warcraft Gold is a game token that can only be earned through completing in-game activities and cannot be bought or exchanged into fiat currencies (Halaburda [2016]). Nevertheless, these centralized digital currencies are generally transacted within that platform as they are designed to support the business of the issuing institutions. It is difficult to use them as a substitute for the fiat money because these digital currencies are not legal tender. Therefore, the decentralized digital currencies seem a potential way out, where no central authority is needed to verify the transactions. But there are still many obstacles to overcome without an intermediary or a central authority. One main obstacle is the double-spending problem as it is possible to spend the same digital coin more than once. This problem has remained unsolved for a long time, discouraging the prevalence of such decentralized coins. To ensure every transaction is accurately reflected in the account balance for digital currencies to prevent double spending, there is a need for a trusted ledger without a central authority.

The first cryptocurrency, eCash, was a centralised system owned by DigiCash, Inc. and

later eCash Technologies. Although it was phased out since the late 1990s, the cryptographic protocols it employed to avoid double-spending and the blind signature it used to protect the privacy of the users served as a good inspiration for subsequent development. Shortly after the discovery of the cryptography protocols, digital gold currency became popular, among which the most used one was e-Gold. It is the first successful online micropayment system. It led to many innovations for making transactions easy and secure. But its failure to resolve the compliance issues finally resulted in its liquidation in 2008, despite the annual transaction volume of over US\$2 billion worth (Lam & Lee [2015]). The global financial crisis in 2008, coupled with the lack of confidence in the financial system, provoked great interest in cryptocurrency. A ground-breaking white paper was published online in 2008 by Satoshi Nakamoto. In the paper, this anonymous person or persons introduced a digital currency that is now widely known as bitcoin. It uses blockchain as the public ledger for all transactions and a scheme called Proof-of-Work (POW) to avoid the need of a trusted authority or central server to timestamp transactions (Nakamoto [2008]). As blockchain is an open and distributed ledger that records all transactions in a verifiable and permanent way, it solves the double-spending problem. Bitcoin has inspired a great many people and hundreds of cryptocurrencies have been created since then.

2.2 Bitcoin

Bitcoins can be obtained by accepting them as a payment for goods and services, and by buying from other people or directly from an exchange/vending machines. Bitcoins can be transacted via software, app or various online platforms that provide bitcoin wallets. Another way to obtain bitcoin is through mining and that is described below. The Bitcoin system runs on a peer-to-peer (P2P) network and transactions happen directly between users without intermediary. Bitcoin decentralizes the responsibilities of verifying the validity of transactions to the entire network. Transactions are recorded in the public ledger, blockchain, and verified by network nodes, which could be any individuals using computer system with Bitcoin software installed in it. Once users make a transfer, the transaction will be broadcast between users and confirmed by the network. Upon

verification, it will be recorded in blockchain and then the transfer is completed. The record-keeping process is referred to as mining and people offering the computing power to do so are called miners. Bitcoins are created as an incentive for solving the cryptography puzzle using the transaction data, and thus successful miners are rewarded with the newly created bitcoins, on top of transaction fees.

Each transaction contains inputs and outputs. An input has the reference to the output from the previous transaction, while the output of a transaction holds the receiving address and the corresponding amount (Nirupama & Lee [2015]). In general, in a transaction, a certain amount of bitcoins is sent from a bitcoin wallet to a specific address, provided that there is enough bitcoin balance in the wallet resulting from previous transactions. Transactions are not encrypted and can be viewed in the blockchain with corresponding bitcoin addresses. But the identity of the sender or receiver remains anonymous. Typically, bitcoin wallets have a private key or seed that is used to sign transactions. This secured piece of data provides a mathematical proof that the coins in the transaction come from the owner of the wallet. With the private key and the signature, the account can be only accessed by the owner and transactions cannot be altered by someone else.

Mining is also the process of adding newly verified transaction records to Bitcoins public ledger, blockchain. The records are grouped and stored in blocks. Each block contains a timestamp and a link to a previous block so that the blocks are chained together, and thus the name blockchain. The blocks are mined in sequence and once recorded, the data cannot be altered retroactively. Complete record of transactions can be found on the main chain. Each block on the chain is linked to the previous one, and can be traced all the way back to the very first one, which is called the genesis block. However, there are also blocks that are not part of the main chain, called detached or orphaned blocks¹. They can occur when more than one miner produce blocks at similar times or they can be caused by attackers attempt to reverse transactions. When separate blocks are validated concurrently, the algorithm will help maintain the main chain by

¹<https://blockchain.info/orphaned-blocks>

selecting the one with the highest value. There are several systems by which miners can earn rewards through the mining process. Bitcoin uses the Hashcash Proof-of-Work (PoW) system and the SHA-256 hashing algorithm. Under PoW system, rewards are given according to the number of blocks that are mined successfully. Therefore, mining is quite competitive, as the miner who first solves a given puzzle or gets the highest value will take all the rewarded newly created bitcoins, while the other miners will receive nothing. In addition, it usually involves large amount of computation and can be quite time-consuming and energy-consuming. So the rewards will encourage miners to take an active part in mining data blocks. Another commonly seen system is Proof-of-Stake (PoS). Unlike PoW, no additional work required under the PoS scheme, as the investors are rewarded based on the number of coins they hold. For example, a user holding 1% of the currency has the probability of mining 1% of that currency's PoS blocks (Nirupama & Lee [2015]). In general, this system does not require to input large amount of work for the computation. It provides for higher currency security, and it is usually used in combination with other systems, such as in the case of first cryptocurrency launched using PoS, Peercoin.

As shown in Figure 1, the current supply of bitcoins on the network is 16.3 million as of 6 May, 2017, with a total market capitalization of US\$ 25.1 billion².

[Insert Figure 1 here.]

As the supply of bitcoins are limited to 21 million, the bitcoin awarded to the successful miner for adding a block will be halved every 210,000 blocks (approximately every four years), according to the bitcoin protocol. When bitcoin was created in 2009, the reward amounted to 50 newly created bitcoins per block added to the blockchain, but the reward has been halved twice to 12.5 since 9 July, 2016 (Table 1).

[Insert Table 1 here.]

²<https://price.bitcoin.com/>

2.2.1 Features of bitcoin

Similar as conventional currencies that are traded digitally, bitcoin can also be used to buy things electronically. But unlike any fiat money or platform-based digital currencies, bitcoin is decentralized. In other words, there is no single group or institution that controls the Bitcoin network. Its supply is governed by an algorithm, and anyone can have access to it via the Internet.

Bitcoin wallets or bitcoin addresses can be easily set up online without any fees or regulations. Also, transactions are not location-specific, so bitcoins can be transferred among different countries seamlessly.

Every transaction will be broadcast to the entire network. Mining nodes or miners will validate the transactions, record them in the block they are creating, and then broadcast the completed block to other nodes. Records of all transactions are stored in blockchain, which is open and distributed, so every miner has a copy and can verify them.

The transactions are broadcast within a few seconds, and it takes about 10 minutes for the transaction to be verified by miners. So one can transfer the bitcoins anywhere in the world and the transactions will usually be completed minutes later.

No transaction fee is required to make a transfer, but the owner can opt to pay extra to facilitate a faster transaction. So far, miners have been incentivised mainly by the newly created coins but that is changing. As bitcoins in circulation gets close to its limit, transaction fees will eventually be the incentive for miners to carry out the costly verifying process.

2.3 Altcoin market

The source code of Bitcoin is open source and available on Github ³. Therefore, coders around the world are enlightened by the invention of Bitcoin and have created hundreds of cryptocurrencies, which are referred to as alternative cryptocurrencies, or altcoins. Bitcoin is not perfect and every pain point is an incentive to invent new coins. Coins are invented to address the issue of high computation cost of PoW, or to increase the number

³<https://github.com/bitcoin/bitcoin>

of transactions per second, or to increase the block size, or to ensure that the ledger is not as transparent, or to accommodate more efficient use of smart contracts and so on. Moreover, developers can raise fund for the project even before the cryptocurrency is launched to pay for development and launch expenses. In particular, Initial Coin Offering (ICO) or Initial Crypto-Token Offering or Initial Token Sales (ITS), has become a popular approach for projects based on blockchain and cryptocurrencies, which allows people to invest in the project by buying part of its cryptocurrency tokens in advance, typically based on a white paper or other documents of the project for investors to evaluate.

As of 27 June, 2017, 787 cryptocurrencies and 135 crypto-tokens have been launched and traded ⁴, with a total market capitalisation of over US\$98 Billion. Different from fiat money, cryptocurrencies have circulating supply, total supply and maximum supply. Maximum supply refers to the best approximation of the maximum amount of coins that will ever be created in the lifetime of the cryptocurrency, and total supply is the total number of coins existing now. But some of the coins have been burned, locked, reserved, or cannot be traded on the public market, so circulating supply is computed by deducting those coins from the total supply. When determining the market capitalization, circulating supply is used, for it denotes the amount of coins that are circulating in the market and accessible to the public. Details on cryptocurrency market value as of 27 June, 2017 are shown in Table 2. Top 15 performers in both market capitalization and monthly volume are selected. The results suggest that Bitcoin still dominates the market with more than half of the total market value and the highest price. Ethereum, Ripple and Litecoin also have large market capitalizations of more than US\$1 billion. Also, the supply of different coins varies a lot due to the unique characteristics of each coin, and some coins are not mined, suggesting a fixed amount of supply. Besides, the prices of the coins range from US\$0.002 to over US\$1000.

[Insert Table 2 here.]

In general, some altcoins are very similar to bitcoins, while others are created adopting

⁴<https://coinmarketcap.com/all/views/all/>

very different methods or ideas. Different categories of altcoins are summarized in Table 3 (Ong, Lee, Guo and Lee [2015]).

[Insert Table 3 here.]

Appcoins, such as MaidSafeCoin, function like digital shares in a Decentralized Autonomous Organization (DAO) and are sold in token sales for a portion of future profits. Most altcoins are direct copies of bitcoins, with some minor changes in the parameters such as block generating time and maximum limit of coin supply. But there are still many altcoins that have adopted other innovative changes. Out of the top 14 altcoins mentioned in Table 2, Ethereum is the coin with new ideas as it provides a decentralized Turing-complete virtual machine that features smart contract functionality, so do the other 4 altcoins that are launched based on Ethereum: Ethereum Classic, Golem, Augur and Gnosis. NEM falls under the third category as it is operated using JAVA programming, same as Nxt (Table 3). The rest are summarized in the Table 4, excluding Stellar Lumens and Factom as they are based on Ripple and Bitcoin protocols, respectively.

[Insert Table 4 here.]

Indeed, there are many other cryptocurrencies other than bitcoin that are traded actively with all kinds of features for investors to invest in.

2.4 Cryptocurrencies in the study

In this study, we choose the top 10 based on the times included in the CRIX index. Developed by the Ladislaus von Bortkiewicz Chair of Statistics at Humboldt University Berlin, Germany, the Sim Kee Boon Institute for Financial Economics (SKBI) at Singapore Management University and CoinGecko, the CRIX is realtime computed and monthly balanced using certain formulas which incorporate inputs such as market value and trading volume of the cryptocurrencies ⁵. Table 5 summarizes the 10 cryptocurrencies

⁵<http://crix.hu-berlin.de/#page-top>

used in this study.

[Insert Table 5 here.]

2.4.1 Bitcoin (BTC)

Bitcoin was created in 2009 by an anonymous person, or people, under the name of Satoshi Nakamoto. It has a maximum limit of 21 million and there are 16.4 million bitcoins in circulation as of June 2016. It is widely accepted as the most popular cryptocurrency and has the largest market capitalization.

2.4.2 Ethereum (XRP)

Ethereum is an open-source blockchain-based platform that runs Turing-complete smart contracts. The value token of the Ethereum blockchain is called ether. It was invented by Vitalik Buterin in 2013 and later on developed using the fund, US\$18 million worth of bitcoins, raised via an online public crowdsale of ether in 2014.

2.4.3 Litecoin (LTC)

Litecoin was released in October 2011 by Charles Lee, using a similar technology as Bitcoin. Compared to Bitcoin, the main differences are that the block generation time decreases from 10 minutes to 2.5 minutes per block, the maximum limit is 84 million for Litecoin, which is four times as many as that of Bitcoin, and adoption of different hashing algorithm.

2.4.4 Dash (DASH)

Dash (formerly known as XCoin and Darkcoin) was initially proposed in January 2014 by Evan Duffield, who is also the lead developer. Dash has released the Decentralized Governance by Blockchain System and it is the first decentralised autonomous organization. It is a privacy-centric cryptocurrency. It uses the coin-mixing service called PrivateSend to anonymize transactions and InstantSend to allow for instant transactions.

2.4.5 Dogecoin (DOGE)

The two creators of Dogecoin, Billy Markus and Jackson Palmer, hoped to create a fun cryptocurrency so that more people would appeal to it. Hence, they used the Shiba Inu dog from the Doge Internet meme as the logo and thus created Dogecoin in 2013. There is no limit of the number of Dogecoins to be produced. The transactions of Dogecoins are made on online communities such as Reddit and Twitter.

2.4.6 Monero (XMR)

Monero (originally named BitMonero) is another open-source privacy-centric altcoin created in 2014. It is a 100% Proof-of-Work cryptocurrency. The privacy of transactions is protected by the ring signatures (that hide the sending address), RingCT (that hides the amount of transactions) and stealth addresses (that hide the receiving address).

2.4.7 BitShares (BTS)

BitShares is an open-source public cryptocurrency platform that offers various of features invented by Daniel Larimer. It allows the users to issue and trade stocks or debts on the distributed ledger.

2.4.8 MaidSafeCoin (MAID)

MaidSafeCoin is designed for the SAFE (Secure Access For Everyone) network. The data of users and transactions are safe and secure. The network encourages users to provide their resource such as storage space, CPU and bandwidth by giving them the coins as a digital token. The maximum number of MaidSafeCoins in circulation is 4.3 billion.

2.4.9 Nxt (NXT)

Nxt was released in 2013 by an anonymous software developer BCNext. It is the first cryptocurrency that uses purely Proof-of-Stake for consensus and thus making the money supply static, 1 billion for the case of Nxt. The block generation rate is 1 minute per

block. Despite the additional risks, the complex core infrastructure of Nxt makes it a flexible platform as it is easier to build external services on top. For example, it allows for currency creation and has a messaging system and marketplace.

2.4.10 Bytecoin (BCN)

Bytecoin is the first cryptocurrency invented with the CryptoNote protocol. It secures the transactions as the identities of the sender, the receiver and the amount of transaction are all concealed. The number of Bytecoins is capped at 184.47 billion and the block generation time is 120 seconds per block.

2.4.11 Other cryptocurrencies

Besides the aforementioned ten cryptocurrencies, the following altcoins have been drawing investors attention.

2.4.12 Ethereum Classic (ETC)

Ethereum Classic is a continuation of Ethereum's original blockchain, so it is also an open-source, blockchain-based platform that supports Turing-complete smart contract. It is created after the hard-fork debate in 2016, and designed to allow smart contracts to run exactly as programmed without any possibility of third party interference.

2.4.13 Factom (FCT)

Launched in 2014, Factom is an open-source, distributed, and decentralized protocol built on top of Bitcoin. Instead of storing only financial transactions, Factom blockchain technology can record any type of data, making it an ideal platform for real-world business record-keeping system.

2.4.14 NEM (XEM)

NEM is a peer to peer-to-peer platform that provides services like payment and messaging system. It uses Proof of Importance algorithm, so it does not require a lot of computing

power and energy to mine. Together with Mijin, which is a licensed version of NEM, it is the first public/private blockchain combination.

2.4.15 Ripple (XRP)

Ripple was created by Chris Larsen and Jed McCaleb. It is one of the first cryptocurrencies that are not developed based on Bitcoins protocol. It is an open source, distributed peer-to-peer payment network, but it is centralized managed by the company. Any currencies, including the ripple digital currency and ad hoc currencies that have been created by users, can be transferred on the payment system. The maximum number of Ripple is 100 billion.

2.4.16 Zcash (ZEC)

Launched in 2016, Zcash provides privacy and selective transparency of transactions. While the transactions are recorded in the public blockchain, Zcash allows for completely transparent transactions using t-addresses, and it can also offer greater level of privacy to its users using z-addresses. It adopts zero-knowledge cryptography to protect the sender, amount, and recipient of a transaction using z-address. Same as bitcoin, the total amount of Zcash is capped at 21 million.

2.5 Cryptocurrencies and alternatives

Alternative investment is widely seen in the portfolio management nowadays and it includes commodities, hedge funds, real estate, private equity, hedge funds and others such as artworks. Typically, alternative investments have lower historical correlation to those conventional asset classes, such as stocks, bonds and cash equivalents, and thus providing good diversification to the portfolio.

Despite the debate on whether cryptocurrencies can become part of the mainstream financial system, billions of US dollars worth of them are being traded worldwide. To begin with, cryptocurrencies provide good liquidity and opportunities to invest in. For example, the global daily exchange traded volume of bitcoin averaged over US\$1 billion

in 2016, which indicates ample liquidity (Burniske & White [2017]). Moreover, researches on bitcoin show that the price of bitcoin does not fluctuate in the same direction as the marketplace, indicating low correlation of returns. Although some may argue that number of bitcoins to be generated is capped at 21 million and thus jeopardizing its investability such as gold with limited supply, we should keep in mind that there are many promising altcoins in place and the number is still growing. So cryptocurrencies as a whole can be a good alternative investment, especially in terms of bringing diversification to mainstream assets.

The valuation of cryptocurrencies, however, is very different from that of traditional instruments. Many cryptocurrencies like bitcoins have fixed supply, so the valuation of fiat money cannot be applied. Also, unlike equities or bonds, digital currencies generate no cash flow, making the discounted cash flow valuation inapplicable. Instead, cryptocurrency tokens are given to investors as a proof of future cash flow, payments, or potential future exchange, or the right to participate, vote, build blocks or purchase. On top of the future cryptocurrency benefits, the network effect of cryptocurrency may be a crucial factor in its valuation, for the associated technology and perceived value of the cryptocurrency by the public.

Next, we analyse the potentials of investing in cryptocurrencies.

3 Diversification Effects of Cryptocurrency

3.1 Data

We collect historical price and trading volume of cryptocurrency data from CoinGecko and data for other traditional asset class are all from Bloomberg. The whole sample period spans from 11 August, 2014 to 27 March, 2017.

Table 6 shows the summary statistics of log returns of cryptocurrencies and traditional asset class. Overall, cryptocurrencies outperform traditional asset class in terms of average daily return and that of Litecoin is the highest among all. The annualized return for CRIX Index is $0.0012 \times 252 = 0.30\%$, which is very high compared to the stock

market (0.12% suggested by Panel B). Meanwhile, CRIX tends to have a high return volatility compared to S&P 500, with a daily maximum drawdown of -22.64% and skewness of -1.04. This high volatility with a negative skewness suggests a high tail risk of the cryptocurrency market. However, a noteworthy fact is that many cryptocurrencies exhibit positive skewness, namely the returns increase fast but decrease slowly, indicating a good volatility to generate additional investment opportunities.

In the case of kurtosis, the return distribution of cryptocurrencies deviates from normal distribution a lot, which makes sense as the market is still developing. As for the 1 lag autocorrelation, denoted by Rho, majority of them are quite low, suggesting a lack of predictability (Fama [1970]).

[Insert Table 6 here.]

Moreover, cumulative returns of CRIX and traditional asset class are depicted in Figure 2. The return of CRIX index has been consistently higher than that of traditional investments since 2016 and the difference has surged over the past a few months. Although the returns of CRIX before 2016 are negative, while in general S&P 500 have positive returns for that period, it probably results from the fact that the cryptocurrency market was in a very early stage and the CRIX index was still developing.

[Insert Figure 2 here.]

3.2 Correlation analysis

Based on the correlation results in Table 7, almost all correlations are less than 0.1. For example, the correlation between CRIX index and S&P 500 index is 0.036. In fact, according to the first row, 7 out of the 11 classes have correlations that are less than 0.05 with the stock market (S&P 500). Even the highest correlation, 0.102 is still very small, and all cryptocurrencies are negatively correlated with some mainstream investment assets. The very low correlations reinforce the assertion that cryptocurrencies may be a

promising investment class in terms of hedging the risk of mainstream assets.

[Insert Table 7 here.]

The correlation test raises a question about whether the correlation from time to time varies much from the average correlation. To address it, we adopt the DCC model to further look at the dynamic correlations. We summarize the DCC between daily returns of traditional asset class and CRIX index in Table 8. Consistent with our expectation, cryptocurrencies still show good diversification potentials over the whole sample period with a maximum DCC of 0.24 (between CRIX and Gold). The persistence of low co-movement with mainstream assets suggests good investment opportunities in cryptocurrency as an alternative asset class.

[Insert Table 8 here.]

3.3 Portfolio analysis

Next, we examine the performance after adding CRIX index into a portfolio that consists of traditional assets such as S&P 500, private equity, REITs, and Gold. From efficient frontier in Figure 3, we can see the return and standard deviation of CRIX and six common investments. CRIX has the highest return and it is the only one that lies on the efficient frontier, while the return of Oil is the lowest with a relatively high level of risk.

According to transition map of a portfolio performance, S&P 500 and CRIX dominate the portfolio, while the other investments only contribute to the portfolio when the portfolio risk is low. Among all seven options, Oil seems to have the lowest contribution. Moreover, if a risk aversion investor is willing to tolerate above 3% daily volatility, transition map suggests investing more than 80% of initial wealth into CRIX.

[Insert Figure 3 here.]

Figure 4 plots the market efficient frontiers of mainstream portfolio with and without

F_2 -test with a p-value of 0, while Bitcoin rejects the test at the 5% level.

In general, although we can jointly reject the spanning test for CRIX, Bitcoin and most altcoins, the evidence is limited to the rejection of $\delta = 0_N$ but not to the rejection of $\alpha = 0_N$. It is safe to conclude that there is strong evidence that global minimum-variance portfolio can be improved by including CRIX and six out of the ten cryptocurrencies, but it is not true for the tangency portfolio. This is not surprising as CRIX shows negative skewness which may suggest an additional investment opportunity accompanied by a high risk. To have an improved portfolio performance, we need to understand risk-return structure of cryptocurrency market. Indeed, we argue that investor sentiment might be the driving force of cryptocurrency market with detailed discussion in the next section.

[Insert Table 9 here.]

4 Investor Sentiment and Cryptocurrency Market

Cryptocurrencies, unlike other alternative investment classes that have real assets, are digital assets and their fundamental value is hard to comprehend. As a result, we believe that the cryptocurrency market is mainly driven by investor sentiment, leading to a high volatility. Therefore, if we can capture the investor sentiment, it may reveal more information about the risk-return structure of cryptocurrency market, thus helping to explore investment opportunities. In this section, we propose a proxy of investors sentiment for each cryptocurrency and investigate its impact on cryptocurrency-based portfolio performance.

4.1 What is investor sentiment?

A widely accepted behavioural finance paper about investor sentiment is written by Baker and Wurgler [2006], who argue that market-wide sentiment should exert stronger impacts on stocks that are difficult to value and hard to arbitrage. The key point is that investor sentiment does not raise or lower all prices equally when sentiment based demands or

constraints vary across stocks. For example, small stocks and illiquid stocks are more likely to be overpriced during a high sentiment period compared to those large and liquid stocks since small (illiquid) stocks are hard to arbitrage due to transaction frictions. This will result in a lower future return of those stocks. In this case, buying large (liquid) stocks and short small (illiquid) stocks today will generate an arbitrage return in the future during a high sentiment period. On top of that, Huang, Jiang, Tu and Zhou [2015] modify the BW sentiment index by removing noise components of BW sentiment index and show a strong return predictability of PLS sentiment. Consistent with prediction of Baker and Wurgler [2006], a higher sentiment index predicts a lower future stock returns. The most related paper that motivates our empirical design is written by Stamburg, Yu and Yuan [2012], who explore sentiment-related overpricing as explanation for most popular 11 asset-pricing anomalies. Importantly, they consider impediments to short selling as the major obstacle to eliminating sentiment-driven mispricing. To some extent such mispricing exists, overpricing should then be more prevalent than underpricing, and overpricing should be more prevalent when market-wide sentiment is high. We agree with all investor sentiment stories documented in stock market and build tests on investor sentiment hypothesis in cryptocurrency market.

4.2 Hypothesis development

Different from above literature, we extend the prediction of market-wide investor sentiment to a firm level investor sentiment. There are two reasons of doing this. First, cryptocurrency market is new to investors and has its own features. In this case, we are lacking in necessary variables to mimic BW investor sentiment. For example, five of six key components of BW sentiment index, including close-end fund discount rate, number of IPO, first-day return of IPO, and dividend premium and equity share in new issues are not available for cryptocurrency market. Second, market-wide sentiment predictions rely on a clear classification of easy-to-arbitrage and hard-to-arbitrage groups. While for the cryptocurrency market, majority of cryptocurrencies are launched in recent years and their market size is also developing. To simply take their current market size as proxy

of transaction friction is not appropriate. As a result, we extend market-wide sentiment effect to individual cryptocurrency index. And our main hypothesis follows that:

Hypothesis 1. *Cryptocurrency with higher investor sentiment today tend to have lower future return than those with lower investor sentiment.*

Above hypothesis implies that the rational investors should come into the market to correct the mispricing or explore the benefit of sentiment induced mispricing. For those cryptocurrencies with high (low) investor sentiment tend to be overpriced so that rational investors will short (buy) those cryptocurrencies to earn abnormal return in the future. While the question is how fast rational investors adjust this mispricing. The adjusting process could take quite a long time due to transactions frictions. To answer this question, we first need to find proxy of investor sentiment for individual cryptocurrency.

4.3 Proxy of investor sentiment

In this section, we discuss two alternative ways to construct investor sentiment. In most recent studies on empirical finance, media news sentiment and overnight return are two popular measures of investor sentiment.

Tetlock [2007] quantitatively measures the interactions between the media and the stock market using daily content from a popular Wall Street Journal column. He finds that high media pessimism predicts lower future market prices followed by a reversion to fundamentals. A strong reversal of return predictability is consistent with theoretical models of noise and liquidity traders but inconsistent with theories of media content as a proxy for new information. In that paper, the author takes media sentiment as content of investor sentiment and emphasizes the return reversal as evidence of sentiment effect. On the contrary, Tetlock, Saar-Tsechansky and Macskassy [2008] point out that media news contains valuable information of firm fundamentals which are not priced by current market. In that paper, he finds those news articles containing earnings have better return predictability around earnings announcement day. Importantly, they find news tone significantly predicts actual earnings represented by SUE (Standard Unexpected Earnings).

This serves as an important evidence that media news contains valuable information about firm fundamentals. So overall, the real effect of media news is not well understood and hence, news tone may not be a clear measure of investor sentiment. Moreover, there is no sentiment dictionary or training sample for cryptocurrency market. In this case, we can only use sentiment dictionary that is designed for stock market as bag-of-words for sentiment classification. While many special words in cryptocurrency market, like Blockchain, Hash, POW, et. al. are not labeled in those general sentiment dictionary, including Loughran and McDonald dictionary (Loughran and McDonald [2011]) and Harvard IV4 dictionary. This gives media sentiment analysis a low accuracy. As a result, for the moment, media news sentiment is not a good proxy of investor sentiment for cryptocurrency market.

Another way to measure investor sentiment is over-night return, proposed by Berkman, Kock, Tuttle and Zhang [2012], which suggests that individuals tend to place orders outside of normal working hours, to be executed at the start of the next trading day. Specifically, Berkman et al. [2012] find that attention-generating events (high absolute returns or strong net buying by retail investors) on one day lead to higher demand by individual investors, concentrated near the open of the next trading day. This creates temporary price pressure at the open, resulting in elevated overnight returns that are reversed during the trading day. Consistent with this return pattern being driven by retail investor demand, Berkman et al. [2012] show that the one-day reversal is more pronounced for firms that are harder to value and more costly to arbitrage. While for cryptocurrency market, many cryptocurrencies are 24-hour traded and cryptocurrency exchanges are open on the weekends (Trimborn and Hrdle [2016]). In other words, there is no close-to-open price as proxy of investor sentiment.

Due to data limitation, after rejecting other alternative measures, such as order imbalance and put/call ratio, we take the past average return as proxy for investor sentiment. This measure is built on the spirit of Berkman et al. [2012]. The key point of using overnight return of the paper is that extreme events draw retail investors attention, thus inducing higher demand by individual investors. Since retail investors tend to be irra-

tional, which creates additional price pressure, resulting in sentiment effect. Given that argument is correct, we should expect retail investors to pay attention to those cryptocurrencies with extreme past returns they will simply buy (sell) those cryptocurrencies with high (low) past returns, driving price to deviate from rational expectation.

We expect that this could be a more direct measure of sentiment with a high (low) past return suggesting investors optimism (pessimism) about the underlying crypto. The point of average is to remove the noise components of individual daily return. The calculation of sentiment follows:

$$Sentiment_{j,t} = \frac{\sum_{n=0}^{N-1} Return_{j,t-n}}{N} \quad (4.1)$$

where $Return_{j,t-n}$ is return of cryptocurrency j at n days before the sentiment calculation day and N is the formation period investor sentiment. In the following analysis, we take N as 10 to smooth daily return. Indeed, our results are not sensitive to the selection of formation period with detail discussion in robustness check.

4.4 Empirical results

We first examine whether our measure captures sentiment effect. According to Berkman et al. [2012], sentiment induced overnight returns are reversed during the trading day since rational investors will adjust for the mispricing. If that is true, we expect a high (low) cryptocurrency sentiment indicates a low (high) subsequent cryptocurrency return. To examine this effect, we employ top 100 cryptocurrencies that have been counted into CRIX over the whole sample period. We first sort and categorize 100 cryptocurrencies into three groups (high, median and low sentiment groups) for each trading day. We then define an event day for a cryptocurrency j as high (low) sentiment event as the day cryptocurrency j is labelled in the high (low) sentiment group. And for each cryptocurrency, it could have multiple high (low) sentiment event days. Last, we compute individual cryptocurrency return preceding one week before their high (low) sentiment event and then plot the mean of their return with 95% confidence interval in Figure 5.

[Insert Figure 5 here.]

The 0 in X-axis stands for the sentiment event day. We separately examine the average cryptocurrencies returns of high and low sentiment groups. 95% confidence interval of average return for both high and low sentiment represented by the grey area. Figure 5 shows average return of high sentiment before the sentiment day is positive while that of low sentiment is negative, both of which are significantly different from 0, consistent with our construction of investor sentiment. Besides, on a high (low) sentiment event day, there is a spike (drop) in the cryptocurrency return, but it then reverses to a negative (positive) return in the next trading day, suggesting that rational investors come to correct the sentiment induced mispricing. Moreover, after the next trading day of event, cryptocurrency returns seem indifferent from 0, suggesting no over-adjustment or under-adjustment for the mispricing. Furthermore, this empirical evidence also answers the question we propose in the end of last section, namely how fast rational investors correct the mispricing. Inconsistent with our expectation, transaction frictions do not show strong impact on the adjustment process and rational investors react very fast in terms of sentiment induced overprice (underprice).

Next, we test the cross-sectional premium of sentiment using Fama-MacBeth regression. Regression results have been shown in Table 10. We have three different sample periods and two additional control variables. The first three columns use the whole sample period, namely from 11 August, 2014 to 27 March, 2017, the middle three columns present results of sample period before 2016 and the last three columns show results of period after 2016. The results shows results are quite consistent across different settings. For the overall sample period, if cryptocurrency j has sentiment that is 1% in excess of average cryptocurrency sentiment, it tends to have 0.38% lower future return compared to the overall cryptocurrency portfolio given other situations fixed.

[Insert Table 10 here.]

Based on the results, we further explore the possibility of generating positive risk-adjusted profits with incorporation of sentiment strategy. We form two equal-weighted portfolios based on each firm's sentiment, defined as the average return of past 10 trading days. All cryptocurrencies are labelled with sentiment in the top decile as short leg and sentiment in the bottom decile as the long leg for each trading day, t . We then hold both the long and short portfolios for one trading day and rebalance at the closing price of the next trading day. Figure 6 shows the cumulative returns of investment strategies based on sentiment in prior trading day with the sample period spanning from 11 August, 2014 to 27 March, 2017. Ignoring trading costs, the cumulative returns of the sentiment portfolio are over 20 times of initial investment after 2016, much higher than that of return rate of CRIX and the equal weighted portfolio based on top 100 cryptocurrencies.

[Insert Figure 6 here.]

To further study the cumulative returns of three groups of sentiment portfolios from high to low as shown in Figure 7, sentiment strategy is very successful in terms of classifying cryptocurrency returns into different patterns. Consistent with our expectation, portfolio of low sentiment has large positive returns while median sentiment group shows slightly negative cumulative return and high sentiment have large negative cumulative returns.

[Insert Figure 7 here.]

Figure 8 further depicts the distribution of the average monthly abnormal returns of the sentiment-based trading strategy. Each frequency bin encompasses a range of abnormal returns described by the two numbers adjacent to the bin. For example, the frequency of the leftmost return bin is the number of months in which the average monthly abnormal return of the trading strategy is between -20% and -10%. To adjust the returns for risk, we calculate daily abnormal return as stock returns minus CRIX index returns. This figure suggests that for most months, average abnormal return on the portfolio is

between 50% and 100%. Importantly, none of monthly return drops below 0, which suggests an extremely good arbitrage opportunity.

[Insert Figure 8 here.]

In order to examine the performance of the sentiment portfolio in a more comprehensive manner, we compare the results with other investment assets, including traditional investment tools (such as S&P 500, Gold and REITs) and other cryptocurrencies (such as the top 10 cryptocurrencies covered in previous section). We also adopt three measures to compute the risk-adjusted returns: daily Sharpe ratio, daily information ratio and daily maximum drawdown. For the information ratio, S&P 500 is used as the benchmark.

[Insert Table 11 here.]

As seen in Table 11, of all investment classes, the sentiment portfolio has the highest average return, as high as 2.34% per day. In terms of Sharpe ratio and information ratio, it has outperformed all others by a huge margin. Meanwhile, the max-drawdown of sentiment-based portfolio is also lower than both CRIX and equal weight portfolio using top 100 cryptocurrencies.

4.5 Robustness check

In this section, we conduct two robustness check. One is transaction cost impact on the portfolio performance and the other one is formation period of sentiment measure.

4.5.1 Transaction cost impact on portfolio performance

Previous analysis is based on the assumption of no transaction costs while it is not true in real life. To take Bitcoin exchanges as an example, significant deviations between pairs of identical Bitcoin are quite common in different exchanges. However, this deviation does not deliver a profitable arbitrage opportunity since it entails transaction costs among other reasons.

Transaction costs usually occur in two ways, namely trading fees and the bid-ask spread. Bid-ask spread is a type of risk premium to compensate market dealer for providing liquidity. To execute a transaction, investor should pay additional premium to the exchange. And usually, exchange will ask for a high premium to reduce loss by providing liquidity to the informed traders. But overall, we find the bid-ask spread is minor issue compared to the normal price deviation. As a result, bid-ask is not supposed to significantly impede arbitrage.

In contrast, other fees create more frictions for investors to make arbitrage. For example, BTC-E charges a 0.2 to 0.5 percent fee per transaction along with fees to deposit or withdraw traditional currency. According to CryptoCoins News⁷, there is currently a \$20 fee for a wire deposit. Bitstamp and Bitfinex also charge trading fees and deposit/withdrawal/fees. Such fees lower the profits from arbitrage, and could explain the price differences among exchanges. We then expect this transaction friction may also affect sentiment-based portfolio performance.

In the following, we recalculate the trading strategy returns after taking transaction costs into consideration. We make following 10 alternative assumptions about a trader's round-trip transaction costs: 1, 2, 3 ... or 10 basis points (bps) per round-trip per trade. The raw annualized portfolio return for each trading cost is summarized in Table 12.

[Insert Table 12 here.]

The results indicate that the advantage of the strategy is less obvious with the trading costs. In particular, when the trading cost rises to 10 bps, the raw annualized return of the sentiment-based trading strategy remains 11.22 times with T-value 15.50. Overall, the sentiment-based portfolio is insensitive to the transaction costs, suggesting a low turnover of the trading strategy.

⁷<https://www.cryptocoinsnews.com/bitcoin-transaction-friction-a-reality-check>

4.5.2 Formation period impact on portfolio performance

To construct sentiment for each cryptocurrency, we use the average of past 10 trading day return. In this section, we show that our results continue to hold when using alternative formation periods. We use the same procedure to construct sentiment measure and report the results in Table 13.

[Insert Table 13 here.]

Table 13 shows estimates of the impact of sentiment formation period on trading strategy's profitability. The results are quite robust in terms of selection of formation period. The annualized portfolio return based on sentiment proxy using past 20-day returns is 11.22 with a T-value of 14.99, suggesting a consistent sentiment effect on the cryptocurrency market.

In addition, our sentiment strategy may explore some investment opportunities on some extreme event days. To handle this issue, we winsorize our data at 1% to reduce the effect of possibly spurious outliers. Under the new setting, the raw annualized return of the portfolio remains 8.1. Regardless of other market microstructure issues, we believe our sentiment-based trading strategy will generate reasonable good investment opportunity.

5 Conclusion

In the first part of this paper, we describe the characteristics of bitcoin and alt coins as well as the market structure of cryptocurrency and crypto-token. In the second part of this paper, we investigate the possibility and performance of investing in cryptocurrencies as an alternative asset class. We compare the characteristics of cryptocurrencies and traditional asset class and examine the static correlations between them, as well as the dynamic conditional correlations following DCC model.

The results show that CRIX index and cryptocurrencies could be a good option to help diversify the portfolio risks as the correlations between cryptocurrencies and traditional assets are consistently low and the average daily return of most cryptocurrencies are higher

than that of traditional investments. Furthermore, the plots of efficient frontier point out that incorporation of CRIX significantly expands the efficient frontier of the traditional asset classes.

Nevertheless, indicated by the mean-variance spanning tests, the expanding effect of CRIX and cryptocurrencies stands only for the global minimum-variance portfolio, not to the tangency portfolio. Moreover, our sentiment analysis suggests a good investment opportunity to provide investors with annualized return of 12.39 and Sharpe ratio of 8.21.

Bitcoin may have been in existence and stood the trail for eight years. But cryptocurrency and crypto-token are still at the experimental stage. We view that while our results are interesting, there are many other issues that need to be addressed before cryptocurrencies and crypto-tokens will form an asset class of great interest to institutions. The technology itself can be very complex and investment into this class of investment entails understanding of the associated complexity and risk. Other issues such as security of safekeeping, reporting standard without custodian and trustee, governance structure of decentralised and autonomous cryptocurrency system, as well as the risk and complexity of dealing with unregulated identities need to be assessed before a clearer picture can emerge. Perhaps a quote from Lee, Smorenberg, Uitermarkt and Wanders [2017] may be a good way to end this paper.

While widely dispersed ownership in proportion to individual needs might sound far-fetched, the current state of blockchain and cryptocurrency already enables anyone to hold fractional, decentralized and fluid assets that are digital and highly usable. Slowly but surely, legislation also is changing to accommodate such a new era. In fact, the groundwork of a whole new ecosystem in digital asset management is quietly being installed. Crossover products based on blockchain technology will find their way into the mainstream. The inherently inclusive nature of its architecture can shift a significant part of the (impact) investment movement from being activists for innovations toward actually becoming the driving solutions themselves. Using a needs-oriented mindset, vs. a wealth-focused investment approach, can position future-thinking financiers at the forefront here.

Nevertheless, the invention of Satoshi Nakamoto has already changed the way start-

ups in the cryptocurrency space are financed through ICOs and very likely that PE/VC may take on a new form in the future.

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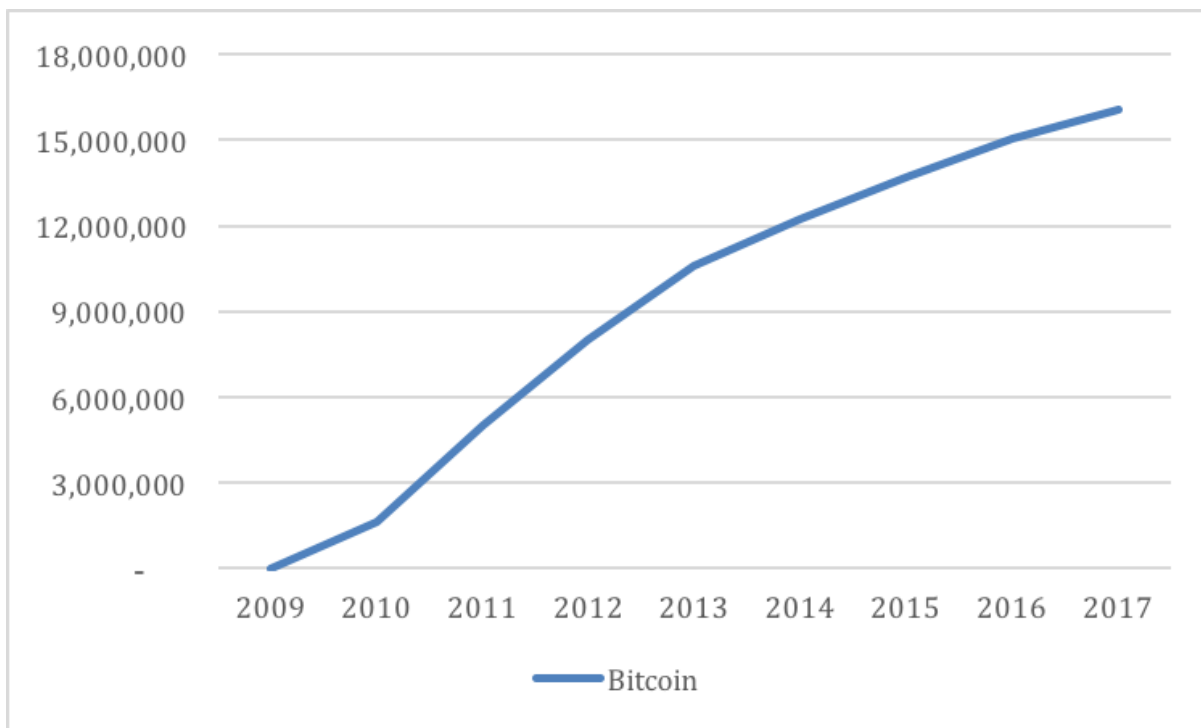


Figure 1: This figure shows the number of bitcoins in circulation (circulating supply) from January 2009 to May 2017. Circulating supply is computed by deducting those coins that have been created after subtracting the number of coins that have been burned, locked, reserved, or cannot be traded on the public market from the total supply.

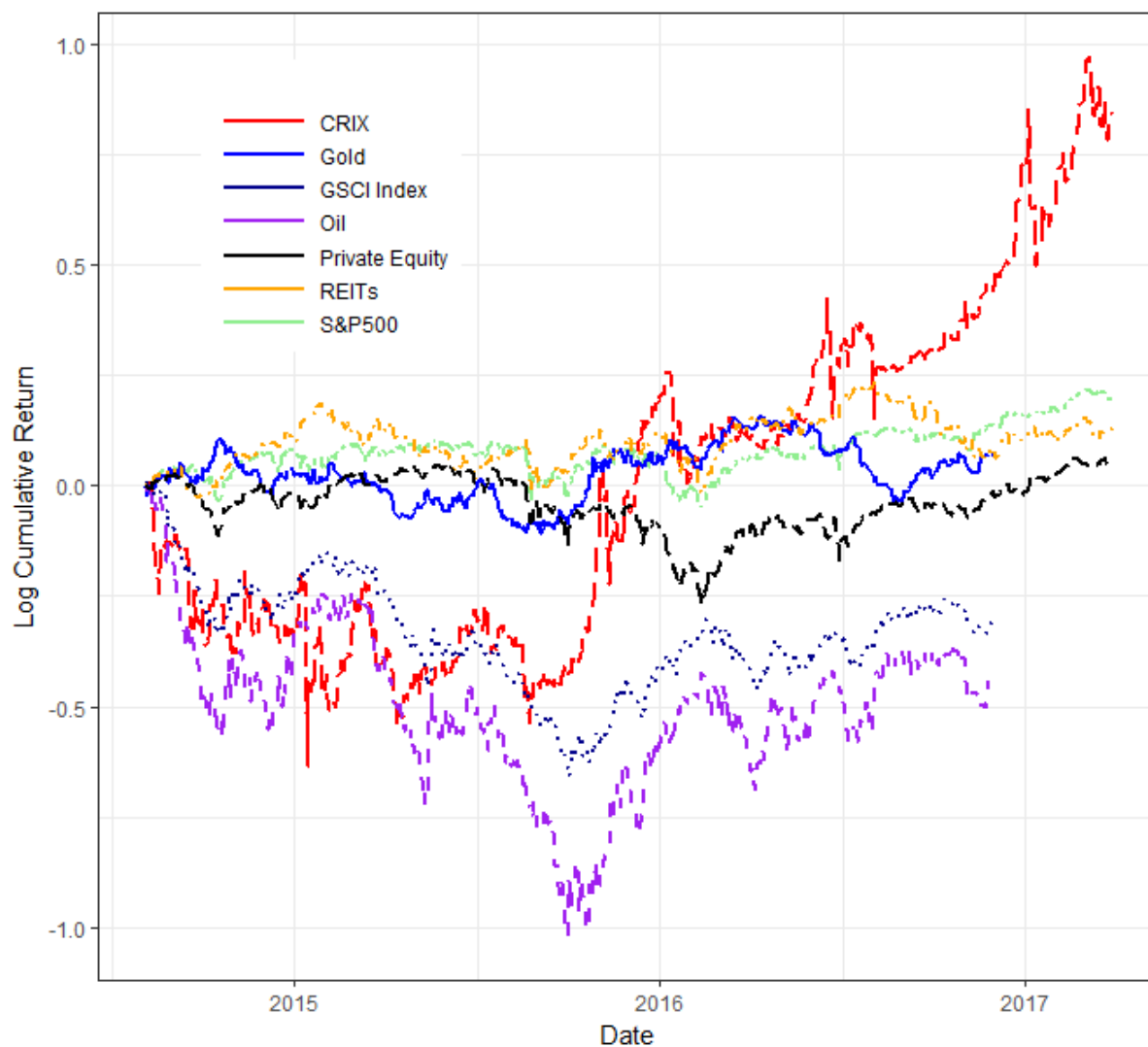


Figure 2: This figure depicts log cumulative daily returns of CRIX index and traditional asset class. For traditional asset class, we use Gold, GSCI Index, Oil, Private Equity, REITs and S&P 500. The data ranges from 11 August, 2014 to 27 March, 2017.

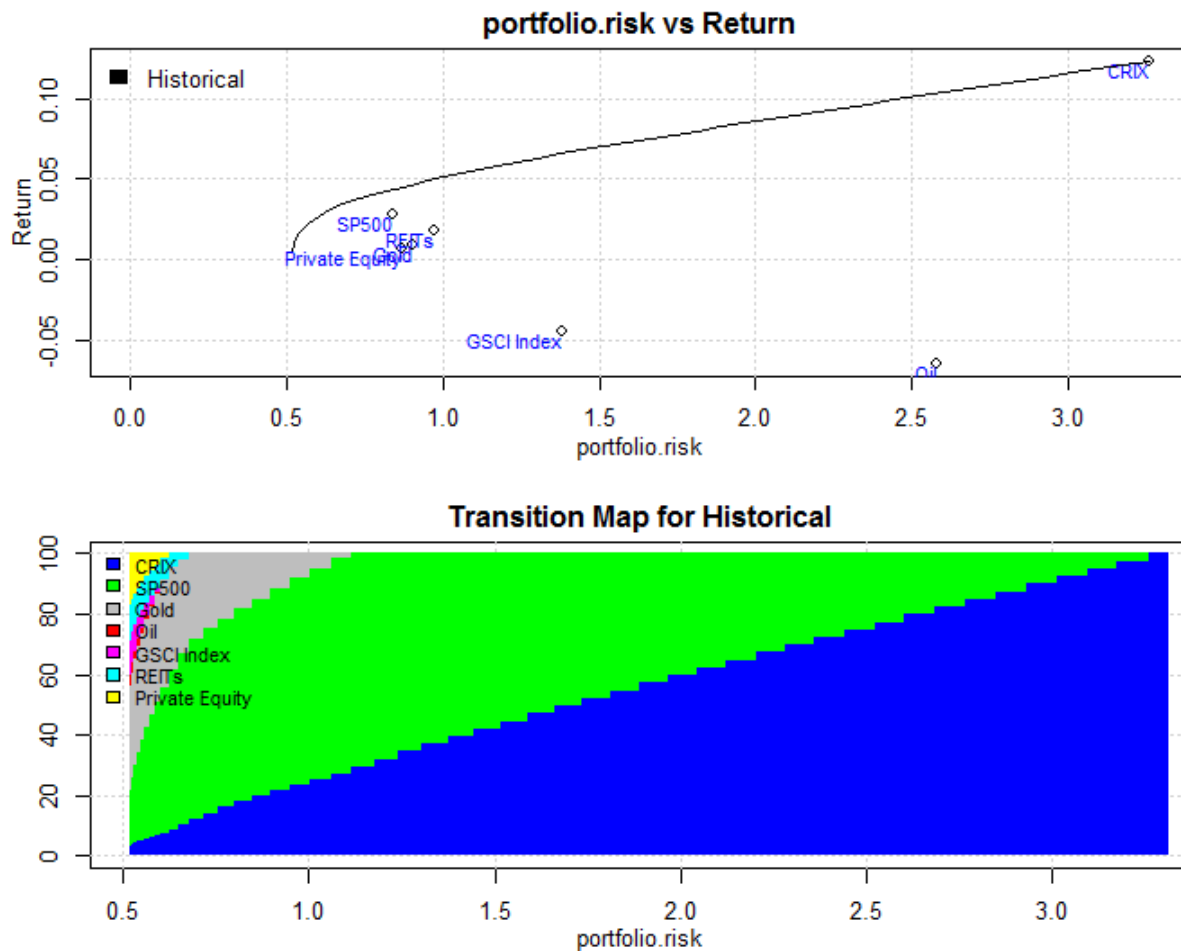


Figure 3: This figure shows the efficient frontier of CRIX and six traditional investment asset classes, including S&P 500, Gold, Oil, GSCI Index, REITs and Private Equity. It depicts the maximum return that can be obtained under the corresponding risk level, or the lowest risk taken for a given rate of return. From it, we can see and compare the return and standard deviation profiles of the asset classes. The closer the portfolio lies to the efficient frontier, the better it is as an investment. The transition map further shows the optimal composition of a portfolio under different risk level. The vertical axis shows the percentage of the investment in each asset class. A larger assigned proportion translates to higher contribution of the asset class in the portfolio under a given risk level.

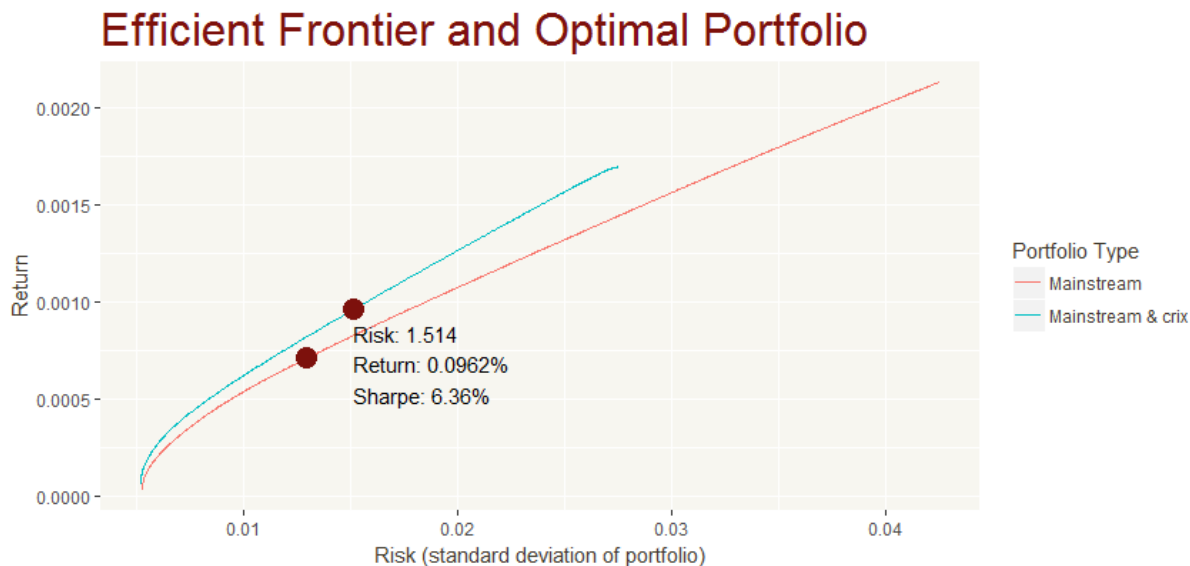


Figure 4: This figure plots the market efficient frontiers of mainstream portfolio with and without CRIX. It is the set of optimal portfolios that offers the highest expected return for a given level of risk, or the lowest risk for a given level of expected return. The red dot on the efficient frontier stands for the tangency portfolio that has the maximized Sharpe ratio. We first plot the market efficient frontiers of only mainstream portfolio, and then plot another one including both mainstream assets and CRIX index in the portfolio.

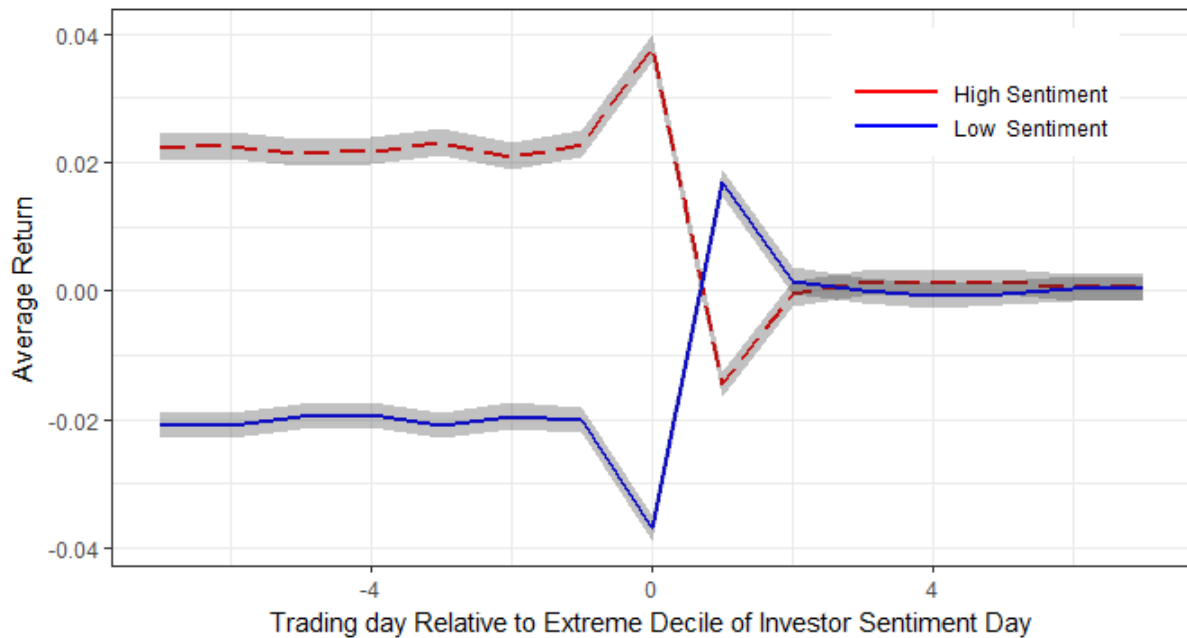


Figure 5: For this figure, we compute individual cryptocurrency return preceding one week before their high (low) sentiment event and then plot the mean of their return with 95% confidence interval. Sentiment is defined as average abnormal return of past 10 trading days. The 0 in X-axis stands for the sentiment event day. We separately examine the average cryptocurrencies returns of high and low sentiment groups. We calculate weekly abnormal return as return of each crypto-currency minus CRIX index returns. 95% confidence interval of average return for both high and low sentiment is represented by the grey area.

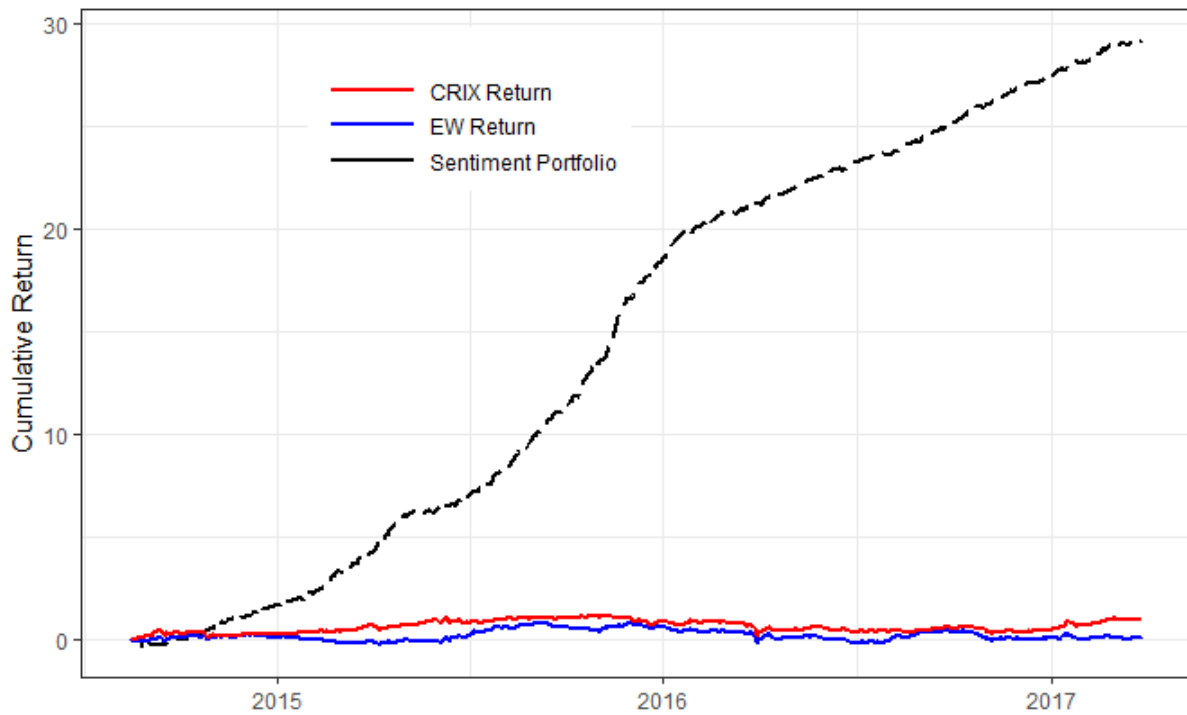


Figure 6: This figure shows the cumulative returns of investment strategies based on sentiment in prior trading day. We form two equal-weighted portfolios based on each firm's sentiment, defined as the average return of past 10 trading days. All cryptocurrencies are labelled with sentiment in the top decile as short leg and sentiment in the bottom decile as the long leg for each trading day, t . We then hold both the long and short portfolios for one trading day and rebalance at the closing price of the next trading day. The sample period spans from 11 August, 2014 to 27 March, 2017, under the assumption of no trading costs. We plot the returns for CRIX index, sentiment portfolio and equal weighted portfolio based on top 100 cryptocurrencies.

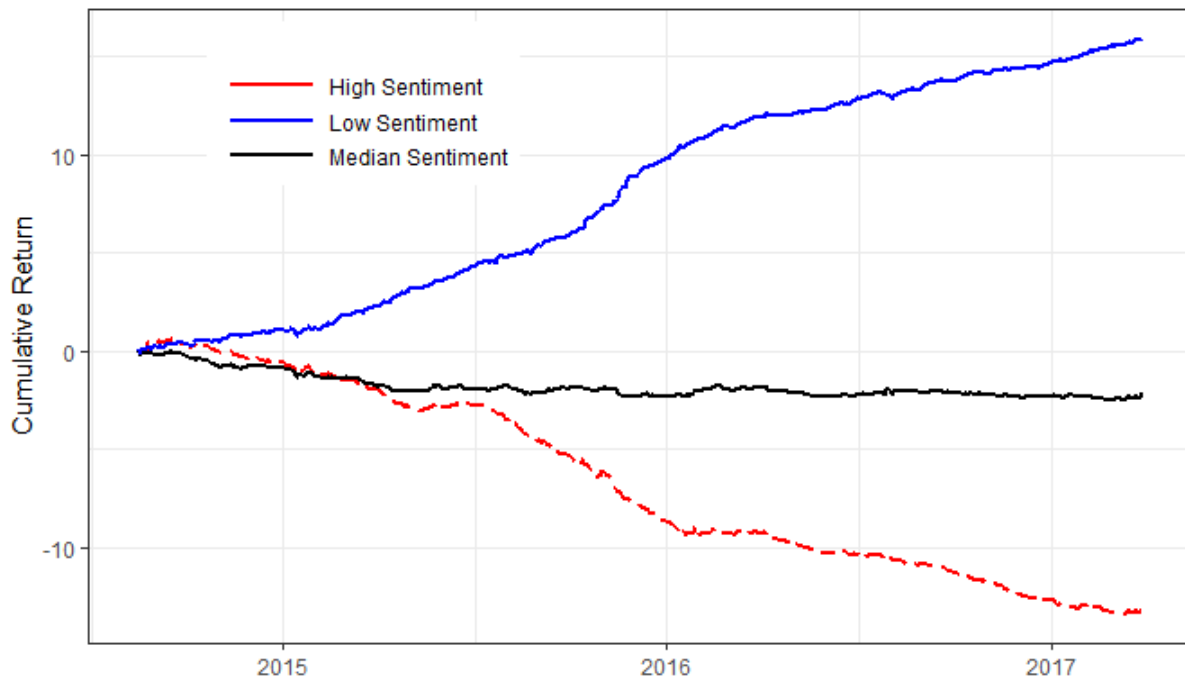


Figure 7: This figure depicts the cumulative returns of three groups of sentiment portfolios, high, median and low sentiment, respectively. As for the sentiment portfolios, we form two equal-weighted portfolios based on each firm's sentiment, defined as the average return of past 10 trading days. All cryptocurrencies are labelled with sentiment in the top decile as short leg and sentiment in the bottom decile as the long leg for each trading day, t . We then hold both the long and short portfolios for one trading day and rebalance at the closing price of the next trading day. The sample period spans from 11 August, 2014 to 27 March, 2017.

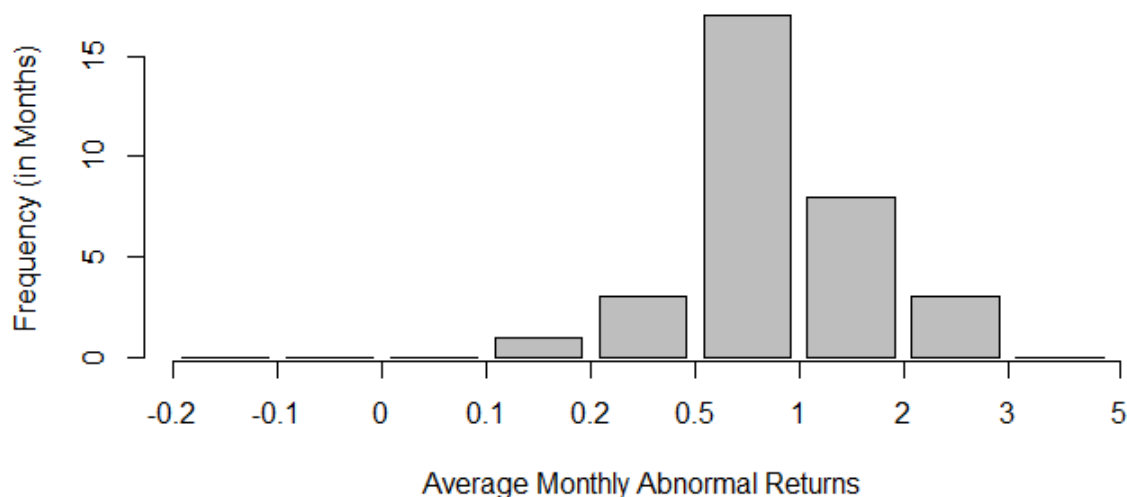


Figure 8: The figure depicts the distribution of the average monthly abnormal returns of the sentiment-based trading strategy described below. Each frequency bin encompasses a range of abnormal returns described by the two numbers adjacent to the bin. For example, the frequency of the leftmost return bin is the number of months in which the trading strategy's average monthly abnormal return is between -20% and -10%. We assemble the portfolio for the sentiment based trading strategy at the close of each day. We form two equal-weighted portfolios based on the sentiment of each firm to the prior trading day. We label all stocks with sentiment in the bottom (top) decile as long (short) leg. We hold both the long and short portfolios for 1 day and rebalance at the close price of next day. To adjust the returns for risk, we calculate daily abnormal return as stock returns minus CRIX index returns.

Table 1: Estimated Mining Rate and Reward of Bitcoins

The table reports the number of blocks, block generation time, estimated mining rate and corresponding reward of bitcoins. BTC/Block shows the number of bitcoins rewarded to miners with each block generated. End BTC % of Limit represents the percentage of total supply of bitcoins out of its limit, which is 21 million, at the end of each reward era with every 52,500 blocks generated.

Date reached	Block	Reward Era	BTC/Block	Year (estimate)	Start BTC	BTC Added	End BTC	% of Limit	BTC Increase
3/1/09	0	1	50.0	2009	0	2,625,000	2,625,000	12.50%	infinite
22/4/10	52,500	1	50.0	2010	2,625,000	2,625,000	5,250,000	25.00%	100.00%
28/1/11	105,000	1	50.0	2011*	5,250,000	2,625,000	7,875,000	37.50%	50.00%
14/12/11	157,500	1	50.0	2012	7,875,000	2,625,000	10,500,000	50.00%	33.33%
28/11/12	210,000	2	25.0	2013	10,500,000	1,312,500	11,812,500	56.25%	12.50%
9/10/13	262,500	2	25.0	2014	11,812,500	1,312,500	13,125,000	62.50%	11.11%
11/8/14	315,000	2	25.0	2015	13,125,000	1,312,500	14,437,500	68.75%	10.00%
29/7/15	367,500	2	25.0	2016	14,437,500	1,312,500	15,750,000	75.00%	9.09%
9/7/16	420,000	3	12.5	2016	15,750,000	656,250	16,406,250	78.13%	4.17%
	472,500	3	12.5	2018	16,406,250	656,250	17,062,500	81.25%	4.00%
	525,000	3	12.5	2019	17,062,500	656,250	17,718,750	84.38%	3.85%
	577,500	3	12.5	2020	17,718,750	656,250	18,375,000	87.50%	3.70%
	630,000	4	6.3	2021	18,375,000	328,125	18,703,125	89.06%	1.79%
	682,500	4	6.3	2022	18,703,125	328,125	19,031,250	90.63%	1.75%
	735,000	4	6.3	2023	19,031,250	328,125	19,359,375	92.19%	1.72%
	787,500	4	6.3	2024	19,359,375	328,125	19,687,500	93.75%	1.69%

Table 2: Market Capitalization of Cryptocurrencies

This table represents the market data of cryptocurrencies as of 27 June, 2017. Top 15 performers in both market capitalization and monthly volume are selected. Circulating supply is computed by deducting those coins that have been created after subtracting the number of coins that have been burned, locked, reserved, or cannot be traded on the public market from the total supply. When determining the market capitalization, circulating supply is used, for it denotes the amount of coins that are circulating in the market and accessible to the public. * means the coin is not minable.

No.	Name	Symbol	Market Cap	Price	Circulating Supply	Volume (24h)
1	Bitcoin	BTC	\$41,008,872,596	\$2,498.53	16,413,200	\$1,669,970,000
2	Ethereum	ETH	\$24,995,499,905	\$269.28	92,822,076	\$2,046,010,000
3	Ripple	XRP	\$10,569,342,023	\$0.28	38,291,387,790*	\$279,029,000
4	Litecoin	LTC	\$2,109,484,112	\$40.78	51,730,682	\$547,445,000
5	Ethereum Classic	ETC	\$1,881,721,498	\$20.24	92,988,807	\$285,136,000
6	NEM	XEM	\$1,482,417,000	\$0.16	8,999,999,999*	\$8,954,510
7	Dash	DASH	\$1,249,325,507	\$169.13	7,386,908	\$44,395,300
8	IOTA	MIOTA	\$1,082,988,384	\$0.39	2,779,530,283*	\$6,107,400
9	BitShares	BTS	\$676,530,938	\$0.26	2,596,370,000*	\$103,575,000
10	Stratis	STRAT	\$666,034,742	\$6.77	98,440,369*	\$11,205,900
11	Monero	XMR	\$625,404,471	\$42.57	14,691,754	\$14,801,000
12	Zcash	ZEC	\$511,623,362	\$329.56	1,552,444	\$35,928,300
13	Bytecoin	BCN	\$434,915,240	\$0.00	183,065,167,227	\$2,490,360
14	Siacoin	SC	\$428,467,781	\$0.02	27,254,659,755	\$28,877,300
15	Waves	WAVES	\$426,407,000	\$4.26	100,000,000*	\$5,813,100

Table 3: Different Categories of Altcoins

This table summarizes different categories of altcoins and compares their features with those of bitcoin. There are five categories of altcoins in total, and the table gives examples of the different aspects and comparison of the corresponding feature with that of bitcoin.

Category of Altcoin	Example		
	Aspect	Altcoin	Bitcoin
Coins with minor changes of parameter	Rewarding system	IxCoin: 96 IXC per block	50 BTC per block
	Max supply	Terracoin: 42 million	21million
Coins with technical innovation	Hashing algorithm	Litecoin: Script	SHA-256
	Timestamping	Peercoin: Proof-of-Stake	Proof-of-Work
Coins that are coded in different programming language	Programming language	Nxt: Java	C++
Coins with new ideas	Unique features	Counterparty: embedded consensus	NA
		Ethereum: Turing-complete	
Appcoins	Unique features	Storjcoin X, SWARM Coin, MaidSafeCoin	NA

Table 4: Comparison of Top Cryptocurrencies

This table shows the comparison between some top cryptocurrencies and bitcoin, in terms of the launched data, consensus tool, distribution, maximum limit of the coin and block generation time.

Coin	Symbol	Launched Date	Consensus Tool	Distribution	Unit cap	Block time
Bitcoin	BTC	3/1/09	SHA-256	Proof-of-work (fixed, halving)	21 million	10 minutes
Ripple	XRP	1/3/11	Ripple	Centralized	100 billion	NA
Litecoin	LTC	7/10/11	Scrypt	Proof-of-work (fixed, halving)	84 million	2.5 minutes
Dash	DASH	19/1/14	Combo11	Proof-of-work (fixed, curve)	18.4 million (estimate)	2.5 minutes
Monero	XMR	18/4/14	CryptoNote	Proof-of-work (random, smooth)	18.4 million then with 1% inflation	2 minutes
Zcash	ZEC	28/10/16	Zerocash	Zero-knowledge proofs, Proof-of-work	21 million	2.5 minutes
Dogecoin	DOGE	6/12/13	Scrypt	Proof-of-work (random)	Unlimited	1 minute

Table 5: 10 Cryptocurrencies Included for Most Times in CRIX

The table summarizes the 10 cryptocurrencies used in this study with the market value as of 6 April, 2017. We choose the top 10 that have been included in the CRIX index for most times.

Number	Cryptocurrency	Symbol	Times included in CRIX	Market Cap (\$million)
1	Bitcoin	BTC	32	18,810
2	Ethereum	XRP	32	4,062
3	Litecoin	LTC	31	537
4	Dash	DASH	29	501
5	Dogecoin	DOGE	28	50
6	Monero	XMR	26	274
7	Bitshares	BTS	26	24
8	MaidSafeCoin	MAID	25	90
9	Nxt	NXT	24	16
10	Bytecoin	BCN	24	23

Table 6: Summary Statistics for Return of CRIX Index and Top Cryptocurrencies

The two tables show the summary statistics of log returns of cryptocurrencies and traditional asset class. Panel A shows the statistics for CRIX index and the top 10 included in CRIX index and panel B for mainstream assets (S&P 500, T-Note, Gold, Oil, GSCI index, REITs and PE). Statistics included are mean, standard deviation, skewness, kurtosis, minimum, maximum and the 1 lag autocorrelation denoted by Rho. The sample period spans from 11 August, 2014 to 27 March, 2017.

Panel A: Cryptocurrency	Mean	SD	Skew	Kurt	Min	Max	Rho
CRIX	0.0012	0.0326	-1.0375	12.8923	-0.2264	0.1932	0.0135
BTC	0.0008	0.0388	-0.5274	10.3023	-0.2518	0.2014	-0.0059
XRP	0.0009	0.0515	1.11	10.1929	-0.1958	0.3286	0.1357
LTC	0.0041	0.0794	-0.0954	36.5501	-0.8635	0.7619	-0.1126
DASH	0.0027	0.0766	0.647	9.7346	-0.374	0.5476	-0.0489
DOGE	0.0005	0.0589	1.7617	17.5638	-0.2752	0.4802	0.0183
XMR	0.0033	0.0839	1.6386	16.0059	-0.3363	0.7203	0.0315
BTS	-0.0008	0.073	1.4375	12.7584	-0.2933	0.5252	0.0572
MAID	0.004	0.121	3.7434	55.4465	-0.49	1.6675	-0.1411
NXT	-0.0019	0.0724	2.0406	20.3759	-0.3636	0.6999	-0.0794
BCN	-0.0008	0.0577	-0.5688	23.7415	-0.5472	0.3744	-0.0451
Panel B: Traditional Asset	Mean	SD	Skew	Kurt	Min	Max	Rho
S&P 500	4.95E-06	6.54E-06	0.9694	2.7994	0	2.00E-05	0.989
T-Note	0.0003	0.0084	-0.3068	5.6039	-0.0402	0.0383	0.0095
Gold	0.0001	0.009	0.3896	5.998	-0.0338	0.0459	-0.0446
Oil	-0.0006	0.0258	0.1879	4.5863	-0.1079	0.1015	-0.1287
GSCI	-0.0004	0.0138	0.0958	4.5697	-0.0659	0.0526	-0.0872
REITs	0.0002	0.0097	-0.5848	4.7931	-0.0486	0.0284	0.0332
PE	7.26E-05	0.0087	-0.7855	7.6016	-0.05	0.0327	0.1888

Table 7: Correlation for Traditional Asset Class against Cryptocurrencies

This table summarizes the correlations between traditional assets and the 10 cryptocurrencies as well as CRIX index. Seven traditional assets, (S&P 500, T-Note, Gold, Oil, GSCI index, REITs and PE) are included. The sample period spans from 11 August, 2014 to 27 March, 2017.

	CRIX	BTC	XRP	LTC	DASH	DOGE	XMR	BTS	MAID	NXT	BCN
S&P 500	0.036	0.038	0.022	0.013	0.102	-0.001	0.084	0.044	0.058	0.057	0.044
T-Note	-0.02	0.017	-0.01	0.006	-0.013	-0.037	-0.011	-0.04	0.058	-0.072	-0.035
Gold	0.036	0.069	-0.064	0.045	0.045	0.01	-0.053	0.02	0.018	0.041	0.047
Oil	-0.065	-0.075	-0.006	-0.076	-0.03	-0.094	0.032	0.005	0.009	-0.021	-0.025
GSCI	0.015	0.03	0.004	0.031	0.043	0.029	-0.01	-0.033	0.028	0.003	-0.015
REITs	-0.014	0.004	0.003	0.043	-0.025	-0.016	-0.045	-0.058	0.011	-0.036	-0.052
PE	-0.037	-0.007	-0.02	-0.029	-0.039	-0.017	-0.02	-0.094	0.024	-0.079	-0.012

Table 8: DCC for Traditional Asset Class against CRIX

This table summarizes estimated parameters of the DCC between daily returns of traditional asset class and CRIX index from 11 August, 2014 to 27 March, 2017. The six traditional assets are S&P 500, Gold, Oil, GSCI index, REITs and PE. Corresponding summary statistics include mean, standard deviation, minimum, median, maximum and the 25th and 75th quantile.

	Mean	SD	Min	Q25	Median	Q75	Max
S&P500	-0.0182	0.025	-0.081	-0.0357	-0.0193	-0.0007	0.0697
Gold	0.0233	0.0494	-0.1326	-0.0081	0.0231	0.0531	0.2442
Oil	-0.0951	1.64E-07	-0.0951	-0.0951	-0.0951	-0.0951	-0.0951
GSCI	0.033	4.60E-08	0.033	0.033	0.033	0.033	0.033
REITs	-0.0263	2.29E-07	-0.0263	-0.0263	-0.0263	-0.0263	-0.0263
PE	-0.0279	7.42E-09	-0.0279	-0.0279	-0.0279	-0.0279	-0.0279

Table 9: Spanning Test for Cryptocurrencies Effect on Portfolios Constructed by Stock Index and Traditional Alternative Investment

The table lists results of spanning tests on CRIX and top 10 cryptocurrencies, using data from 11 August, 2014 to 27 March, 2017. We report two mean-variance spanning tests on each of the 11 cryptocurrency variables as well as a joint test on all of them. Corrected HK F-test is used for the first test and the step-down test for the second. In the step-down test, there are two statistics, F_1 and F_2 . In F_1 , the null hypothesis $\alpha=0_N$ is tested, while in F_2 , $\delta=0_N$ is tested conditional on $\alpha=0_N$. Both tests are exact under normality assumption on the residuals.

Asset	Alpha	Delta	F-test	p-value	Step-Down Test				
					F-1	p-value	F-2	p-value	Joint-p
CRIX	0.0012	1.0345	10.07	0	0.904	0.342	19.24	0	0
BTC	0.0007	0.6991	3.226	0.04	0.238	0.626	6.22	0.013	0.008
XRP	0.0010	1.4652	7.824	0	0.254	0.615	15.412	0	0
DASH	0.0040	0.7682	1.775	0.17	1.782	0.182	1.766	0.184	0.034
Maid	0.0025	0.3155	0.538	0.584	0.758	0.384	0.319	0.573	0.22
DOGE	0.0005	1.2310	4.217	0.015	0.053	0.819	8.393	0.004	0.003
XMR	0.0034	1.7714	4.801	0.009	1.112	0.292	8.488	0.004	0.001
BTS	-0.0009	1.6988	5.264	0.005	0.11	0.74	10.431	0.001	0.001
BCN	0.0040	1.1405	1.208	0.3	0.732	0.393	1.684	0.195	0.076
NXT	-0.0018	1.4013	3.82	0.022	0.441	0.507	7.205	0.007	0.004
LTC	-0.0010	0.7264	1.623	0.198	0.188	0.665	3.061	0.081	0.054

Table 10: Fama-MacBeth Regression of Cryptocurrencies Returns on Sentiment

This table reports the Fama-MacBeth results of regressing Crypto's excess returns at day t on lagged sentiment, as well as other firm characteristics. Sentiment is defined as average abnormal return in the past 10 trading days. The first three columns use the whole sample period, namely from 11 August, 2014 to 27 March, 2017. The middle three columns present results of sample period before 2016. The last three columns show results of post 2016. Newey-West t-statistics with 12 lags in parentheses. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Whole Sample Period			Before 2016			After 2016		
Sentiment	-0.888*** (-12.18)	-0.387*** (-6.09)	-0.384*** (-6.37)	-1.001*** (-8.33)	-0.472*** (-4.55)	-0.453*** (-4.72)	-0.762*** (-9.99)	-0.294*** (-4.26)	-0.308*** (-4.42)
Lagged Ret		-0.241*** (-20.77)	-0.240*** (-21.45)		-0.254*** (-14.58)	-0.257*** (-15.71)		-0.226*** (-15.08)	-0.221*** (-14.70)
Volume			0.001*** (-6.97)			0.002*** (-4.84)			0.001*** (-5.18)
Intercept	-0.002* (-1.79)	-0.002 (-1.50)	-0.014*** (-6.52)	-0.004** (-2.05)	-0.004** (-2.25)	-0.017*** (-5.03)	0 (-0.19)	0.001 (-0.54)	-0.011*** (-4.18)
N	77,322	77,322	76,606	35,474	35,474	35,156	41,848	41,848	41,450
Average Adj. R^2	0.0728	0.1888	0.21	0.087	0.2139	0.2318	0.057	0.1611	0.1859

Table 11: Performance Evaluation

This table reports the mean return, volatility and other risk-adjusted returns of the sentiment portfolio and equal weighted portfolio based on top 100 cryptocurrencies. We adopt three measures to compute the risk-adjusted returns: daily Sharpe ratio, daily information ratio and daily maximum drawdown. For the information ratio, S&P 500 is used as the benchmark. We compare the results with other investment assets, traditional investment tools (S&P 500, Gold, Oil, GSCI Index, REITs and PE) and cryptocurrencies (CRIX index and the top 10 cryptocurrencies covered in study).

	Mean Return	Volatility	Sharpe Ratio	Information Ratio	Maximum Drawdown
S&P 500	0.0003	0.0084	0.0354		-4.02%
Sentiment Portfolio	0.0234	0.0382	0.6106	0.5929	-15.59%
Equal-Weight Portfolio	5.96E-05	0.0287	0.0021	0.0141	-17.89%
CRIX	0.0008	0.0316	0.0268	0.0274	-22.64%
Gold	0.0001	0.009	0.0109	-0.0158	-3.38%
Oil	-0.0006	0.0258	-0.0239	-0.0336	-10.79%
GSCI Index	-0.0005	0.0139	-0.0325	-0.0484	-6.59%
REITs	0.0002	0.0098	0.0189	-0.0144	-4.86%
PE	0.0001	0.0087	0.0093	-0.0338	-5.00%
BTC	0.0008	0.039	0.0213	0.0134	-25.18%
XRP	0.0008	0.0516	0.0157	0.0098	-19.58%
DASH	0.0039	0.0796	0.0491	0.0451	-86.35%
MAID	0.0026	0.0768	0.0333	0.0295	-37.40%
DOGE	0.0008	0.0589	0.013	0.0078	-27.52%
XMR	0.0032	0.084	0.0381	0.0344	-33.63%
BTS	-0.0007	0.0733	-0.0099	-0.0138	-29.33%
BCN	0.004	0.1214	0.0329	0.0303	-49.00%
NXT	-0.0017	0.0725	-0.0234	-0.0271	-36.36%
LTC	-0.0008	0.0578	-0.013	-0.018	-54.72%

Table 12: Sensitivity of Sentiment Based Trading Returns to Trading Cost Assumptions

This table summarizes the raw annualized portfolio return under trading cost assumptions. We form two equal-weighted portfolios based on each firm's sentiment, defined as the average abnormal return of past 10 trading days. We label all stocks with sentiment in the top (bottom) decile as short (long) leg. We hold both the long and short portfolios for 1 trading day and rebalance at the close price of next trading day. The sample period spans from 11 August, 2014 to 27 March, 2017. We make following 10 alternative assumptions about a trader's round-trip transaction costs: 1, 2, 3 ... or 10 basis points (bps) per round-trip per trade and recalculate the trading strategy returns. The abnormal raw annualized cumulative strategy returns for each trading cost assumption are shown below.

Trading Cost (bps)	Whole Sample Period		Before 2016		After 2016	
	Raw Annualized Return	t-value	Raw Annualized Return	t-value	Raw Annualized Return	t-value
1	11.58	15.97	13.76	11.77	9.22	11.38
2	11.54	15.91	13.72	11.73	9.18	11.33
3	11.50	15.86	13.68	11.70	9.14	11.29
4	11.46	15.81	13.64	11.67	9.10	11.24
5	11.42	15.76	13.60	11.63	9.06	11.19
6	11.38	15.71	13.56	11.60	9.03	11.15
7	11.34	15.65	13.52	11.57	8.99	11.10
8	11.30	15.60	13.48	11.53	8.95	11.06
9	11.26	15.55	13.44	11.50	8.91	11.01
10	11.22	15.50	13.39	11.47	8.87	10.96

Table 13: Sensitivity of Sentiment Based Trading Returns to the Formation Period

This table shows estimates of the impact of sentiment formation period on trading strategy's profitability. We form two equal-weighted portfolios based on each firm's sentiment, defined as the average abnormal return of past 10 trading days. We label all stocks with sentiment in the top (bottom) decile as short (long) leg. We hold both the long and short portfolios for 1 trading day and rebalance at the close price of next trading day. The sample period spans from 11 August, 2014 to 27 March, 2017. Now we recalculate the trading strategy returns for 10 alternative formation period of sentiment measure, namely, 11, 12, 13 ... or 20 trading days as estimation window to calculate the past average abnormal return as proxy for sentiment. The abnormal raw annualized cumulative returns for each formation period is shown below.

Formation Period (day)	Whole Sample Period		Before 2016		After 2016	
	Raw	Annualized Return	t-value	Raw	Annualized Return	t-value
11	11.53	16.00	13.57	16.00	9.28	16.00
12	11.62	16.95	13.66	16.95	9.33	16.95
13	11.27	16.14	13.73	16.14	8.42	16.14
14	11.21	15.53	14.25	15.53	7.58	15.53
15	11.53	15.64	14.42	15.64	7.93	15.64
16	12.01	16.52	14.77	16.52	8.44	16.52
17	11.60	15.42	14.41	15.42	7.80	15.42
18	11.44	15.08	13.91	15.08	7.93	15.08
19	11.21	15.00	13.59	15.00	7.62	15.00
20	11.22	14.99	13.32	14.99	7.87	14.99