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Cryptocurrency: *A New Investment Opportunity?*

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The invention of Bitcoin[1] by Satoshi Nakamoto (Nakamoto [2008]) in 2008 spurred the creation of many new cryptocurrencies known as altcoins. These altcoins use similar cryptographhy technology but employ different algorithmic designs. Many of these altcoins were invented for different purposes or to address the pain points of the Bitcoin network, such as the high usage of energy caused by its proof of work (PoW) consensus algorithm or the supply limit of 21 million coins, among others. As the network effect weighs in, the prices of bitcoin and its variants have risen in tandem. These innovations and the perceived investment potential have led to rapid growth in the number of altcoins and the market size of cryptocurrency. According to CoinMarketCap,[2] nearly 869 cryptocurrencies are currently trading around the world with a combined market capitalization of US$148.3 billion by circulating supply and US$321.5 billion by total supply as of October 6, 2017. The price of bitcoin surged to US$4,780.15 on September 2, 2017. Many have argued that, despite their payment utility, bitcoin and cryptocurrencies have no intrinsic value and may be the perfect vehicle for forming a bubble.

Even for those who believe that there is intrinsic value to cryptocurrencies, when their prices are rising, there will be doubts about prices running ahead of values. Technologists will argue that their value is higher than Linux and lower than the Internet—yet both are facilitators rather than an asset class. Finance traditionalists will argue that cryptocurrency is just another form of value transfer that raises funds globally using cryptography and creates little value beyond that. For perspective, with US$40 billion and US$100 billion market capitalization for bitcoin and total cryptocurrency, respectively, this investable asset class is minute in size compared to the 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 the organizations issuing them, cryptocurrency has very different characteristics. The blockchain technology used by cryptocurrency, such as Bitcoin, is an open distributed ledger that records transactions. This solves the double-spending problem and does not require a trusted third party. 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 of traditional financial systems. As a result, blockchains and cryptocurrencies have become two of the most pressing topics in the financial industry. In this article, we focus on the diversification role of cryptocurrencies and explore the possibility that they may generate new investment opportunities based on historical data.

We first evaluate the comovement between traditional asset classes and the cryptocurrency index (CRIX) by studying their correlation coefficients (Chen et al. [2016]). Results suggest a very low correlation between CRIX and traditional assets based on historical data. This observation suggests that cryptocurrency as an asset class is a good diversifier in a traditional portfolio. We then employ a multivariate dynamic conditional correlation (DCC) model to examine dynamic comovements for robustness (Engle [2002]). Consistent with our expectations, cryptocurrencies are considered a potentially better portfolio diversifier under the DCC setting. The largest DCC was between CRIX and gold, with a value of 0.24. Next, we investigate whether the 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 only of traditional assets, it also provides additional utility to investors, as evidenced by the mean–variance spanning test. However, it seems that cryptocurrencies may not lead to a large improvement in the utility of a mean–variance investor. There are various explanations for this finding. First, the current sample period of CRIX is too short to fully explore the investment opportunity of cryptocurrencies. Second, over the sample period, the 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 making an investment commitment. In this article, we conjecture that the high volatility of cryptocurrency is driven mainly by investor sentiment, not by a change in fundamentals. We do not argue that there are no fundamentals, but rather that there has not been any meaningful interpretation using traditional fundamental analysis. Either the old economy framework is not suitable for a new and complex technology such as cryptocurrency, or immeasurable fundamentals are proxied by sentiments.

We then propose an investor sentiment measure based on the past average returns for the cryptocurrency market. Our measure of investor sentiment reveals a 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 use the Fama–MacBeth regression (Fama and MacBeth [1973]) to examine the cross-sectional premium of investor sentiment by using the top 100 cryptocurrencies that are components of CRIX. After controlling trading volume and lagged return, the Fama–MacBeth results suggest that any cryptocurrency with 1% investor sentiment in excess of the average cryptocurrency sentiment tends to have a 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 investor sentiment. The strategy that buys low-sentiment and sells high-sentiment cryptocurrencies generates an annualized return of 8.54 with a Sharpe ratio of 11.64. We also conduct two analyses to assess the robustness of our findings. Our sentiment strategy survives after assuming reasonable transaction costs from 1 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% with a t-value >15. Overall, our results provide some evidence of cryptocurrencies being a potential candidate as a new investment vehicle.

The rest of the article is organized as follows. We first introduce the background of the cryptocurrency market. The next section presents empirical results on the diversification role of cryptocurrencies, and the following section explains the sentiment impact on the cryptocurrency market with robustness checks. The last section concludes.

CRYPTOCURRENCY

From Centralization to Decentralization

The major drawback of the traditional fiat currency payment system is high transaction fees with a long settlement period, which has led people to alternative currencies that allow for shorter peer-to-peer (P2P) 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. The most common 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, and verification of the digital currencies.

In other words, these platform-based digital currencies are centralized. A notable example is the loyalty points of e-commerce companies like Rakuten and iHerb, which function like cash on the platform. Q-coin, introduced by the Chinese social platform Tencent, can be bought using the 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]).

These centralized digital currencies are transacted within a specific platform and are designed to support the business of the issuing institutions. It is difficult to use them as a substitute for fiat money because these centralized digital currencies are not legal tender. Therefore, decentralized digital currencies seem a potential replacement for fiat money as no central authority is needed to verify the transactions. However, there are still many obstacles to overcome without the use of an intermediary or central authority. One main obstacle is the *double-spending problem*: 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 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 centralized system owned by DigiCash, Inc. and later eCash Technologies. Although it was phased out in the late 1990s, the cryptographic protocols it employed avoided double spending. A blind signature was used to protect the privacy of users and served as a good inspiration for subsequent development. Shortly after the discovery of cryptography protocols, digital gold currency became popular, among which the most used was e-Gold. It was the first successful online micropayment system and led to many innovations, making transactions more accessible and more secure. However, the failure to address compliance issues finally resulted in its liquidation in 2008, despite an annual transaction volume of over US$2 billion (Lam and Lee [2015]).

The global financial crisis in 2008, coupled with a lack of confidence in the financial system, provoked considerable interest in cryptocurrency. A groundbreaking white paper by Satoshi Nakamoto was circulated online in 2008. In the paper, this pseudonymous person, or persons, introduced a digital currency that is now widely known as bitcoin. Bitcoin uses blockchain as the public ledger for all transactions and a scheme called PoW to avoid the need for a trusted authority or central server to timestamp transactions (Nakamoto [2008]). Because blockchain is an open and distributed ledger that records all transactions in a verifiable and permanent way, it solves the double-spending problem.

Bitcoin and "bitcoin"

The cryptocurrency, denoted by *bitcoin or BTC*, can be accepted as a payment for goods and services or bought either from other people or directly from exchanges/vending machines. These bitcoins can be transacted via software, apps, or various online platforms that provide wallets. Another way to obtain bitcoin is through mining.

The *Bitcoin system* runs on a P2P network, and transactions happen directly between users with no intermediary. Bitcoin decentralizes the responsibilities of verifying the validity of transactions to the entire network. Transactions are recorded in the public ledger called blockchain and are verified by network nodes, which could be any individual using a computer system with Bitcoin software installed. Once users have made a transfer, the transaction will be broadcast between users and confirmed by the network. Upon verification, it will be recorded in the blockchain, and then the transfer is completed. This 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 transaction data; 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, and the output of a transaction holds the receiving address and the corresponding amount (Nirupama and Lee [2015]). In general, in a transaction, a certain number of bitcoins is sent from a bitcoin wallet to a specific address, if there is a sufficient bitcoin balance in the wallet 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 only be accessed by the owner, and transactions cannot be altered by someone else.

Mining is also the process of adding newly verified transaction records to Bitcoin's public ledger. 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, thus the name blockchain. The blocks are mined in sequence, and once recorded, the data cannot be altered retroactively. A 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 block, which is called the *genesis block*. However, there are also blocks that are not part of the main chain, called *detached* or *orphaned blocks*. They can occur when more than one miner produces 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 selecting the block with the highest value.

There are several systems by which miners can earn rewards through the mining process. Bitcoin uses the Hashcash PoW system and the SHA-256 hashing algorithm. Under the PoW system, rewards are given according to the number of blocks that are mined successfully. Therefore, mining is quite competitive; the miner who first solves a given puzzle or gets the highest value will take all the newly created bitcoins, and the other miners will receive nothing. Rewards thus encourage miners to take an active part in mining data blocks. In addition, mining usually involves a large amount of computation and can be quite energy consuming.

Another commonly seen system is proof-of-stake (PoS). Unlike PoW, no additional work is required under the PoS scheme because investors are rewarded based on the number of coins they hold. For example, a user holding 1% of the currency has a probability of mining 1% of that currency's PoS blocks (Nirupama and Lee [2015]). In general, this system does not require a large amount of work for the computation. It provides for higher currency security and is usually used in combination with other systems, as in the case of Peercoin, the first cryptocurrency launched using PoS.

Because the supply of bitcoins is limited to 21 million, the bitcoins awarded to a miner for successfully adding a block will be halved every 210,000 blocks (approximately every four years), according to the Bitcoin protocol. When Bitcoin was first run 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 as of July 9, 2016. The supply of bitcoins on the network is 16.606 million as of October 6, 2017, with a total circulating supply market capitalization of US$ 73.1 billion.[3]

Features of Bitcoin

Decentralized. Similar to conventional currencies that are traded digitally, bitcoin can also be used to buy things electronically. Unlike any fiat money or platform-based digital currencies, however, 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.

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

Transparent. 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 broadcast the completed block to other nodes. Records of all transactions are stored in the blockchain, which is open and distributed, so every miner has a copy and can verify them.

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

Low transaction fees. No transaction fee is required to make a transfer historically, but the owner can opt to pay extra to facilitate a faster transaction. Currently, low priority for mining transactions (a function of input age and size) is mostly used as an indicator for spam transactions, and almost all miners expect every transaction to include a fee. Miners historically have been incentivized mainly by newly created coins, but that is changing. As the number of bitcoins in circulation nears its limit, transaction fees will eventually be the incentive for miners to carry out the costly verification process.

Altcoin Market

Bitcoin is open source and the source code is available on GitHub.[4] Therefore, coders around the world have been 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. Every new purpose or pain point is an incentive to invent new coins. Coins are invented to address specific issues such as high computation cost of PoW, to increase the number of transactions per second, to increase the block size, to ensure that the ledger is not as transparent, to accommodate more efficient use of smart contracts, and so on. Moreover, to pay for development and launch expenses, developers can raise funds for the project even before the cryptocurrency is launched. In particular, initial coin offerings (ICOs), initial crypto-token offerings, and initial token sales are similar approaches to raising funding to develop new crypto-tokens and cryptocurrencies. ICOs allow people to invest in a project by buying part of its cryptocurrency tokens or prelaunched ERC20-compliant tokens residing on the Ethereum network in advance, typically based on a white paper or other documents on the project for investors to evaluate.

As of October 6, 2017, 869 cryptocurrencies and 269 crypto-tokens were launched and traded,[5] with a total market capitalization of over US$148.4 billion. Different from fiat money, cryptocurrencies have a 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 at the present moment. However, some coins will have been burned, locked, or reserved or cannot be traded on the public market, so the circulating supply is computed by deducting those coins from the total supply. When determining the market capitalization, circulating supply is used because it denotes the amount of coins circulating in the market and accessible to the public.

Based on cryptocurrency market value as of June 27, 2017, Bitcoin dominated 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. In addition, the supply of different coins varies substantially due to the unique characteristics of each coin, and some coins are not mined, suggesting a fixed amount of supply. The price of the coins ranges from US$0.002 to well over US$1,000.

In general, some altcoins are very similar to bitcoins, whereas others are created by adopting very different methods or ideas. Market capitalization, different categories of altcoins, and their features are summarized in Appendix A (Ong et al. [2015]).

Appcoins, such as MaidSafeCoin, function like digital shares in a decentralized autonomous organization and are sold in token sales for a portion of future profits. Most altcoins are direct copies of Bitcoin, with some minor changes in parameters such as block-generating time and the maximum limit of coin supply. However, many altcoins have adopted other innovative changes. Among the widely accepted altcoins, Ethereum is the one with the most innovative ideas and widely followed besides Bitcoin. The value token of the Ethereum blockchain is called ether and denoted by XRP. It provides a decentralized Turing-complete virtual machine that features smart contract functionality, as do four other altcoins that have launched based on Ethereum: Ethereum Classic, Golem, Augur, and Gnosis. NEM falls under the third category in Appendix A (i.e., coins coded in a different programing language): It is operated using JAVA programming, as is Nxt. Stellar Lumens and Factom are excluded because they are based on Ripple and Bitcoin protocols, respectively.

To conclude, many cryptocurrencies other than bitcoin are traded actively with a wide assortment of features for investors to invest in.

Cryptocurrencies in the Study

In this study, we choose the top 10 cryptocurrencies based on the frequency with which they are included in the CRIX. Developed by Trimborn and Härdle [2016] as a collaboration of the Ladislaus von Bortkiewicz Chair of Statistics at Humboldt University, Berlin, Germany; the Sim Kee Boon Institute for Financial Economics at Singapore Management University; and CoinGecko, the CRIX is computed in real time and balanced monthly using certain formulas that incorporate inputs such as market value and trading volume of the cryptocurrencies.[6] More details on the 10 cryptocurrencies used in this study can be found in Appendix B.

Cryptocurrencies and Alternatives

Alternative investments are widely seen in portfolio management presently and include commodities, real estate, private equity (PE), hedge funds, and others, such as artworks. Typically, alternative investments have a lower historical correlation to conventional asset classes, such as stocks, bonds, and cash equivalents, and thus provide good diversification to the portfolio.

Despite the debate on whether cryptocurrencies can become part of the mainstream financial system, the global daily exchange-traded volume of bitcoin averaged over US$1 billion in 2016, which indicates ample liquidity (Burniske and White [2017]). Moreover, research on bitcoin shows that the price of bitcoin does not fluctuate in the same direction as the stock market, indicated primarily by low return correlations. Although some may argue that the number of bitcoins to be generated is capped at 21 million, potentially limiting future supply, we should keep in mind that there are many promising altcoins in place, and their number is still growing. Thus, cryptocurrencies can be a good alternative investment, especially in terms of bringing diversification to mainstream assets (Trimborn, Li, and Härdle [2017]).

The valuation of cryptocurrencies, however, is very different from that of traditional instruments. Many cryptocurrencies like Bitcoin have a fixed supply, so the valuation of fiat money with an unlimited supply cannot be applied. Furthermore, 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 proof of future cash flow; payments; possible future exchange; and 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 analyze the potential of investing in cryptocurrencies.

DIVERSIFICATION EFFECTS OF CRYPTOCURRENCY

Data

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

Descriptive Statistics

Overall, cryptocurrencies outperform traditional asset class in terms of average daily return, and that of Litecoin is the highest among all (see Appendix C). The annualized return for the CRIX Index is $0.0012 \times 252 = 30.24\%$, which is very high compared to the stock market (0.12%, suggested by Appendix C). Meanwhile, CRIX tends to have a high return volatility compared to the S&P 500, with a daily maximum drawdown of −22.64% and skewness of −1.04. This high volatility with negative skewness suggests high tail risk of the cryptocurrency market. However, a noteworthy fact is that many cryptocurrencies exhibit positive skewness (i.e., 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 greatly deviates from the normal distribution, which makes sense because the market is still developing. As for the one-lag autocorrelation, denoted by Rho, the majority are quite low, suggesting a lack of predictability (Fama [1970]). To some extent, the maximum autocorrelation, 0.1357, basically suggests that current return has around 10% temporary effects on the next period return, and it only has 1% ($10\%^2$) left for predicting the next two-period return (see Appendix C). Moreover, there is an upward trend in the price of CRIX.

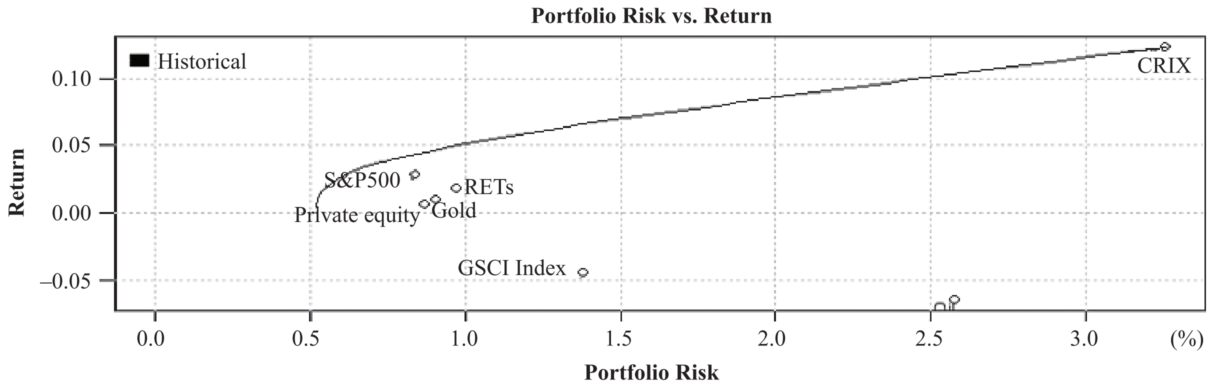
Correlation Analysis

Almost all correlations in Appendix D are less than 0.1. For example, the correlation between CRIX and the S&P 500 is 0.036. In fact, according to the first row, 7 out of the 11 classes have correlations with the stock market (S&P 500) that are less than 0.05. 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.

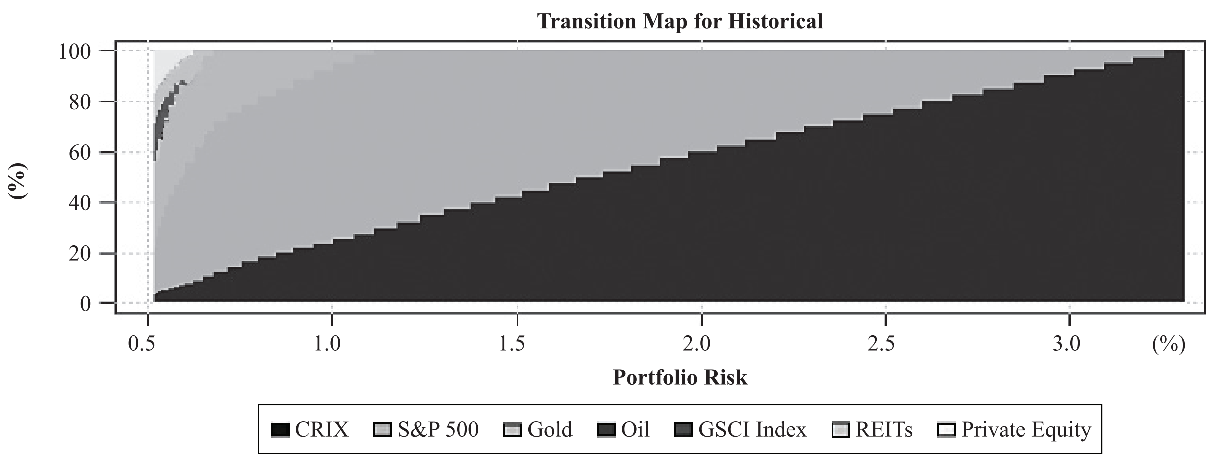
The correlation test raises a question about whether the correlation from time to time varies much from the average correlation. To address this question, we adopt the DCC model to further look at the dynamic correlations (see Appendix D). Consistent with our

EXHIBIT 1
Efficient Frontier and Transition Map

Panel A: Efficient Frontier



Panel B: Transition Map



expectation, cryptocurrencies still show good diversification potential over the whole sample period, with a maximum DCC of 0.24 (between CRIX and gold). The persistence of low comovement with mainstream assets further suggests good investment opportunities in cryptocurrency as an alternative asset class.

Portfolio Analysis

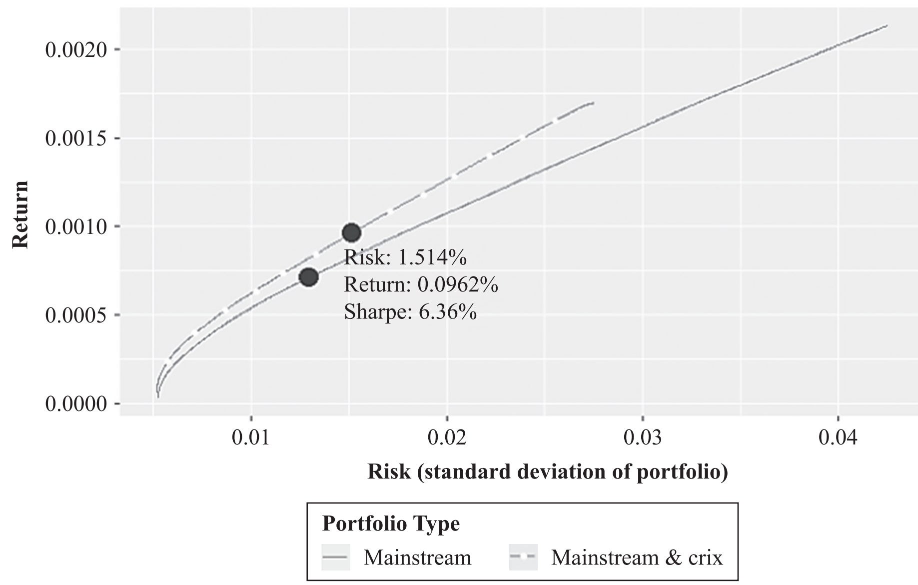
Next, we examine the performance after adding CRIX to a portfolio that consists of traditional assets, such as S&P 500, PE, real estate investment trusts (REITs), and gold. From the efficient frontier in Exhibit 1, we can see the return and standard deviation of CRIX and six common investments. CRIX 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 the transition map of our portfolio performance, S&P 500 and CRIX dominate the portfolio, whereas 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-averse investor is willing to tolerate daily volatility above 3%, the transition map suggests investing more than 80% of initial wealth into CRIX.

Exhibit 2 plots the market-efficient frontiers of a mainstream portfolio with and without CRIX. The inclusion of CRIX shifts the efficient frontier upward. This means that, under the same level of risk, a portfolio

E X H I B I T 2

Efficient Frontier and Optimal Portfolio



with CRIX has a higher return than a portfolio consisting of only mainstream assets.

Indeed, this result should be carefully stated. Within the sample period, traditional assets cannot generate returns as high as those of CRIX. Therefore, investors who want to achieve a high return should take CRIX risk. In this case, our finding could be driven by the nature of high risk in CRIX given the risk–return relation held for the cryptocurrency market.[7]

This mean–variance analysis is limited because of the highly nonnormal return distribution of cryptocurrencies. We employ a Cornish–Fisher expansion to extend the mean–variance framework to incorporate high moments, including skewness and kurtosis. We then construct the conditional value at risk (CVaR) at a confidence level of $\alpha = 0.01$. CVaR provides the solution by solving the following optimization problem:

$$\min_{w_t \in R^p} CVaR_\alpha(w_t),$$

$$s.t. u_{p,t}(w_t) = r_{Target},$$

$$w_t 1_p = 1,$$

$$w_{i,t} \succeq 0$$

According to Cornish–Fisher, we can rewrite our objective function as

$$CVaR_\alpha(w_t) = -\frac{1}{1-\alpha} q_\alpha^*(W_t)\sigma_{p,t}(w_t)$$

where

$$q_\alpha^*(w_t) = \left\{1 + \frac{S_{p,t}(w_t)}{6} z_{\alpha^*} + \frac{K_{p,t}(w_t)}{24}(z_{\alpha^*}^2 - 1) - \frac{S_{p,t}^2(w_t)}{36}(2z_{\alpha^*}^2 - 1)\right\}\psi(z_{\alpha^*})$$

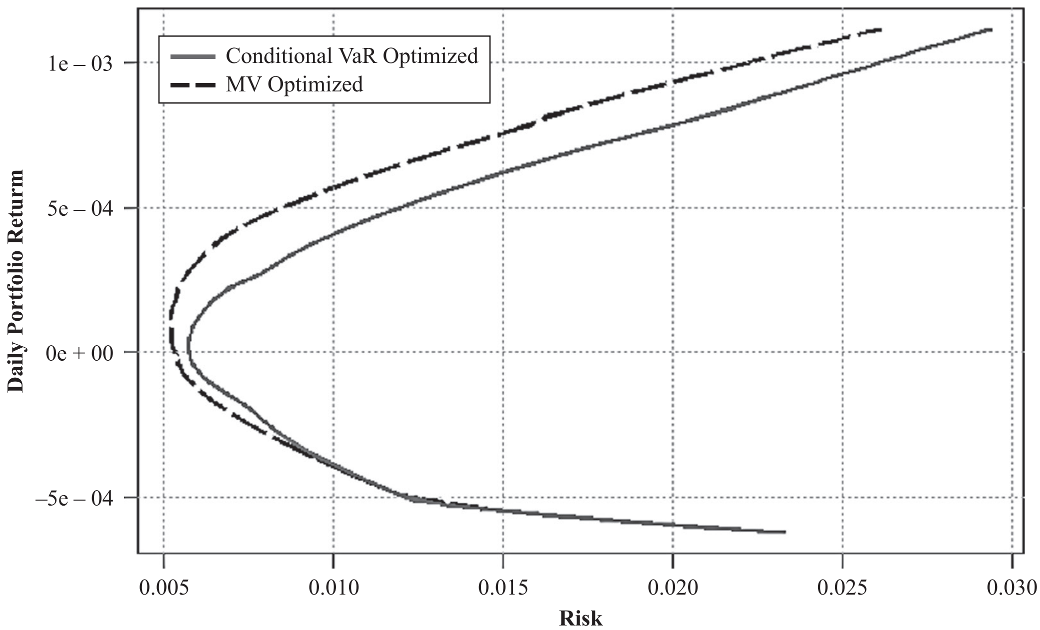
and $\alpha^* \stackrel{def}{=} 1-\alpha$ and $\psi(z_{\alpha^*})$ is the density function of a normal distribution z, where $z \sim N(0,1)$, an assumption of the Cornish–Fisher expansion. Importantly, in this equation, skewness and excess kurtosis are well incorporated with labels, S_p and K_p, respectively. Following Härdle et al. [2014] and Härdle et al. [2017], we express skewness and kurtosis as moment expression:

$$S_p(w) = \frac{1}{\sigma_p^3(w)}(m_3 - 3m_2m_1 + 2m_1^3),$$

$$K_p(w) = \frac{1}{\sigma_p^4(w)}(m_4 - 4m_3m_1 + 6m_2m_1^2 + 3m_1^4) - 3$$

EXHIBIT 3

Efficient Frontier under Skewness and Kurtosis



where we compute portfolio noncentral moments from the return samples as

$$m_1 = u_p(w) \overset{def}{=} w'u,$$

$$m_2 = \sigma_p^2 + m_1^2,$$

$$m_3 = \sum_{i=1}^{d}\sum_{j=1}^{d}\sum_{k=1}^{d} w_i w_j w_k S_{ijk},$$

$$m_4 = \sum_{i=1}^{d}\sum_{j=1}^{d}\sum_{k=1}^{d}\sum_{l=1}^{d} w_i w_j w_k w_l K_{ijkl}$$

where $\sigma_p^2(w) = w'\Sigma w$. Meanwhile, $S_{ijk} = E(r_i * r_j * r_k)$ and $K_{ijkl} = E(r_i * r_j * r_k * r_l)$ can be computed as sample averages from returns data. Indeed, S_{ijk} and K_{ijkl} determine the d-dimensional portfolio coskewness and cokurtosis tensors. After that, we solve the optimization problem by using a nonlinear constrained algorithm, DONLP2, based on equal weight as initial value input. The fitted parameters hence can be used to evaluate the efficient frontier under CVaR optimization. As a comparison, we plot the mean–variance-efficient frontier as well. Exhibit 3 shows the results.

The mean–variance analysis underestimates the risk of the portfolio. Given a target return, risk suggested by mean–variance is always lower than the efficient frontier suggested by CVaR because mean–variance only deals with the return and second-moment risk whereas CVaR considers higher moments risks.

In addition, although the efficient frontiers under CVaR seem to be different from mean–variance analysis, it suggests a similar asset allocation. For example, for a risk-averse investor who is willing to bear 31.75% annualized return volatility (2% daily return volatility),[8] CVaR will suggest an investment of 62.76% of risky investment into cryptocurrency (CRIX), and this weight is 72.50% under mean–variance. The reduced weight accounts for the high-moment risk. It is worth noticing that in the plot, the x-axis indicates the volatility instead of CVaR to be aligned with the mean–variance frontier, but the objective function that estimates the portfolio weight of CVaR considers high-moment measures. The plot allows us to directly observe how skewness and kurtosis affect our asset allocation.

On top of that, a risk-averse investor is more interested in knowing whether including CRIX in the portfolio statistically improves his or her utility. To answer this question, we employ two types of mean–variance spanning tests. Meanwhile, in CRIX, Bitcoin seems to overwhelmingly dominate the other

EXHIBIT 4

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

					Step-Down Test				
Asset	**Alpha**	**Delta**	***F*-Test**	***p*-Value**	**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

currencies as a result of the large market cap. In this case, to better understand other cryptocurrency contribution, we apply spanning tests to each of the top 10 cryptocurrencies. Exhibit 4 lists spanning tests on CRIX and the top 10 cryptocurrencies. The corrected Huberman–Kandel (HK) *F*-test (Huberman and Kandel [1987]) is used for the first test and the step-down test (Kan and Zhou [2012]) 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; in F_2, $\delta = 0_N$ is tested conditional on $\alpha = 0_N$. This helps to find the sources of rejection that are unclear in the traditional HK F-test.

The results suggest that the traditional *F*-test rejects the majority of the variables at the 5% level, except Dash coin, MaidSafeCoin, Bytecoin, and Litecoin. The joint test rejects all but MaidSafeCoin at the 10% level. CRIX and most cryptocurrencies play a significant role in improving the benchmark portfolio performance. However, according to the step-down test, we can see that none of them can improve the tangency portfolio; the statistics for F_1 fail to reject the hypothesis for all cryptocurrencies and CRIX. The results of the F_2 test are, however, in line with the traditional *F*-test. In particular, CRIX and Ethereum seem to have the best performance in rejecting the F_2-test, with a *p*-value of 0, whereas 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 $\delta = 0_N$ and not to the rejection of $\alpha = 0_N$. It is safe to conclude that there is strong evidence that a global minimum-variance portfolio can be improved by including CRIX and 6 out of the 10 cryptocurrencies, but this is not true for the tangency portfolio. This is not surprising because CRIX shows negative skewness, which may suggest an additional investment opportunity accompanied by high risk. To have improved portfolio performance, we need to understand the risk–return structure of the cryptocurrency market. Indeed, we argue that investor sentiment might be the driving force of the cryptocurrency market, with detailed discussion in the next section.

INVESTOR SENTIMENT AND CRYPTOCURRENCY MARKET

Cryptocurrencies, unlike 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 high volatility. Therefore, if we can capture the investor sentiment, it may reveal more information about the risk–return structure of the cryptocurrency market. In this section, we propose a proxy of investors' sentiment for each cryptocurrency and investigate its impact on cryptocurrency-based portfolio performance.

What Is Investor Sentiment?

A widely accepted behavioral finance paper about investor sentiment was written by Baker and Wurgler [2006], who argued 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 large and liquid stocks because small (illiquid) stocks are hard to arbitrage as a result of transaction frictions. This will result in a lower future return of those stocks.

During a high-sentiment period, buying large (liquid) stocks and short, small (illiquid) stocks will generate an arbitrage return in the future. On top of that, Huang et al. [2015] modified the Baker–Wurgler (BW) sentiment index by removing the noise components of the BW sentiment index and found a strong return predictability of partial least squares sentiment. Consistent with the prediction of Baker and Wurgler [2006], a higher sentiment index predicts lower future stock returns.

The most related paper that motivates our empirical design was written by Stambaugh, Yu, and Yuan [2012], who explored sentiment-related overpricing as an explanation for the 11 most popular asset-pricing anomalies. Importantly, they considered impediments to short selling as the major obstacle to eliminating sentiment-driven mispricing. To the extent that 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 the stock market and build tests on investor sentiment hypothesis in the cryptocurrency market.

Hypothesis Development

Different from the aforementioned literature, we extend the prediction of market-wide investor sentiment to firm-level investor sentiment. There are two reasons for doing this. First, the cryptocurrency market is new to investors and has its own features. In this case, we lack the necessary variables to mimic BW investor sentiment. For example, five of six key components of the BW sentiment index, including closed-end fund discount rate, number of initial public offerings (IPOs), the first-day return of IPOs, the dividend premium, and equity share in new issues are not available for the cryptocurrency market. Second, market-wide sentiment predictions rely on a clear classification of easy-to-arbitrage and hard-to-arbitrage groups. For the cryptocurrency market, a majority of cryptocurrencies were launched in recent years, and their market size is also developing. To simply take their current market size as a proxy of transaction friction is not appropriate. As a result, we extend the market-wide sentiment effect to individual cryptocurrencies. Our main hypothesis is that cryptocurrencies with higher investor sentiment today tend to have lower future return than those with lower investor sentiment.

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

Proxy of Investor Sentiment

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

Tetlock [2007] quantitatively measured the interactions between the media and the stock market using daily content from a popular *Wall Street Journal* column. He found that high media pessimism predicted 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 took media sentiment as the content of investor sentiment and emphasized the return reversal as evidence of the sentiment effect.

Contrary to this, Tetlock, Saar-Tsechansky, and Macskassy [2008] pointed out that media news contains valuable information on firm fundamentals that are not priced by the current market. In that paper, they found that news articles containing "earnings" have better return predictability around earnings announcement days. Importantly, they found that the tone of news significantly predicts actual earnings represented by Standard Unexpected Earnings. This serves as important evidence that media news contains valuable information about firm fundamentals. Overall, the real effect of media news is not well understood; hence, the tone of news may not be a clear measure of investor sentiment. Moreover, there is no sentiment dictionary or training sample for the cryptocurrency market. In this case, we can only use a sentiment dictionary that is designed for the stock market as bag-of-words for sentiment classification. However, many special words in the cryptocurrency market, like *blockchain*, *hash*, *PoW*, and so on are not labeled in those general sentiment dictionaries, including the Loughran and McDonald dictionary (Loughran and McDonald [2011]) and the Harvard IV4 dictionary.[9] This makes the accuracy of media sentiment analysis low. As a result, for the moment, media news sentiment is not a good proxy of investor sentiment for the cryptocurrency market.

Another way to measure investor sentiment is overnight return, as proposed by Berkman et al. [2012], which suggests that individuals tend to place orders outside of regular working hours, to be executed at the start of the next trading day. Specifically, Berkman et al. [2012] found that attention-generating events (high absolute returns or strong net buying by retail investors) on one day led 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] showed that the one-day reversal was more pronounced for firms that are harder to value and costlier to arbitrage. Yet many cryptocurrencies are traded 24 hours a day, and cryptocurrency exchanges are open on the weekends (Trimborn and Härdle [2016]). In other words, there is no close-to-open price as a proxy of investor sentiment.

Due to data limitations, after rejecting other alternative measures, such as order imbalance and put–call ratio, we take the past average return as a proxy for investor sentiment. This measure is built on the spirit of the work by Berkman et al. [2012]. The key point of using the overnight return is that extreme events draw retail investors' attention, thus inducing higher demand by individual investors. Because retail investors tend to be irrational, it creates additional price pressure, resulting in a sentiment effect. If this 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 expectations.

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 cryptocurrency. The point of "average" is to remove the noise components of individual daily return. The calculation of sentiment is as follows:

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

where $Return_{j,t-n}$ is return of cryptocurrency j at n days before the sentiment calculation day, t; and N is the formation-period investor sentiment. In the following analysis, we set N as 10 to smooth daily return. Indeed, our results are not sensitive to the selection of a formation period, as illustrated later by robustness checks.

Empirical Results

We first examine whether our measure captures a sentiment effect. According to Berkman et al. [2012], sentiment-induced overnight returns are reversed during the trading day because rational investors will adjust for the mispricing. If that is true, we expect that a high (low) cryptocurrency sentiment indicates a low (high) subsequent cryptocurrency return. To examine this effect, we employ the top 100 cryptocurrencies that have been included in 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 a high (low) sentiment event as the day cryptocurrency j is labeled in the high (low) sentiment group. Each cryptocurrency could have multiple high (low) sentiment event days. Last, we compute individual cryptocurrency returns one week before their high (low) sentiment event and then plot the mean of their return with a 95% confidence interval in Exhibit 5.

The 0 in the x-axis stands for the sentiment event day. We separately examine the average cryptocurrency returns of high and low sentiment groups. The 95% confidence interval of the average return for both high and low sentiment is represented by the gray area.

EXHIBIT 5

Average Cryptocurrency Return around Extreme Decile of Sentiment

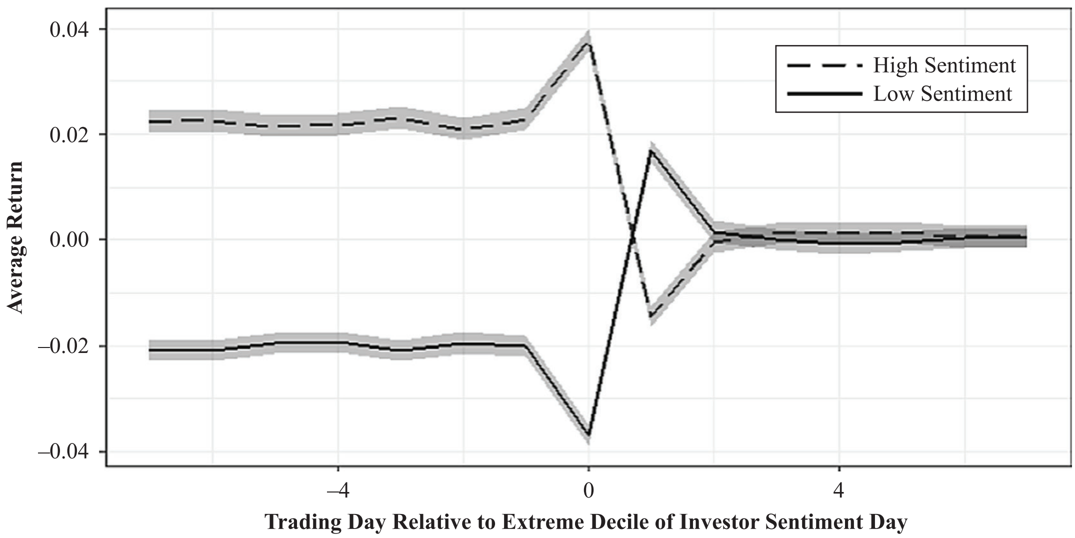


EXHIBIT 6

Fama–MacBeth Regression of Cryptocurrencies' Returns on Sentiment

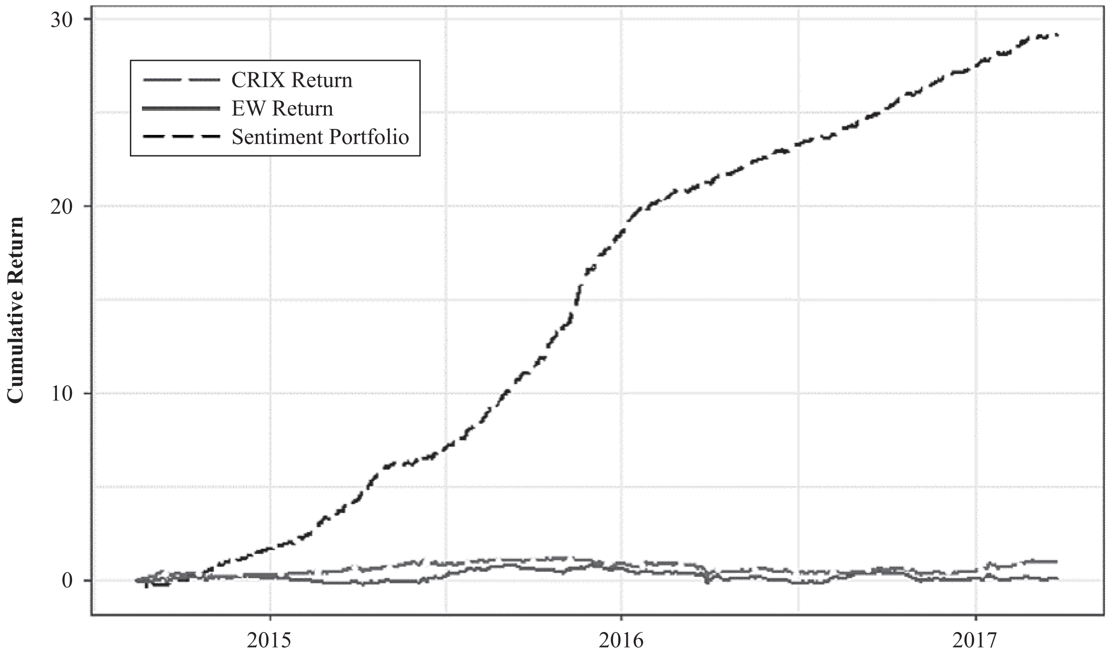
	Whole Sample Period			Before 2016			After 2016		
Sentiment	–0.888***	–0.387***	–0.384***	–1.001***	–0.472***	–0.453***	–0.762***	–0.294***	–0.308***
	(–12.18)	(–6.09)	(–6.37)	(–8.33)	(–4.55)	(–4.72)	(–9.99)	(–4.26)	(–4.42)
Lagged Ret		–0.241***	–0.240***		–0.254***	–0.257***		–0.226***	–0.221***
		(–20.77)	(–21.45)		(–14.58)	(–15.71)		(–15.08)	(–14.70)
Volume			0.001***			0.002***			0.001***
			(6.97)			(4.84)			(5.18)
Intercept	–0.002*	–0.002	–0.014***	–0.004**	–0.004**	–0.017***	–0.000	0.001	–0.011***
	(–1.79)	(–1.50)	(–6.52)	(–2.05)	(–2.25)	(–5.03)	(–0.19)	0.54	(–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

Notes: Newey–West t*-statistics with 12 lags are given in parentheses.*
****$p \leq 0.01$; **$p \leq 0.05$; *$p \leq 0.10$.*

Exhibit 5 shows that the average return of high sentiment before the sentiment day is positive, whereas that of low sentiment is negative; both are significantly different from 0, consistent with our construction of investor sentiment. Furthermore, 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 on the next trading day, suggesting that rational investors come to correct the sentiment-induced mispricing. Moreover, after the next trading day, cryptocurrency returns do not seem different from 0, suggesting no overadjustment or underadjustment for the mispricing. Furthermore, this empirical evidence also answers the question we proposed at the end of the last section, namely how fast rational investors correct the mispricing. Inconsistent with our expectation, transaction frictions do not have a strong impact on the adjustment process, and rational investors react very fast in terms of sentiment-induced over- or underpricing.

Next, we test the cross-sectional premium of sentiment using Fama–MacBeth regressions. Regression results are shown in Exhibit 6. We have three different

EXHIBIT 7
Cumulative Returns of Sentiment Portfolio



sample periods and two additional control variables. The first three columns use the whole sample period, namely from August 11, 2014 to March 27, 2017; the middle three columns present the results of sample period before 2016; and the last three columns show the results of period after 2016. The 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 a 0.38% lower future return compared to the overall cryptocurrency portfolio, given other situations are fixed.

Based on the results, we further explore the possibility of generating positive risk-adjusted profits with the sentiment strategy. We form two equal-weighted portfolios based on each firm's sentiment, defined as the average return of the past 10 trading days. All cryptocurrencies are labeled with sentiment in the top decile as the 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. Exhibit 7 shows the cumulative returns of investment strategies based on sentiment in the prior trading day with the sample period spanning from August 11, 2014 to March 27, 2017. Ignoring trading costs, the cumulative returns of the sentiment portfolio are over 20 times the initial investment after 2016, much higher than those of the return rate of CRIX and the equal-weighted portfolio based on the top 100 cryptocurrencies.

To further study the cumulative returns of three groups of sentiment portfolios from high to low, as shown in Exhibit 8, the sentiment strategy is very successful in terms of classifying cryptocurrency returns into different patterns. Consistent with our expectation, a portfolio of low sentiment has large positive returns, whereas the median sentiment group shows a slightly negative cumulative return and the high sentiment group has large negative cumulative returns.

Exhibit 9 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 returns. This figure suggests that, for

EXHIBIT 8
Cumulative Returns by Sentiment Level

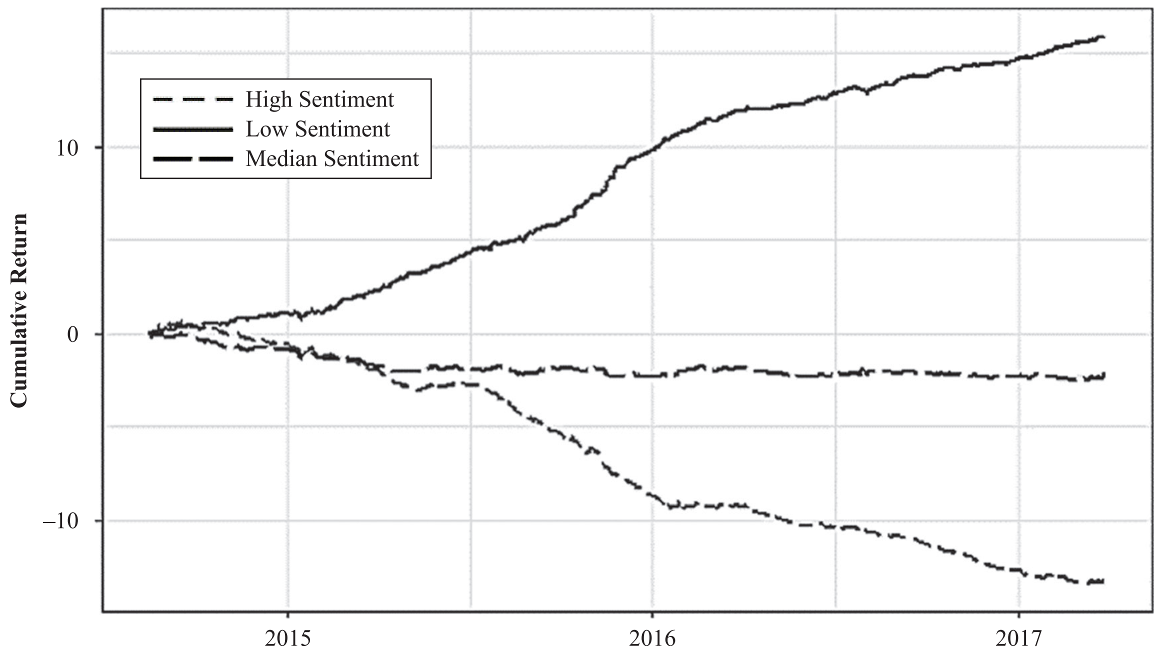
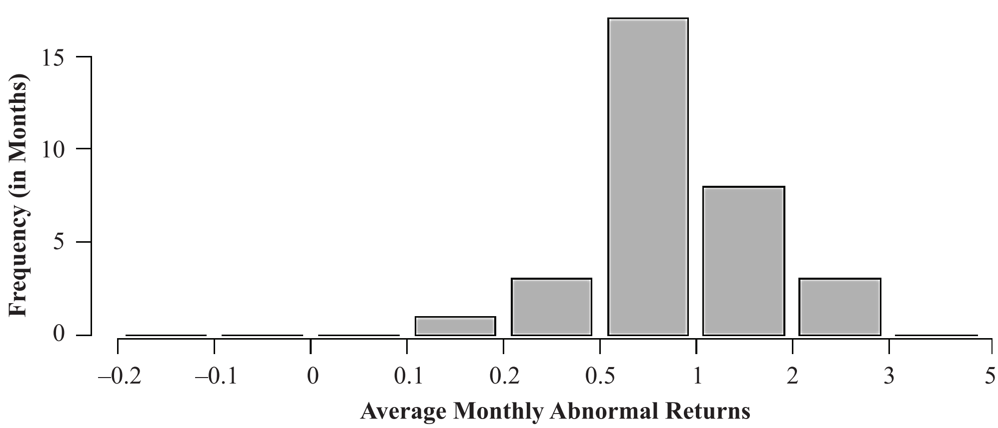


EXHIBIT 9
Distribution of Monthly Abnormal Returns for the Sentiment-Based Portfolio



most months, average abnormal return on the portfolio is between 50% and 100%. Importantly, none of the monthly returns drop below 0, which suggests an extremely good arbitrage opportunity.

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 (e.g., the S&P 500, gold, and REITs) and other cryptocurrencies (e.g., the top 10 cryptocurrencies covered in the 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, the S&P 500 is used as the benchmark.

As seen in Exhibit 10, of all investment classes, the sentiment portfolio has the highest average return,

EXHIBIT 10
Performance Evaluation

	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	0.0090	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	0.0390	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	0.0130	0.0078	–27.52%
XMR	0.0032	0.0840	0.0381	0.0344	–33.63%
BTS	–0.0007	0.0733	–0.0099	–0.0138	–29.33%
BCN	0.0040	0.1214	0.0329	0.0303	–49.00%
NXT	–0.0017	0.0725	–0.0234	–0.0271	–36.36%
LTC	–0.0008	0.0578	–0.0130	–0.0180	–54.72%

EXHIBIT 11
Sensitivity of Sentiment-Based Trading Returns to Trading Cost Assumptions

	Whole Sample Period		Before 2016		After 2016	
Trading Cost (bps)	Raw Annualized Return	*t*-Value	Raw Annualized Return	*t*-Value	Raw Annualized Return	*t*-Value
1	8.46	18.78	9.65	14.64	7.15	11.87
2	8.43	18.71	9.61	14.59	7.12	11.82
3	8.40	18.64	9.58	14.54	7.09	11.77
4	8.36	18.57	9.54	14.49	7.06	11.72
5	8.33	18.50	9.51	14.44	7.02	11.66
6	8.30	18.43	9.47	14.40	6.99	11.61
7	8.26	18.36	9.44	14.35	6.96	11.56
8	8.23	18.29	9.41	14.30	6.93	11.51
9	8.20	18.22	9.37	14.25	6.89	11.45
10	8.16	18.15	9.34	14.20	6.86	11.40

as high as 2.34% per day (or an annualized return of 8.54), with a daily Sharpe ratio of 0.61 (or an annualized Sharpe ratio of 11.64). In terms of the Sharpe ratio and information ratio, it has outperformed all others by a huge margin. Meanwhile, the max-drawdown of the sentiment-based portfolio is also lower than both CRIX and the equal weight portfolio using the top 100 cryptocurrencies.

Robustness Check

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

Transaction cost impact on portfolio performance. The previous analysis assumes no transaction

EXHIBIT 12

Sensitivity of Sentiment-Based Trading Returns to the Formation Period Assumptions

	Whole Sample Period		Before 2016		After 2016	
Formation Period (days)	Raw Annualized Return	*t*-Value	Raw Annualized Return	*t*-Value	Raw Annualized Return	*t*-Value
11	8.03	17.91	9.09	17.91	6.85	17.91
12	8.14	18.48	9.43	18.48	6.66	18.48
13	7.67	17.27	9.01	17.27	6.09	17.27
14	7.51	16.53	8.97	16.53	5.71	16.53
15	7.56	16.50	8.84	16.50	5.94	16.50
16	7.77	17.07	8.86	17.07	6.32	17.07
17	7.46	16.16	8.60	16.16	5.88	16.16
18	7.19	15.85	8.11	15.85	5.83	15.85
19	6.98	15.48	8.00	15.48	5.40	15.48
20	6.71	14.69	7.33	14.69	5.69	14.69

costs, but that 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 because it entails transaction costs, among other reasons.

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

In contrast, other fees create more frictions. For example, BTC-E charges a 0.2% to 0.5% fee per transaction along with fees to deposit or withdraw traditional currency. According to *CryptoCoins News*,[10] 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 that 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 the following 10 alternative assumptions about a trader's roundtrip transaction costs: 1, 2, 3 … or 10 bps per roundtrip per trade. The raw annualized portfolio return for each trading cost is summarized in Exhibit 11.

The results indicate that the strategy is less profitable with the trading costs. Yet when the trading cost rises to 10 bps, the raw annualized return of the sentiment-based trading strategy is still high at 8.16 with a *t*-value of 18.15. Overall, the sentiment-based portfolio is relatively insensitive to the transaction costs, suggesting a low turnover for the trading strategy.

Formation period impact on portfolio performance. To construct sentiment for each cryptocurrency, we initially used the average of the past 10 trading days' returns. In this section, we show that our results continue to hold when using alternative formation periods. We use the same procedure to construct the sentiment measure and report the results in Exhibit 12.

Exhibit 12 shows estimates of the impact of the sentiment formation period on the trading strategy's profitability. The results are quite robust in terms of selection of formation period. The annualized portfolio return based on the sentiment proxy using the past 20-day returns is 6.71 with a *t*-value of 14.69, suggesting a consistent sentiment effect on the cryptocurrency market.

In addition, our sentiment strategy may explore some investment opportunities on some extreme event days. Due to liquidity constraints, investors are not able to fully capture these investment opportunities. To handle this issue, we have winsorized our data at 1% to reduce the effect of possibly spurious outliers. Regardless of other market microstructure issues, we believe our sentiment-based trading strategy will generate a reasonably good investment opportunity. Moreover, many cryptocurrencies have a fixed total supply, 21 million coins for BTC as an example. This could be another liquidity issue, but we believe it does not affect our analysis too much. Many altcoins are still developing, and they are far from the limit of total supply. Additionally, cryptocurrency can be divided into small fractions of a coin. As far as we know, computers can record a 10^{-8} unit of cryptocurrency.[11] By 2025, technological innovations will make it possible to record a 10^{-32} unit of cryptocurrency. Indeed, it could be the case that one unit of cryptocurrency can be divided into infinite pieces. Hence, a fixed supply may not be an issue in the future.

CONCLUSION

In the first part of this article, we described the characteristics of Bitcoin and altcoins as well as the market structure of cryptocurrencies and crypto-tokens. In the second part of this article, we investigated the possibility and performance of investing in cryptocurrencies as an alternative asset class. We compared the characteristics of cryptocurrencies and traditional asset classes and examined the static correlations between them, as well as the dynamic conditional correlations.

The results show that the CRIX and cryptocurrencies can be a good option to help diversify portfolio risks because the correlations between cryptocurrencies and traditional assets are consistently low and the average daily return of most cryptocurrencies is higher than that of traditional investments. Furthermore, the plots of the efficient frontier illustrate that incorporation of the CRIX significantly expands the efficient frontier relative to traditional asset classes alone.

Nevertheless, as 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 an annualized return of 8.54 and Sharpe ratio of 11.64.

Bitcoin may have been in existence and stood the trail for eight years. However, cryptocurrency and crypto-token are still at the experimental stage. We believe that, although our results are interesting, many other issues 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 in this class of investment entails an understanding of the associated complexity and risk. Other issues, such as security of safekeeping, reporting standard without custodian and trustee, and the governance structure of a decentralized 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 et al. [2017] may be a good way to end this article:

> 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 it is very likely that PE/venture capital may take on a new form in the future.

APPENDIX A

MARKET CAPITALIZATION AND COMPARISON OF TOP CRYPTOCURRENCIES

EXHIBIT A1

Market Capitalization of Cryptocurrencies

No.	Name	Symbol	Market Cap	Price	Circulating Supply	Volume (24 hours)
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	$0.276024	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	$0.164713	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	$0.38963	2,779,530,283*	$6,107,400
9	BitShares	BTS	$676,530,938	$0.260568	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	$0.002376	183,065,167,227	$2,490,360
14	Siacoin	SC	$428,467,781	$0.015721	27,254,659,755	$28,877,300
15	Waves	WAVES	$426,407,000	$4.26	100,000,000*	$5,813,100

**Not mineable.*

EXHIBIT A2

Different Categories of Altcoins

No.	Category of Altcoin	Example		
		Aspect	Altcoin	Bitcoin
1	Coins with minor changes of parameter	Rewarding system Max supply	IxCoin: 96 IXC per block Terracoin: 42 million	50 BTC per block 21 million
2	Coins with technical innovation	Hashing algorithm Timestamping	Litecoin: Scrypt Peercoin: PoS	SHA-256 PoW
3	Coins that are coded in different programming language	Programming language	Nxt: Java	C++
4	Coins with new ideas	Unique features	Counterparty: embedded consensus Ethereum: Turing-complete	NA
5	Appcoins	Unique features	Storjcoin X, SWARM Coin, MaidSafeCoin	NA

EXHIBIT A3
Features of Cryptocurrencies

Coin	Symbol	Launch Date	Consensus Tool	Distribution	Unit Cap	Block Time
Bitcoin	BTC	January 3, 2009	SHA-256	PoW (fixed, halving)	21 million	10 minutes
Ripple	XRP	March 1, 2011	Ripple	Centralized	100 billion	NA
Litecoin	LTC	October 7, 2011	Scrypt	PoW (fixed, halving)	84 million	2.5 minutes
Dash	DASH	January 19, 2014	Combo11	PoW (fixed, curve)	18.4 million (estimate)	2.5 minutes
Monero	XMR	April 18, 2014	CryptoNote	PoW (random, smooth)	18.4 million with 1% annual inflation	2 minutes
Zcash	ZEC	October 28, 2016	Zerocash	Zero-knowledge proofs, PoW, with a portion of each block subsidy distributed to founders for the first four years	21 million	2.5 minutes
Dogecoin	DOGE	December 6, 2013	Scrypt	PoW (random)	Unlimited	1 minute

APPENDIX B

INTRODUCTION OF CRYPTOCURRENCIES

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 16.4 million bitcoins are in circulation as of June 2016. It is widely accepted as the most popular cryptocurrency and has the largest market capitalization.

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 developed using a fund, US$18 million worth of bitcoins, raised via an online public crowd sale of ether in 2014.

Litecoin (LTC)

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

EXHIBIT B1
Introduction of the 10 Cryptocurrencies Included for Most Times in CRIX

Number	Cryptocurrency	Symbol	Times Being Included in CRIX[a]	Market Cap[b] ($ millions)
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	BTC	26	24
8	MaidSafeCoin	MAID	25	90
9	Nxt	NXT	24	16
10	Bytecoin	BCN	24	23

[a] *Source: CRIX—Crypto Index http://crix.hu-berlin.de/.*

[b] *Market capitalization as of April 6, 2017 (source: CoinMarketCap https://coinmarketcap.com/).*

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 decentralized autonomous organization. It is a privacy-centric cryptocurrency. It uses a coin-mixing service called PrivateSend to anonymize transactions and InstantSend to allow for instant transactions.

Dogecoin (DOGE)

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

Monero (XMR)

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

BitShares (BTS)

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

MaidSafeCoin (MAID)

MaidSafeCoin is designed for the secure-access-for-everyone network. The data of users and transactions are safe and secure. The network encourages users to provide their resources, such as storage space, central processing unit power, and bandwidth, by giving them the coins as a digital token. The maximum number of MaidSafeCoins in circulation is 4.3 billion.

Nxt (NXT)

Nxt was released in 2013 by an anonymous software developer, BCNext. It is the first cryptocurrency that uses purely PoS for consensus, thus making the money supply static—1 billion in 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 because it is easier to build external services on top. For example, it allows for currency creation and has a messaging system and marketplace.

Bytecoin (BCN)

Bytecoin is the first cryptocurrency invented with the CryptoNote protocol. It secures transactions because the identities of the sender and 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.

Other Cryptocurrencies

In addition to the aforementioned 10 cryptocurrencies, the following altcoins have also been drawing investor attention.

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 was created after the hard-fork debate in 2016 and is designed to allow smart contracts to run exactly as programmed without any possibility of third-party interference.

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 systems.

NEM (XEM). NEM is a P2P platform that provides services like payment and messaging system. It uses a proof of importance algorithm, so it does not require much computing power and energy to mine. Together with Mijin, which is a licensed version of NEM, it is the first public/private blockchain combination.

Ripple (XRP). Ripple was created by Chris Larsen and Jed McCaleb. It is one of the first cryptocurrencies not developed based on Bitcoin's protocol. It is an open-source, distributed P2P 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.

Zcash (ZEC). Launched in 2016, Zcash provides privacy and selective transparency of transactions. Although the transactions are recorded in the public blockchain, Zcash allows for completely transparent transactions using t-addresses, and it can also offer a 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 a z-address. As with bitcoin, the total amount of Zcash is capped at 21 million.

APPENDIX C

EXHIBIT C1

Summary Statistics of CRIX, Cryptocurrencies, and Traditional Asset Class

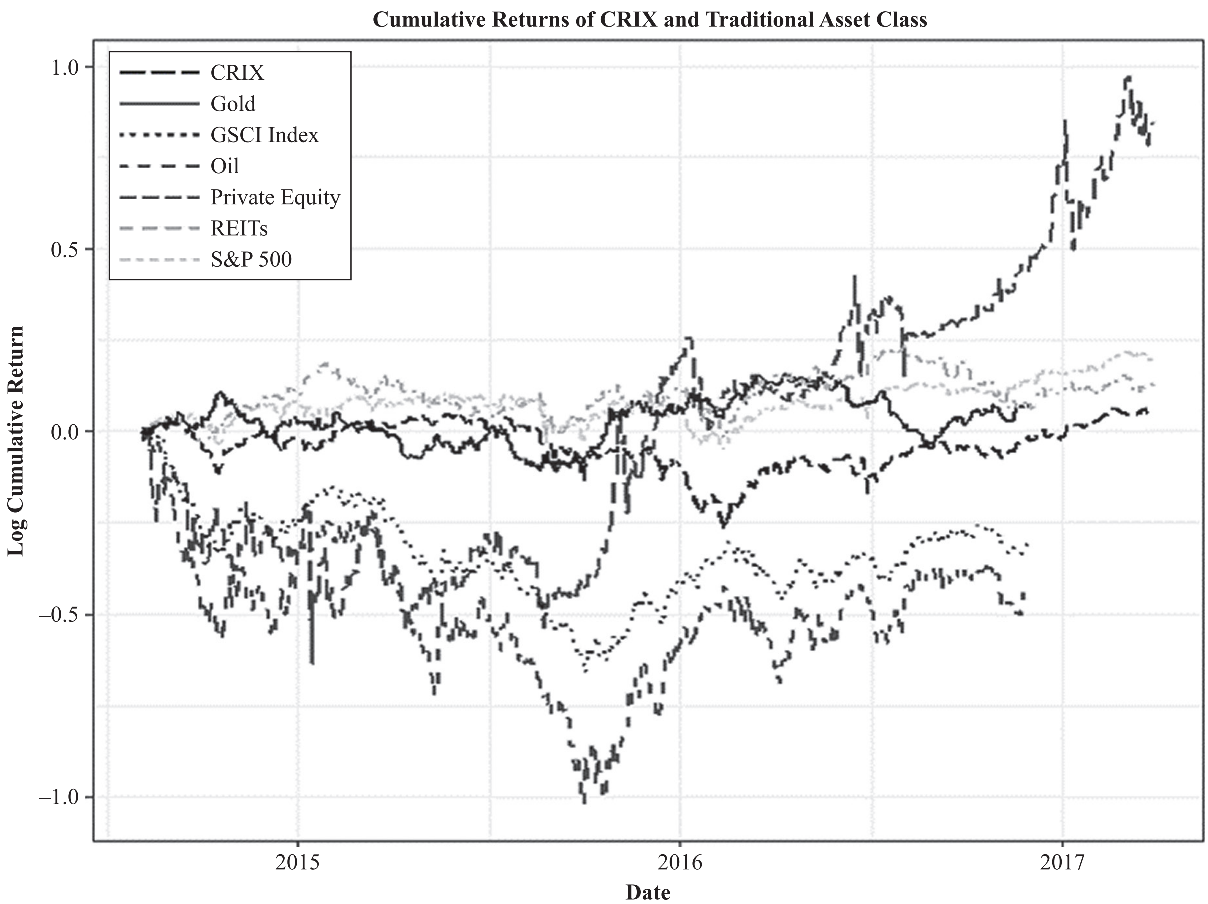


EXHIBIT C2

Summary Statistics for Return of CRIX Index and Cryptocurrencies

	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	1.1100	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	0.6470	9.7346	–0.3740	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	0.0730	1.4375	12.7584	–0.2933	0.5252	0.0572
MAID	0.0040	0.1210	3.7434	55.4465	–0.4900	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

EXHIBIT C3

Summary Statistics for Return of Traditional Asset Class

	Mean	SD	Skew	Kurt	Min	Max	Rho
T-Note	4.95E-06	6.54E-06	0.9694	2.7994	0	2.00E-05	0.989
S&P 500	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

APPENDIX D

EXHIBIT D1

Correlations for Traditional Asset Class against Cryptocurrencies

Panel A: Static Correlation

	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

Panel B: DCC

	Mean	SD	Min	Q25	Median	Q75	Max
S&P 500	–0.0182	0.0250	–0.0810	–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	0.0330	4.60E-08	0.0330	0.0330	0.0330	0.0330	0.0330
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

ENDNOTES

[1]Note that Bitcoin with a capital letter denotes the network or protocol, and lowercase bitcoin refers to the currency or coin.

[2]Available at https://coinmarketcap.com/.

[3]See: https://price.bitcoin.com/.

[4]See: https://github.com/bitcoin/bitcoin.

[5]See: https://coinmarketcap.com/all/views/all/.

[6]See: http://crix.hu-berlin.de/#page-top.

[7]Although we are not able to disentangle this alternative channel using the current data sample, we are not totally in favor of this argument. The main reason is that the cryptocurrency market is still developing, and many altcoins are not financialized or included in institutional portfolios. Under such circumstances, the risk of cryptocurrency is not fully understood by investors, and the risk–return relation is not fully revealed by the market. Hence, a high realized return of CRIX is not a compensation for high risk; instead, it may reflect increased demand by institutional investors.

[8]Annual volatility = Daily volatility × ($252^{0.5}$), where 252 is the number of trading days per year for the equity market.

[9]See: http://www.wjh.harvard.edu/~inquirer/homecat.htm.

[10]See: https://www.cryptocoinsnews.com/bitcoin-transaction-friction-a-reality-check.

[11]10^{-8} of a bitcoin is known as a *Satoshi*.

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