Cryptocurrencies as an Asset Class

Sinan Krückeberg and Peter Scholz

Abstract Cryptocurrencies are a new emergence at the intersection of technology and finance. It is therefore of particular interest whether cryptocurrencies can form a new asset class or need to be subsumed under an existing one. We find that cryptocurrencies show characteristics of a distinct asset class based on strong internal correlation, an absence of correlation with any traditional asset class as well as sufficient market liquidity, while market stability has room for improvement. Adding cryptocurrency to traditional portfolio structures may lead to significant and persistent risk-adjusted outperformance. These results support the careful introduction of cryptocurrencies into the asset management mainstream.

1 Introduction

Economic turbulences such as the Subprime Crisis have served to highlight the fragility of our monetary and financial system. As a reaction to what has become one of the most severe crises in history, *Bitcoin* was launched in 2009 setting the stage for a multitude of further projects which led to the development of a new bridge between technology and finance: *cryptocurrency*. Increasing investment continues to flow into the sector amounting to a total market capitalization of over US$400 billion by December 2017. However, it remains an essential question whether cryptocurrencies can qualify as a distinct asset class in their own right, enabling diversification and outperformance compared to portfolios comprising only traditional asset classes. If cryptocurrencies were to constitute a distinct asset class, this would carry significant implications for fund managers, regulators and policy makers alike.

S. Krückeberg (✉)
Krückeberg Family Office, Hamburg, Germany
e-mail: sinan@krueckeberg.us

P. Scholz
Hamburg School of Business Administration (HSBA) Department of Banking & Finance, Hamburg, Germany
e-mail: peter.scholz@hsba.de

S. Goutte et al. (eds.), *Cryptofinance and Mechanisms of Exchange*, Contributions to Management Science, https://doi.org/10.1007/978-3-030-30738-7_1

While existing literature has touched upon the nature and performance impact of cryptocurrencies, significant scope remains to form a comprehensive picture. Attempts at answering the question of whether cryptocurrencies are investable and constitute a distinct asset class have so far exclusively focused on correlation between Bitcoin, as a proxy for cryptocurrencies, and traditional assets. We increase the granularity of inquiry by covering a broad selection of individual cryptocurrencies and extend as well as embed correlation analyses in a theoretical framework for the definition of asset classes provided by Sharpe (1992). Beyond correlation, we add liquidity and stability as criteria to evaluate the investability of cryptocurrency. On the side of analyses regarding the impact of cryptocurrency on portfolio performance, we significantly extend time-series length and provide multiple weighting methods that aim to reflect implementable allocations to cryptocurrency and thereby portfolio structures that can be applied in asset management practice. We thereby aim to provide a robust fundament to comprehensively evaluate cryptocurrencies as an asset class as well as their real-world impact on portfolio performance.

Under the umbrella term cryptocurrencies, we therefore differentiate between cryptographic *coins*, which use their own blockchains, and *tokens*, which operate atop a third party's blockchain architecture. The 10 largest coins and tokens by market capitalization as of mid-December 2017 with at least a price history of 3 months are selected. First, we are interested whether either coins or tokens or both can qualify as asset classes in their own right. We evaluate cryptocurrencies on the basis of parametric and non-parametric correlation measures, market liquidity and market stability against Market Wide Circuit Breaks and Limit Up-Limit Down triggers. Second, we are interested whether adding cryptocurrencies to traditional portfolios will lead to superior results regarding the Sharpe ratio for quarterly rebalancing intervals via *ex-post* optimizations. Third, we use the results of previous *ex-post* optimizations for *ex-ante* portfolio calibration. Three different weighting approaches are applied. *Dynamic* weighting uses the dynamic quarter-by-quarter allocations of the *ex-post* optimization to rebalance portfolios. *Average* weighting employs the average weights for the respective asset classes over all optimized quarters with rebalancing to initial weights at the end of each quarter. *Conservative* weighting utilizes traditionally defensive portfolio allocations vs. such allocations plus the addition of 1% of the asset class cryptocurrencies. Thereby, we test for risk-adjusted outperformance of portfolios containing cryptocurrencies versus portfolios that only contain traditional asset classes via three different weighting rules.

We find that cryptocurrencies qualify as a distinct asset class. Strong correlation among cryptocurrencies is contrasted by almost no statistically significant correlation of cryptocurrencies with traditional asset classes. Absolute market liquidity for some cryptocurrencies is already on equal footing with traditional equities while liquidity in relation to market capitalization is significantly stronger for cryptocurrencies than for traditional assets. Market stability needs to improve as evidenced by numerous market breaks as well as Limit-Up-Limit-Down trigger signals. Moreover, we find evidence for the existence of two distinct sub-asset classes coins and tokens. *Ex-post* portfolio optimizations employing the Sharpe ratio show that adding cryptocurrencies to traditional portfolios leads to superior results regarding risk-adjusted returns. Using the previously calculated *ex-post* Sharpe-optimal weights for *ex-ante* portfolio calibration, dynamic weighting underperforms while both the averages and conservative weightings consistently outperform.

These findings imply that investment practitioners can find attractive upside and diversification effects in adding even small cryptocurrency positions to their portfolios. Furthermore, defining cryptocurrencies as an asset class could have an impact both on regulatory treatment of such as well as future policy debate.

2 The Technology Behind Cryptocurrency

Merkle's (1980) seminal work has tied together essential strands of research on protocols for public key crypto systems, forming a vital foundation for the future development of cryptocurrency. Merkle reviews both conventional and digital cryptographic protocols and concludes that centralized key distribution for some use cases is inferior to public key distribution, due to vulnerabilities regarding loss of security and function as well as proneness to destruction (for types and merits of decentralization, see also Buterin 2017b). He provides the key building blocks for future development of decentralized cryptocurrencies by outlining Authenticated Public Key Distribution, a Basic Digital Signature Protocol, Time Stamping and Witnessed Digital Signatures. Authenticated Public Key Distribution establishes a system in which each participant holds a randomly computed public enciphering key as well as a private deciphering key. Encrypted information is signed with the sender's private key and encrypted with the recipients public key. This way, information transmitted can be authenticated as sent by the sender while only being decipherable by the recipient. To implement a full-fledged cryptocurrency, a consensus mechanism, generating consensus about the legitimate state of a system, is needed in addition to a general encryption mechanism. Such consensus mechanisms are used to record valid transactions by implementing Time Stamping and Witnessed Digital Signatures. Time stamps provide a proof of existence for each transaction at or before a certain point in time, while Witnessed Digital Signatures serve as proof of validity. The combination of an encryption protocol together with a consensus mechanism enables the maintenance of a public ledger of transactions. The technology for such a ledger is most prominently realized as a *Blockchain* (for a primer on Blockchain technology, see Voshmgir and Kalinov 2017).[1] Individual transactions are aggregated into blocks by individual participants of the system for a reward and subsequently integrated into a chain of blocks and marked with a time stamp. Individual blocks in a chain subsequently get confirmed by other participants of the system through the addition future blocks atop the previous block. In the case

[1]Bleeding edge alternatives such as the 'Tangle' and 'Hashgraph' are emerging, see Popov (2017) and Baird (2016) respectively.

of branching of the blockchain, one branch will ultimately 'outgrow' others, emerging as the dominant branch while the alternative branches will 'die off'. A copy of the decentralized ledger of transactions is held by each participant of the ecosystem. In order to allow for scaling of the public ledger, Merkle Trees are utilized to minimize storage needs (Merkle 1990). Initial attempts seeking to implement such a design can be found in Wei Dai's *B-Money* (WeiDai 1998) followed by Szabo's *BitGold* (Szabo 2008). *Bitcoin* has so far without doubt emerged as the most prominent system based on Nakamoto's work (Nakamoto 2008). Buterin (2013a, b) proposes *Ethereum*, launching a platform with increased functionality (see also Wood 2014; Buterin 2016). Upon Ethereum, a large variety of projects has been built, such as *EOS*, *FileCoin* and *Golem* (cf. EOSProject 2017; ProtocolLabs 2017; GolemProject 2016).

Three mechanisms for achieving consensus regarding the validity of a mined block are Proof of Work (PoW), Proof of Stake (PoS) and Proof of Burn (PoB) which will be explained below. These mechanisms are primarily relevant for reasons of system security, aiming to make the counterfeiting of the distributed ledger as expensive as possible to prevent attacks on ledger integrity. However, tightly linked are economic implications regarding token supply as well as volatility arising from possible insecurity. Together, these factors have given rise to the emerging field of *Cryptoeconomics*, seeking to balance considerations of cryptography and economic incentives.

In a PoW mechanism, the influence individual miners can exert on the development of the blockchain is defined by the computational effort or work invested into the maintenance of the system. The work invested is directed at solving a computational puzzle as originally described by Dwork and Naor (1992), who propose the implementation of pricing functions in order to gain access to certain information. Jakobsson and Juels (1999) formalize the concept of PoW. The meaning is hereby shifted from an authentication mechanism to a verification of computational resources invested during a certain period of time. Juels and Brainard (1999) highlight PoW schemes as protection against the flooding of a server with requests to carry out denial-of-service attacks. This development has culminated in Back's (2002) *Hashcash* cost function, which currently forms the basis for most crypto tokens in circulation. Miners willing to mine an incremental block of transactions are provided with a randomly generated hash. The aim of the miner is then to iterate a nonce a vast amount of times until one is found that conforms to the required number of zero bits on the resulting bit string. The number of zero bits required defines the difficulty of the puzzle and therefore the frequency at which blocks will be mined. The nonce as the solution to the puzzle is difficult to compute yet simple to verify, which allows all participants to easily check and consensually confirm the validity of a nonce, ending the puzzle and generating a new hash. Once computing power has been invested into finding an appropriate nonce, the newly mined block can not be changed without redoing the entire work, not only of the last incremental block but of all following blocks, since all blocks are linked to each other transitively with the longest chain commanding legitimacy. This provides increasing protection against double-spending with increasing length of a Blockchain as detailed by Rosenfeld (2012).

Proof of Stake consensus is based on the expectation that token holders of a certain crypto system are interested in successfully maintaining an accurate ledger of transactions. The participant with the largest relative stake in the crypto asset is determined as the miner of the incremental block. There exists no mining reward, thus token supply need not be inflated. However, transaction fees can be collected by the miner to incentivize participation. This approach is less resource intensive while security is assured through the self-interest of participants not to implement malicious transactions and therefore protect the value of participants' own token holdings. An extension of this concept is Delegated Proof of Stake, through which stakeholders 'elect' the miners of an incremental block (cf. EOSProject 2017).

Within Proof of Burn systems, miners "bid" for the right to mine an incremental block by sending existing tokens to a burn address (for an example, see P4Titan 2014). This burn address is predetermined and invalid, tokens sent to it get "burned", that is, they disappear and the token supply decreases by that specific amount. This leads to a relative wealth transfer to all other token holders since the existing value of the system is now divided by a token quantity which is smaller by exactly the amount of tokens burned. The participant sending the largest amount of tokens to the burn address has the right to mine the incremental block and to collect transaction fees. Each miner will bid exactly that amount of tokens for which he can still make a profit after accounting for tokens burned and equipment as well as opportunity costs invested. Proof of Burn can be validated by back checking transfers to the burn address. In contrast to a PoW mechanism, resources invested do not take the form of mining equipment but rather tokens burned. Again, security is ensured by the self-interest of participants and comparative cost for attackers that need to be incurred to break the system.

Consensus mechanisms can generally be used in parallel and switches between mechanisms can occur. Tying all considerations above together, the combination of an encryption protocol with a consensus mechanism then enables the existence of a Decentralized Autonomous Organization (DAO). Such a DAO constitutes a network for the internal transaction of value that is governed by the automatic mechanisms of a blockchain. Adding a cryptographic currency that can be traded between participants then finally enables the operation of Decentralized Applications (DApps) that provide value to participants. It is these currencies specifically, which will be evaluated as to their suitability to constitute a distinct asset class, leading to diversification effects and potential outperformance.

3 The Rise of Cryptocurrency

The starting point for the rapid development of cryptocurrency is marked without doubt by the publishing of the Bitcoin whitepaper in October of 2008, incepting the cryptocurrency that has ever since evolved to become the sector stalwart. The first transaction of Bitcoin (BTC) was soon thereafter executed between the Bitcoin founder(s) 'Satoshi Nakamoto' and cryptographer Hal Finney in 2009, totalling 10 BTC (Higgins 2014). The cryptocurrency sphere as a whole subsequently started to broaden in 2011 with the introduction of Litecoin, among others, as a variation of Bitcoin. 2013 brought the first instance of a so called fork of the Bitcoin network, albeit accidental—an event describing significant changes to the currency's underlying protocol splitting the block chain into two competing strands. The issue was quickly resolved, however, marking a significant step forward in Bitcoin's maturation process (Buterin 2013a). Regarding the surrounding infrastructure servicing cryptocurrencies, 2014 saw the most significant cryptocurrency exchange Mt. Gox file for insolvency after a significant amount of Bitcoin had been stolen (Dougherty and Huang 2014). Nevertheless, Bitcoin and by extension the crypto sphere as a whole recovered anew, underlining cryptocurrencies' resilience against external shocks. 2016 brought a crucial step forward in the technology of cryptocurrencies with the launch of the Ethereum network, henceforth enabling the implementation of DApps. Subsequently, in the governmental domain the Swiss canton Zug introduced the initiative 'CryptoValley' aiming to become a global hub for the cryptocurrency sector and allowing fees owed to the government to be paid in Bitcoin up to the amount of 200 CHF (Swissinfo 2016).

The year 2017 saw a further Swiss initiative, this time by the city of Chiasso in the canton Ticino, allowing tax payments in Bitcoin up to the amount of 250 CHF, tied to the initiative 'CryptoPolis' (Allen 2017). Other countries, such as Estonia, have launched even more comprehensive programs which, however, still await final implementation (Ummelas 2018). Crucially, in the United States both the Chicago Board Options Exchange (10th of December 2017) and Chicago Mercantile Exchange (17th of December 2017) launched Bitcoin futures trading in short sequence, paving the way for Bitcoin to access established capital markets infrastructure for the very first time (cf. CBOE 2017; CME 2017). With cryptocurrency gaining more and more legitimacy within the wider public realm, institutional arrangements, regulatory frameworks and infrastructure continue to evolve and adapt. With cryptocurrencies having risen from an initial total market capitalization of US$1.3 billion in early 2013 to a peak of US$813 billion as of early 2018, special interest lies in the question whether cryptocurrency can qualify as a new asset class and if so, whether adding this asset class can generate outperformance against traditional portfolios.

4 Potential Assets: Cryptographic Coins and Tokens

When evaluating the suitability and performance of cryptographic currencies as assets, different types of DApps can be distinguished along multiple criteria, leading to a classification of different cryptocurrencies. Since cryptocurrencies operate within the framework of a DApp, the nature of the DApp is important to derive the value basis for the currency. Following Johnston et al. (2015), three types of

DApps can be distinguished. Type I operates its proprietary blockchain, protocol and currency. Type II uses its own protocol and currency but not its own blockchain and therefore operates on the blockchain of a Type I DApp. Type III is a protocol that uses its own currency, however based on a protocol of a Type II DApp and the blockchain of a Type I DApp.

In order to simplify further economic analysis, we will distinguish between cryptographic *coins* that are used in DApps of Type I versus cryptographic *tokens* that run on Types II and III. The reason for this distinction is that coins are native units of an independent system and often find primary application in functioning as a means of payment, while tokens are non-native units usually securitizing additional utility. Therefore tokens are sometimes also referred to as *utility tokens*. This classification seems akin to the classic monetary theory's fiat money and commodity money, however, the lines seem to be too blurred for such clear cut distinction.

Ultimately, the value of a DApp maintained by the DAO is 'securitized' by coins and tokens (for approaches to token valuation, see Buterin 2017a; Kalla 2017). Empirical analyses regarding the question whether cryptocurrencies can constitute an asset class in their own right, therefore need to focus on the empirical properties of coins and tokens.

5 Cryptocurrencies as Investments

Contributions on cryptocurrencies as investments have to date followed two strands of analysis. One strand focuses on the question of investability, specifically an absence of correlation between cryptocurrencies and traditional asset classes, to set cryptocurrency apart as a distinct asset class. A second strand focusses on the potential performance impact that cryptocurrency can have when added to traditional portfolios.

5.1 Investability

Multiple contributions attempt to shed light onto the investability of cryptocurrency, all of which focus on correlation as the measure to distinguish cryptocurrencies from traditional asset classes. Briere et al. (2015) study weekly return data for Bitcoin and a broad range of traditional asset class indices for developed and emerging economies from July 2010 to November 2013. They find that correlation between Bitcoin and traditional asset classes is negligible and therefore conclude that cryptocurrency seems to form an attractive new investment opportunity. Eisl et al. (2015) concur, having studied correlations between Bitcoin returns and a range of traditional asset class index returns from July 2010 to April 2015. Lee et al. (2018) follow a similar approach in studying correlations between the cryptocurrency index CRIX and various indices of traditional asset classes from August 2014 to March 2017, confirming previous findings of low correlation and therefore cryptocurrency as a new investment opportunity.

However, we identify multiple gaps in the data coverage and methodology of existing studies which provide opportunity to extend and complement the body of literature. Due to the rather short history and limited data availability of cryptocurrency at the time of writing, early contributions such as by Briere et al. (2015) are limited in both length and granularity of the time series by only studying weekly closing prices from 2010 to 2013. Despite extending time series length by one and a half years to April 2015, Eisl et al. (2015) still remain limited in sample length. Unfortunately, Eisl et al. do not to explicitly specify the granularity of data used. Lee et al. (2018) use a comparatively long dataset ending in March 2017. However, all data sets used in previous studies are either directly focused on Bitcoin as a proxy for cryptocurrency or dominated by Bitcoin via its disproportionate representation in the CRIX index. The CRIX index, while providing an improvement in coverage of cryptocurrencies, blends cryptocurrency prices based on market capitalization weighting and thereby smooths individual fluctuations of cryptocurrencies by supplying one aggregate figure. While compromises will need to be made regarding the quantity of cryptocurrencies analyzed, we see potential for even clearer insight into the nature of cryptocurrency by analyzing individual cryptocurrencies. Besides correlation between cryptocurrencies and traditional asset classes, a further open question remains whether correlation within the group of cryptocurrencies is significant enough in order to constitute one single asset class. This question is of particular interest since, as we show above, cryptocurrency can naturally be subdivided into coins and tokens. Both an analysis of intra-cryptocurrency correlation and differences along the coin/token distinction have not been supplied to date.

Correlation analyses on their own; however, appear to paint an incomplete picture when aiming to answer the question of investability and the potential for cryptocurrency to form a distinct asset class. Nevertheless, other factors playing a role for the investability of cryptocurrency have so far received little attention. Some studies have acknowledged liquidity as an important factor for the ability to enter and exit investment positions. Fink and Johann (2014) observe that the price impact of individual trades decreases from 2011 to May 2014 while absolute liquidity increases over the same timeframe. Briere et al. (2015) consider liquidity in passing, mentioning a general increase of absolute liquidity over time without providing a specific measure or benchmark. Dyhrberg et al. (2018) briefly touch upon the subject of absolute Bitcoin liquidity which is, however, limited to three exchanges and does not put primary focus on such analysis. Trimborn et al. (2018) compare average absolute liquidity across 42 cryptocurrencies to that of the S&P500 and find that such averages are lower for cryptocurrencies than for the S&P500. Wei (2018) studies the impact of liquidity on return predictability and volatility, as well as an illiquidity premium. She finds that both return predictability and volatility decrease as liquidity increases, while no evidence could be found of an illiquidity premium. Elendner et al. (2018) provide an overview of absolute daily liquidity from April 2014 to June 2016. While, therefore, liquidity has been acknowledged as a factor for investability, we find scope to extend previous contributions by studying individual cryptocurrencies rather than Bitcoin alone, by distinguishing between the two groups of coins and tokens, as well as by studying relative liquidity.

Besides correlation and liquidity, the factor stability has not received attention so far. However, besides having defined cryptocurrency as a distinct asset class via correlation and knowing that adequate liquidity is available to enter and exit investment positions, market stability seems an essential feature for investability, as market breaks due to high volatility might lead to frequent halts in trading that can negatively impact investability of cryptocurrency.

5.2 *Impact on Portfolio Performance*

Within the second strand of literature turning to the impact of cryptocurrency on portfolio performance, to the best of our knowledge, the first contribution seems to be Briere et al. (2015). By using a time series of weekly Bitcoin data over approximately three and a half years (July 2010 to Dec 2013), the performance of different portfolios consisting of traditional as well as alternative asset classes is explored. As weighting-schemes, Briere et al. (2015) use equal-weighted portfolios and Markowitz mean-variance optimization. For both weighting schemes, portfolio performance including and excluding Bitcoin is analyzed over the three and a half years without rebalancing. Due to the time series properties of Bitcoin within this timeframe—high returns, high volatility but low correlation—this leads to superior performance as measured by the Sharpe ratio for the portfolios including Bitcoin in both weighting schemes.

Eisl et al. (2015) extend the approach of Briere et al. (2015) by applying the CVaR (Conditional Value-at-Risk) instead of variance as a measure of risk. Furthermore, the “single point in time” approach is replaced by a backtest with rebalancing as well as the introduction of different constraints. Despite the extended framework, results widely confirm the findings of Briere et al. (2015). Inclusion of Bitcoin with a weight between 1.65% and 7.69% appears valuable “even in already well-diversified portfolios”.

A further contribution which analyzes the performance of portfolios including cryptocurrencies as an asset has been supplied by Lee et al. (2018). Using the cryptocurrency index CRIX and a time series of approximately two and a half years, Lee et al. (2018) explore the performance of a portfolio consisting of similar assets like those of Eisl et al. (2015) while following the CVaR and mean-variance approach and comparing the performance of both optimization methods. However, they also rely on a “single point in time” approach like Briere et al. (2015). In general, the results of Briere et al. (2015) and Eisl et al. (2015) are confirmed, in that an inclusion of cryptocurrencies improves the risk/return characteristics, especially for the minimum-variance portfolio. Interestingly, Lee et al.’s weights for the CRIX of up to 72.5% seem to be significantly higher than those of Eisl et al. (2015).

We add to the existing literature in multiple ways. Our time series stretch more than 4 years of daily data while we also employ different rebalancing schemes applied on a quarterly basis and go beyond ex-post optimization. While Eisl et al.

(2015) apply out-of-sample tests by using the optimized weights of each previous quarter for rebalancing, we supply additional insight by using three different methods. First, dynamic weighting quarter-by quarter; second, average weighting across all quarters with rebalancing to initial weights at the end of each quarter; and third, a static allocating of 1% to Bitcoin across each quarter. By and large, we use similar traditional asset classes for diversification as employed by Eisl et al. (2015) by including stocks, bonds, real estate, gold, and oil. In contrast to previous findings, however, we do not detect beneficial impact from adding Bitcoin to minimum-variance portfolios. More importantly, we do find general benefit from adding Bitcoin to traditional portfolios. An allocation of Bitcoin to traditional portfolio structures as low as 1% significantly increases the Sharpe ratio. However, due to high volatility and negative returns on a quarterly basis, assigning large allocations to cryptocurrency can have significant negative impact on portfolio performance.

The following chapters will present our analyses that aim to extend existing literature discussed above in order to close remaining research gaps and supply a sound fundament on which to evaluate whether cryptocurrency does in fact constitute a distinct asset class and can lead to improvements of portfolio performance when added to traditional portfolios.

6 Dataset and Methodology

6.1 Data

We use the platform *coinmarketcap.com* as our data source for correlation and liquidity analyses, which grants open access to their data for any use or purpose. Coinmarketcap.com aggregates the daily volume weighted average prices and the total trading volume for more than 1300 cryptocurrencies over all cryptocurrency exchanges that the respective currencies are listed on. The data consist of daily opening, high, low and closing prices as well as trade volume and market cap time series. All data relate to the 24 h window of UTC—Coordinated Universal Time (for details, see separate annex). All data have been sourced by December 8th, 2017. We select the top 10 coins and tokens by market cap, respectively, as of December 8th, 2017, 11:00UTC, for cryptocurrencies with a price history >3 months (Fig. 1).

For analyses regarding market stability, we download tick-by-tick data from *Poloniex*, one of the largest cryptocurrency trading platforms, through its native API (for details, see separate annex). Poloniex supplies quotes against the Tether (USDT), a dollar-pegged cryptocurrency which is employed as a dollar surrogate on major exchanges. While the Tether shows episodes of fluctuation around the perfect peg of USD\USDT 1, prices quoted in USDT are well within the individual range of prices in USD as quoted on different globally operating exchanges. Nevertheless, we source daily USDT closing prices against the USD from the platform coinmarketcap.com to eliminate potential noise added to daily tick-by-tick data by the USDT.

Rank	Coin	Market Cap	Token	Market Cap
1	Bitcoin (BTC)	US$ 265,539,107,455	EOS (EOS)	US$ 2,349,608,345
2	Ether (ETH)	US$ 43,175,564,793	Populous (PPT)	US$ 1,065,186,620
3	Bitcoin Cash (BCH)	US$ 25,196,957,992	OmiseGO (OMG)	US$ 837,498,937
4	IOTA (MIOTA)	US$ 11,761,165,463	Ardor (ARDR)	US$ 518,629,589
5	Ripple (XRP)	US$ 9,626,871,230	Veritaseum (VERI)	US$ 311,322,142
6	Litecoin (LTC)	US$ 5,451,485,929	Augur (REP)	US$ 294,514,000
7	Dash (DASH)	US$ 5,397,079,086	Golem (GNT)	US$ 236,430,309
8	Monero (XMR)	US$ 4,132,314,200	Binance Coin (BNB)	US$ 232,213,574
9	Ethereum Classic (ETC)	US$ 2,639,390,342	MaidSafeCoin (MAID)	US$ 215,912,303
10	Stellar Lumens (XLM)	US$ 2,394,395,573	TenX (PAY)	US$ 207,612,454

Fig. 1 Top 10 coins and tokens by market cap with price history >3 months as of the 8th of Dec. 2017 have been included

Indices	Equities	Currencies	Bonds	Commodities	Real Estate
S&P500	Facebook (A)	EUR\USD	J.P. Morgan	WTI Spot	MSCI World
NASDAQ100	Amazon	USD\CHF	Government Bond	NYMEX Brent Crude	Real Estate
FTSE100	Apple	USD\JPY	Index	Gold Handy & Harman	Price Index
EUROSTOXX50	Netflix	USD\SGD			
DAX30	Alphabet (A)				
TecDAX30	Alibaba ADR				
Hang Seng	Baidu ADR				
Nikkei225	RenRen ADR				
	Tencent ADR				

Fig. 2 All traditional asset classes included in empirical analyses

Financial market data regarding traditional asset classes are sourced from Reuters Datastream and Bloomberg Terminal for the time period from April 28th 2013 to November 3rd 2017 (Fig. 2). Data include daily open, close, high and low prices, daily volume and market cap for relevant assets on the respective exchanges. The selection of traditional asset classes and particular assets within a class has been guided by multiple considerations. With the inclusion of equities, bonds, currencies, real estate and commodities it is the aim to incorporate all essential classes typically available to a reasonably sophisticated investor. Among indices, we select those that represent the globally most significant exchanges and simultaneously cover a sufficiently broad geographic area. In addition to equity indices, we include specific equities from the tech sector for purposes of comparability with cryptocurrency as a phenomenon emerging from the sphere of technology. Special consideration will be given to the FAANG group of stocks (Facebook, Amazon, Apple, Netflix, Google/Alphabet) due to their significance to the sector. Regarding currencies, we focus on the four globally most relevant pairs while the individual assets from within the remaining three classes (Bonds, Commodities and Real Estate) are selected considering relevance and geographic scope.

Portfolio optimization simulations rely on data as reported above.

6.2 Methodology

Our methodology is guided by three aims. First, to analyze cryptocurrencies' suitability to form a distinct asset class. For the definition of an asset class, we follow Sharpe (1992) who distinguishes asset classes along the three criteria of (1) mutual exclusivity between asset classes, (2) exhaustiveness within an asset class and (3) differing returns between asset classes. Preceding the analysis of mutual exclusivity *between* asset classes we test for mutual necessity, that is, the correlation *within* the class of cryptocurrency in order to be able to define cryptocurrency as a consistent whole. Internal exhaustiveness is reached by considering the entire spectrum of cryptocurrency and selecting the currencies representing the lion's share of total market capitalization. The differing returns criterion as well as mutual exclusivity are satisfied via correlation analyses between the group cryptocurrency and all traditional asset classes. To the necessary condition of correlation, we add the sufficient conditions liquidity and stability. The liquidity analysis is aimed at comparing liquidity of crypto markets relative to traditional tech equities as an indicator whether investment positions can effectively be entered and exited. The stability criterion serves as a test for the maturity of the cryptocurrency space as a whole. Second, we analyze whether there are significant differences between cryptographic coins and tokens, requiring the creation of sub-groups within the potential new asset class. Third, we evaluate whether portfolio structures can either increase returns or mitigate volatility by including cryptocurrencies. This is done both via quarterly *ex-post* optimization of portfolio Sharpe ratios, as well as *ex-ante* portfolio construction using three different structuring approaches.

6.2.1 Correlation

Inputs into the correlation analyses are simple daily returns. We test all time series for normality using the Kolmogorov-Smirnov test with Lilliefors and Stephens modification as well as by estimating the Shapiro-Wilk W. Due to non-normality of the cryptocurrency time series, correlation is estimated via three different measures: the parametric Pearson's r, as well as the non-parametric Kendall's tau and Spearman's rho. Parametric and non-parametric results serve as a robustness check for each other while both non-parametric tests serve as an internal consistency check. We test for dependencies between individual cryptocurrencies as well as between cryptocurrencies and traditional asset classes. Thereafter, coins and tokens are analyzed for correlation between these two sub groups using equally weighted mean and median daily returns of the groups. All time series are tested for time dependent variations. To gain deeper insight we further analyze the correlation of daily returns of an individual title with the correlation between this specific title and all other titles in the respective group. This is done both for all cryptocurrency pairs as well as among all FAANG stock pairs. We thereby aim at conclusions regarding the question whether cryptocurrencies and traditional FAANG stocks show comparable return dependent correlation behavior, which would serve to emphasize cryptocurrencies' behavior as analogous to established asset classes. Simple returns for discrete trading weeks and months are calculated together with the corresponding Pearson correlations for these time frames. Thereafter, correlation between returns and their respective correlation pairs are calculated for all three correlation measures (Spearman, Kendall, Pearson) and the mean correlation for all three measures is extracted for comparison.

6.2.2 Liquidity

We test for the liquidity criterion via two metrics, both spanning the previous 3 months leading up to December 8th, 2017.[2] First, we compare absolute daily trading volume of Bitcoin (BTC) and Ether (ETH) to the five stocks comprising the FAANG group, Facebook, Amazon, Apple, Netflix, Google/Alphabet. Thereafter, we compare the equally weighted averages of absolute daily liquidity for the top 10 cryptographic coins and top 10 cryptographic tokens by market cap to the FAANG basket's equally weighted daily liquidity. Second, we compare the ratio of daily trading volume to daily market capitalization for both the individual titles as well as the equally weighted baskets. Measures of comparison are the minimum, mean, maximum and standard deviation of values due to their significance to investment management, as well as the ratio between standard deviations and mean values for purposes of comparison.

6.2.3 Stability

Market Stability is tested as the resistance of cryptocurrency markets to trigger Market Wide Circuit Breaks (MWCB) and Limit Up-Limit Down levels (LULD) as an indicator for market maturity. For Market Wide Circuit Break rules, we use trigger levels and computations as established by the SEC filing Release No. 34–67,090 of the 31st of May 2012 as submitted by the Self-Regulatory Organizations (SRO)[3] (SEC 2012). MWCBs are specified as intraday market drops of an index of more than 7, 13 and 20% relative to the previous day's closing price, which are denoted as levels 1, 2 and 3 respectively. MWCBs lead the market to

[2]While alternative timeframes of 6, 9 and 12 months have been examined, results of the 3 month window are robust to such changes. Therefore, we limit our analysis to the three most recent months.

[3]The organizations participating in the SRO are: BATS Exchange, Inc.; BATS Y-Exchange, Inc.; NASDAQ OMX BX, Inc.; Chicago Board Options Exchange, Incorporated; C2 Options Exchange, Incorporated; Chicago Stock Exchange, Inc.; EDGA Exchange, Inc.; EDGX Exchange, Inc.; Financial Industry Regulatory Authority, Inc.; International Securities Exchange LLC; The NASDAQ Stock Market LLC; New York Stock Exchange LLC; NYSE Amex LLC; NYSE Arca, Inc.; National Stock Exchange, Inc. and NASDAQ OMX PHLX LLC.

halt for 15 minutes for levels 1 and 2 and to halt for the remainder of the trading day after breaking level 3. We construct a cryptocurrency index using some of the largest cryptocurrencies by market capitalization for which tick-by-tick data are available, representing 87% of total cryptocurrency market capitalization (for details, see separate annex).

Within our index, cryptocurrencies are weighted with their market capitalization relative to the total capitalization of cryptocurrencies included in the index. Individual weightings are rebalanced daily. Additionally, we run an MWCB test for Bitcoin alone due to the fact that Bitcoin represents 64% of total market capitalization of all existing cryptocurrencies as of the writing of this paper. We apply the MWCB criteria to our index and Bitcoin tick-by-tick time series to test for market breaks.

Limit Up-Limit Down levels are triggered by price moves of individual securities exceeding ±5%, 10% and 20% within a 5 min interval, if after triggering one of these levels the price of the individual security does not retract back below or above the threshold within 15 s. We apply the LULD criteria to Bitcoin due to its significance and position as an indicator for the larger crypto space. LULD trigger frequencies are approximated via fixed 5 min intervals yielding 288 discrete time windows per day. Tick-by-tick returns are calculated for each transaction against the first tick of the respective 5 min interval. After the passage of a 5 min interval, the incremental transaction defines the closing price against which to calculate returns for the following 5 min.

6.2.4 Portfolio Optimizations

Portfolio optimization proceeds in two steps. In the first step, we select four different portfolios composed exclusively of traditional asset classes, including stocks, bonds, real estate, gold and oil. The simplest allocation of portfolio 1 with only stocks and bonds (P1(B)) is extended by adding real estate (P2(B)), real estate and gold (P3(B)) and finally real estate, gold and oil (P4(B)). These are our benchmark portfolios, hence the notation (B). For each of the benchmark portfolios, we create a second version including the new asset class cryptocurrency represented by Bitcoin, which we label crypto portfolios (for details, see separate annex). We choose Bitcoin as a proxy for cryptocurrency due to its dominance of and correlation with the crypto sphere as a whole. Then, we optimize the Sharpe ratio of each benchmark and crypto portfolio retrospectively for each quarter using Excel's Solver.[4] Within the optimizations, negative asset class weightings (short positions) are permitted, except for constellations without convergence in solutions. Portfolio metrics include the daily returns:

$$r_{PF} = \mathrm{w} \cdot r$$

the portfolio variance:

[4]We also performed a check on Minimum-Variance optimization. Due to the high volatility levels of cryptocurrencies, we did not find any significant volatility reduction.

$$\sigma^2{}_{PF} = \mathrm{w} \cdot \Sigma \cdot w$$

and the Sharpe ratio for portfolios:

$$S_{PF} = \frac{r_{PF}}{\sigma_{PF}}$$

The risk-free rate for optimizations is fixed at 0%, firstly, because the risk-free rate for the time periods considered (Q2 2013 to Q3 2017) has been fluctuating around this marker and secondly, because we want to exclude interest rate effects from our estimations. This step in the analysis is not intended for purposes of investment advice but rather to evaluate how stable asset allocations will be over time and how large the contribution of cryptocurrency can be in the context of optimizations. This yields quarterly *ex-post* optimal asset class weightings for each portfolio.

The *ex-post* optimal weightings for each quarter of the first step are used in a second step to calibrate portfolio structures *ex-ante* for each following quarter. That is, the optimal weight for each preceding quarter is used to define portfolio allocation for the following quarter. With quarterly changing weights this approach is labelled *dynamic*. Due to wildly fluctuating portfolio weights for cryptocurrency under the dynamic approach we implement a second approach using the average of quarterly optimized weights for each asset class uniformly for all quarters, called the *averages* approach. Since after each quarter, asset allocations will have departed from the averages initially used due to positive or negative performance of the asset classes, allocations are rebalanced to their averages at the end of each quarter. For both the dynamic and averages approaches, allocation to cryptocurrency is comparatively high at 10% (for details, see separate annex). Therefore we implement a third approach where the proportion of cryptocurrency added to traditional portfolios is kept at a flat 1% for all four portfolios (for details, see separate annex). Hereby, the 1% share allocated to cryptocurrency is taken out of the allocation to equities due to the fact that the risk/return profile of cryptocurrency matches that of equities most closely compared to the other asset classes considered. Due to an emphasis on risk reduction, this approach is called *conservative*.

7 Results

7.1 Correlation

All cryptocurrency return time series are non-normal for both Lilliefors' and Stephens' modification of Kolmogorov-Smirnov, as well as Shapiro Wilk's *W*. Therefore, Spearman's rho seems most appropriate to evaluate correlation, showing strong correlation within the class of cryptocurrencies. 95% of cryptocurrency pairs

Correlation within Cryptocurrencies	Spearman ρ		Kendall τ		Pearson r	
	Significant	Not Significant	Significant	Not Significant	Significant	Not Significant
negative	0	0	0	0	0	5
positive	180	10	183	7	140	45

Fig. 3 Clear statistically significant correlation within 190 cryptocurrency pairs, both for parametric and non-parametric tests

Instances of Correlation between a Cryptocurrency and a Traditional Asset Class/ Asset					
Trad. Asset Class	**Spearman ρ**	**Kendall τ**	**Pearson r**	**Consensus**	**of Total**
Indices	5	5	9	1	160
Equities	5	5	11	3	180
Currencies	1	1	2	0	80
Bonds	0	0	3	0	20
Commodities	6	5	3	0	60
Real Estate	1	1	3	1	20
Total	18	17	31	5	520

Fig. 4 Only 1% of pairs (5 out of 520) between cryptocurrencies and traditional asset classes show statistically significant correlation over all three measures

showing significant positive correlation and therefore mutual necessity confirms cryptocurrencies as a coherent whole (Fig. 3).

Analyses of correlation between asset classes show that cryptocurrencies as a whole move independently of all traditional asset classes. For Spearman's rho, only 18 out of 520 pairs total show statistically significant correlation. When considering pairs with significant correlation over all three correlation measures, only five positively correlated pairs remain. Among those five, Bitcoin, as the dominant cryptocurrency to this date, shows only one instance of weak positive correlation to real estate with rho and r of 0.06 (Figs. 4 and 5).

The conclusions drawn are robust to adjustments in timeframes considered (for details, see separate annex). These results suggest a clear distinction of cryptocurrency as separate from traditional asset classes by fulfilling both the criterion of mutual exclusivity as well as differing returns.

Support for the classification of cryptocurrency specifically as an asset class is found in cryptocurrency's analogous behavior to traditional assets of increasing correlation for decreasing returns. This tendency shows striking similarity to behavior of the five FAANG stocks, both for discrete trading weeks as well as months (Fig. 6).

Moderate correlation between coins and tokens both measured via equally weighted daily mean and median returns do support the idea of two distinct sub asset classes. Results show robustness over time as evidenced by comparison of multiple 100 day slices (for details, see separate annex) (Fig. 7).

Following Sharpe's definition of an asset class in the evaluation of cryptocurrency, the three conditions of mutual exclusivity, exhaustiveness and

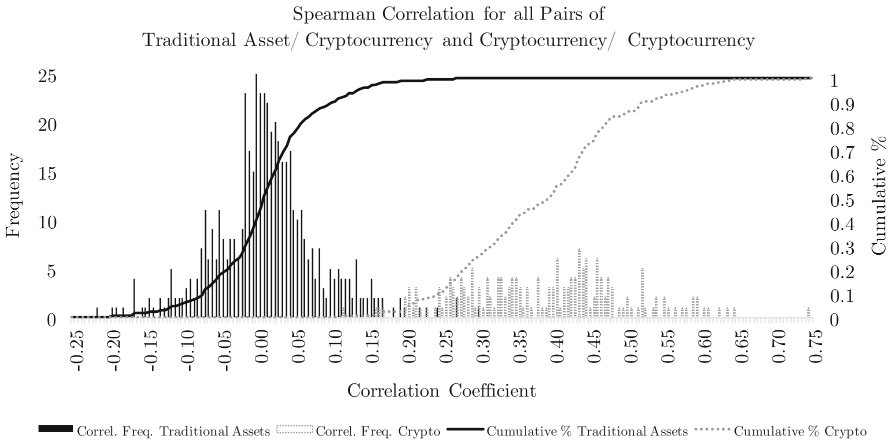

Fig. 5 Chart displays frequency and cumulative probability distribution of Spearman correlation for pairs of cryptocurrencies and traditional assets (blue) as well as pairs of cryptocurrencies (yellow). Cryptocurrencies and traditional assets largely uncorrelated, cryptocurrencies positively correlated among each other

Correlation of Asset Returns with Correlations of Asset Pairs

	Asset	Mean Spearman ρ	Mean Kendall τ	Mean Pearson r
By Trading Week	FAANG	-0.197	-0.132	-0.203
	Cryptocurrencies	-0.207	-0.140	-0.187
	Δ	0.010	0.008	0.016
	Asset	**Mean Spearman ρ**	**Mean Kendall τ**	**Mean Pearson r**
By Trading Month	FAANG	-0.453	-0.345	-0.412
	Cryptocurrencies	-0.414	-0.281	-0.205
	Δ	0.039	0.064	0.207

Fig. 6 FAANG stocks and cryptocurrencies both show increasing correlation for decreasing returns and vice versa. This supports cryptocurrencies as an asset class

Correlation between Coins and Tokens

Measure	Spearman ρ	Kendall τ	Pearson r
Mean Daily Returns	**0.36**	0.25	0.37
Median Daily Returns	**0.42**	0.29	0.44

Fig. 7 Both mean and median equal weight daily returns indicate only moderate correlation between coins and tokens

differing returns seem to be satisfied by our results. The findings of our correlation analyses therefore confirm cryptocurrency as a new asset class, while the liquidity and stability criteria will shed light onto the maturity of the crypto space.

7.2 Liquidity

In terms of absolute daily liquidity Bitcoin is squarely positioned in the midst of the group of FAANG. While the Ether is not quite on equal footing yet, it is closing in with just over one standard deviation difference to Netflix. Taking the equally weighted means of the FAANG basket, coin and token baskets highlights a substantial difference in maturity between the three groups. Here, FAANG clearly outperforms coins which in turn outperform tokens in absolute daily liquidity (Fig. 8).

Considering the ratio between daily liquidity and market capitalization, cryptocurrencies show significantly stronger liquidity compared to FAANG stocks across the board. Volatility of daily liquidity is highest for coins followed by tokens and FAANG stocks. Considering individual titles, both Bitcoin and Ether show stronger relative liquidity than all the components of the FAANG group. The most liquid traditional tech title, Netflix, is on average approximately half as liquid as Bitcoin relative to market capitalization. When considering the baskets of stocks and cryptocurrency, minimum relative liquidity of tokens (1.04%) is still higher than mean liquidity of the FAANG basket (0.73%), and minimum relative liquidity in coins (1.75%) outperforms even maximum daily liquidity of the FAANG basket (1.58%) (Fig. 9).

While in absolute terms both the Bitcoin and Ether can already compete with staple names in the equity sphere, the coins as a group still can't reach comparable trading volume. This emphasizes the relative dominance of the top two cryptocurrencies at this moment and points to relatively weak liquidity in smaller coins. However, the fact that beyond Bitcoin there are in fact further coins within only one standard deviation to the group of FAANG stocks shows that cryptocurrencies are in the process of catching up to legacy tech titles. Cryptographic

Daily Trading Volumes Sep. to Dec. 2017: Equally Weighted Index & Individual

	Mean US$	Max US$	St.Dev. US$	St.Dev.\Mean
Top 10 Tokens	9,405,893	32,388,998	6,805,623	72.4 %
Top 10 Coins	582,942,401	2,089,626,410	422,109,317	72.4 %
FAANG	2,819,931,843	7,503,183,600	993,767,795	35.2 %
BTC	3,105,646,815	12,656,300,000	2,248,090,467	72.4 %
ETH	764,654,761	2,675,940,000	485,548,077	63.5 %
Facebook	2,777,700,092	7,459,686,000	1,330,500,617	47.9 %
Amazon	3,769,808,831	17,942,740,000	2,356,693,359	62.5 %
Apple	4,688,643,769	11,599,890,000	1,961,176,666	41.8 %
Netflix	1,323,544,711	4,787,650,000	812,804,793	61.4 %
Alphabet\Google	1,539,961,812	5,412,848,000	659,235,131	42.8 %

Fig. 8 Bitcoin on equal footing with FAANG equities, Ether closing in

Daily Trading Volume to Market Cap Ratio
Sep. to Dec. 2017: Equally Weighted Index & Individual

	Min %	Mean %	Max %	St.Dev. %	St.Dev.\Mean
Top 10 Tokens	1.04	2.58	5.73	1.25	48.3 %
Top 10 Coins	1.75	5.21	18.20	3.01	57.8 %
FAANG	0.39	0.73	1.58	0.25	34.1 %
BTC	1.49	2.99	7.91	1.31	43.8 %
ETH	0.91	2.51	9.51	1.46	58.3 %
Facebook	0.28	0.55	1.44	0.26	47.6 %
Amazon	0.42	0.74	3.38	0.42	57.1 %
Apple	0.27	0.56	1.40	0.23	41.3 %
Netflix	0.50	1.58	5.56	0.94	59.7 %
Alphabet\Google	0.11	0.22	0.76	0.09	41.0 %

Fig. 9 Significantly stronger liquidity and volatility of liquidity in cryptocurrencies

tokens still seem to be in their infancy stages and will need to grow in order to prove a serious investment alternative, at least in terms of liquidity.

While the spheres of coins and especially tokens on average still show a need for volume growth, in absolute terms liquidity relative to market capitalization is very strong, outperforming the staple equities by orders of magnitude. How this ratio will evolve with increasing maturity of the sector remains to be seen.

Volatility of individual cryptocurrency liquidity is in line with FAANG equities despite being at the top end for both absolute and relative measures. Comparing the basket of FAANG equities to baskets of coins and tokens, volatility of liquidity is decidedly higher in cryptocurrencies. This is illustrated by column 6 of Table 8 above, which shows the ratio between the standard deviation and mean for the ratio between daily liquidity and market capitalization. The pronounced difference between cryptocurrencies and FAANG stocks might mainly be traced back to mitigating averaging effects among FAANGs which seem to be absent among cryptocurrencies. That is, particularly high or low relative daily liquidity in individual FAANGs seems to be compensated by the basket as a whole, while no compensating effect seems to occur within the basket of cryptocurrencies, indicating correlation among individual cryptocurrency liquidity.

Our results point to the conclusion that despite its infancy, the cryptocurrency sphere already possesses significant liquidity. Both robust absolute daily liquidity as well as strong ratios between trading volume and market capitalization point to the conclusion that the cryptocurrency sphere does provide the necessary liquidity for investment positions to be entered and adjusted effectively, especially when compared to FAANG stocks as the benchmark.

7.3 Stability

Bitcoin, representing about two thirds of total cryptocurrency market capitalization as of Dec. 2017, shows rather unstable behavior, with a total of 92 Market Wide Circuit Breaks over the years 2016 and 2017. In comparison, MWCB have only been triggered once in the US since their inception in 1988 (Ackert 2012). Interestingly, MWCB events increase in frequency from 2016 to 2017, possibly due to intermediate overdue price corrections. Market breaks are less frequent for our cryptocurrency index (Fig. 10).

Two level 3 breaks following an intraday drop of −20% or more are eliminated through diversification. However, this cannot alleviate the fact that a comparatively high amount of market breaks occur in cryptocurrencies and especially in Bitcoin, which repeatedly points to a need for maturation of the sector (Fig. 11).

Limit-Up Limit-Down triggering, as an indicator for wild short-term fluctuations within a 5 min interval, has so far been comparably prevalent in Bitcoin. However, the quantity of trigger signals has steadily decreased since Q1 2016, indicating a gradual increase in stability. Generally, short term volatility is higher in the first half of a year compared to the second half.

The interplay of a decreasing quantity of Limit-Up Limit-Down trigger signals concurrent with an increase in Market Wide Circuit Breaks points to decreased short-term volatility clustering possibly at the expense of higher longer-term volatility. While these results can be interpreted as a step toward the smoothing out of market behavior and therefore maturation of the sector, investors in the asset class cryptocurrency will, at least for the time being, encounter significant 'bumps in the road'.

BTC: Number of Days with MWCB

		Level 3 -20%	Level 2 -13%	Level 1 -7%
2016	Q1		2	6
	Q2		2	5
	Q3	1	1	3
	Q4			1
2017	Q1	1	4	14
	Q2	2	4	16
	Q3	1	1	19
	Q4		2	7
Total		**5**	**16**	**71**

INDEX: Number of Days with MWCB

		Level 3 -20%	Level 2 -13%	Level 1 -7%
2016	Q1		2	4
	Q2		1	6
	Q3	1	1	3
	Q4			1
2017	Q1	1	3	11
	Q2	1	4	13
	Q3		1	15
	Q4		1	6
Total		**3**	**13**	**59**

Fig. 10 Both BTC and our cryptocurrency index show significant volatility and quantity of market breaks. Index slightly more stable

BTC: Number of Limit-Up Limit-Down Triggers

		±20%		±10%		±5%		Total		
		Pos	Neg	Pos	Neg	Pos	Neg	20%	10%	5%
2016	Q1			2	5	12	10		7	22
	Q2					3	1			4
	Q3					1	1			2
	Q4									
2017	Q1					7				7
	Q2					6	2			8
	Q3									
	Q4					1	3			4
Total		**0**	**0**	**2**	**5**	**30**	**17**	**0**	**7**	**47**

Fig. 11 Limit-Up-Limit-Down triggering reinforces picture of instability

7.4 Portfolio Optimization

For nearly all quarters between Q2 2013 and Q3 2017, we find a positive impact from adding cryptocurrency to portfolios when considering the *ex-post* Sharpe ratio (for details, see separate annex). Adding cryptocurrency does not improve minimum variance portfolio structures, as expected. While these results are a good *ex-post* indicator for how a portfolio should have been allocated in hindsight it does not follow that these allocations automatically deliver outperformance if used as a rule to calibrate portfolios *ex-ante* for the following quarter (Fig. 12).

For the implementation of our *ex-post* weights in *ex-ante* calibration, we find distinct results for each of our three approaches (dynamic, averages, conservative). The dynamic approach, using each past quarter's optimized weights for the allocation in the following quarter, leads to underperformance of crypto portfolios compared to traditional portfolios. Portfolio variance is higher for portfolios one, two, and three when compared to purely traditional portfolios. Moreover, all crypto portfolios underperform traditional portfolios when considering the Sharpe ratio. Not only do portfolios structured this way underperform but allocation to cryptocurrency is (a) comparatively high at an average of 10% and (b) fluctuating wildly with an average range of 107% across portfolios. While an average portfolio weight of 10% might be tolerable, the significant variability raises doubts as to the implementability of such portfolios. Thus, in a next step, we test our second approach using average cryptocurrency allocation of about 10% while eliminating the variability of the allocation.

Implementing the averages approach, using the average of quarterly weights for each asset class with rebalancing to initial weights at the end of each quarter, delivers the best results with significant and persistent outperformance of crypto portfolios

Quarterly Ex-Post Allocation to Cryptocurrency

	Mean	Min	Max	Range
P1: Stocks, Bonds	9.96%	-11.45%	95.35%	106.80%
P2: Stocks, Bonds, Real Estate	10.02%	-10.95%	95.35%	106.30%
P3: Stocks, Bonds, Real Estate, Gold	9.94%	-10.61%	95.35%	105.96%
P4: Stocks, Bonds, Real Estate, Gold, Oil	9.63%	-13.31%	95.35%	108.66%
Mean	**9.89%**	**-11.58%**	**95.35%**	**106.93%**

Fig. 12 High 10% mean and 107% range of allocation to cryptocurrency across portfolios

Effects of adding Cryptocurrencies to Traditional Portfolios
Ex-Ante Simulation Results

		Dynamic	Averages	Conservative
P1: Stocks, Bonds	Δ Daily σ	0.63%	0.81%	0.03%
	Δ Sharpe	-45.29%	37.12%	26.24%
P2: Stocks, Bonds,	Δ Daily σ	0.61%	0.80%	0.03%
Real Estate	Δ Sharpe	-44.31%	43.43%	25.97%
P3: Stocks, Bonds,	Δ Daily σ	0.59%	0.78%	0.03%
Real Estate, Gold	Δ Sharpe	-53.33%	43.56%	29.65%
P4: Stocks, Bonds,	Δ Daily σ	-0.18%	0.57%	0.03%
Real Estate, Gold, Oil	Δ Sharpe	-20.87%	50.08%	50.62%

Fig. 13 Averages and Conservative portfolios strongly outperform benchmark for risk-adjusted returns

over benchmark portfolios (Fig. 13). Crypto portfolios remain more volatile than traditional portfolios. However, the averages mechanism consistently outperforms traditional portfolios in terms of the Sharpe ratio, improving the ratio on average by 43.5%. Adding additional asset classes into portfolios going from P1 to P4 increases outperformance of crypto portfolios (Fig. 14).

Due to the fact that an allocation of 10% to a newly emerging asset class remains comparatively high in light of typical investment management practice, we finally

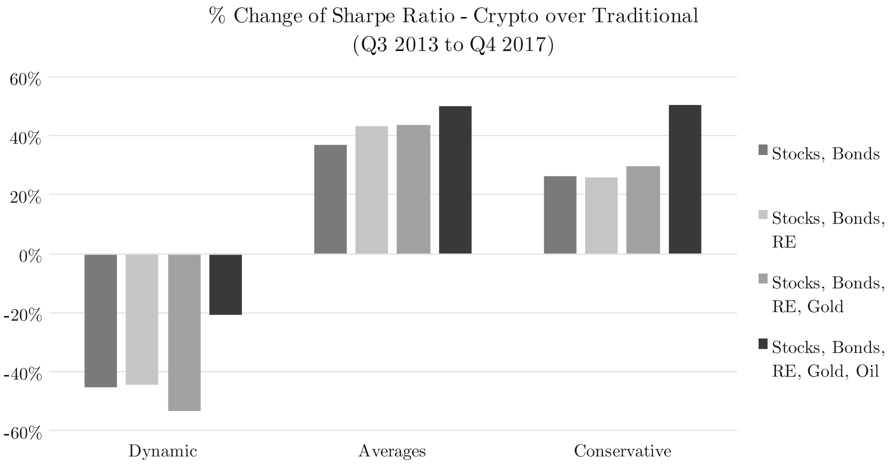

Fig. 14 Averages approach with strongest risk-adjusted outperformance

implement our conservative approach with a flat 1% allocation to cryptocurrency. We find that the conservative crypto portfolios can maintain outperformance in terms of the Sharpe ratio, albeit at a lower level than averages portfolios. Moreover, the gap between crypto portfolios and traditional portfolios in terms of volatility narrows significantly to only 0.03%. Risk-adjusted outperformance again generally increases when adding asset classes from P1 to P4.

Our results show that using Sharpe optimized *ex-post* weights for quarter-by-quarter *ex-ante* cryptocurrency asset allocation leads neither to reduced portfolio volatility nor to risk-adjusted outperformance. However, keeping the allocation to the asset class cryptocurrency stable at the average of optimized quarters causes volatility to increase, but also leads to strong risk-adjusted outperformance of crypto portfolios that is the best of all approaches implemented. The conservative approach also produces outperformance, albeit not as strongly as the averages approach. However, portfolio volatility is nearly similar to that of purely traditional portfolios.

Equity curves for the best performing averages approach highlight that while P1 to P3 deliver higher absolute returns than P4, the combination of cryptocurrency with stocks, bonds, real estate, gold and oil in P4 shows strongest risk-adjusted performance of all portfolios (Fig. 15).

These findings suggest that conservatively supplementing traditional portfolio structures with cryptocurrency, while not a free lunch, appears to be a risk-effective way of increasing portfolio performance. For investors with an increased risk budget, using averages of ex-post Sharpe optimized weights might provide an effective way to maximize risk-adjusted returns. However, our results also suggest that with increasing allocation to cryptocurrency there might be a tipping point of negative marginal utility beyond which crypto portfolios will generate inferior results. With cryptocurrency, as is often the case, the poison might ultimately be in the dose.

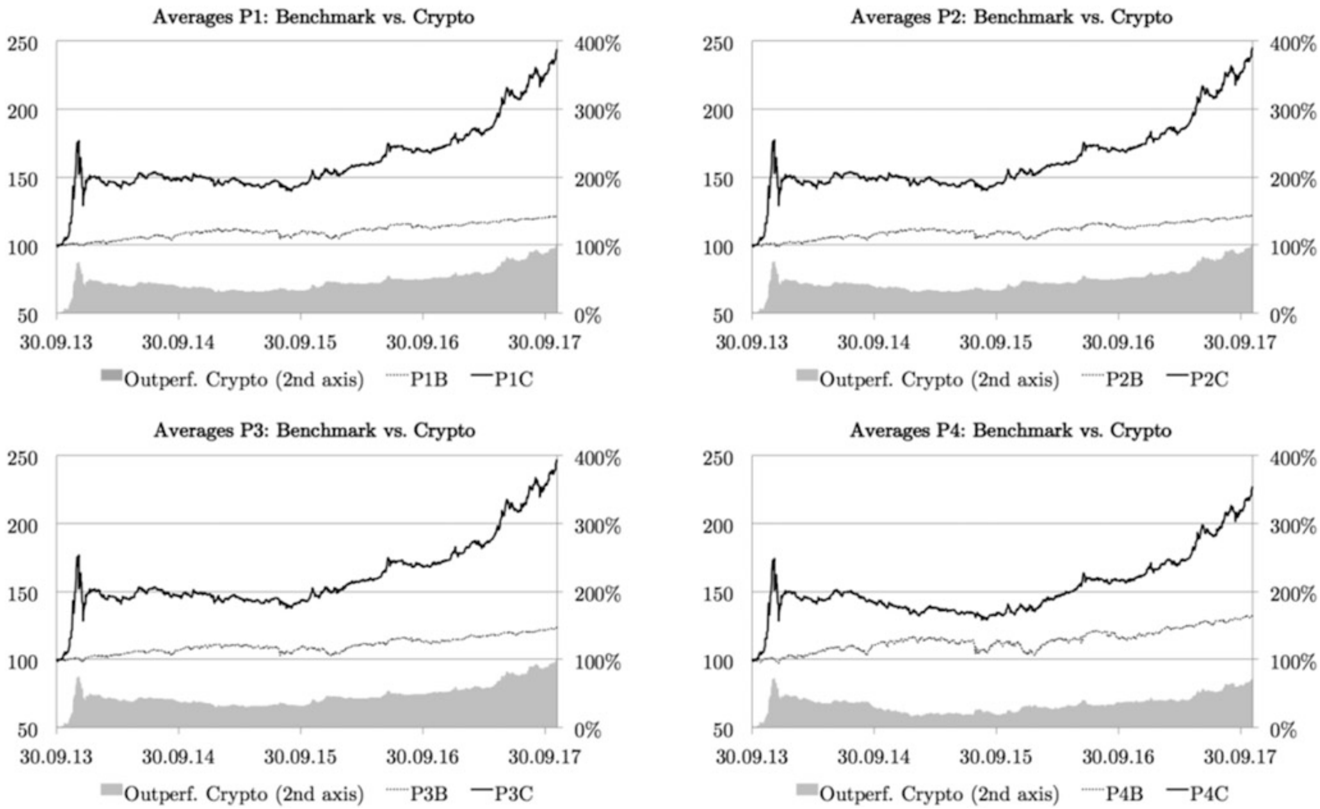

Fig. 15 P1 to P3 with very similar return curves. P4 weakest in absolute returns but with strongest risk-adjusted outperformance

8 Conclusion

We find that cryptocurrencies constitute a new distinct asset class and that supplementing traditional portfolios with cryptocurrency can lead to significant and persistent outperformance in risk-adjusted returns within the scope of our analyses.

Cryptocurrency qualifies as a distinct asset class by exhibiting high correlation among individual cryptocurrencies while being mostly uncorrelated with all traditional asset classes, aligning along Sharpe's (1992) asset class criteria of mutual exclusivity, exhaustiveness and differing returns. Absolute liquidity of Bitcoin is already on equal footing with FAANG equities, the Ether is closing in, while the remaining crypto space can not yet match the liquidity of traditional assets. Relative to their market capitalization, cryptocurrencies show significantly higher liquidity than the FAANG equities, both for coins and tokens. However, at least in terms of market stability there is still significant need for maturation of cryptocurrencies. With frequent Market Wide Circuit Break signals and, although decreasing, still a significant amount of Limit-Up Limit-Down interruptions, cryptocurrency trading would today remain rather discontinuous, were the rules of traditional equities exchanges applied.

Quarterly optimization of four traditional portfolio structures with and without cryptocurrency shows that adding cryptocurrencies to portfolios reliably improves quarterly *ex-post* Sharpe ratios while failing to reduce portfolio volatility. Turning to the analysis whether such *ex-post* weights lead to superior performance when implemented via *ex-ante* asset allocation in portfolios, we use three approaches. First, *ex-post* optimized portfolio weights of previous quarters are used for asset allocation in each following quarter (our dynamic approach) but fail to improve volatility or the Sharpe ratio. Second, asset allocation for each asset class using the average quarterly weight over all previously optimized quarters with quarterly rebalancing (the averages approach) leads to the strongest outperformance regarding Sharpe ratios but increases portfolio volatilities. Asset allocation to cryptocurrencies under the dynamic approach swings wildly between -10.61% and 95.35% with a mean of 10%, which is uniformly used as the basis for the averages approach. Finally, reducing the allocation to cryptocurrency to a conservative 1% for all quarters (our conservative approach), in order to accommodate risk consciousness of investment management practice, we find nearly similar volatilities of crypto portfolios and traditional portfolios paired with strong outperformance in Sharpe ratios which, however, can't match the outperformance of our averages approach.

Our results suggest that there is significant upside to be captured by investment practitioners from the careful addition of cryptocurrency to traditional portfolio structures. Comparatively conservative addition to otherwise conventional portfolio structures leads to persistent risk-adjusted outperformance. However, this requires a certain absolute level of risk appetite. Cryptocurrency consistently exhibits both significant short-term volatility clustering and an increase in long-term portfolio volatility, as evidenced by our stability analyses. In the future, possibilities for intra-asset class diversification regarding cryptocurrencies might develop as one means to improve the inherent risk profile. However, our results suggest that such effects are so far rather negligible. This might change in the future when individual cryptocurrencies might be differentiated based on specific value propositions tied to use cases or backing media of individual cryptocurrencies. Such differentiation might lead to a decoupling of return synchronicity and therefore greater potential to mitigate individual coin volatility. Investment professionals may want to look out for changing correlation and return dynamics as the asset class continues on its path to maturation.

Acknowledgements We thank Christian Gombert of the Hauck & Aufhäuser Privatbankiers as well as Johannes Bernius for their invaluable support with data acquisition. Lars Geiger, the participants of the 6th Crowdinvesting Symposium, and the participants of the 26th Annual Conference of the Multinational Finance Society have provided valuable feedback.

References

Ackert LF (2012) The impact of circuit breakers on market outcomes. Technical report. Economic Impact Assessment EIA9. UK Government Office for Science – Foresight Project. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/289039/12-1070-eia9-impact-circuit-breakerson-market-outcomes.pdf

Allen M (2017) Chiasso accepts tax payments in Bitcoin. swissinfo.ch. https://www.swissinfo.ch/eng/business/swiss-fintech_chiasso-accepts-taxpayments-in-bitcoin/43503464

Back A (2002) Hashcash-a denial of service counter-measure. ftp://sunsite.icm.edu.pl/site/replay.old/programs/hashcash/hashcash.pdf

Baird L (2016) The Swirlds hashgraph consensus algorithm: fair, fast, Byzantine fault tolerance. Technical report Swirlds-Tr-2016-01

Briere M, Oosterlinck K, Szafarz A (2015) Virtual currency, tangible return: portfolio diversification with Bitcoin. J Asset Manag 16(6):365–373

Buterin V (2013a) A next-generation smart contract and decentralized application platform. Technical report. Ethereum project white paper. https://github.com/ethereum/wiki/blob/master/drafts/%5Benglish%5D-old-ethereumwhitepaper.md

Buterin V (2013b) Bitcoin network shaken by blockchain fork. bitcoinmagazine.com. https://bitcoinmagazine.com/articles/bitcoin-network-shaken-by-blockchainfork-1363144448/

Buterin V (2016) "Ethereum 2.0". Ethereum project mauve paper. https://cdn.hackaday.io/files/10879465447136/Mauve%20Paper%20Vitalik.pdf

Buterin V (2017a) On medium-of-exchange token valuations. http://vitalik.ca/general/2017/10/17/moe.html

Buterin V (2017b) The meaning of decentralization. Technical report. Medium. https://medium.com/@VitalikButerin/the-meaning-of-decentralization-a0c92b76a274

CBOE (2017) XBT-Cboe Bitcoin futures. Technical report. Chicago Board Options Exchange. http://cfe.cboe.com/cfe-products/xbt-cboe-bitcoin-futures

CME (2017) Now available: Bitcoin futures. cmegroup.com. https://www.cmegroup.com/trading/bitcoin-futures.html

Dougherty C, Huang G (2014) Mt. Gox seeks bankruptcy after 480 million Bitcoin loss. bloomberg.com. https://www.bloomberg.com/news/articles/2014-02-28/mt-gox-exchange-files-for-bankruptcy

Dwork C, Naor M (1992) Pricing via processing or combatting junk mail. In: Annual international cryptology conference. Springer, Heidelberg, pp 139–147. https://link.springer.com/chapter/10.1007/3-540-48071-4_10

Dyhrberg AH, Foley S, Svec J (2018) How investible is Bitcoin? Analyzing the liquidity and transaction costs of Bitcoin markets. Econ Lett 171:140–143

Eisl A, Gasser S, and Weinmayer K (2015) Caveat emptor: does Bitcoin improve portfolio diversification? Available at SSRN 2408997

Elendner H et al (2018) The cross-section of crypto-currencies as financial assets - investing in crypto-currencies beyond bitcoin. In: Handbook of blockchain, digital finance, and inclusion, vol 1. Elsevier, Amsterdam, pp 146–170

EOSProject (2017) EOS.IO technical white paper. Technical report EOS Project. https://github.com/EOSIO/Documentation/blob/master/TechnicalWhitePaper.md

Fink C, Johann T (2014) Bitcoin markets. Available at SSRN 2408396

GolemProject (2016) The Golem project - crowdfunding whitepaper. Technical report. The Golem Project. http://golemproject.net/doc/DraftGolemProjectWhitepaper.pdf

Higgins S (2014) Hal Finney on Bitcoin: in his own words. coindesk.com. https://www.coindesk.com/hal-finney-bitcoin-words/

Jakobsson M, Juels A (1999) Proofs of work and bread pudding protocols. In: Secure information networks. Springer, Berlin, pp 258–272. https://link.springer.com/content/pdf/10.1007/978-0-387-35568-9_18.pdf

Johnston D et al (2015) The general theory of decentralized applications, DApps. GitHub 9. https://github.com/TarantulaTechnology/Documents-Blockchain/blob/master/The%20General%20Theory%20of%20Decentralized%20Applications%2C%20DApps.pdf

Juels A, Brainard JG (1999) Client puzzles: a cryptographic countermeasure against connection depletion attacks. In: NDSS, vol 99, pp 151–165. http://www.isoc.org/isoc/conferences/ndss/99/proceedings/papers/juels.pdf

Kalla S (2017) A framework for valuing crypto tokens. Technical report. Acupacy. https://www.coindesk.com/framework-valuing-crypto-tokens/

Lee DKC, Li G, Wang Y (2018) Cryptocurrency: a new investment opportunity? J Altern Invest 20 (3):16–40

Merkle RC (1980) Protocols for public key cryptosystems. In: Security and privacy, 1980 IEEE Symposium on. IEEE, pp 122–134. https://www.researchgate.net/profile/Ralph_Merkle/publication/220713913_Protocols_for_Public_Key_Cryptosystem/links/00b495384ecda07784000000/Protocols-for-Public-Key-Cryptosystems.pdf

Merkle RC (1990) A certified digital signature in Conference on the theory and application of cryptology. In: Brassard G (ed) Advances in cryptology. CRYPTO'89 LNCS 435. Springer, Heidelberg, pp 218–238. https://link.springer.com/content/pdf/10.1007/0-387-34805-0_21.pdf

Nakamoto S (2008) Bitcoin: a peer-to-peer electronic cash system. Technical report. https://bitcoin.org/bitcoin.pdf

P4Titan (2014) Slimcoin - a peer-to-peer crypto-currency with proof-of-burn. Technical report. slimcoin

Popov S (2017) The tangle. Technical report. IOTA Project. https://iota.org/IOTA_Whitepaper.pdf

ProtocolLabs (2017) Filecoin: a decentralized storage network. Technical report. Protocol Labs. https://filecoin.io/filecoin.pdf

Rosenfeld M (2012) Analysis of hashrate-based double spending. arXiv preprint arXiv:1402.2009. https://arxiv.org/pdf/1402.2009.pdf

SEC (2012) Approval order. Technical report Release 34-67090. Securities and Exchange Commission. https://www.sec.gov/rules/sro/bats/2012/34-67090.pdf

Sharpe WF (1992) Asset allocation: management style and performance measurement. J Portf Manag 18(2):7–19

Swissinfo (2016) Zug first to accept Bitcoin for government services. swissinfo.ch. https://www.swissinfo.ch/eng/business/crypto-valley_zug-firstto-accept-bitcoin-for-government-services/42143908

Szabo N (2008) Bit gold. http://unenumerated.blogspot.de/2005/12/bitgold.html

Trimborn S, Li M, Härdle WK (2018) Investing with cryptocurrencies - A liquidity constrained investment approach

Ummelas O (2018) Estonia scales down plan to create national cryptocurrency. bloomberg.com. https://www.bloomberg.com/news/articles/2018-06-01/estonia-curbs-cryptocurrency-plan-that-drew-rebuke-from-draghi
Voshmgir S, Kalinov V (2017) Blockchain - A beginners guide. Technical report Version 1.0. BlockchainHub. https://blockchainhub.net/blockchaintechnology
Wei WC (2018) Liquidity and market efficiency in cryptocurrencies. Econ Lett 168:21–24
WeiDai (1998) B-Money. http://www.weidai.com/bmoney.txt
Wood G (2014) Ethereum: a secure decentralised generalised transaction ledger. Ethereum project yellow paper EIP-150 revision. http://www.cryptopapers.net/papers/ethereum-yellowpaper.pdf