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Efficiency of cryptocurrency exchanges
Risk exposure analysis of identical assets

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Title

Efficiency of cryptocurrency exchanges – Risk exposure analysis of identical assets

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Abstract

The cryptocurrency market is continuously growing but is still a relatively unexplored field within academic research. The ambition with this thesis is to increase existing research on market efficiency of cryptocurrencies, by studying the risk exposure of identical investments between different cryptocurrency exchanges. The study includes four cryptocurrencies and nine different exchanges, the data is tested on a full sample period and two subsample periods. The results reveal significant Sharpe ratio differences for identical investments on selected exchanges, but also improved efficiency between the first and second subsample periods. The study concludes that there are significant market inefficiencies on the cryptocurrency market, but the results also suggests that the market is becoming more efficient over time.

Keywords

Alternative investment, Bitcoin, Cryptocurrency, Ethereum, Market efficiency, Sharpe ratio

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1. Introduction

The introductory chapter builds a foundation for this thesis and the background content explains the cryptocurrencies and potentially minimize any existing knowledge gaps. In depth technological aspects of cryptocurrencies are not the focus of this thesis and will not be discussed further. Additional reading of technological aspects of individual cryptocurrencies can be found on their websites or whitepapers. The problematization is built from existing theories and cryptocurrency research, to shape the research question and purpose of this thesis. The chapter concludes with a structured disposition of the thesis.

1.1 Background

Bitcoin, a peer-to-peer (P2P) electronic cash system created by the pseudonym Satoshi Nakamoto in 2009. Bitcoin solved problems earlier electronic cash systems had and is the first working decentralized cryptocurrency, that changed the way regular payments work (Nakamoto, 2008). Roughly ten years after the initial release of bitcoin there are more than 2150 cryptocurrencies (CoinMarketCap, 2019) and the majority of them share the underlying blockchain technology (ElBahrawy, Alessandretti, Kandler, Pastor-Satorras, & Baronchelli, 2017). Blockchain technology is based on earlier cryptology research and is used to decentralize the regular payment systems by eliminating the trusted third-party, the financial institution (Nakamoto, 2008).

The blockchain technology compiles data of network transactions in “blocks” that are chained together and publicly announced with timestamps in chronological order, available for everyone to verify. The transactions of a block are verified by nodes on the network and only accepted if all transaction amounts are unspent. Anyone willing to support the network with computer processing power (CPU) can become a “miner” and host a node. This consensus algorithm is called “Proof-of-Work” (PoW) and is used on the Bitcoin network. Proof-of-Work reward miners with payments, in exchange for supporting the network with CPU. The Bitcoin network reward successful verification with bitcoins and transaction costs for each block (Nakamoto, 2008).

There exist other consensus algorithms on the cryptocurrency market and another commonly used consensus algorithm is “Proof-of-Stake” (PoS). Proof-of-Stake substitutes the validators requirement of CPU with an economic stake in the network. The Ethereum network have a scheduled consensus algorithm change from PoW to PoS, called Casper (Ethereum Foundation, 2019).

Majority of cryptocurrencies are clones of Bitcoin, or only a slight modification of specifications with no real innovation, and often referred to as “altcoins”. A few cryptocurrencies have introduced new innovations that provide substantially different services. Dash introduced a secondary service incentivized peer-to-peer network, called “masternodes”. Masternodes are like the nodes on the Bitcoin network, but operators provide additional services for a share of the network rewards (Duffield & Diaz, 2018). Ethereum introduced “smart contracts” which enables non-monetary use cases, in form of new applications built on top of the existing blockchain network (Hileman & Rauchs, 2017). The competitive market cause cryptocurrencies to frequently emerge and disappear, and most of the listed cryptocurrencies are not actively traded (ElBahrawy *et al*., 2017; Hileman & Rauchs, 2017). Cryptocurrencies are mainly bought on exchanges (Böhme, Christin, Edelman, & Moore, 2015) and the first exchange emerged in early 2010 (Hileman & Rauchs, 2017). Exchanges are run by centralized companies, which increase the possible risk of fraud and hacking attempts (Böhme *et al*., 2015). Hileman and Rauchs (2017) imply that the most common use case of cryptocurrencies are speculative investments, but acknowledge other use cases: *medium of exchange*, *payment rail* and *non-monetary*.

The medium of exchange increases as specific cryptocurrency networks grow, resulting in more businesses accepting cryptocurrencies as payment for goods and services. However, the high volatility of bitcoin often forces businesses to exchange cryptocurrencies back into fiat currencies, reducing the exposed risk to price fluctuations (Tasca, Hayes & Liu, 2018; Hileman and Rauchs, 2017). Tasca, Hayes and Liu (2018) study show a decline of black market and online gambling usage and an increasing demand for exchanges, to buy and sell cryptocurrencies. Companies can use cryptocurrency networks as a payment rail to make fast and cost-effective international payments. Majority of the payment rail usage is on the Bitcoin network, but other networks such as Ethereum and Ripple are also used. The Ethereum network have majority of the non-monetary usage, in form of decentralized applications (dApps) built on the network for different use cases (Hileman and Rauchs, 2017).

Corbet, Meegan, Larkin, Lucey and Yarovaya (2018) conclude that cryptocurrencies can be considered as a new investment asset class. The characteristics of bitcoin are substantially different compared to other asset classes, in terms of *basis of value*, *governance* and *use cases*. They also differ in *price independence* and *risk-reward characteristics* (Burniske & White, 2017). Bitcoin is a decentralized open network and the network is governed by the community, resulting in no underlying authority or accountability. The basis of value is then solely dependent on the potential value. Miners, who allocate computer processing power and run the open-source code on the network, have bigger influence on decisions. Potential changes to the network can result in new use cases for bitcoin, making it unique compared to other asset classes (Burniske & White, 2017). The characteristics of Bitcoin result in a different correlation in relation to other assets. Burniske and White (2017) conclude that bitcoin is the only asset that consistently maintain a low correlation with every other asset[1]. Bitcoin had the highest Sharpe ratio compared to the other asset classes during the six year period 2011-2017, thus resulting in the better risk compensation for investors (Burniske & White, 2017).

1.2 Problematization

Efficient market theories have been a central focus in economic research, the efficient market hypothesis created by Fama (1970) is commonly referenced for discussion regarding market efficiency. An efficient market always assumes prices fully reflect all available information and identical assets are not experiencing any price differences (Krugman, Obstfeld, & Melitz, 2015; Fama, 1970). The efficient market hypothesis states that investors cannot make excess short-term returns if the market is efficient (Fama, 1970). Malkiel (1973) support the efficient market hypothesis and argues that determine future price behavior with historical price data is no more predictable than a series of coin flips, no one can consistently "beat the market".

Shiller (1981) argues against the efficient market hypothesis and concludes that the market is inefficient over longer periods. Psychological aspects could cause anomaly events, suggesting that people overreact to news and create market inefficiencies (Shiller, 2015; Bondt & Thaler, 1985). Psychological aspects with focus on market inefficiency are within the field of prospect theory, also known as behavioral finance. Psychological variables include overestimated risk management abilities and irrational economic decisions (Kahneman & Tversky, 1979; Shiller, 1981, 2015). Markowitz (1952) suggested that investors should select a portfolio based on expected return and the risk involved, which Sharpe (1964) extended to the capital asset pricing model. The theoretical development later led to another performance model called Sharpe ratio, a measure of reward per unit of risk taken (Sharpe, 1966, 1994). Arbitrage opportunities occur when there is a price difference between identical assets on competitive markets and the requirements for an efficient market is not attained, thus an inefficient market. Investors can

[1] Assets referred to are S&P 500, US bonds, gold, US real estate, oil and emerging market currencies.

exploit arbitrage opportunities by performing simultaneous trades on exchanges, resulting in a positive net present value investment and risk-free profits (Berk & DeMarzo, 2017).

Cryptocurrencies are a relatively new field and there are a lot of future research to be done. Majority of the market efficiency research on cryptocurrencies involve the weak form test[2] from efficient market hypothesis, and the studies are also heavily weighted towards bitcoin. Research on other large and established cryptocurrencies are starting to attract researchers, as the cryptocurrency market grows. Urquhart (2016) is the first to study the weak form efficiency of bitcoin and through several tests, explore if the historical return data is randomly distributed, independent and not autocorrelated. Wei (2018) extends the weak form efficiency research of Urquhart (2016), by including over 400 altcoins and an additional test examining the liquidity. Both studies conclude that the cryptocurrency market is not weak form efficient (Urquhart, 2016; Wei, 2018). Kurihara and Fukushima (2017) explores daily price anomalies with focus on regression analysis and perform autocorrelation tests to determine price randomness. They conclude that bitcoin prices are not moving randomly, resulting in market inefficiency (Kurihara & Fukushima, 2017). Bariviera, Basgall, Hasperué and Naiouf (2017) investigates the bitcoin returns over different short time scales (e.g. 5h return, 10h return) to explore daily and intra-daily long-range dependence. The study concludes that the volatility of bitcoin reduces over time and the long-range memory is similar over the studied time scales and not related to the market liquidity (Bariviera *et al*., 2017). Caporale, Gil-Alana and Plastun (2018) examines two different long-memory methods for four major cryptocurrencies to explore the market efficiency. They find that there is a positive correlation between past and future returns, thus the cryptocurrency market is inefficient and suggests potential for abnormal profits (Caporale *et al*., 2018). All previous cryptocurrency market research on the weak form efficiency concludes that the current cryptocurrency market is not weak form efficient. However, they all argue that the results indicate a potential change in the future as the market matures (Urquhart, 2016; Wei, 2018; Kurihara & Fukushima, 2017; Bariviera *et al*., 2017; Caporale *et al*., 2018).

There are no published peer-reviewed articles regarding the focus of this study, exploring market efficiency for cryptocurrencies on different exchanges with Sharpe ratio. Previous studies explore the weak form market efficiency of cryptocurrency returns in fiat currencies, with a focus on long-time memory return, autocorrelation and random walks. This study will focus on risk

[2] The weak form tests involve analysis of historical price data to study how random the returns are, the random walk theory is applied to determine the efficiency of the market (Fama, 1970).

exposure comparisons for identical investments on different exchanges to explore if there is market inefficiency between them and potential for arbitrage opportunities. The Sharpe ratio calculations are used to investigate if there is a risk difference between the same cryptocurrency on different exchanges for investors and includes four established cryptocurrency pairs (BTC/ETH, BTC/LTC, BTC/DASH and BTC/XRP). Bitcoin is used as the base currency instead of a fiat currency to isolate the cryptocurrency market, as majority of cryptocurrency exchanges do not support fiat currency pairs. Focusing only on bitcoin as the base currency also allows for a one variable study, to potentially produce better results. A fiat currency base would require currency conversion between several cryptocurrencies and stable coins, the risk for mispricing errors would increase.

To calculate Sharpe ratios and study the market efficiency, historical price data of the studied cryptocurrency pairs is collected from selected exchanges. The study include price data from January 2018 through June 2019 and a total of nine different exchanges are used. The most covered trading pair (BTC/ETH) is collected from seven exchanges, while the lowest covered trading pair (BTC/DASH) is collected from three exchanges. Investments with the same asset weight should have identical efficient frontiers, i.e. identical expected return and risk (Markowitz, 1952). If there is a significant difference between the Sharpe ratios, there are different efficient frontiers and thus market inefficiency.

1.3 Research question

How does risk exposure of identical investments on cryptocurrency exchanges perform against each other?

1.4 Research purpose

The purpose of this study is to expand current cryptocurrency research regarding market efficiency and explore Sharpe ratios for four trading pairs on different exchanges to determine potential arbitrage opportunities.

1.5 Disposition

The first chapter introduces cryptocurrencies and builds a problematization of current cryptocurrency research based on market inefficiency, to form a research question. The second chapter elaborates on the selected cryptocurrencies and presents the included exchanges. The chapter also includes a section of use cases and concludes with a comparison table of the selected cryptocurrencies. The third chapter develops a theoretical framework that is the foundation of the research. The fourth chapter specify the selected research approaches, rooted in research philosophy. The chapter also includes the strategic choices made to develop the thesis. The fifth chapter analyzes the empirical material and presents both the descriptive statistics and test results of studied cryptocurrencies. The final chapter summarizes the findings and critically review the thesis, suggestions for future research are also presented.

2. Cryptocurrencies

This chapter presents an overview of previous research on cryptocurrencies, with a focus on market efficiency and risk exposure. A general cryptocurrency market analysis is captured and compared to the regular stock market. The individual introduction of the five selected cryptocurrencies are highlighted with important aspects and a concluding section dedicated to the use cases of selected cryptocurrencies.

2.1 Previous research

The initial research of the cryptocurrency market started with studies on ethical and legal aspects of bitcoin. It is not until recently that studies consider the economic aspects of cryptocurrencies. The market efficiency research of cryptocurrencies started with Urquhart (2016) study, focusing on bitcoin. The study analyzed aggregated bitcoin data from all available exchanges with volume weighted average bitcoin price, between the sample period 2010 until 2016. Urquhart (2016) used several statistical tests to determine the efficiency of bitcoin and concluded that bitcoin is not weak form efficient. Wei (2018) extended the cryptocurrency weak form efficiency research with a total of 456 cryptocurrencies. Wei (2018) performed the same statistical tests as Urquhart (2016) but included one additional test to explore the connection between liquidity and volatility. Wei (2018) concluded that the cryptocurrencies with higher liquidity experience less volatility and are more efficient compared to illiquid cryptocurrencies. The current cryptocurrency market is not weak form efficient, but the efficiency of cryptocurrencies is improving (Urquhart, 2016; Wei, 2018). Brauneis and Mestel (2018) concludes that bitcoin is the most efficient cryptocurrency, supporting the assumptions of both Urquhart (2016) and Wei (2018). Brauneis and Mestel (2018) study also suggests that the liquidity and size of cryptocurrencies is connected to efficiency. Kurihara and Fukushima (2017) examined price anomalies of bitcoin with similar aggregated data from previous studies and found daily price anomalies. The evidence of efficiency improved during the second half of the data sample, suggesting that the cryptocurrency market efficiency is improving (Kurihara & Fukushima, 2017). Bariviera *et al*. (2017) studied long-range memory and other statistical properties of bitcoin with a focus on daily and intraday prices. They used the sample period from 2011 until 2017 and concluded that long-range memory is not related to liquidity. The empirical result also suggested that the volatility of bitcoin is reducing over time (Bariviera *et al*., 2017). Caporale *et al*. (2018) extended the long-range memory study with two different methods and included three additional cryptocurrencies besides bitcoin. The study concluded that there is a positive correlation between past and future values, a persistence that is evidence of market inefficiency and suggests potential for abnormal profits.

There is not much research on cryptocurrency Sharpe ratios and portfolio selection. Majority of risk exposure studies are focused on portfolio diversification and use cryptocurrencies as an alternative asset class. Bitcoin Sharpe ratio outperform other US based asset classes over the period 2011-2017, even as the highest volatility asset class it is worth including in the portfolio. Bitcoin have low correlation to other mainstream asset classes and thus reduces risk exposure (Burniske & White, 2017). Lee, Guo and Wang (2018) also concludes that cryptocurrencies are an option to diversify portfolio risk, because of the low correlation. Including the CRIX index[3] in a portfolio significantly expand the efficient frontier and provide better opportunities for investors. However, they argue that cryptocurrencies are still at an experimental phase and there are still unexplored complex factors that could impact risk exposure (Lee *et al*., 2018). Borri (2019) support previous cryptocurrency correlation research but argues that due to liquidity only a small share of cryptocurrencies in a portfolio is optimal. Brauneis and Mestel (2019) suggests that several cryptocurrencies significantly reduce risk exposure compared to only include one cryptocurrency. Supporting the findings of Lee *et al*. (2018), by including the CRIX index in a portfolio.

Previous studies have not explored potential market inefficiencies with Sharpe ratios. The market efficiency research on cryptocurrencies all suggests that there still are market inefficiencies but presents evidence of efficiency improvements as the market matures.

2.2 Market overview

The cryptocurrency market is different from the regular stock exchange with central authority and heavily regulated networks of brokerage firms supporting the stock exchange traffic. The cryptocurrency market is instead built around privately owned exchanges without any regulation

[3] The CRIX index is a cryptocurrency index with several cryptocurrencies and is constantly updated, it can be found on https://thecrix.de/.

requirements and majority of the cryptocurrency exchanges are unregulated. However, fiat deposits are almost only exclusively available for regulated exchanges, creating entry barriers for customers on unregulated exchanges. The unregulated exchanges only support cryptocurrency to cryptocurrency trading and often substitute fiat trading with stable coins, e.g. Tether (USDT). Tether is a cryptocurrency pegged to the US dollar 1-to-1 (Tether, 2019) and can often be used on every exchange, with or without regulation. The regulation certificates of exchanges can vary, but the result of regulation often limits the variety of cryptocurrencies on the exchange (Coinpaprika, 2019), see Table 1. Limited variety of cryptocurrencies exposes a higher risk for customers that are interested in less popular cryptocurrencies, since unregulated exchanges are not liable to ensure customer safety. Unregulated exchanges can still voluntarily protect customers, as Binance did after the recent security breach of 7000 BTC (Zhao, 2019). Table 1 displays the nine selected exchanges used in the study with a variation in both exchange size and location.

Table 1
Exchange comparison

Exchange	Founded	Headquarters	Regulated	Fiat	Cryptocurrencies	Data in study
Binance	2017	Malta	No	No	155	ETH, LTC, DASH, XRP
Bitfinex	2012	Hong Kong	No	No	107	LTC, XRP
Bitstamp	2011	London	Yes	Yes	5	LTC
Bittrex	2014	Seattle	Yes	Yes	227	ETH, LTC, XRP
Cex.io	2013	London	Yes	Yes	12	ETH
Gemini	2014	New York	Yes	Yes	5	ETH
Kraken	2011	San Francisco	Yes	Yes	20	ETH, LTC
OKEx	2014	Malta	No	No	148	ETH, LTC, DASH
Poloniex	2014	Boston	Yes	No	57	ETH, LTC, DASH, XRP

Note. Exchanges actively list and delist cryptocurrency pairs, the data are only current estimations (Coinpaprika, 2019).

Another important difference between the regular stock market and the cryptocurrency market is the business hours. Regular stock exchanges often have restrictive opening hours, with roughly eight hours trading on weekdays and closed on weekends, including holidays (Avanza, 2019). The cryptocurrency market never sleeps, it is open for trading whenever and wherever you want. It is how the technology of a decentralized system is designed to work, to be accessible for anyone. A decentralized network requires to always be operational (Nakamoto, 2008).

Cryptocurrency investors are liable to their respective government agencies for taxation of profits. There are various interpretations from different governments of what asset class cryptocurrencies should be included in. The Swedish Supreme Administrative Court concludes that cryptocurrencies are not like regular stocks nor foreign currencies, thus be capital gains taxed for 30% (Skatteverket, 2018). The German government enforce taxation for all cryptocurrencies actively traded on a progressive taxation between 25% up to 45%. However, speculative investing in cryptocurrencies without trading the asset over a one-year period is tax-free (Cryptotax, 2019).

2.3 Bitcoin

The launch of the Bitcoin (BTC) network in early 2009, created by the pseudonym Satoshi Nakamoto, solved the *double-spending* problem earlier electronic transactions system had. The double-spending problem was a crucial aspect for Bitcoin to succeed, by eliminating faulty and damaging transactions that try to use the same bitcoins for several transactions. The anonymous creator(s) proposed the first decentralized solution, a peer-to-peer network using proof-of-work (PoW) to record a public ledger of all transactions on the network. Allowing anyone to connect, as a node, to the network and assist the network with computer processing power (CPU). There is no central authority, making Bitcoin a decentralized network that requires no trusted third-party to process transactions, reducing both transaction costs and possible fraud attempts. Transactions on the network are global, pseudonymous, non-reversible and not limited to a certain amount, making micro-transactions an option (Nakamoto, 2008). The smallest unit of a bitcoin is called "satoshi" and is one hundred millionth of a single bitcoin (Bitcoinwiki, 2018a). The network is scarce and only 21 million bitcoins are going to be produced, a predetermined variable set by Satoshi Nakamoto, creating a natural price stability (Böhme *et al*., 2015). There are currently over 17.6 million bitcoins in circulation (Blockchain, 2019), and the Bitcoin network will automatically create the remaining bitcoins as rewards for miners supporting the network with computer processing power. This is done with mathematical puzzles and the miner who solves it first, called a "block", will be the recipient of the reward (Böhme *et al*., 2015). The block also includes an amount of network transactions and the transaction fees are also rewarded to the first validator. Once a block is correctly validated, in line with consensus rules, it is chained together with the other blocks, creating the blockchain. The difficulty automatically adjusts to find a solution roughly every 10 minutes. The reward started at 50 bitcoins per block in 2009 and is halved approximately every four years, as of July 2016 the block reward is reduced to 12.5 bitcoins, and will eventually stop (Antonopoulos, 2017). This reward design created incentive for miners to offer computer processing power to the network and bootstrap the platform in the infant stage. It is not as profitable today and require expensive specialized hardware (ASIC) and low-cost electricity, to be effective (Böhme *et al*., 2019; Antonopoulos, 2017). The currently estimated date for the last bitcoin to be mined is in early 2140, but this can change due to increased mining power and technological progression (Bitcoinwiki, 2018). Figure 1 displays the price development of Bitcoin from 17th July 2010 until 30th June 2019.

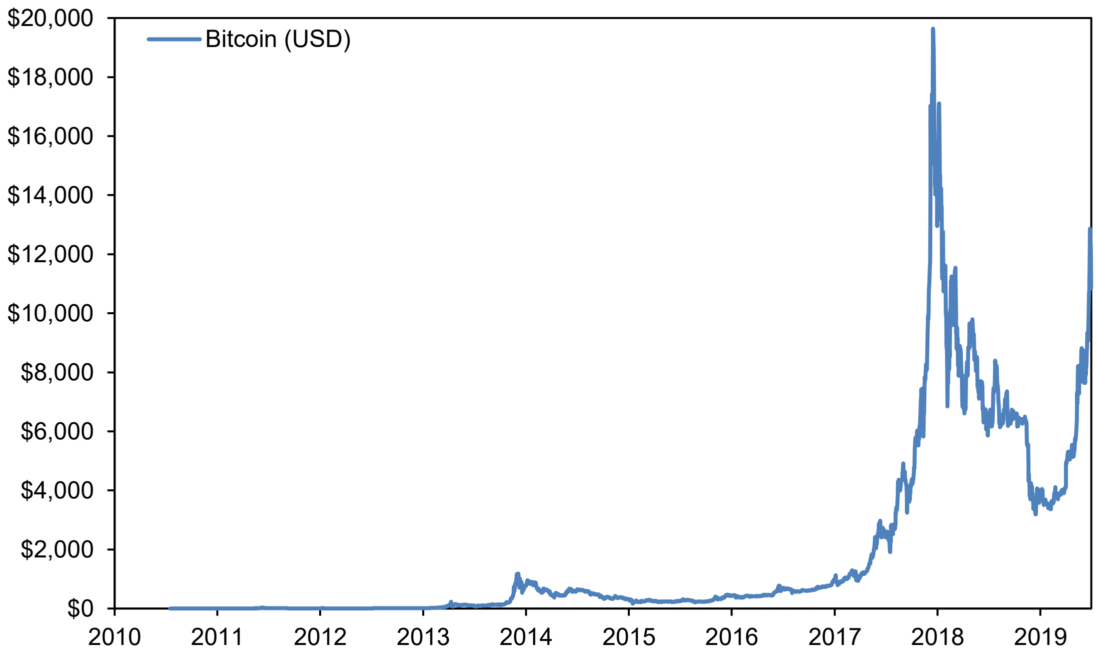

Figure 1. Market price average of Bitcoin (Coin Metrics, 2019)

2.4 Ethereum

Vitalik Buterin wrote the initial draft of the Ethereum (ETH) whitepaper in late 2013 and with the assistance of three members, founded Ethereum in 2014. The Ethereum foundation initiated both a pre-sale and an initial coin offering (ICO) of Ether (currency of Ethereum) during 2014 to bootstrap the project (Buterin, 2014). There is currently over 105.5 million Ether in circulation, of which 72 million was distributed during the crowdsale and pre-sale (Etherscan, 2019a). The characteristics of Ethereum are like Bitcoin, but the intention behind Ethereum was to create a blockchain with another layer of functionality. A blockchain that allows anyone to build their own smart contracts or decentralized applications (dApps). The alternative framework proposed by Ethereum creates a network of projects, increasing the security of individual ones, and at the same time, lowering production costs, development time and bootstrapping efforts (Ethereum Foundation, 2019a). Projects built on the Ethereum platform issue their own cryptocurrencies and share an underlying token contract. The result of this is that all issued tokens on Ethereum can be stored in the same wallet, creating a more user-friendly approach for beginners (Antonopoulos & Wood, 2018). Figure 2 displays the price development of Ether in both USD and BTC, from 7th August 2015 until 30th June 2019.

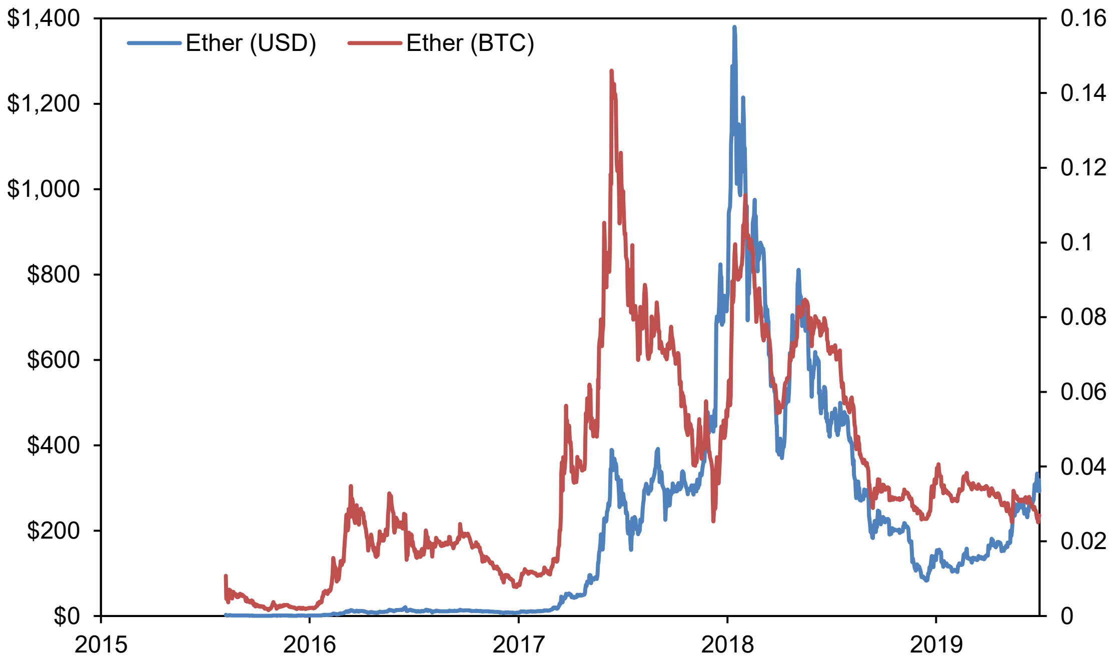

Figure 2. Market price average of Ether (Coin Metrics, 2019)

Ethereum currently use the same consensus algorithm as Bitcoin, Proof-of-Work (PoW), an algorithm that reward miners that solve cryptographic puzzles to validate and create blocks (Ethereum Foundation, 2019). However, the Ethereum network will migrate to a Proof-of-Stake (PoS) protocol, called Casper. The implementation occur over different phases and the first phase is planned for late 2019. Both the PoW and PoS chains will be active during the first phase and the PoW chain will continue handle all user transactions and smart contracts (EthHub, 2019). The Proof of Stake consensus algorithm operates by allowing validators to propose and vote on blocks. The requirement to become a validator is to own the underlying asset (Ether) and the participating validators are randomly assigned rewards for their services. The consensus algorithm change is motivated by certain benefits compared to PoW. PoS reduce electricity consumption and hardware purchases, it also increases resistance against network attacks, by using economic penalties to discourage creation of centralized groups (Ethereum Foundation, 2019).

2.5 Litecoin

Charles Lee created Litecoin (LTC) in October 2011, with support of Bitcoin community members. The cryptocurrency is almost identical to Bitcoin, with a few different features (Litecoin, 2018). Litecoin uses a different type of PoW algorithm called Scrypt, the algorithm is used to reduce the efficiency and economic incentive to develop specialized hardware (ASIC), thus eliminating potential entry barriers and implies an increased decentralized mining pool. However, Scrypt can increase the incentive for harmful network attacks. Litecoin generates a new block every 2.5 minutes on average, which is four times faster than Bitcoin. Faster generated blocks results in quicker transactions and potentially be an option for customer transactions. The total Litecoin supply is 84 million and the initial block reward for miners was 50 Litecoins and reduced by 50% every 840,000 blocks (Comparison between Litecoin and Bitcoin, 2018). Figure 3 shows the price development of Litecoin from 30th March 2013 until 30th June 2019.

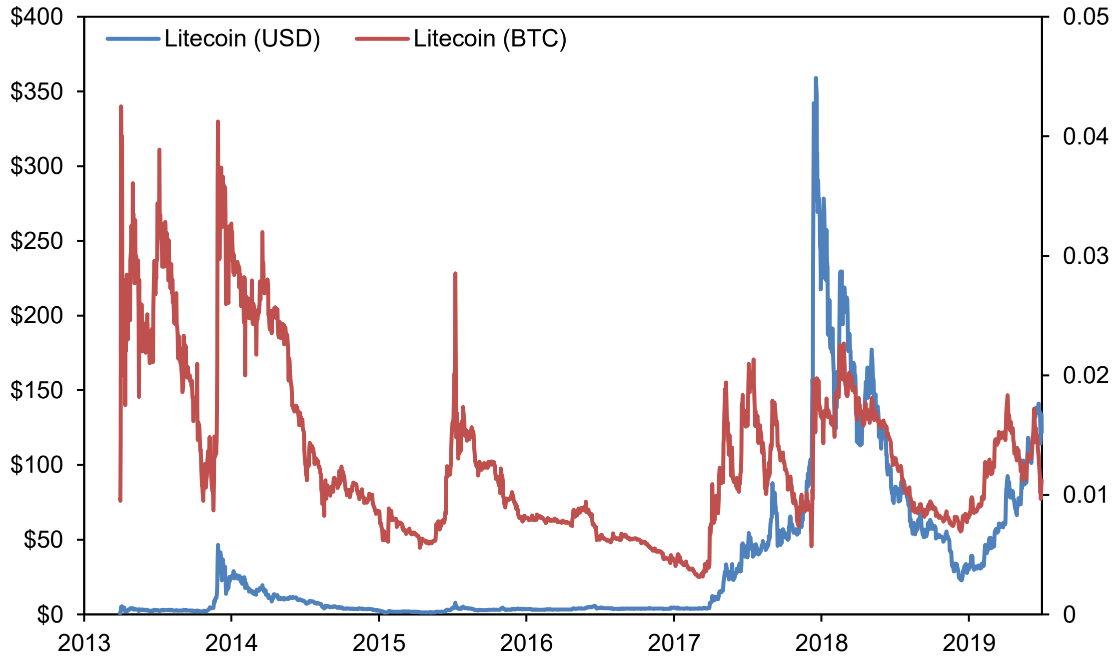

Figure 3. Market price average of Litecoin (Coin Metrics, 2019)

2.6 Dash

Dash was founded by Evan Duffield and the network launched in early 2014 (Dash Core Group, 2018) under the name Darkcoin and was the first privacy focused cryptocurrency, based on the Bitcoin network (Duffield & Hagan, 2014). Dash introduced a secondary network for masternodes to provide services and receive payments in return. A masternode require 1000 DASH in collateral to be operational and 45% of the block rewards are dedicated to the masternode reward program (Duffield & Diaz, 2018). Remaining reward allocation is 45% to miners and 10% to a decentralized governance pool reserved to budget approved projects (Dash Core Group, 2018). Figure 4 shows the price development of Dash from 7th February 2014 until 30th June 2019.

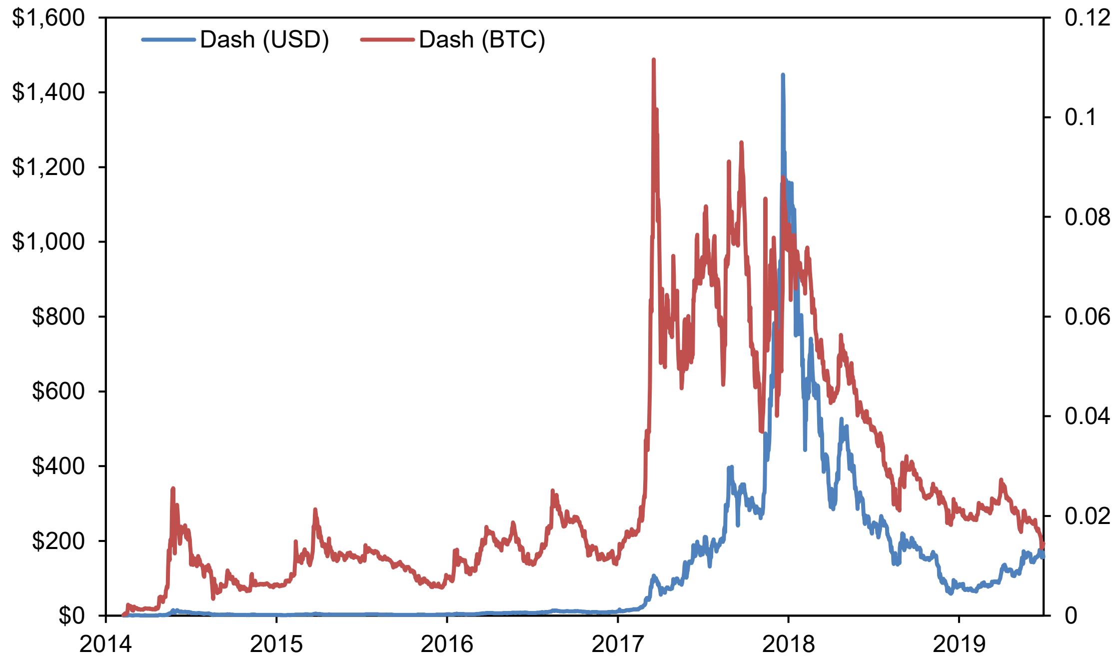

Figure 4. Market price average of Dash (Coin Metrics, 2019)

Masternodes currently enables three services: *InstantSend*, *PrivateSend* and *Governance*. InstantSend reduces the average transaction time, by locking the inputs of a transaction and the masternodes broadcast this on the network. Transactions trying to use the same inputs are rejected after the first transaction are locked, thus preventing double spending attempts. This network function results in real world use cases, allowing vendors to accept Dash payments in exchange for their services (Duffield, Schinzel & Gutierrez, 2014; Duffield & Diaz, 2018; Dash Core Group, 2018).

PrivateSend increases the anonymity of users on the network, by implementing a decentralized mixing service. A certain set of denominations (e.g. 0.001, 0.01, 0.1, 1 DASH) are selected and once three users have submitted the same denominations, their funds are mixed. The system is randomizing certain inputs into the selected denominations and then automatically request the wallets to send an amount of transactions that match the balance and denominations to itself. This procedure can be repeated to increase the anonymity of each user. PrivateSend results in increased privacy and untraceable transactions (Duffield & Diaz, 2018; Dash Core Group, 2018).

Masternodes are the foundation of the decentralized governance on the Dash network. The purpose of the governance system is to maintain a steady network growth, by financing both new and established projects. Masternodes receive one vote each (yes, no, abstain) for every proposal and if a proposal exceed 10% (yes votes) of the current total masternode count, it is added to the budget and receive payment directly from the blockchain. The allocated budget for the governance system is 10% from every block reward and awarded to selected proposals roughly every 30 days (Dash Core Group, 2018a).

2.7 Ripple

Jed McCaleb and Chris Larsen co-founded the cryptocurrency Ripple (XRP) in 2012, under the company Ripple. Figure 5 displays the price development of Ripple from 14th August 2014 until 30th June 2019.

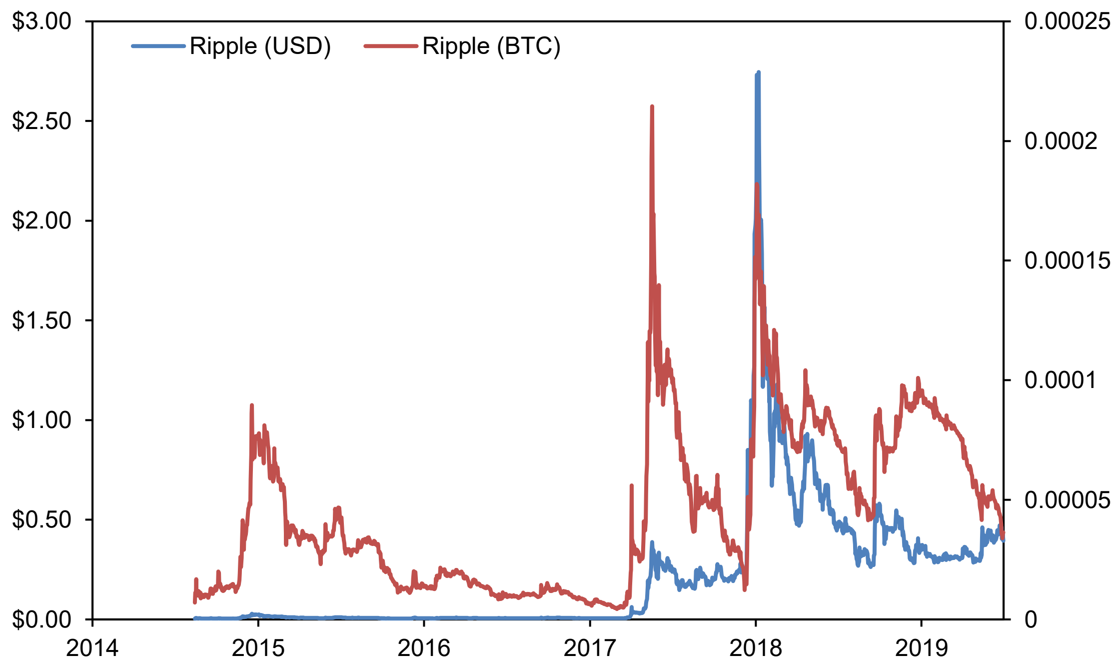

Figure 5. Market price average of Ripple (Coin Metrics, 2019)

The XRP token launch occurred early 2013 and have a max token supply of 100 billion. The XRP allocation at launch was 80% of tokens to the Ripple company and 20% to three founders, resulting in a centralized organizational structure (Bitmex research, 2018; CoinMarketCap, 2019a). However, the XRP Ledger Consensus Protocol (XRP LCP) work as a decentralized open network and compared to other consensus algorithms, offer fast and cheap transactions (Chase & MacBrough, 2018). RippleNet is a proposed solution to create a global network of banks, to create real-time settlements and minimize transaction costs (Ripple, 2017). The solution is based on an interledger protocol (IPL) called xCurrent, that enables interoperations between different ledgers and networks. The IPL verify trade conditions between parties and once verified executes the payments simultaneously. The system is operational without the XRP token (Ripple, 2017a).

2.8 Use cases

Bitcoin increased anonymity for individuals and were used early on as the only payment method for purchases on the black market 'Silk Road'. The marketplace operated during February 2011 to July 2013 before the U.S. government shut it down and during this period estimated to have managed transactions of 9.9 million bitcoins. Bitcoin have also been actively used for gambling sites, as an alternative method for both anonymity and successful transaction processing. An increased consumer exposure of cryptocurrencies can be observed with the increased availability of exchanges and adoption of cryptocurrency supported payment services (Böhme *et al*., 2015). Burniske and White (2017) reported that during 2016, 54% of Coinbase[4] users consider bitcoin strictly as a speculative investment and 46% of the users actively use bitcoin as a transactional medium. All five cryptocurrencies can be used as speculative investments or as alternative payment methods. Dash allow users to use their Dash as collateral and create masternodes to help secure the network, and in return receive payments (Duffield & Diaz, 2018). The Ethereum network allow developers to create decentralized applications and the possibility to launch new cryptocurrencies. The Ethereum network is the biggest blockchain system for non-monetary use, the non-monetary use of Bitcoin has recently increased with the feature for metadata embedding in transactions (Hileman & Rauchs, 2017). Average daily on-chain[5] transactions and other features of the five cryptocurrencies are displayed in Table 2.

[4] Coinbase is one of the biggest regulated exchanges in the world, storing over one billion dollars of bitcoin as of early 2017 (Burniske & White, 2017).

[5] On-chain transactions are published and displayed on the blockchain. Off-chain transactions are internal transactions that occur on centralized cryptocurrency exchanges that have their own records of purchases and sales.

Table 2
Cryptocurrency comparison

Category	Bitcoin	Ethereum	Litecoin	Dash	Ripple
Abbreviation	BTC	ETH	LTC	DASH	XRP
Launch	2009-01-09	2015-07-30	2011-10-08	2014-01-19	2012
Circulating supply	17,850,000 BTC	107,100,000 ETH	63,000,000 LTC	8,950,000 DASH	42,870,000,000 XRP
Maximum supply	21,000,000 BTC	Unlimited	84,000,000 LTC	18,900,000 DASH	100,000,000,000 XRP
Supply growth per block	12.5 BTC	2 ETH	25 LTC	3.11 DASH	-
Block time	10m	13s	2m 20s	2m 30s	-
Block count	588,000 blocks	8,258,000 blocks	1,677,000 blocks	1,113,000 blocks	-
Block reward reduction	210,000 blocks	None	840,000 blocks	210,000 blocks	-
Blockchain size	232 GB	290 GB	25.4 GB	14 GB	-
Daily transactions	330,000	700,000	30,000	15,000	1,000,000
Timestamping	Proof-of-Work	Proof-of-Work	Proof-of-Work	Proof-of-Work	-
Hash function	SHA-256	SHA-3	Scrypt	X11	-

Note. Majority of the parameters are dynamic data and the table displays an overview of current estimations (Blockchain, 2019a; Etherscan, 2019; BitInfoCharts, 2019).

3. Theoretical framework

This chapter introduces theories regarding efficient markets and evidence against efficient markets. The theories are the foundation of the thesis and are important for the empirical analysis. A discussion regarding portfolio selection and Sharpe ratio concludes the chapter.

3.1 Efficient markets

Fama (1965) argues that earlier chart theories do not produce valuable information about future price development, because the theories all assume that historical price information is important to notice "patterns" for future price behavior. Fama (1965) suggests that historical price data cannot be used to predict future movements or increase returns compared to a buy-and-hold strategy and that future price behavior follows the random walk theory. The random walk theory states that historical price data do not reflect future price behavior, price changes are independent and have no memory. Malkiel (1973) illustrates the random walk theory by flipping a coin, 50% chance that the daily market closed higher or lower than the previous day. The simulated charts from the illustration formed different patterns, regularly used in technical analysis. Malkiel (1973) concludes that price patterns used to determine future price behavior are no more predictable than a series of coin flips. Fama (1965) differentiates intrinsic value and actual value of a security. The intrinsic value depends on company prospects, e.g. economic and political. The intrinsic value is never known exactly and thus disagreements can occur between investors regarding the price development. It is unreasonable to assume that price independence is perfect, and the random walk theory cannot be completely accurate to reality (Fama, 1965).

Fama (1970) argues that efficient markets are studied in three test forms: *weak form test*, *semi-strong form test* and *strong form test*. The weak form test focus mainly on the random walk theory and is interested in the historical price data from an asset. Semi-strong form test focus on the correlation between publicly announced information and the speed of price adjustment. The strong form test explores if certain individuals or groups have monopolistic access to information that affect the asset price. Malkiel (1973) argues that with the technological advances in society every investor instantly has access to all publicly and legally available information that impact the prices, resulting in that no investor can consistently "beat the market". In practice a perfectly reflected price of an asset with all available information is unrealistic. Transaction costs, available information and implication of information on the price can separately be enough for market efficiency. However, the conditions can also be the potential source for market inefficiency (Fama, 1970). The empirical evidence shows that stock prices are too unpredictable in the short-term, proving the efficiency of the stock market and eliminating any arbitrage opportunities (Fama, 1970; Malkiel 1973).

Lo and MacKinlay (1988) presents evidence against the random walk theory and concludes that the random walk hypothesis cannot explain the short-term stock market prices. However, Lo and MacKinlay (1988) acknowledge that the rejection of the random walk hypothesis does not imply market inefficiency but could impose restrictions on existing economic pricing models. Lo, Mamaysky and Wang (2000) argues that technical analysis can increase investment value by identifying nonlinear patterns of historical price data, though it might not gain excessive profits, it is still conflicting with the random walk hypothesis and could imply possible market inefficiency. Malkiel (2003) acknowledge that market irregularities and potential profits through technical analysis exist due to mistakes or irrational decisions, which create incentive for investors. However, Malkiel (2003) defends the efficient market hypothesis and argues that observed pricing errors are not persistent enough to obtain abnormal returns and “bubble” anomalies are exceptions rather than rebuttals.

The law of one price states that identical assets in a competitive market should have the same price regardless of location (Krugman *et al.*, 2015). If a price difference would occur, there would be an opportunity to exploit this and directly profit through the trade without any risk or investment. Simultaneously buying and selling the same asset for potential profit is called arbitrage trading. However, since there is no risk or investment involved in the exchange and the net present value is positive, resulting in investors taking advantage over the situation and quickly equalizing the price, thus eliminating arbitrage opportunities (Berk & DeMarzo, 2017). One of the two cornerstones in this study is to explore potential market inefficiencies between cryptocurrency exchanges, with the use of historical price data. Market inefficiencies on cryptocurrencies is already well researched with the weak form test developed by Fama (1970) with several different long-term memory statistical tests. With focus on theories of market efficiency the first hypothesis of this study will focus on the cryptocurrency market efficiency.

H1: The cryptocurrency market is not efficient.

3.2 Behavioral finance

Behavioral finance is a collaboration between finance and other social sciences, a field that has improved the knowledge of the financial sector (Shiller, 2003). Efficient markets theories assume investors always are rational and tries to maximize profits. According to Shiller (1981) large price volatility cannot realistically be described by new objective information, nor due to rational mistakes because of the frequent reoccurrences. Shiller (1981) raises concern regarding the efficient market model proposed by Fama (1970) since it does not describe the observed movements in data. Shiller (1981) concludes that the market is inefficient over a longer period and could be caused by psychological variables, thus making it possible to "beat the market", which contradicts earlier findings of both Fama (1970) and Malkiel (1973). Shiller (2015) argues that psychological decisions cause anomaly events such as the "dot-com bubble", similar to the recent cryptocurrency event during 2017-2019, with parabolic market movements (Blockchain, 2019b). Shiller defined this behavior as irrational exuberance (Shiller, 2015). The psychological aspect of market inefficiency is consistent with prospect theory developed by Kahneman and Tversky (1979). They conclude that individuals overestimate their own risk management abilities, resulting in irrational economic decisions (Kahneman & Tversky, 1979). Psychology aspects also suggests that people overreact to unexpected and dramatic news events, resulting in a violation of Bayes' rule[6] (Bondt & Thaler, 1985).

Fama (1998) criticize behavioral finance and argues that market efficiency should not be discarded as a result. He argues that investors overreaction is canceled out by underreaction, and that market anomalies disappear as methodology improves and time passes. Shiller (2003) defends behavioral finance and argues that there is no psychological principle stating that people always overreact or underreact. Shiller (2003) also argues that new research in all fields often improve initial discovery claims. Economic analysis theories explaining optimal behavior are essential and should not be ignored, instead additional data from descriptive theories should be considered. Market efficiency theories should not be expected to give extremely inaccurate results to not be able to continuously produce profits. However, incorrect interpretations of major market events "bubbles" can occur. The behavioral approach offers opportunities to improve already established theories (Thaler, 2016; Shiller, 2003).

3.3 Modern portfolio theory

Markowitz (1952) propose portfolio selection by observing the connection between expected return and the risk involved, i.e. return variance. An investor can increase expected returns by taking on more variance or decrease expected returns for less variance, thus selecting a portfolio

[6] The probability of an event is not accurately measured by prior related knowledge.

with certain combinations of weighted securities. A set of securities can produce a certain amount of attainable combinations of expected returns and variances, of which a few are efficient combinations. The efficient combinations are portfolios with maximized expected return for the risk taken and the efficient portfolios are plotted graphically as the critical line, also known as the efficient frontier. A single undiversified portfolio can sometimes yield higher expected return and lower variance. However, majority of efficient portfolios are diversified. The diversification should be for the "right reason" and not depend solely on amount of securities. A diversified portfolio includes several different sectors and securities included in the portfolio have low covariances (Markowitz, 1952).

3.4 Sharpe ratio

The theoretical development and empirical results of Markowitz (1952), Sharpe (1964) and Fama (1965) created empirical material relevant for evaluation of fund performance. Sharpe (1966) extended the fund performance research of Treynor's index and suggested another performance model, *reward-to-variability ratio*. The reward-to-variability ratio is a measure of reward per unit of risk taken by the investor (Sharpe, 1966) and later renamed Sharpe ratio (Sharpe, 1994). The Sharpe ratio requires several investments returns to operate correctly and can provide helpful insight for past (ex-post) and future (ex-ante) investments. The correlation between assets is not considered in the Sharpe ratio, thus requires asset classes with similar correlation (Sharpe, 1994). The Sharpe ratio is the excess return of the portfolio divided by the portfolio volatility, i.e. standard deviation. A higher Sharpe ratio results in a better risk-to-reward investment. The standard deviation measures the return spread compared to the return mean value. A small standard deviation results in less volatility and a higher Sharpe ratio (Sharpe, 1966). The Sharpe ratio can be plotted as the capital market line and the line contains all the efficient portfolios. The intersection between the capital market line and the efficient frontier outlined by Markowitz (1952) creates the most efficient portfolio, with the best risk-to-reward ratio (Sharpe, 1964, 1966, 1994). The Sharpe ratio is the second cornerstone of this thesis and used to explore market inefficiencies between cryptocurrency trading pairs on different exchanges. If identical investments have different Sharpe ratios, they also have different efficient frontiers resulting in potential arbitrage opportunities, all else equal. A second hypothesis is required to confirm the first hypothesis and the study will analyze the weekly Sharpe ratios of cryptocurrencies between exchanges.

H2: Sharpe ratios for identical cryptocurrencies differ between exchanges.

4. Empirical method

This chapter introduces the selected empirical methods for this study, with basis in academic research philosophy. The data selection includes accessibility and quality review of gathered data. The chapter concludes with the data structure used in the analysis of selected data.

4.1 Research design

Scientific research requires methodology to connect the research question with the theoretical framework and the gathered empirical material. Selection of methodology is crucial for the overall research efficiency and academic credibility (Lind, 2014). The relationship between theory and research can be explained through different approaches (Bell *et al*., 2019). The purpose with this study is to explore potential risk exposure differences between identical investments on various cryptocurrency exchanges, thus explore market efficiency. A deductive approach is applied as the study requires a theoretical framework to analyze potential market inefficiencies. The ambition with the deductive approach is to create hypotheses around already existing theories within a field, with the intention to draw conclusions about a certain case (Bell *et al*., 2019). Another important consideration when conducting research is epistemology, this study has a positivistic epistemology. Positivism is the 'objective' approach to study science, based on the natural science philosophy. The concept is often associated with the deductive approach, with a clear distinction between theory and research. The empirical data is collected to test the created hypotheses and the positivistic epistemology requires the researchers to objectively review the material (Bell *et al*., 2019; Denscombe, 2016).

This academic research, with the deductive approach and the positivistic epistemology, is often referred to as a quantitative study. Numerical data analysis and no subjective interpretations are common characteristics of quantitative studies (Denscombe, 2016; Lind, 2014). The empirical material collected for this study consist of historical price data for selected trading pairs from several cryptocurrency exchanges.

4.2 Data selection

The secondary data collected for the thesis analysis is historical price data[7] on four cryptocurrency trading pairs from nine exchanges. The data is limited to available free services

[7] The data is downloaded from https://www.cryptodatadownload.com/, a free service providing historical price data of cryptocurrencies collected via APIs.

for cryptocurrency data, resulting in certain trading pairs missing from exchanges that normally have support for the all selected trading pairs. Selection of the four trading pairs are based on both availability and relevance. All four cryptocurrencies are well established on the cryptocurrency market and majority of exchanges support them on their platforms (CoinMarketCap, 2019; Coinpaprika, 2019). The timeframe of this thesis also limits the possibility for further coverage of cryptocurrencies. Besides the limited accessibility of historical price data, the selection of exchanges is based on certain requirements. The exchange needs to be fully functional and operational for business, including support for studied trading pairs. A complete orderbook for the selected time period is required and exchanges with temporarily trading stops[8] are included.

The historical price data collected is hourly timestamped with an OHLC (Open, High, Low, Close) price format in BTC. The hourly data is converted into weekly average and is the basis for the Sharpe ratio calculations to explore potential market inefficiencies and arbitrage opportunities. The time period of this study is from January 2018 through July 2019 and covers a total of 82 weeks. Arbitrage opportunities are constantly changing, and the time period limitation choice is to analyze more recent and relevant market development. As the ambition with this study is not to compare earlier arbitrage opportunities with recent ones, but to explore if there currently are any on the market. A secondary data study has several benefits, it is often both cheaper and less time consuming compared to collecting all data yourself. There is also more time for data analysis to yield better conclusions (Bell *et al*., 2019). A problem with secondary data is trustworthiness (Denscombe, 2016) and to strengthen the trustworthiness of this study, the trading pair data collected is randomly sampled against respective exchange.

In academic research the empirical data is reviewed to endorse the importance and quality of the study. Quantitative studies use three concepts: *reliability*, *validity* and *transferability*. Reliability determines if the results of the study are consistent, and reproductions of the study achieves identical results (Lind, 2014). The cryptocurrency market is constantly changing, and the empirical material analyzed in this study is limited to only recent time. A reproduction with another time period could differ the results significantly as the cryptocurrency market is very volatile. Arbitrage opportunities can also be exclusively limited to certain cryptocurrencies, and

[8] Temporarily trading stops can occur when exchanges are upgrading their platforms with new software or finds security flaws that can harm the platform or users. An exchange is excluded if the platform or selected trading pair is not operational within 72 hours.

earlier studies suggests that the market is becoming more efficient, resulting in less arbitrage opportunities (Urquhart, 2016; Wei, 2018; Kurihara & Fukushima, 2017; Bariviera *et al*., 2017; Caporale *et al*., 2018). Validity concern measurements, to determine if they are suitable and correctly captures the intended phenomenon (Bell *et al*., 2019). The study is based on established financial theories regarding market efficiency and is not limited to a single decision factor (Fama, 1970). Sharpe ratio is only one way to explore arbitrage opportunities and it can be argued that there are other theories better suitable for the study. The empirical data is always exposed for a human error risk as the data is manually collected and analyzed. It is the researcher's obligation to ensure the integrity of the study (Denscombe, 2016). Transferability or generalization refers to the possibility that the results can be suitable for similar studies (Lind, 2014). The possibility for generalization of small sample size results can be hard, as it only involves a specific field (Denscombe, 2016). However, the study can be useful for future research on the cryptocurrency market with a focus on market efficiency and arbitrage opportunities.

4.3 Data structure

The hourly historical price data for selected cryptocurrency pairs are sorted in Excel. The hourly return (1) is calculated by using the closing price (P_c) and opening price (P_o) for each cryptocurrency and exchange separately. The data output from (1) is used to compute weekly geometric means (2) for the studied period, where (x) are the hourly returns and (n) is amount of data points. The cryptocurrency market is always operational, resulting in no excluded days from the weekly geometric means.

$$R_h = \frac{(P_c - P_o)}{P_o} \tag{1}$$

$$(\prod_{i=1}^{n} x_i)^{\frac{1}{n}} = \sqrt[n]{x_1 x_2 \dots x_n} \tag{2}$$

$$\sigma_i = \sqrt{\frac{\sum_{i=1}^{n}(E[R_i] - \overline{E[R]})^2}{n-1}} \tag{3}$$

$$Sharpe\ ratio = \frac{E[R_i] - r_f}{\sigma_i} \tag{4}$$

The standard deviation (3) is calculated hourly for each week and then converted into weekly standard deviations. The weekly Sharpe ratios (4) are calculated by dividing the weekly geometric mean returns with the weekly standard deviations. The risk-free return is excluded because we analyze identical assets. The research covers all 52 weeks 2018 and 30 weeks 2019, a total of 82 weekly data points are studied. The converted weekly Sharpe ratios for each cryptocurrency and exchange will be statistically tested against each other with the paired sample t-test in SPSS. The tests will be performed over three periods. The first test covers weekly Sharpe ratios over the period 2018-01-01 – 2018-10-14 and includes the first 41 weeks. The second test covers weekly Sharpe ratios over the period 2018-10-15 – 2019-07-28 and includes the last 41 weeks. The last tests include all data points between the period 2018-01-01 – 2019-07-28 and includes all 82 weekly Sharpe ratios. The statistical tests are conducted to determine if there is a significant difference between the Sharpe ratios on the significance level $\alpha = 0.05$.

$$H_0: \mu_1 = \mu_2 \tag{5}$$

$$H_1: \mu_1 \neq \mu_2 \tag{6}$$

The null hypothesis (5) assumes that there is no difference between the Sharpe ratios. It is a two-tailed test and the alternative hypothesis (6) assumes that there is a difference between the Sharpe ratios.

5. Empirical analysis

This chapter analyzes the empirical material and results from the tests performed in SPSS. The descriptive statistics from each cryptocurrency pair is presented and interpreted. Results from the paired sample t-tests for each group are presented with their respective *p*-values.

5.1 Descriptive statistics

The summary of descriptive statistics for each cryptocurrency and exchange includes the sample period with number of data points. The Sharpe ratio data is described with several measures, including skewness and kurtosis. The data covers identical assets and assumed to be relatively similar throughout the study but analyzed to explore explanations for the significant result differences.

5.1.1 Ether

The cryptocurrency Ether data cover seven different exchanges and the descriptive statistic summary is displayed in Table 3. There is a slight positive skewness for all 82 data points, with the highest skewness (0.2652) on Bittrex and lowest skewness (0.1597) on Binance. The kurtosis for the same sample period is almost zero and assumed to be normally distributed.

Table 3
Descriptive statistics of Ether

Exchange	Sample period	N	Mean	SD	Min	Max	Skewness	Kurtosis
Binance	2018-01-01 - 2019-07-28	82	-0.22266	1.02202	-2.27245	2.22167	0.1597	0.0141
Bittrex	2018-01-01 - 2019-07-28	82	-0.20021	0.96409	-2.04758	2.24695	0.2652	-0.0074
Cex.io	2018-01-01 - 2019-07-28	82	-0.18307	0.91959	-2.11693	2.02209	0.1886	0.1062
Gemini	2018-01-01 - 2019-07-28	82	-0.18331	0.91602	-2.00842	2.10861	0.2131	0.0718
Kraken	2018-01-01 - 2019-07-28	82	-0.20393	1.00072	-2.29223	2.25410	0.2021	-0.0526
OKEx	2018-01-01 - 2019-07-28	82	-0.20767	1.02679	-2.22776	2.24190	0.1824	-0.0179
Poloniex	2018-01-01 - 2019-07-28	82	-0.20804	0.99604	-2.17230	2.25835	0.2249	0.0086
Binance	2018-10-15 - 2019-07-28	41	-0.12788	0.85976	-1.86620	2.22167	0.5181	0.9123
Bittrex	2018-10-15 - 2019-07-28	41	-0.13191	0.83947	-1.84058	2.24695	0.5204	0.9240
Cex.io	2018-10-15 - 2019-07-28	41	-0.11252	0.75113	-1.81055	2.02209	0.4747	1.0979
Gemini	2018-10-15 - 2019-07-28	41	-0.11967	0.77684	-1.76996	2.10861	0.4259	1.1468
Kraken	2018-10-15 - 2019-07-28	41	-0.13071	0.83401	-1.81748	2.25410	0.5269	1.0253
OKEx	2018-10-15 - 2019-07-28	41	-0.12184	0.87118	-1.84595	2.24190	0.5284	0.7936
Poloniex	2018-10-15 - 2019-07-28	41	-0.13642	0.84507	-1.82829	2.25835	0.4930	1.0166
Binance	2018-01-01 - 2018-10-14	41	-0.31745	1.16514	-2.27245	2.20503	0.1325	-0.5216
Bittrex	2018-01-01 - 2018-10-14	41	-0.26851	1.08069	-2.04758	2.07275	0.2262	-0.5045
Cex.io	2018-01-01 - 2018-10-14	41	-0.25362	1.06679	-2.11693	1.98734	0.1903	-0.4578
Gemini	2018-01-01 - 2018-10-14	41	-0.24694	1.04277	-2.00842	1.94771	0.2096	-0.4757
Kraken	2018-01-01 - 2018-10-14	41	-0.27715	1.14950	-2.29223	2.06129	0.1709	-0.6296
OKEx	2018-01-01 - 2018-10-14	41	-0.29351	1.16657	-2.22776	2.18340	0.1409	-0.5171
Poloniex	2018-01-01 - 2018-10-14	41	-0.27965	1.13329	-2.17230	2.08823	0.2012	-0.5273

Table 3 show a distinctive difference between the two 41 weekly Sharpe ratio tests. The data for the first period (2018-01-01 – 2018-10-14) is during a more volatile market compared to the second half (2018-10-15 – 2019-07-28), see Figure 2. During the more volatile market period Ether had a better distribution of skewness overall compared to the less volatile period. The second period had less extreme negative and slightly higher positive weekly Sharpe ratios, resulting in a better opportunity for investors during the second half. The unregulated exchange Binance had overall the lowest Sharpe ratio average (*M* = -0.22266, *SD* = 1.02202) and the regulated exchange Cex.io had the best Sharpe ratio average (*M* = -0.18307, *SD* = 0.91959) for Ether. Table 3 shows a 0.284 difference in negative Sharpe ratio between the exchanges Gemini and Kraken, the data do not overall show any extreme cases that would indicate major differences.

5.1.2 Litecoin

The Litecoin data collected covers seven different cryptocurrency exchanges and a summary of descriptive statistics are displayed in Table 4. There is less volatility on the Litecoin market (See Figure 3) compared to Ether (See Figure 2), resulting in more similar market conditions and data over the two 41-week periods. The full sample period shows a positive skewness resulting in a longer tail of positive Sharpe ratios and the kurtosis for same period is negative, suggesting a flatter distribution of Sharpe ratios. The first period (2018-01-01 – 2018-10-14) is more normally distributed in skewness compared to the second period but experiences a negative average of weekly Sharpe ratios. There is also a smaller data variance during the first period of the weekly Sharpe ratios. The second period (2018-10-15 – 2019-07-28) have a positive weekly Sharpe ratio average suggesting better opportunity for investors compared to the first period. There is a deviation in the maximum Sharpe ratios between Binance (*Max* = 2.31889) and Bitfinex (*Max* = 1.81959). The regulated European Bitstamp exchange (*M* = -0.07921, *SD* = 0.82296) had the highest Sharpe ratio average and with one of the lowest data variances over the studied period. Binance (*M* = -0.09155, *SD* = 0.87141) had the lowest Sharpe ratio average and highest data variance.

Table 4
Descriptive statistics of Litecoin

Exchange	Sample period	N	Mean	SD	Min	Max	Skewness	Kurtosis
Binance	2018-01-01 - 2019-07-28	82	-0.09155	0.87141	-1.81487	2.31889	0.3387	-0.2792
Bitfinex	2018-01-01 - 2019-07-28	82	-0.08794	0.84049	-1.82414	1.81959	0.1738	-0.5922
Bitstamp	2018-01-01 - 2019-07-28	82	-0.07691	0.82296	-1.66317	2.04444	0.3072	-0.3787
Bittrex	2018-01-01 - 2019-07-28	82	-0.07921	0.82130	-1.71600	2.04088	0.2949	-0.2853
Kraken	2018-01-01 - 2019-07-28	82	-0.09075	0.84374	-1.74892	2.06720	0.2383	-0.4210
OKEx	2018-01-01 - 2019-07-28	82	-0.08673	0.85877	-1.79407	2.03237	0.2558	-0.4991
Poloniex	2018-01-01 - 2019-07-28	82	-0.08630	0.86055	-1.81065	2.03432	0.2362	-0.5117
Binance	2018-10-15 - 2019-07-28	41	0.07235	0.97272	-1.73631	2.31889	0.2819	-0.5858
Bitfinex	2018-10-15 - 2019-07-28	41	0.05293	0.92569	-1.73792	1.81959	0.1389	-0.8492
Bitstamp	2018-10-15 - 2019-07-28	41	0.06884	0.92356	-1.61661	2.04444	0.2465	-0.6916
Bittrex	2018-10-15 - 2019-07-28	41	0.05921	0.92734	-1.68167	2.04088	0.2300	-0.6064
Kraken	2018-10-15 - 2019-07-28	41	0.06337	0.94766	-1.71604	2.06720	0.1318	-0.7137
OKEx	2018-10-15 - 2019-07-28	41	0.05919	0.96037	-1.78437	2.03237	0.1940	-0.7922
Poloniex	2018-10-15 - 2019-07-28	41	0.05892	0.95818	-1.69810	2.03432	0.1842	-0.8010
Binance	2018-01-01 - 2018-10-14	41	-0.25545	0.73242	-1.81487	1.14662	-0.0146	-0.7191
Bitfinex	2018-01-01 - 2018-10-14	41	-0.22881	0.73002	-1.82414	1.14233	-0.1021	-0.7431
Bitstamp	2018-01-01 - 2018-10-14	41	-0.22265	0.68917	-1.66317	1.14320	-0.0377	-0.7667
Bittrex	2018-01-01 - 2018-10-14	41	-0.21762	0.68314	-1.71600	1.08847	-0.0496	-0.6417
Kraken	2018-01-01 - 2018-10-14	41	-0.24486	0.70345	-1.74892	1.09792	-0.0313	-0.6661
OKEx	2018-01-01 - 2018-10-14	41	-0.23266	0.72626	-1.79407	1.16920	-0.0444	-0.7640
Poloniex	2018-01-01 - 2018-10-14	41	-0.23152	0.73367	-1.81065	1.19925	-0.0593	-0.7211

5.1.3 Dash

Dash is the least covered cryptocurrency with three exchanges and a summary of the descriptive statistics are displayed in Table 5. The overall data shows a positive skewness range between 0.8886 to 0.9411 and is the cryptocurrency with the highest positive skewness. The kurtosis range is between 0.9700 to 1.3279, suggesting a larger distribution of more extreme positive and negative weekly Sharpe ratios. All the three exchanges Binance (*M* = -0.26428, *SD* = 0.78347), OKEx (*M* = -0.25409, *SD* = 0.73146) and Poloniex (*M* = -0.24854, *SD* = 0.74164) experienced a negative average Sharpe ratio mean over the total sample period. The standard deviation for the three exchanges experienced the lowest variance of weekly Sharpe ratios, between all cryptocurrencies. Like the other cryptocurrencies the second period (2018-10-15 – 2019-07-28) shows better Sharpe ratio means compared to the first period. The overall data do not suggest any extreme differences between the exchanges.

5.1.4 XRP

The empirical material on XRP the cryptocurrency developed by Ripple covers four exchanges and a summary of the descriptive statistics are displayed in Table 6. The average weekly Sharpe ratios over the full period (2018-01-01 – 2019-07-28) shows a range of -0.28291 to -0.30390, suggesting that investors take on a higher risk for the returns compared to the other three cryptocurrencies. The data shows a positive skewness range from 0.4326 to 0.4762 and the kurtosis range -0.0557 to 0.3489 suggests that the Sharpe ratios are normally distributed. The Sharpe ratio maximum values differ of roughly 0.287 between Poloniex (1.79245) and Bitfinex (2.07979). Over the full period the exchange Binance (*M* = -0.30390, *SD* = 0.82638) shows the lowest average mean of Sharpe ratios combined with the highest variance. During the same period Bittrex (*M* = -0.28291, *SD* = 0.79605) displays the highest return with the lowest variance, see Table 6.

5.1.5 Summary

There is a positive skewness throughout all the collected data, combined with a variation of kurtosis. Dash has the highest positive skewness range 0.8276 to 0.9411 (See Table 5) and Ether has the lowest positive skewness range 0.1597 to 0.2652 (See Table 3). Ether also has the most normally distributed kurtosis range -0.0526 to 0.1062 (See Table 3). The best weekly Sharpe ratio (2.37548) over the sample period occurred on Binance with the cryptocurrency Dash (See Table 5). The worst weekly Sharpe ratio (-2.43426) over the 82 data point weeks occurred on Binance with the cryptocurrency XRP (See Table 6).

Table 5
Descriptive statistics of Dash

Exchange	Sample period	N	Mean	SD	Min	Max	Skewness	Kurtosis
Binance	2018-01-01 - 2019-07-28	82	-0.26428	0.78347	-1.63976	2.37548	0.8886	1.1684
OKEx	2018-01-01 - 2019-07-28	82	-0.25409	0.73146	-1.44873	2.23564	0.9411	1.3279
Poloniex	2018-01-01 - 2019-07-28	82	-0.24854	0.74164	-1.50369	2.16427	0.8276	0.9700
Binance	2018-10-15 - 2019-07-28	41	-0.19933	0.81584	-1.52780	2.37548	1.0482	1.3928
OKEx	2018-10-15 - 2019-07-28	41	-0.21957	0.78743	-1.44873	2.23564	0.9877	1.1944
Poloniex	2018-10-15 - 2019-07-28	41	-0.20155	0.77313	-1.50369	2.16427	0.8987	1.0294
Binance	2018-01-01 - 2018-10-14	41	-0.32922	0.75416	-1.63976	1.82363	0.6960	0.9648
OKEx	2018-01-01 - 2018-10-14	41	-0.28861	0.67895	-1.42024	1.82194	0.8480	1.6182
Poloniex	2018-01-01 - 2018-10-14	41	-0.29553	0.71524	-1.45014	1.79892	0.7465	1.0725

Table 6
Descriptive statistics of XRP

Exchange	Sample period	N	Mean	SD	Min	Max	Skewness	Kurtosis
Binance	2018-01-01 - 2019-07-28	82	-0.30390	0.82638	-2.43426	2.06423	0.4614	0.2886
Bitfinex	2018-01-01 - 2019-07-28	82	-0.28630	0.82446	-2.36332	2.07979	0.4593	0.1720
Bittrex	2018-01-01 - 2019-07-28	82	-0.28291	0.79605	-2.38629	2.03049	0.4762	0.3489
Poloniex	2018-01-01 - 2019-07-28	82	-0.29379	0.80610	-2.28358	1.79245	0.4326	-0.0557
Binance	2018-10-15 - 2019-07-28	41	-0.26377	0.73653	-1.52561	1.34549	0.2718	-0.8163
Bitfinex	2018-10-15 - 2019-07-28	41	-0.25093	0.73310	-1.48028	1.30457	0.2589	-0.9213
Bittrex	2018-10-15 - 2019-07-28	41	-0.26444	0.72957	-1.53324	1.34024	0.2837	-0.8402
Poloniex	2018-10-15 - 2019-07-28	41	-0.26169	0.72915	-1.44676	1.34001	0.3148	-0.8584
Binance	2018-01-01 - 2018-10-14	41	-0.34404	0.91493	-2.43426	2.06423	0.6129	0.7613
Bitfinex	2018-01-01 - 2018-10-14	41	-0.32168	0.91458	-2.36332	2.07979	0.6090	0.6104
Bittrex	2018-01-01 - 2018-10-14	41	-0.30138	0.86618	-2.38629	2.03049	0.6178	0.9889
Poloniex	2018-01-01 - 2018-10-14	41	-0.32589	0.88435	-2.28358	1.79245	0.5407	0.3177

Binance showed the worst weekly Sharpe ratios on respective cryptocurrency over the full sample period (2018-01-01 – 2019-07-28), the exchange also had the highest Sharpe ratio variance for all cryptocurrencies except for Ether. Cex.io (*M* = -0.18307, *SD* = 0.91959) had the best average Sharpe ratios for Ether, see Table 3. Bitstamp (*M* = -0.07691, *SD* = 0.82296) showed the best weekly average Sharpe ratios for Litecoin, see Table 4. Best performing exchange for weekly average Sharpe ratios for Dash was Poloniex (*M* = -0.24854, *SD* = 0.74164), see Table 5. The average Sharpe ratios for XRP performed best on Bittrex (*M* = -0.28291, *SD* = 0.79605), see Table 6.

5.2 Results

The significance tests are performed on the weekly Sharpe ratios individually for each cryptocurrency, exchange and time period. Market efficiency is not measured on overall cryptocurrency performance between all exchanges. All sample paired t-tests are performed with an alpha (α) 0.05. Table 7 reports the *p*-values of Ether on the full period (2018-01-01 – 2019-07-28) and a statistical difference can be found on two occasions. The difference between Binance and Cex.io shows a *p*-value of 0.025 and between Binance and Gemini shows a *p*-value of 0.028.

Table 7
P-values of Ether (2018-01-01 - 2019-07-28)

	Bittrex	Cex.io	Gemini	Kraken	OKEx	Poloniex
Binance	0.134	0.025	0.028	0.206	0.184	0.184
Bittrex		0.194	0.133	0.771	0.574	0.476
Cex.io			0.981	0.176	0.123	0.061
Gemini				0.176	0.139	0.056
Kraken					0.745	0.641
OKEx						0.966

The descriptive statistical data summarized in Table 3 shows the largest deviation of means and extreme values between the Binance and the two exchanges (Cex.io and Gemini).

Table 8
P-values of Ether (2018-10-15 - 2019-07-28)

	Bittrex	Cex.io	Gemini	Kraken	OKEx	Poloniex
Binance	0.761	0.507	0.678	0.771	0.674	0.328
Bittrex		0.363	0.474	0.924	0.537	0.761
Cex.io			0.63	0.308	0.69	0.232
Gemini				0.493	0.923	0.354
Kraken					0.508	0.372
OKEx						0.27

The second sample period (2018-10-15 – 2019-07-28) with lower variance (See Figure 2) shows no significant difference between any of the studied exchanges, see Table 8. The observed data in Table 3 also suggests smaller differences between the mean values. The first sample period (2018-01-01 – 2018-10-14) shows a significant difference between Binance and Cex.io (p = 0.018) and between Binance and Gemini (p = 0.018), see Table 9. The first period experienced higher price variance (See Figure 2) and could affect the efficiency between Binance and the other two exchanges.

Table 9
P-values of Ether (2018-01-01 - 2018-10-14)

	Bittrex	Cex.io	Gemini	Kraken	OKEx	Poloniex
Binance	0.068	0.018	0.018	0.151	0.174	0.06
Bittrex		0.353	0.149	0.703	0.235	0.499
Cex.io			0.632	0.356	0.069	0.149
Gemini				0.248	0.055	0.082
Kraken					0.386	0.88
OKEx						0.208

Litecoin show no significant differences between the exchanges, see Table 10. The Sharpe ratio data from Binance and Bitstamp showed the lowest p-value of 0.102 over the full sample period. Litecoin had less overall difference in price volatility between the two periods (See Figure 3) compared to Ether (See Figure 2).

Table 10
P-values of Litecoin (2018-01-01 - 2019-07-28)

	Bitfinex	Bitstamp	Bittrex	Kraken	OKEx	Poloniex
Binance	0.723	0.102	0.233	0.939	0.523	0.428
Bitfinex		0.218	0.408	0.806	0.887	0.813
Bitstamp			0.778	0.169	0.271	0.19
Bittrex				0.307	0.459	0.466
Kraken					0.717	0.635
OKEx						0.946

The second period (2018-10-15 – 2019-07-28) did not show any statistically significant differences between the exchanges (See Table 11), suggesting a similar trend to Ether over the same period (See Table 8). Binance and Poloniex showed the lowest p-value of 0.166 over the second period.

Table 11
P-values of Litecoin (2018-10-15 - 2019-07-28)

	Bitfinex	Bitstamp	Bittrex	Kraken	OKEx	Poloniex
Binance	0.251	0.781	0.328	0.558	0.297	0.166
Bitfinex		0.235	0.672	0.53	0.678	0.602
Bitstamp			0.364	0.687	0.533	0.34
Bittrex				0.772	0.999	0.982
Kraken					0.805	0.723
OKEx						0.982

Table 12 displays the *p*-values of Litecoin during the first period (2018-01-01 – 2018-10-14) and shows significant differences between Binance and the rest of the exchanges, besides Kraken. The lowest *p*-value of 0.004 was between Binance and OKEx, two of the largest unregulated exchanges on the market. The data also suggests that the first period had market inefficiencies between Litecoin on Binance and the other exchanges, see Table 12.

Table 12
P-values of Litecoin (2018-01-01 - 2018-10-14)

	Bitfinex	Bitstamp	Bittrex	Kraken	OKEx	Poloniex
Binance	0.017	0.009	0.014	0.47	0.004	0.006
Bitfinex		0.611	0.464	0.311	0.637	0.737
Bitstamp			0.688	0.14	0.279	0.377
Bittrex				0.12	0.274	0.358
Kraken					0.401	0.343
OKEx						0.8

Table 13 reports the *p*-values of Dash over all time periods and only shows a statistically significant difference between the exchanges Binance and Poloniex (p = 0.018) during the first sample period (2018-01-01 – 2018-10-14). Figure 4 displays the price development of Dash and over the full period not experiencing extreme volatility compared to 2017.

Table 13
P-values of Dash

	Sort by period					
	2018-01-01 - 2019-07-28		2018-10-15 - 2019-07-28		2018-01-01 - 2018-10-14	
	OKEx	Poloniex	OKEx	Poloniex	OKEx	Poloniex
Binance	0.501	0.108	0.245	0.868	0.099	0.018
OKEx		0.649		0.236		0.719

The *p*-values for the four cryptocurrency exchanges covering XRP are displayed in Table 14. There is a significant difference between Binance and Bitfinex (p = 0.046) over the full sample. During the first period (2018-01-01 – 2018-10-14) there is also a significant difference between the same exchanges (p = 0.036), suggesting that all cryptocurrencies experienced market inefficiencies connected to Binance during the first 41 weeks of 2018.

Table 14
P-values of XRP

	Sort by period								
	2018-01-01 - 2019-07-28			**2018-10-15 - 2019-07-28**			**2018-01-01 - 2018-10-14**		
	Bitfinex	**Bittrex**	**Poloniex**	**Bitfinex**	**Bittrex**	**Poloniex**	**Bitfinex**	**Bittrex**	**Poloniex**
Binance	0.046	0.062	0.255	0.134	0.944	0.744	0.152	0.036	0.277
Bitfinex		0.706	0.248		0.217	0.21		0.154	0.669
Bittrex			0.164			0.696			0.08

A study with alpha (α) 0.10 would include a few more data points with significant differences between the exchanges, majority from Sharpe ratios including Ether on the first time period (See Table 9).

5.3 Hypotheses

The two hypotheses for the study was (1) *The cryptocurrency market is not efficient* and (2) *Sharpe ratios for identical cryptocurrencies differ between exchanges*. The first hypothesis relates to the second hypothesis and is true if there are statistically significant differences between the exchanges and cryptocurrencies. The data presented in this chapter suggests that there are differences between the weekly Sharpe ratios on certain exchanges, on the significance level ($\alpha = 0.05$). At least one difference occurred between two exchanges on each of the studied cryptocurrencies, but all significant difference involved Binance during the three studied time periods. The results suggest that there might be other underlying variables connected with Binance not displayed in this study affecting the outcome. A significance level ($\alpha = 0.10$) would include exchanges not directly related to Binance. There are significant differences between the studied Sharpe ratios and the second hypothesis is accepted, also resulting in the acceptance of the first hypothesis. The cryptocurrency market is not efficient and potential arbitrage opportunities exists between certain exchanges for all four cryptocurrencies. The results suggest that the market is improving over time, between the first and second period. Supporting the statements from earlier cryptocurrency research data on market efficiency (Urquhart, 2016; Wei, 2018; Kurihara & Fukushima, 2017; Bariviera *et al*., 2017; Caporale *et al*., 2018).

6. Conclusion

The concluding chapter of this thesis will summarize the findings with focus on the research question. Discussion regarding the contribution for the researched field and a critical review of the thesis will also be included. The chapter concludes with suggestions for future research within the cryptocurrency field.

6.1 Summary of findings

The purpose of the study was to explore market efficiency on the cryptocurrency market with focus on weekly Sharpe ratios for identical investments between different exchanges. The study covered four cryptocurrencies on nine different cryptocurrency exchanges over 82 weeks, between 1st January 2018 through 28th July 2019. The results showed instances of significant Sharpe ratios differences for the four cryptocurrencies and always included the Binance exchange on the significance level alpha 0.05. The data also suggested a performance efficiency difference between the first period (2018-01-01 – 2018-10-14) and the second period (2018-10-15 – 2019-07-28) with an overall better market efficiency performance during the latter period. The worst efficiency problems occurred with Litecoin during the first period and all instances including Binance. The two hypotheses of the study are accepted and conclude a risk exposure difference between identical investments on certain exchanges and thus answering the research question of investment performance. The study present evidence of market inefficiencies on the cryptocurrency market, resulting in potential arbitrage opportunities for investors. The presented results suggest an improved market efficiency over time, which support conclusions of earlier cryptocurrency research.

6.2 Contribution

This study expands existing market efficiency research of cryptocurrencies with a new focus comparing the risk exposure between exchanges. Unlike earlier studies with a focus on weak form tests based on the market efficiency hypothesis, this study focuses on differences of efficient frontiers between identical investments. This study also suggests an exclusive research focus on the cryptocurrency market by using bitcoin trading pairs and excluding fiat currency pairs completely.

6.3 Critical review

The study shows evidence of market inefficiencies between cryptocurrency exchanges only on a few selected cryptocurrencies and exchanges. The limited accessibility of historical price data also reduces potential comparisons between efficiency of different cryptocurrencies on all exchanges. The inefficiencies are heavily weighted towards Binance on the significance level alpha 0.05 and could be caused by underlying variables excluded in this study. It is also the only study that analyzes market efficiency with Sharpe ratios, limiting the possibility for comparison and evaluation of outcomes. The study also differs from earlier studies by exclusively studying bitcoin pairs and excluding fiat currencies, another variable that is hard to evaluate without future research.

6.4 Future research

To evaluate the results of this study future research is required using the same methods outlined in this study with other exchanges and cryptocurrencies. The studied cryptocurrencies and exchanges could be studied with more complete data to find the cryptocurrency with most potential for arbitrage opportunities. A comparison between the weekly Sharpe ratios of exchanges with bitcoin trading pairs and fiat currency pairs, could provide useful information regarding which pairs are less effective for arbitrage traders. A more extensive coverage of data could provide comparison of market efficiency between regulated and unregulated exchanges, a ranking of exchange size based on volume would also be possible. Future research could include other time periods, e.g. daily and monthly Sharpe ratios, but also a larger sample size of price data.

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