The Cross-Section of Crypto-Currencies as Financial Assets[1]

Investing in Crypto-Currencies Beyond Bitcoin

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Contents

Chapter Points

- Hundreds of crypto-currencies have been created following Bitcoin and form an asset class for alternative investments.
- Returns on crypto-currency investments exhibit high expected returns with very high volatilities; however, their returns show very little correlation with those of standard financial assets, or with each other.
- Portfolios of crypto-currencies therefore provide diversification benefits.

7.1 Introduction

With Bitcoin, Satoshi Nakomoto permanently changed the world's investment universe to include purely virtual assets: in 2008 he invented the first digital currency. Less than a decade later, not only the original Bitcoin technology has evolved from a technical proof-of-concept to a serious and dependable investment asset: the underlying blockchain technology has spread and gained recognition, and several hundred of different crypto-currencies have been created and are actively traded. Virtual assets are no longer *one* alternative investment: cryptographic claims nowadays form an entire asset class for alternative investments, with a large cross-section to choose from.

The wide and fast proliferation of the blockchain technology owes to the open-source nature of Bitcoin, with its source code publicly available at `github.com` and a free-software license that allows derivative works. Computer programmers worldwide can copy, modify and experiment upon the Bitcoin concept, thereby creating many alternative crypto-currencies (altcoins). This has brought about a vibrant ecosystem that allows for diverse experimentation in the development of digital currencies.

Crypto-currency traders worldwide have seized upon the altcoin growth to invest in an alternative asset free from direct government intervention, or to speculate on the often volatile values of these crypto-currencies. Some altcoins have led to significant improvements to the development of digital currencies as a whole, such as Ethereum, Ripple, Dash (formerly

Darkcoin), Namecoin and others. For example, Ethereum is a crypto-platform that introduces a Turing-complete scripting language allowing for the creation of smart contracts; Dash allows for anonymity of blockchain transactions; Namecoin implements a decentralized Domain Name System.

Many altcoins, however, have been created as a simple clone of Bitcoin with minimal changes (see `dillingers.com/blog/2015/04/18` for a how-to): some due to a belief of different parameters being preferable; some with little other purpose than to pump-and-dump the market for a quick return.

There exist altcoin developers who have conducted outright scams via Initial Coin Offerings, with the creators disappearing after crowdsourcing bitcoins from the community. An example of an Initial Coin Offering (ICO) scam is Edgecoin, where the organizers changed their original ICO announcement to one informing that they had been hacked, see `bitcointalk.org`. Meanwhile, some altcoins have also been created with illegitimate aims such as stealing users' personal details or bitcoin private keys through the installation of malware and trojans onto altcoin wallets.

The presence of free-riders and fraudsters, however, does not imply a fundamental weakness of the asset class; it stems from the sudden growth in the early stages of a new market and from the presence of many unknowledgable participants (Böhme et al., 2015). After all, in the early days when the first joint-stock corporations publicly floated their shares, stock scams were widespread, and physical currencies are plagued by counterfeiting to this day. Yet who would exclude stocks and currencies from investment considerations?

These nuisances should not distract from the fact that crypto-currencies are a new asset class that is here to stay. The cryptographic claims are based on a strong, highly competitive and remarkably resilient technology: the blockchain. As the economy is becoming more and more digital, the role of digital assets in investment decisions will also grow. To exclude digital assets from investment choices, in particular in light of their properties this chapter will point out, will become as restrictive as excluding entire other asset classes.

This chapter serves as an introduction to crypto-currencies as alternative investments: We consider their properties as financial assets, with a particular focus on their returns, as well as their diversification effect in investment portfolios. We investigate the movements of the crypto-currencies, analyze the co-movements of the altcoins and Bitcoin and compare their relation with established assets like stock indices, real estate, gold and US Treasury Bills.

7.2 The Dynamic Environment of a Multiplicity of Crypto-Currencies

While Bitcoin still is the most valuable crypto-currency, the investment universe of block-chain-based crypto-currencies has seen higher than proportional growth for alternative implementations, so-called *altcoins*.

At the time of writing (31 August 2016), `coinmarketcap.com` lists 767 active altcoins. This list is not exhaustive: many more have been and are being created; only the most liquid ones are traded on altcoin exchanges and listed on Coinmarketcap. The others are deemed too illiquid. However, the existence of many insignificant crypto-currencies must not detract from the fact that the importance of altcoins as alternative investment vehicles is growing: Altcoin market capitalization as a percentage of total market capitalization of crypto-currencies including Bitcoin has already reached 19%.

One major factor enabling such growth has been the relative ease of setting up new crypto-currencies.

7.2.1 Starting Yet Another Crypto-Currency

In 2014, altcoins were rapidly being created each day, with the number of altcoins listed on Coinmarketcap increasing from 69 in January 2014 to 590 by December 2014, see `web.archive.org`. Growth in active altcoins has since tapered off and the number of active altcoins has been hovering between 650 and 770 since June 2015.

There are two types of altcoins listed on Coinmarketcap, namely crypto-currencies and crypto-assets. Crypto-currencies have their own blockchain and require their own time-stamping mechanism. Examples of crypto-currencies are Litecoin, Peercoin, Ether, Dogecoin, Stellar, etc.

Crypto-assets do not have their own blockchain or timestamping mechanism but instead are created off crypto-currency platforms and rely on the main crypto-currency's blockchain. Examples of crypto-currency platforms (which also serve as a crypto-currency) are Counterparty, NXT, Ethereum, Omni (previously Mastercoin), and Bitshares. Some examples of crypto-assets that are based on these crypto-currency platforms are MaidSafeCoin (a crypto-asset of Omni), DigixDAO (a crypto-asset of Ethereum), Storjcoin X (a crypto-asset of Counterparty), SuperNET (a crypto-asset of NXT) and others.

It requires technical knowledge to create or even to clone an existing crypto-currency. Creating a crypto-asset on the other hand is relatively simple and does not require strong technical expertise.

7.2.2 A Brief History of Altcoins and Approaches to Generate Value

The first altcoin ever created was the Bitcoin Testnet 1, created by Gavin Andresen (see `reddit.com`); it has by now been abandoned. One of the earliest crypto-currencies still in active use is Ripple, an exceptional altcoin with respect to its development, which to a large degree is independent of Bitcoin's. Not only do these two crypto-currencies employ different timestamping models, with Ripple using the Consensus protocol, see Schwartz et al. (2014), against Bitcoin's SHA-256 Proof-of-Work: Ripple is also implemented with an entirely different source code – a rarity, since most crypto-currencies are built as edited versions of Bitcoin's source code.

Namecoin was one of the earliest designs of innovative altcoins, in the sense that it was created with the aim of functionality beyond coin transfers, i.e., for a different use-case: Namecoin was built to improve decentralization by serving as an alternative decentralized Domain Name System (DNS) system and identity storage. DNS servers, the machines which store the look-up information to link internet domain names to those computers effectively serving the associated content, are until today controlled by governments and large corporations – an infrastructure setup that allows for certain websites to be censored. Namecoin enables the creation of `.bit` websites which cannot be censored. Furthermore, Namecoin also allows for the storage of key/value data, which proves useful for identity management. For instance, the startup Onename used to store information on individual identities on the Namecoin blockchain (but has since moved to the Bitcoin blockchain due to security reasons, `blog.onename.com`). Namecoin is also noteworthy for being the first fork of Bitcoin and the first altcoin to implement merged mining with Bitcoin on the SHA-256 Proof-of-Work algorithm, see `namecoin.info`.

The first major altcoin to make use of a different hashing algorithm was Tenebrix, which used the Scrypt Proof-of-Work algorithm. However, likely due to an excessive pre-mine of 7.7 million coins out of a cap of 10.5 million, Tenebrix did not survive. Pre-mining refers to mining before the general public is invited to participate in the operation of the blockchain, and hence before anybody but the developers can participate in the seignorage, obtaining newly created coins. Naturally, large pre-mining is perceived very critically by potential altcoin investors, as it effectively allocates a significant fraction of the aggregate (also long-run) money supply to the developers before the coin's launch.

In the early days of altcoin creation, however, debates about altcoin designs centered mostly on the concrete parameterization of the blockchain. Parameters such as total coins available for mining, transaction time and distribution period were pivotal in arguments about pros and cons of an altcoin. Hence, many altcoins were purely a reincarnation of the Bitcoin blockchain with a different set of parameter choices. A classical example of such parameter

Table 7.1: Comparison of parameters of Bitcoin and Litecoin.

	Bitcoin	Litecoin
Coin Limit	21 million	84 million
Timestamping	proof of work	proof of work
Proof-of-Work Hashing Algorithm	SHA-256	Scrypt
Block Time	10 minutes	2.5 minutes
Difficulty Retarget	2,106 blocks	2,106 blocks
Block Reward Halving	every 210,000 blocks	every 840,000 blocks
Initial Block Reward	50 BTC	50 LTC
Created By	Satoshi Nakamoto	Charlie Lee
Creation Date	3 January 2009	7 October 2011

Source: coindesk.com

tweaking to "improve" Bitcoin is Litecoin. Table 7.1 compares the parameters of Bitcoin and Litecoin.

Following the trend of tweaking parameters for altcoins, developers started innovating on the *proof-of-work* concept. In order to prevent adversaries from undermining the network, the blockchain requires every new block to contain proof that a certain (expected) amount of effort has been invested. This proof of work is rewarded with newly created coins (seignorage) and transaction fees (if any). The proof is delivered in the form of a number that solves a computational problem which is hard to solve but very easy to verify. In this context, "hard to solve" means that the only way to come up with a solution is a trial-and-error approach that requires sizable computational resources ("number crunching;" the difficulty of the problem is re-set periodically so that on average a new block is found after a given block time).

This proof-of-work approach makes the propagation of a fraudulent continuation of the blockchain prohibitively expensive ("51% attack"), but it does imply that sizable amounts of computational power (and hence electricity) are used to ensure the blockchain's operation. While the frequently voiced position that this energy be "wasted" certainly overlooks the fact that other payment systems also require far from negligible expenses to operate and maintain, even if they do not achieve independence from a trusted third party, it led to the development of an alternative approach to ensure the blockchain cannot be extended illegitimately: *proof of stake*.

The proof-of-stake idea was first mooted by the Bitcointalk user QuantumMechanic in July 2011, see `bitcointalk.org`. Sunny King, the founder of Peercoin (previously known as PPCoin) was the first to implement a proof-of-stake altcoin, see King and Nadal (2012). The aim the proof-of-stake design was to remove the need to expend computational resources in securing the blockchain. The right to extend the blockchain is not obtained by providing

the solution to a computational riddle, but rather requires a party to prove ownership of a certain amount of coins. In order to attack a proof-of-stake altcoin, an attacker would not need to surpass the entire remaining community in terms of computational power, but rather buy a significant portion of the coins outstanding. In this case, however, attacking the coin (and thus destroying its value) will no longer be incentive compatible; at least unless the threat to do it anyway is credible (Houy, 2014). For more information, see the article of Vitalik Buterin, the founder of Ethereum, explaining the differences between Proof-of-Work and Proof-of-Stake, in `bitcoinmagazine.com`.

The debate about the relative merits of proof of work vs. proof of stake is still active, however, and development of proof-of-work altcoins has kept progressing. For instance, tweaking Bitcoin's SHA-256 algorithm allowed more individual miners to participate in the network in order to keep it decentralized. As a result of these innovations, we see many altcoins launching with algorithms such as Scrypt, X11, X13, X15, Blake-256, Groestl and more. Developers also started launching altcoins using multiple hashing algorithms, such as Myriadcoin which uses five hashing algorithms: SHA256d, Scrypt, Myr-Groestl, Skein, and Qubit.

The third approach to ensure the integrity of a blockchain is *proof of burn,* first used by Counterparty. The Counterparty tokens, XCP, were distributed proportionately to everyone who destroyed bitcoins by sending them to an unrecoverable address during the proof-of-burn period in January 2014, see `counterparty.io`. The proof of burn was used by the team launching Counterparty to ensure the legitimate distribution of coins. This process helped the Counterparty team establish credibility as the developers do not gain anything from the bitcoins "burnt."

Another trend that started in 2014 was altcoin developers launching sovereign altcoins, associated with particular countries. The first such sovereign altcoin was Auroracoin, created in February 2014 to serve as the crypto-currency for the nation of Iceland. Like most of these sovereign altcoins, Auroracoin distributed the coins to residents via an airdrop: Icelandic residents entered their resident ID on Auroracoin's official website, and received their reserved 50% of the total supply of Auroracoin, see `coindesk.com`.

A sizable hype ensued, making Auroracoin the second-largest crypto-currency in terms of market capitalization in March 2014, see `blogs.wsj.com`. The success of Auroracoin inspired other developers to launch similar sovereign altcoins for other nations or territories such as Pesetacoin (Spain), Scotcoin (Scotland), eGulden (Netherlands), Mazacoin (Lakota Nation – a Native American territory in USA) and others. For a list, see `coindesk.com`.

Next, development efforts were directed at altcoins with anonymity as a design goal. The pseudonymous nature of Bitcoin was sufficient to attract transfers for illegitimate or illegal purposes, but the public and unalterable trace of all transactions also provided the basis for

successes by law enforcement in identifying the agents behind certain transactions. Altcoins such as Dash (previously known as Darkcoin), Monero, ShadowCash and others aimed at providing the possibility of transferring coins without disclosing one's identity. Dash, for example, has a PrivateSend (previously known as DarkSend) implementation that extends the idea of CoinJoin, first proposed by Bitcoin core developer Gregory Maxwell as a way to improve bitcoin transaction anonymity by combining bitcoin transactions with another person's transactions, see bitcointalk.org. Duffield and Diaz (2015) in their Dash whitepaper point out three methods in which bitcoin transactions can be de-anonymized: through linking and forward linking via identified exchanges, and also CoinJoin amount tracing. PrivateSend requires at least three participants and for it to work each participant needs to submit transaction inputs and outputs in common denominations of 0.1DASH, 1DASH, 10DASH and 100DASH.

Potentially the most important developments, however, were those to add *smart-contract* capabilities onto the blockchain. Some platforms that are built on top of the Bitcoin blockchain to add this functionality include Omni (previously Mastercoin), Counterparty and Rootstock. Other developers have created new platforms such as Ethereum, Bitshares and NXT. Platforms such as Ethereum introduced new concepts into the protocol such as a Turing-complete programming language, allowing to create arbitrarily complex smart contracts.

These platforms allow for the creation of crypto-assets and supported the growth of crypto-assets. For example, Counterparty has a total of 50,520 assets (according to blockscan.com), NXT has 685 assets (nxtreporting.com), and Bitshares has 198 active assets (cryptofresh.com), at the time of writing. Despite the high number of crypto-assets, most of these are not actively traded. CoinMarketCap lists only 59 actively traded crypto-assets, see coinmarketcap.com. The most successful crypto-asset is the DAO: it raised USD 162 million worth of tokens; however, on 17 June 2016, a vulnerability in the code resulted in the loss of 3.6 million ethers worth USD 60 million, see coindesk.com. The resolution of this problem by re-defining the blockchain led to a fork and heated debate.

Finally, the growth of enthusiasm about Bitcoin has been reflected in the growth of bitcoin transactions, to the point that today developers are discussing how to ensure the protocol can accommodate such high growth rates well into the future. To this end, the blockchain itself will likely need to be decentralized, and work is progressing on so-called *pegged sidechains* (Back et al., 2014). To get onto a sidechain, a user will send bitcoins to a specially-formed Bitcoin address. Bitcoins sent to the address are immobilized (not within anyone's control). Once the transaction is confirmed, tokens on the sidechain are released so that they can be controlled by the same user. The reverse can happen once the tokens in the sidechain are no longer needed. Sidechains are essentially altcoins in a Bitcoin ecosystem. There are numerous

interesting applications that can take place once this proposal goes live and may well be the future direction of crypto-currencies.

7.2.3 Altcoin Trading Platforms

Both the desire to innovate and the ease of building on the Bitcoin implementation have thus led to the breadth of various altcoins available for investment and as media of exchange. They are traded online with huge discrepancies in liquidity.

Trading activity of popular altcoins is conducted at online crypto-currency exchanges. Similarly to exchanges trading BTC for sovereign currencies, these exchanges commonly operate continuously, i.e., 24 hours per day, 7 days every week. The complete alignment of trading hours with calendar time provides an aspect of liquidity that the world's largest stock exchanges do not provide.

Altcoin exchanges operate one order book per currency pair, where prices are determined from active trading. Most altcoins are thereby traded against bitcoins, effectively making it the virtual reserve currency. Only the most popular altcoins sometimes have trading pairs with fiat currencies such as the US Dollar, the Euro, the Chinese Yuan, or the Russian Ruble.

One of the largest altcoin exchanges by trading volume at the time of writing is `poloniex.com`. Poloniex is a US-based exchange that does not support fiat-currency trading. Poloniex supports trading of 115 altcoins across 135 market pairs with 4 base currencies of bitcoin (BTC), ether (ETH), monero (XMR) and tether (USDT). Poloniex's 24-hour trading volume on 24 July 2016 was 67,906 BTC.

Most trading volume occurs on the BTC base currency. There are 108 markets with bitcoin, 15 markets with monero, 8 markets with tether and 4 markets with ether as base currency. The most popular market pair on Poloniex is ETH/BTC with 24-hour trading volume of over 41,000 BTC. This is followed by ETC/BTC, NXT/BTC, LSK/BTC, DAO/BTC and STEEM/BTC.

One of the oldest altcoin exchanges is `btc-e.com`. Btc-e has been in operation since July 2011. Its owner and location, however, are uncertain, with its terms of use claiming that it is bound by the laws of Cyprus, website description claiming it is operating from Bulgaria, and the website having a strong Russian language design. Despite its shady circumstances, btc-e has been in operation for a long time and has withstood many competitors who have since ceased to exist.

Currently, btc-e supports trading of 7 altcoins across 18 market pairs with 5 base currencies of US Dollar, Euro, Russian Ruble, bitcoin (BTC) and litecoin (LTC). Btc-e's 24-hour trading volume on 24 July 2016 was 4,721 BTC; a small number compared to Poloniex.

Yobit, Bittrex, C-Cex are exchanges which offer support for many altcoins. Yobit supports 618 altcoins, Bittrex supports 205 altcoins and C-Cex supports 143 altcoins, and these three exchanges offer traders more opportunities in trading their altcoins when the altcoins are not listed on Poloniex.

It is quite common for altcoin exchanges to disappear overnight in this industry with the most popular narrative being that the exchange has been hacked. Without proper security precautions in place, hackers can run away with funds in an exchange making it insolvent. Users are advised to not store any altcoins on the exchanges to reduce counterparty risk. Some of the popular altcoin exchanges that have disappeared with users' funds over the years are Cryptsy, Mintpal and Vircurex.

7.2.4 Altcoin Information Platforms

There are many sources of information that can be used to analyze the crypto-currency ecosystem. One of the primary sources of information is to use blockchain data. The blockchain.info provides online Bitcoin wallets and also data such as price, mined blocks, number of transactions and various others statistics.

Alternative block explorers providing blockchain information for Bitcoin are kaiko.com and blockr.io. Since each crypto-currency has its own blockchain, the information for each altcoin needs to be obtained from each individual altcoin's block explorer. BitInfocharts.com provides statistics for selected altcoins.

While block-explorer services are suitable for the average user to obtain information related to the blockchain, application developers prefer more flexibility in interacting with the blockchain and may opt for Application Program Interface (API) services such as BlockCypher.com and BitGo.com. Traditionally, developers need to host a bitcoin node in order to obtain the latest transactions and blocks. With these services, the barriers to entry for developers to build apps on top of the bitcoin blockchain are reduced.

To get more information on the level of decentralization in Bitcoin, one can use Bitnodes (available at bitnodes.21.co). Bitnodes attempt to estimate the size of the Bitcoin network by finding reachable Bitcoin nodes in the network.

To get information on the latest price for bitcoin, it needs to be obtained from the dozens of exchanges operating worldwide. Each of these exchanges has its own market and order book, and due to differences (including transaction volume) each exchange will quote somewhat different bid/ask prices. So far, there has not been a global standard in determining the bitcoin "spot price." There are several initiatives to identify the true spot price of bitcoin such as the CoinDesk Bitcoin Price Index and the Winkdex.

In September 2013, the CoinDesk Bitcoin Price Index (BPI) was launched by CoinDesk. The aim of BPI is to establish the standard retail price reference for industry participants and accounting professionals. Due to the growing importance of the bitcoin market in China, a specialized BPI for the Chinese Yuan market was introduced in March 2014. At the time of writing, the following exchanges are included in the USD index: Bitstamp, Bitfinex, GDAX, itBit and OKCoin while the following exchanges are included in the CNY index: BTC China, Huobi and OKCoin. The minimum criteria for a Bitcoin exchange to be included in the BPI are the following, see `coindesk.com/price` and `coindesk.com` for reference:

1. USD exchanges must serve an international customer base.
2. The exchange must provide bid–offer quotes for an immediate sale (offer) and an immediate purchase (bid).
3. Minimum trade size must be less than 1,500 USD (9,000 CNY) or equivalent.
4. Daily trading volume must meet minimum acceptable levels as determined by CoinDesk.
5. The exchange must represent at least 5% of the total 30-day cumulative volume for all of the exchanges included in the XBP.
6. The stated and/or actual time for a majority of fiat currency and bitcoin transfers (whether deposits or withdrawals) must not exceed two business days.

In July 2014, the Winkdex price index was launched by Cameron and Tyler Winklevoss. The Winkdex formula is calculated based on the top three highest-volume Bitcoin exchanges in the previous two-hour period using a volume-weighted exponential moving average. Transactions executed on exchanges with higher volumes and most recent by time would provide a higher weight to the Winkdex formula, see `winkdex.com`.

Finally there is `BitcoinWisdom.com`, a real-time bitcoin market chart website. BitcoinWisdom offers real-time price charts allowing users to apply technical analysis onto Bitcoin and selected altcoin markets. BitcoinWisdom gives a real-time overview on what is happening in major bitcoin exchanges by streaming data on order books and executed trades.

For altcoin pricing, volume and trading data, one will have to refer to other online services such as `CoinMarketCap.com`, `CoinGecko.com`, and `CoinHills.com`. CoinMarketCap is a website that tracks the market capitalization of all active crypto-currencies using the following formula: weighted average price multiplied by total available supply.

CoinGecko is a website that tracks crypto-currencies beyond market capitalization. The website ranks crypto-currencies based on several other metrics such as liquidity, developer activity, community and public interest, see `coingecko.com`. CoinGecko was based on the premise that a strong community and developer team form the foundation of a crypto-currency with good growth.

CoinHills is a website that tracks the price and trading activity of various crypto-currencies from different exchanges. CoinHills does not rank altcoins but provides insights on the exchanges and altcoins with the most trading volume on a real-time basis. Using CoinHills, traders can learn more about unusual activities in the crypto-currency markets and obtain potential trading ideas.

To capture the evolution of the values of crypto-currencies in the cross-section, `crix.hu-berlin.de` offers an index which tracks the average price movement of the most representative altcoins, similar to a stock-market index. CRIX determines the coins included via an information criterion and weighs their return contributions by the respective amounts of coins at the start of each month. Thus, CRIX mimics a monthly rebalanced portfolio. While S&P500 and the CSI300 provide a summary statistic about the current state of the US and Chinese markets, respectively, CRIX does the same for the crypto-currency market. CRIX was proposed by Härdle and Trimborn (2015) and further investigated by Trimborn and Härdle (2016). The first publication proposes a first version of CRIX and compares the dynamics of the index against other markets. The latter further develops the methodology of CRIX and evaluates the performance of the methodology on other markets.

7.3 Properties of Crypto-Currency Dynamics

While there is ongoing debate about whether altcoins should legitimately be characterized as *currencies* or rather as *digital assets* (Yermack, 2015), indisputably they represent an alternative investment with the evolution of their value of key importance. From the perspective of their owner, next to their usefulness as media of exchange, their capabilities as stores of value are critical; or put differently: the financial returns to holding the digital coins. The emergence of a broad cross-section of different coins has prompted the necessity to assess the risk and return profiles of hundreds of different assets, as well as considerations of diversification and portfolio management.

This section provides an overview of the returns to the price processes of crypto-currencies in general from the perspective of an altcoin investor. While it cannot claim completeness, it is aimed to characterize the cross-section broadly.

7.3.1 The Universe of Crypto-Currencies

There currently exist 767 crypto-currencies while our data set consists of 327. Some altcoins have effectively already gone extinct, while permanently new ones emerge. This nascent market constantly exhibits substantial changes.
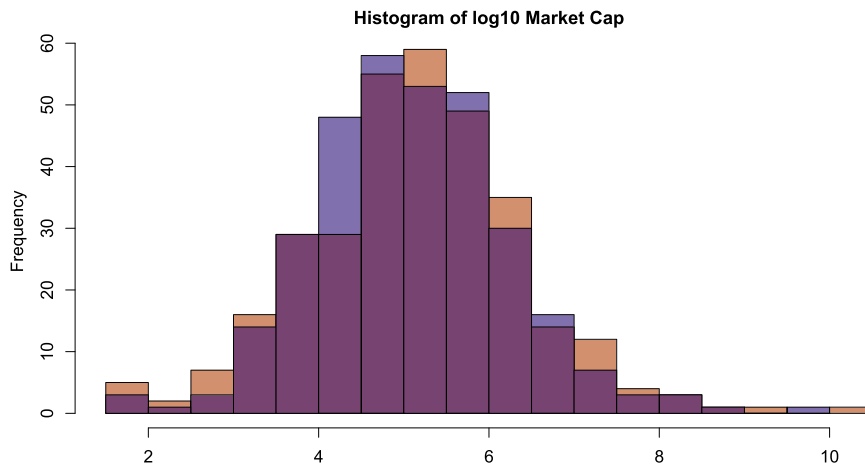
Histogram of log10 Market Cap

Figure 7.1: *Histogram of market capitalizations.* **Frequency of market capitalization on a log scale on 2016-07-24 (shaded red) and in the time period 2015-07-25 until 2016-07-24 (shaded blue) for all crypto-currencies. The overlapping area is displayed in purple. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this chapter.)**
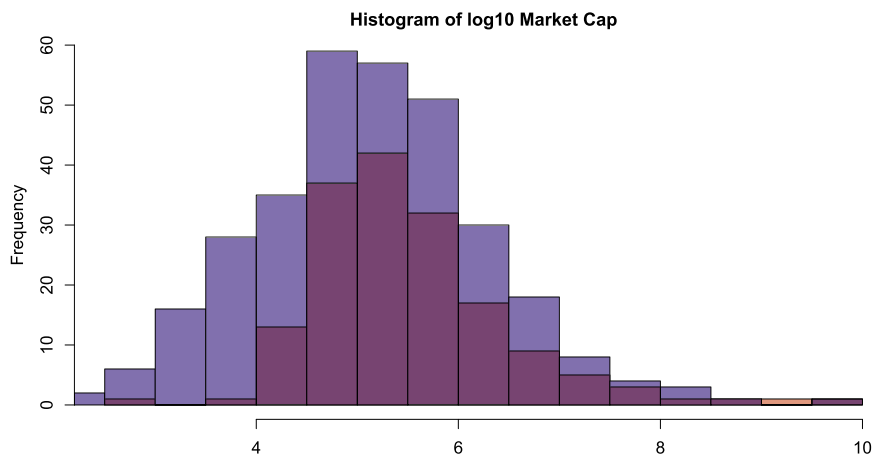
Histogram of log10 Market Cap

Figure 7.2: *Histogram of market capitalizations over time.* **Frequencies cover the periods 2014-03-30 to 2014-08-01 (shaded red) and 2016-01-01 to 2016-07-24 (shaded blue), with overlapping areas in purple. Time intervals cover periods of high market capitalization, compare Fig. 7.4. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this chapter.)**

Fig. 7.1 shows that in the last year most of the crypto-currencies exhibited aggregate market valuations in the range of 1,000 to 10,000,000 USD. Comparing distribution at the end of our sample with the mean over the last year, a shift of mass in the direction of the tails becomes
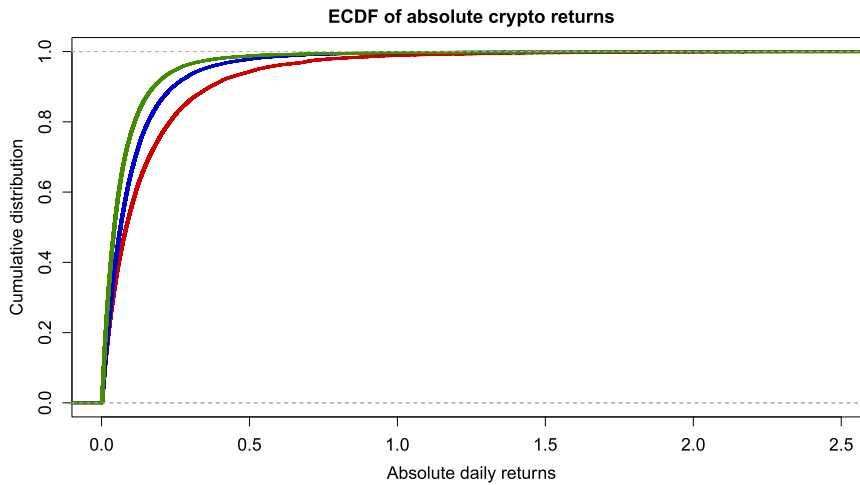
Figure 7.3: *Empirical distribution of absolute returns.* **The figure shows the empirical cumulative distribution of the absolute returns of all crypto-currencies in the data set, divided into three groups depending on their mean market value. Group1 has a mean market value below or equal 50,000, group2 between 50,000 and 500,000, and group3 above 500,000. Excluded were returns where the daily trading volume was below 10 USD. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this chapter.)**

visible. Mostly crypto-currencies with market capitalization between 10,000 and 32,000 USD either gained or lost in value or vanished from the market.

To analyze structural shifts in the market, a closer look over certain time horizons is called for. For instance, Fig. 7.4 reveals that the aggregate crypto-currency market exhibited fairly high market capitalization in the beginning of the observed time period, declined subsequently, and achieved again similar values at the end of the time period.

Fig. 7.2 shows the surprising result that in the earlier subperiod in 2014, more crypto-currencies with high market capitalization were present in the market, as compared to the later subperiod in 2016. In the latter period, the recovery of the aggregate market value was driven mainly by crypto-currencies with smaller valuations having become more frequent in the market.

Assets with differences in certain features, like market value, often exhibit differences in the behavior of their returns. Stocks have an often-observed size effect, see e.g., Gabaix (2009). Fig. 7.3 shows the empirical cumulative distribution function (ecdf) of the absolute returns of all crypto-currencies for different sizes of market value. Apparently, crypto-currencies with smaller mean market value exhibit higher returns; crypto-currencies therefore share the size effect with stocks.

Figure 7.4: *Aggregate market capitalization and trading volume.* **Evolution of aggregate market capitalization on** $\log_{10}$ **scale over the period 2014-03-30 to 2016-07-24. The width of the line (spanned in red) indicates the daily trading volume of the aggregate market. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this chapter.)**

7.3.2 The Evolution of the Crypto-Currency Universe Over Time

As detailed, the relative ease of constructing a new crypto-currency and the diversity of objectives regarding their desired properties lead to a dynamic environment with new currencies being introduced and some established ones fading out of usage over often short intervals of time. At the same time, the distribution of trading volumes attracted by various currencies is highly skewed, with BTC generally still generating the dominating fraction of aggregate daily trading volume.

The entire market showed a high increase in daily trading volume over the observed time period 2014-03-30 to 2016-07-24. Fig. 7.4 shows that the relatively thin trading volume in 2014 was accompanied by a frequent change in the market capitalizations. After a strong decline of capitalization in early 2015, market cap increased until the end of the observation period while showing deepening liquidity.

7.3.3 Liquidity of Crypto-Currencies

Fig. 7.5 displays the evolution of daily trading volume for the 10 major crypto-currencies, using a logarithmic scale due to the high skewness of volumes across crypto-currencies.

More results on standard liquidity measures are reported by Fink and Johann (2014).
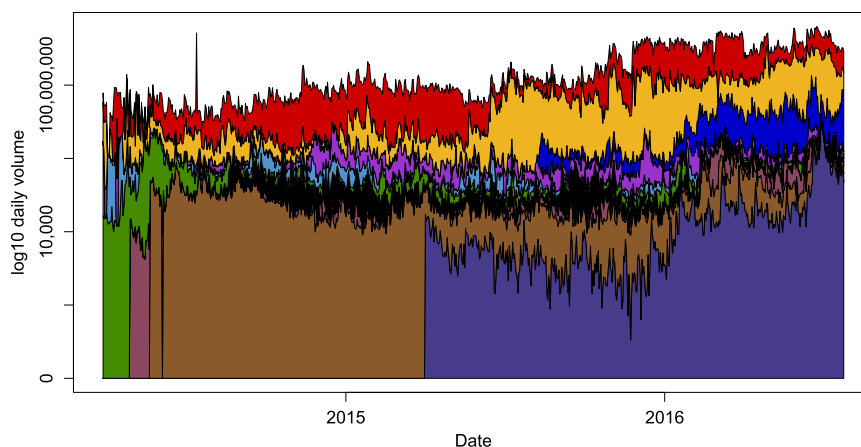
Figure 7.5: *Crypto-currencies' volume evolution.* **Daily USD trading volume of the ten major crypto-currencies over 2014-03-30 to 2016-07-24, on log scale. Color code is BTC, ETH, XRP, LTC, DASH, DOGE, MAID, BTS, XEM, XMR. Crypto-currencies entering the data set display a spike. The volume per crypto-currency is depicted by the height of its colored area; hence the upper contour describes aggregate volume over all 10 crypto-currencies. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this chapter.)**

7.3.4 Financial Returns on Investing in Crypto-Currencies

7.3.4.1 Summary Statistics

Compared to standard financial assets, crypto-currencies exhibit remarkably higher dispersion in their returns. Table 7.2 displays summary statistics for the currently most important (in terms of market capitalization) 10 crypto-currencies.

The first interesting fact which these crypto-currencies share can be inferred from the mean and median. The means are – except for LTC – positive while the medians are mostly negative. Obviously most of the returns are negative but with a smaller absolute degree than the positive ones. The row 'percent negative' shows the extent of this implication. Notice that BTC is the only crypto-currency with more positive returns than negative ones, a fact which strengthens its special role in the crypto-currency market.

Crypto-currencies thus lose value more frequently than they gain, but gain in stronger movements. The quantiles, maximal and minimal values support this result. Mostly the maximal simple return is higher than the minimal one, where LTC is the exception again. Also the upper deciles are mostly greater than or at least very close to the lower ones in absolute value. These two findings imply that the returns in the positive tails are sizably bigger than the ones in the negative tails, measured in absolute values.

Table 7.2:   Descriptive statistics on simple daily returns (in percent) of the 10 crypto-currencies with the largest final market capitalizations over the time period 2014-03-30 to 2016-07-24.

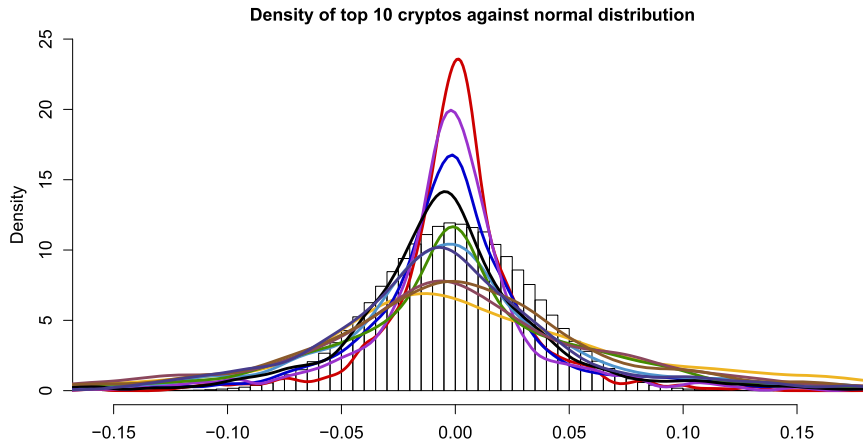|	BTC	ETH	XRP	LTC	DASH	MAID	DOGE	XEM	XMR	BTS
maximum	22.31	55.24	86.02	41.82	114.24	72.91	61.65	69.50	123.93	64.31
upper decile q_{90}	3.37	11.88	4.92	4.12	7.85	9.02	5.15	10.09	9.03	6.65
upper quartile q_{75}	1.32	4.95	1.73	1.29	2.76	4.07	1.74	3.88	3.42	2.40
median	0.09	−0.07	−0.22	−0.18	−0.20	−0.07	−0.39	−0.13	−0.09	−0.61
mean	0.09	1.07	0.10	−0.01	0.66	0.54	0.08	1.10	0.38	0.18
lower quartile q_{25}	−1.21	−3.39	−1.97	−1.60	−2.82	−3.55	−2.35	−3.41	−3.56	−3.34
lower decile q_{10}	−3.07	−7.29	−4.73	−4.41	−6.39	−7.66	−4.90	−8.00	−7.63	−6.58
minimum	−22.26	−48.33	−34.22	−42.14	−40.80	−31.20	−28.62	−24.87	−29.43	−23.74
percent negative	47.85	50.57	53.24	52.98	52.73	51.19	56.90	51.98	50.51	55.71
volatility	3.34	9.28	6.03	5.34	9.07	8.44	6.10	10.04	8.77	7.70
N	848	351	848	848	848	817	848	479	794	733

Figure 7.6: *Probability density of daily returns.* **The probability density functions of the distributions of daily returns for the main 10 crypto-currencies with the following color code: BTC, ETH, XRP, LTC, DASH, DOGE, MAID, BTS, XEM, XMR. A normal distribution with the same mean and standard deviation as the returns on BTC is displayed as a histogram in the background. The observation period is 2014-03-30 to 2016-07-24. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this chapter.)**

Fig. 7.6 shows the densities of the returns of the top 10 crypto-currencies by market capitalization (and for comparison the normal distribution). Apparently the crypto-currencies with higher market cap have more weight around zero. All of the crypto-currencies show devi-

Table 7.3: Risk measures, including value at risk, expected shortfall, and the CAPM β, for daily log returns of the 10 crypto-currencies with highest final market capitalizations and for three crypto-currency portfolios over the time period 2014-03-30 to 2016-07-24. The portfolios are investments into the crypto-currency index CRIX, into an equally-weighted portfolio (EW), or a value-weighted portfolio (VW) of all crypto-currencies in our data set.

|	BTC	ETH	XRP	LTC	DASH	MAID	DOGE	XEM	XMR	BTS	CRIX	EW	VW
volatility	0.034	0.092	0.057	0.054	0.083	0.081	0.058	0.092	0.081	0.071	0.032	0.045	0.062
skewness	−0.564	−0.612	1.152	−0.805	1.268	0.500	1.062	1.334	1.164	1.774	−0.680	2.495	0.614
excess kurtosis	8.617	9.550	22.953	20.637	16.581	6.603	11.059	6.357	14.511	10.549	8.990	28.897	29.354
VaR at 1%	0.072	0.207	0.064	0.117	0.104	0.170	0.069	0.124	0.121	0.119	0.064	0.103	0.068
exp. shortfall at 1%	0.098	0.306	0.085	0.194	0.138	0.231	0.101	0.134	0.148	0.147	0.089	0.135	0.093
VaR at 5%	0.034	0.107	0.036	0.042	0.063	0.116	0.038	0.086	0.078	0.082	0.031	0.058	0.034
exp. shortfall at 5%	0.056	0.178	0.055	0.082	0.092	0.172	0.061	0.107	0.107	0.111	0.052	0.089	0.055
CAPM β	0.103	−0.519	0.436	−0.098	0.614	0.032	0.052	−0.501	0.374	0.605	0.009	−0.099	−0.270
N	838	350	819	840	842	717	840	479	792	727	724	724	723
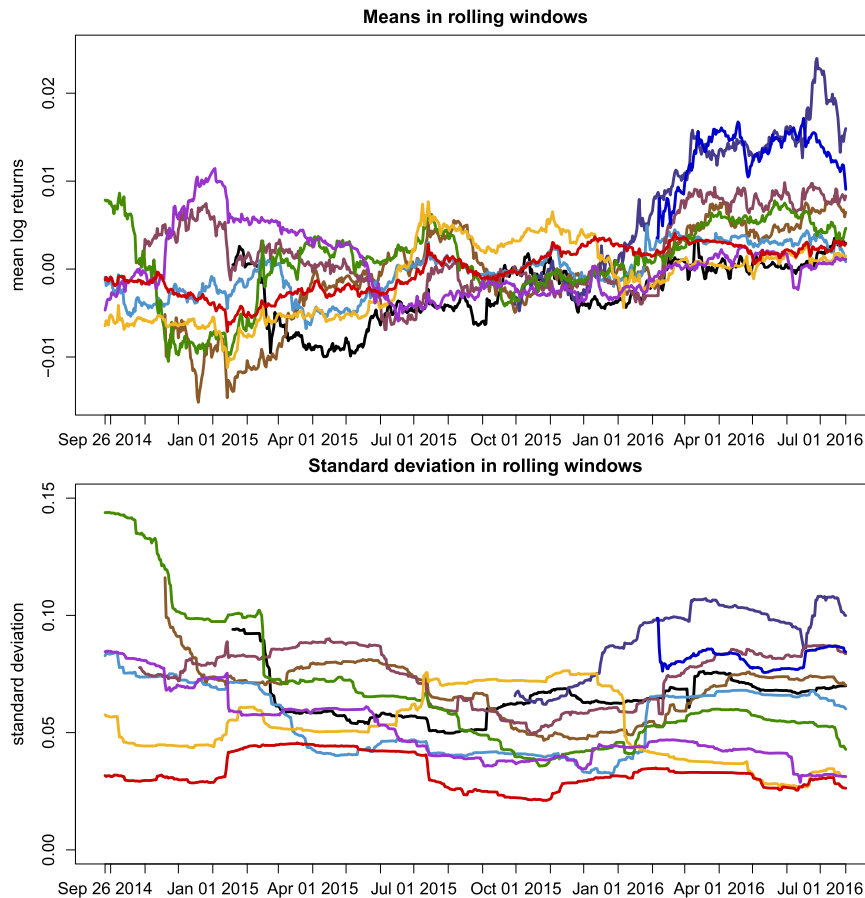
Figure 7.7: *Measures over time in rolling windows.* **Calibrated parameters in rolling windows of 180 days. The upper panel displays means, the lower panel displays the standard deviations in the respective windows. Colors denote BTC, ETH, XRP, LTC, DASH, DOGE, MAID, BTS, XEM, XMR. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this chapter.)**

ations from the Gaussian distribution. Especially the tails are heavier. This visual result is supported by the measures of skewness and kurtosis, see Table 7.3.

7.3.4.2 Returns and Their Stability Over Time

Having established that crypto-currencies, unlike most fiat currencies, exhibit sizable fluctuations in their market value even over short time horizons, the question arises how the risk inherent in an altcoin position and the related expected returns evolve over time. Fig. 7.7 displays the evolution of the main parameters of the return distribution of the crypto-currencies

over time, evaluated in rolling windows of 180 trading days. Since crypto-currencies are traded on all days including weekends, this corresponds to half a year. The upper panel shows the means; standard deviation serves as a risk measure and is depicted in the lower panel. The figure showcases the high instability of crypto-currencies' risk and return properties over time: Some, like BTC, even have a lower mean when the standard deviation is higher. Others, like LTC, exhibit the opposite pattern. Apparently, the higher standard deviations result from opposing reasons: for some crypto-currencies from higher positive and for others from higher negative returns. However, since idiosyncratic risk will not be priced, we need to turn to risk compensation in the following.

At this point the analysis has showed that even simple properties of the return process as means and standard deviations are unstable over time. In the following, we investigate the risk of investment in the crypto-currency market further.

7.3.4.3 Risk Measures

The measures of value at risk (VaR) and expected shortfall (ES) are given in Table 7.3, both at a risk level of 1% and 5%. Definitions and calculation details are in Section A.1.

XRP bears the lowest risk in terms of the two risk measures, but must still be considered highly risky in comparison to standard financial assets. Its ES at the 1% level is 8.53%, which means that the expected loss over the days which are the worst with a 1 in 100 chance is 8.53%. ETH exhibits the highest value with 30.57% of daily expected loss at the same risk level. Clearly, these crypto-currencies are not stable investments but entail high risk. However, due to their low correlations especially with established assets (see Section 7.3.4.4) they provide strong diversification benefits in a portfolio.

Next we investigate βs in the context of the CAPM, with the S& P500 as the market index. The βs, see Table 7.3, show very different sensitivities of crypto-currencies to the market excess rate. This measure implies that movements of the top 10 crypto-currencies are little correlated with the stock market.

In the following, we investigate the question of the co-movement of crypto-currencies deeper by means of correlations and PCA.

7.3.4.4 Diversification in a Crypto-Currency Portfolio

In light of the similarity of many crypto-currencies and the fact that their implementations often share large parts of their source code (and arguably the investor base), it may be expected that the returns among the class of altcoins exhibit a high degree of co-movement. This intuition, however, is wrong. Table 7.4 shows that among the top 10 crypto-currencies, most pairs

Table 7.4: The upper triangular displays the correlations of the crypto-currencies BTC, ETH, XRP, LTC, DASH, DOGE, MAID, BTS, XEM, XMR against each other. Missing values were pairwise omitted. The lower triangular shows the corresponding *p*-values.

	BTC	ETH	XRP	LTC	DASH	MAID	DOGE	XEM	XMR	BTS
BTC		0.08	0.17	0.58	0.33	0.24	0.43	0.32	0.31	0.27
ETH	0.13		0.03	0.05	0.10	0.29	0.05	−0.01	0.12	0.19
XRP	0.00	0.61		0.12	0.07	0.19	0.13	0.10	−0.02	0.16
LTC	0.00	0.33	0.00		0.20	0.08	0.43	0.23	0.21	0.20
DASH	0.00	0.06	0.03	0.00		0.11	0.17	0.11	0.15	0.11
MAID	0.00	0.00	0.00	0.02	0.00		0.12	0.02	0.14	0.14
DOGE	0.00	0.37	0.00	0.00	0.00	0.00		0.20	0.15	0.28
XEM	0.00	0.82	0.03	0.00	0.02	0.73	0.00		0.04	0.12
XMR	0.00	0.02	0.65	0.00	0.00	0.00	0.00	0.38		0.22
BTS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	

exhibit low return correlations. More importantly, Table 7.8 displays the results of a principal-component analysis of the altcoins' daily returns: the single-strongest factor only explains 26% of the variation of crypto-currency returns. Moreover, each subsequent factor is providing only slowly declining additional information content, so that seven factors are needed in order to account for 90% of the variation from these ten crypto-currencies, visualized in Fig. 7.8.

This result already shows a distinct movement of the crypto-currencies. The rotation matrix – upper part of the Table 7.8 – shows that the returns are adequately displayed by different factors of the PCA. For explanation, consider the two most important crypto-currencies in terms of market value in the data set, ETH and BTC. While ETH shows strong representation in the first factors, BTC is represented by the latter factors. This observation is supported by the low correlation of the two crypto-currencies, see Table 7.4.

However, the question arises whether the return co-movements are only this low unconditionally, and are subject to spikes for (strong) negative-return times as is common for stocks? We thus calculate pairwise correlations separately for days on which CRIX moves up vs. down and report the results in Table 7.5. Clearly, correlations indeed are stronger on days of negative movements; however, most crypto-currency pairs still exhibit surprisingly low correlations after all. Results are qualitatively similar if we partition the days into positive and negative ones by following the S&P500 index instead of CRIX.

Focusing on correlations of volatilities, and restricting the days of positive/negative market movements to the tenth/first decile of the market's return distribution yields the results in Table 7.6. Here correlations are somewhat higher, and again differences between positive and negative conditions pertain. However, correlations are still lower than in public stock markets.
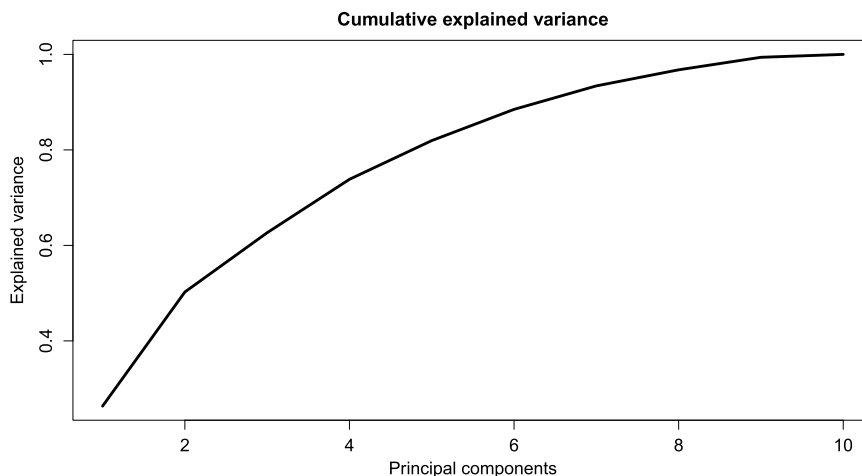
Cumulative explained variance

Figure 7.8: *Principal components of crypto-currency returns.* **Representation of the cumulated fraction of explained variance by the PCA components of BTC, ETH, XRP, LTC, DASH, DOGE, MAID, BTS, XEM, XMR.**

Table 7.5: **Pairwise crypto-currency correlations of returns separately for positive (upper triangular matrix) and negative (lower triangular matrix) market-movement days, as defined by returns on CRIX.**

	BTC	ETH	XRP	LTC	DASH	MAID	DOGE	XEM	XMR	BTS
BTC		0.02	0.07	0.31	0.25	0.11	0.30	0.25	0.25	0.11
ETH	−0.08		−0.03	0.03	0.05	0.22	0.02	−0.03	0.17	0.19
XRP	0.16	0.02		0.05	0.07	0.11	0.14	0.09	−0.01	0.16
LTC	0.69	−0.11	0.08		0.12	−0.05	0.23	0.15	0.08	0.13
DASH	0.36	0.09	0.08	0.32		0.05	0.17	0.08	0.17	0.05
MAID	0.28	0.35	0.12	0.13	0.20		0.08	−0.06	0.12	0.11
DOGE	0.40	−0.01	0.05	0.39	0.20	0.09		0.15	0.04	0.23
XEM	0.32	−0.07	0.03	0.27	0.04	0.11	0.16		−0.09	0.08
XMR	0.41	−0.01	0.10	0.29	0.15	0.18	0.18	0.14		0.16
BTS	0.30	0.17	0.10	0.16	0.07	0.10	0.25	0.14	0.22	

It can be concluded that various crypto-currencies are not close substitutes. Rather, their different technical properties give rise both to different usability as media of exchange and stores of value as well as different price dynamics.

This fact also strengthens the rationale for capturing the aggregate crypto-market movement via an index like CRIX, proposed by Härdle and Trimborn (2015), further investigated by Trimborn and Härdle (2016) and available at `crix.hu-berlin.de`. Table 7.3 shows that an investment strategy based on CRIX also exhibits the lowest risk in terms of Value-at-Risk

Table 7.6: Pairwise crypto-currency correlations of volatilities separately for days with returns in the highest decile (upper triangular matrix) and lowest decile (lower triangular matrix) of market movements, as defined by returns on the S&P500.

	BTC	ETH	XRP	LTC	DASH	MAID	DOGE	XEM	XMR	BTS
BTC		0.15	0.22	0.65	0.32	0.14	0.56	0.47	0.34	0.23
ETH	−0.06		0.01	0.11	0.19	0.37	0.19	0.06	0.04	0.23
XRP	0.11	−0.04		0.16	0.18	0.17	0.21	0.17	0.03	0.26
LTC	0.52	−0.03	0.07		0.26	0.02	0.55	0.43	0.15	0.25
DASH	0.41	−0.01	0.04	0.21		0.12	0.21	0.19	0.04	0.18
MAID	0.27	0.26	0.21	0.09	0.13		0.14	0.04	0.11	0.10
DOGE	0.41	−0.06	0.06	0.45	0.24	0.11		0.38	0.16	0.43
XEM	0.26	−0.08	0.08	0.11	0.07	−0.02	0.12		0.12	0.22
XMR	0.29	0.16	−0.08	0.23	0.15	0.16	0.17	−0.03		0.15
BTS	0.28	0.18	0.07	0.19	0.13	0.25	0.23	0.01	0.30	

Table 7.7: Correlations between BTC, ETH, XRP, LTC, DASH, DOGE, MAID, BTS, XEM, XMR and conventional financial assets: 3 exchange rates, gold, 3 stock indices, real estate and the US Treasury Bills Rates.

	BTC	ETH	XRP	LTC	DASH	MAID	DOGE	XEM	XMR	BTS
USD/EUR	−0.05	−0.04	0.04	−0.06	−0.01	−0.03	−0.06	−0.01	−0.05	−0.03
JPY/USD	0.02	−0.04	−0.03	−0.04	0.09	0.02	0.05	−0.05	0.02	0.06
USD/GBP	−0.06	−0.09	0.04	−0.09	−0.01	−0.01	−0.02	−0.17	−0.04	−0.03
Gold	0.05	0.04	0.04	0.05	−0.01	0.07	0.01	0.09	0.02	−0.01
SP500	0.00	−0.05	0.05	−0.05	0.02	0.00	0.01	−0.05	0.03	0.04
XWD	0.01	−0.03	0.02	−0.07	0.03	0.03	0.01	−0.07	0.05	0.07
EEM	0.00	−0.09	0.04	−0.09	0.00	−0.01	0.02	−0.04	0.02	0.04
REIT	0.03	−0.09	0.04	0.05	0.00	−0.03	0.01	0.05	−0.01	−0.05
DTB3	0.02	0.09	0.00	0.02	0.03	0.04	0.04	0.07	0.03	0.05
DGS10	−0.02	−0.08	0.00	−0.02	0.01	−0.03	−0.01	−0.01	−0.02	−0.01

(VaR) and Expected Shortfall (ES), the risk measure currently proposed by the Basel Committee on Banking Supervision (BCBS, 2014). This holds despite the fact that equally-weighted (EW) and value-weighted (VW) portfolios are rebalanced daily for all crypto-currencies in the data set (Section A.2), while CRIX is rebalanced monthly, with a quarterly selection of index constituents; and even though BTC has a high influence in CRIX (and naturally the VW portfolio) due to its high market value.

So far, we have addressed the potential for diversification of a portfolio consisting exclusively of crypto-currencies. Prior studies, in particular Eisl et al. (2015) and also Briere et al. (2013), have shown that, at least for BTC, including the digital asset in a standard financial portfolio provides a sizable effect on diversification as well. Table 7.7 shows the correlation of the

Table 7.8: PCA of the crypto-currencies BTC, ETH, XRP, LTC, DASH, DOGE, MAID, BTS, XEM, XMR. Due to the late market entry of ETH and XEM, the reported results are based on an analysis starting in August 2015.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
BTC	−0.13	−0.04	0.11	−0.07	0.19	−0.23	0.03	0.05	0.46	0.81
ETH	−0.44	0.70	−0.46	−0.32	0.07	−0.01	−0.04	0.02	−0.02	−0.01
XRP	−0.08	−0.01	0.08	0.02	−0.01	−0.08	0.09	0.97	−0.15	−0.02
LTC	−0.14	−0.05	0.12	−0.10	0.17	−0.32	0.00	0.05	0.70	−0.58
DASH	−0.12	0.02	0.15	−0.09	0.12	−0.33	0.86	−0.17	−0.26	−0.04
MAID	−0.28	0.34	0.16	0.87	−0.10	−0.08	0.00	−0.05	0.05	0.00
DOGE	−0.18	−0.02	0.32	−0.15	0.00	−0.65	−0.49	−0.11	−0.41	−0.01
XEM	−0.74	−0.60	−0.25	0.06	−0.03	0.15	−0.01	−0.04	−0.07	−0.02
XMR	−0.18	0.11	0.49	−0.07	0.69	0.45	−0.09	−0.02	−0.13	−0.05
BTS	−0.25	0.14	0.55	−0.30	−0.65	0.27	0.06	−0.03	0.13	0.03
Standard deviation	0.10	0.10	0.07	0.07	0.06	0.05	0.05	0.04	0.03	0.02
Proportion of Variance	0.26	0.24	0.12	0.11	0.08	0.07	0.05	0.03	0.03	0.01
Cumulative Proportion	0.26	0.50	0.63	0.74	0.82	0.88	0.93	0.97	0.99	1.00

top 10 crypto-currencies by market value and 10 standard financial assets. The correlations between these assets and the crypto-currencies are very close to zero, which is especially surprising for the fiat-currency returns on USD/EUR, USD/JPY, USD/GBP. This result hints that the findings by Eisl et al. (2015) and Briere et al. (2013) for BTC may hold for other crypto-currencies, too.

7.3.5 The Power Law in Crypto-Currency Returns

To investigate the evolution of the return dynamics of crypto-currencies from their emergence in the market as they mature, we study the power-law parameter of their absolute-returns distributions over time. We divide each time series of returns into periods of 90 days, compute the scaling parameter alpha per period for every crypto-currency in our data set, and then average over the cross-section in the corresponding periods, taking into account the size of the crypto-currencies in terms of market value. For the definition of the power law and the specifications of the estimation, see Section A.3.

Fig. 7.9 shows the results, partitioned into three distinct groups by mean market value. Thus the three alphas for period one display the means over all first periods of the crypto-currencies in the three respective groups. Clauset et al. (2009) state that α, referred to as the scaling
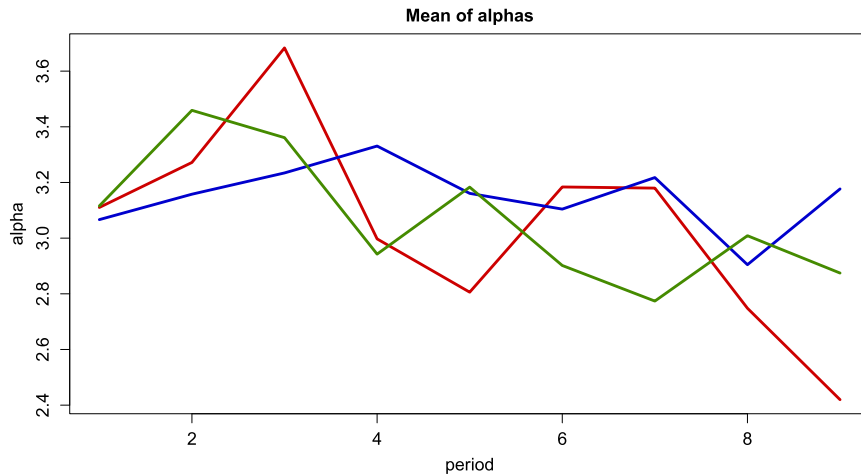
Figure 7.9: *Scaling parameters of the power-law distribution.* **Power-law alphas of all crypto-currencies in the data set, divided into three groups: Group1 has a mean market value $\leq$ 50,000 USD, group2 between 50,000 and 500,000 USD, and group3 $>$ 500,000 USD. Crypto-currencies with daily trading volume $<$ 10 USD were excluded. Each alpha is calculated in time windows of 90 days.**

parameter, typically lies in the range $2 < \alpha < 3$ for stocks. Interestingly, the mean over the alphas for the crypto-currencies in the first periods is higher than 3.

The mean alpha levels of group2 and group3 are less volatile than those of group1 with low-market-value crypto-currencies. Higher alpha implies a narrower distribution, i.e. more prevalence of lower absolute returns. Therefore, the higher alphas for the less successful crypto-currencies in terms of market capitalizations in the first periods indicate that they show lower absolute returns compared to the other two groups. After the first year, the returns increase for group1, while the medium-value crypto-currencies show smaller absolute returns. After 1.5 to 2 years, the three groups converge to alphas as known from standard financial assets. Since the analysis is performed based on event time, common market shocks should not drive the results. Also, as shown before, movements of crypto-currency returns share little common variation.

For results about power-law parameters regarding the wealth distribution of crypto-currencies, see Li and Xiangjun (2017).

7.4 Conclusion

From the perspective of an investor into the alternative asset class of crypto-currencies, we document that returns of crypto-currencies are weakly correlated both in their cross-section

and with established assets, and thus interesting investments for diversifying portfolios. An investment strategy based on the CRypto-currency IndeX (CRIX) bears lower risk than any single of the most liquid crypto-currencies.

Furthermore, we show that crypto-currencies exhibit a size effect like stocks. The market's deepening liquidity is accompanied by increases in market valuations. At the same time, the structure of the market has evolved over the past years. For instance, more crypto-currencies with comparatively smaller market valuations exist today.

We conclude that this still new alternative asset market can provide valuable contributions to portfolio allocation: crypto-currencies display high expected returns with large volatilities and at the same time remarkably low correlations with each other and with standard financial assets, allowing for diversification benefits. Thus, investors in alternative assets should keep a close eye on further developments in the crypto-currency market.

Appendix A Technical Appendix

A.1 Value at Risk and Expected Shortfall

We calculate Expected Shortfall (ES) and Value-at-Risk (VaR) among our risk measures. Following Artzner et al. (1999) and Franke et al. (2015), the VaR is specified as follows:

Definition. Given $\alpha \in (0, 1)$, the *VaR*$_\alpha$ for a random variable X with distribution function $F(\cdot)$ is determined as

$$VaR_\alpha(X) = \inf\{x \,|\, F(x) \le \alpha\}. \quad \square$$

ES is then determined as

$$\mathrm{E}[X \,|\, X > VaR_\alpha] \tag{7.1}$$

A common approach to determine (7.1) was investigated in McNeil and Frey (2000). The authors define $\{\varepsilon_t^{neg}\}_{t \in \mathbb{Z}}$ as a strictly stationary time series which represents the negative log returns of the underlying. It is assumed that the negative log returns follow the process

$$\varepsilon_t^{neg} = \mu_t + \sigma_t Z_t \tag{7.2}$$

with Z_t a strict white-noise process. They propose an ARMA-GARCH approach to obtain the realizations of Z_t.

Here, we employ a GARCH(1,1) model, defined as

$$\sigma_t^2 = \beta_0 + \beta \varepsilon_{t-1}^{2,neg} + \gamma \sigma_{t-1}^2$$

with $\beta_0 > 0$, $\beta, \gamma \ge 0$ and $\varepsilon_t^{neg} | (\varepsilon_{t-1}^{neg}, \sigma_{t-1}^2, \dots) \sim \mathrm{N}(0, \sigma_t^2)$.

A pseudo-ML approach is used to obtain the parameters of the model. Afterwards a threshold u is chosen and a General Pareto Distribution (GPD) is fitted to the data beyond this threshold. McNeil and Frey (2000) state that it is assumed that the tails begin with the threshold u. Hence the choice of u is critical for the analysis.

The GPD has the following distribution function, as given in McNeil and Frey (2000):

$$
G_{\xi,\zeta}(z_t) = \begin{cases} 1 - (1 + \xi \frac{z_t}{\zeta})^{-1/\xi} & \xi \neq 0 \\ 1 - \exp(-\frac{z_t}{\zeta}) & \xi = 0 \end{cases}
$$

where $\zeta > 0$, the support is $z_t \leq 0$ when $\xi \leq 0$ and $0 \geq z_t \geq -\frac{\zeta}{\xi}$ when $\xi < 0$. McNeil and Frey (2000) further show that for a random variable W with an exact GPD distribution with parameter $\xi < 1$ and ζ it can be shown that

$$
E[W|W > w] = \frac{w + \zeta}{1 - \xi},
$$

where $\zeta + w\xi > 0$.

McNeil and Frey (2000) also show that in case the excesses of the threshold have exactly this distribution, it follows that

$$
E\left[Z_t | Z_t > z_{t,\alpha}\right] = z_{t,\alpha} \left(\frac{1}{1 - \xi} + \frac{\zeta - \xi u}{(1 - \xi) z_{t,\alpha}} \right)
$$

with $z_{t,\alpha}$ as the $VaR_{t,\alpha}$, where t indicates dependence on time.

A.2 Portfolios

In order to contrast the results we find for investments into a single crypto-currency, we also perform the same analyses on portfolios of crypto-currencies. We consider three portfolios: first, an investment according to the market index CRIX, as well as two portfolios of investment into all crypto-currencies: one equally-weighted portfolio (EW), and one value-weighted (VW) by market capitalization.

The log returns on the equally-weighted portfolio are defined as the log return on an investment of equal amount into all crypto-currencies i, each yielding ε_{it}:

$$
\epsilon_t^{EW} = \frac{1}{n} \sum_{i=1}^{n} \varepsilon_{it} \tag{7.3}
$$

where n is the number of assets in the portfolio.

The value-weighted portfolio is constructed similarly to the CRIX index (Trimborn and Här-dle, 2016). Denote by MV_{it} the market value of a single crypto-currency at time t; the log return on the value-weighted portfolio VW_t is then defined as the log return to a portfolio with invested amounts proportional to the MV_{it}:

$$\epsilon_t^{VW} = \frac{1}{\sum_{i=1}^n MV_{it}} \sum_{i=1}^n MV_{it}\varepsilon_{it} \tag{7.4}$$

A.3 Power Law

In Section 7.3.5 we investigated the behavior of groups of crypto-currencies (clustered by market capitalization) with a power-law analysis. Following Clauset et al. (2009), the defini-tion of the probability density function of a power law in the discrete case is

$$p(x) = Cx^{-\alpha} \tag{7.5}$$

where x is the observed value, α the power law parameter and C a normalizing constant. Since the distribution would diverge at 0, a lower bound $x_{min} > 0$ has to be chosen. Solving for C, it follows that

$$p(x) = \frac{x^{-\alpha}}{\zeta(\alpha, x_{min})}$$

with

$$\zeta(\alpha, x_{min}) = \sum_{i=0}^{\infty}(i + x_{min})^{-\alpha}$$

the Hurwitz zeta function, see Clauset et al. (2009).

To compute the αs, we use the R-package by Csardi and Nepusz (2006). The x_{min} and α are computed as proposed by Clauset et al. (2009). We have not fixed x_{min}; it was chosen by comparing the p-values of a Kolmogorov–Smirnov test between the fitted distribution and the original sample, see Csardi and Nepusz (2006). The x_{min} was chosen such that the p-value is largest. More details are in the cited articles.

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Note