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Portfolio optimization in the cryptocurrency market

An evaluation of the performance of momentum strategies in the cryptocurrency market and cryptocurrency's place in an optimized investment portfolio.

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NORWEGIAN SCHOOL OF ECONOMICS

1. Abstract

In this paper, we rigorously investigate the benefit of utilizing an active investment strategy based on momentum when investing in cryptocurrencies. We also examine how including cryptocurrencies in a more traditional asset allocation can optimize an investment portfolio. First, we create strategies with the use of exponential moving averages and simple average filters to generate a trading signal. Second, we provide evidence that the active strategies receive positive return, but significantly less than the passive buy-and-hold alternative/benchmark. Third, we find evidence that including a portion of cryptocurrency in a portfolio with more traditional assets will improve the risk-adjusted return, due to low historical correlation. And fourth, we look at and evaluate the extreme volatility and risk related to cryptocurrencies and the suggested cryptocurrency bubble. Our results have important implications for portfolio managers and first-time investors alike.

Acknowledgements

This thesis was written as a part of the Master of Science in Economics and Business Administration at NHH.

When exploring a possible subject for the master thesis, we both found great interest in cryptocurrencies and the blockchain technology. We have Financial Economics as our major, which motivated us to study the subject from an investment perspective. As a result of working with this thesis, we have gained a deeper knowledge about the blockchain technology and the cryptocurrency market, which we believe to be valuable in the future.

Because this subject is new and narrowly studied, it brought challenges to find complementary research. During the semester, potential questions and new interesting research topics emerged, but due to the time and extent of the thesis, we had to make tough limitations.

We would like to express our sincere gratitude to supervisor, Aksel Mjøs, for with insightful and helpful feedback throughout the semester.

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2. Introduction

In the wake of the financial crisis in 2008/09, an unidentified programmer under the pseudonym, Satoshi Nakamoto, revealed a new invention called Bitcoin. Bitcoin is a decentralized digital currency for peer-to-peer transactions without the need for an intermediary. Cryptocurrency is built on a disruptive technology called the Blockchain, which is an open, public distributed ledger. Transactions are not verified by a third party, a bank, like other transactions, but verified through cryptographic proof, hence the name cryptocurrency.

The adaption of Bitcoin and the Blockchain technology has to lead to a surge in innovation and development of new cryptocurrencies. These innovations strive to improve upon different aspects of the blockchain technology. From the emergence of Bitcoin in 2008, there are 1,091 cryptocurrencies competing for adaption as of September 30th, 2017.

Due to increased optimism and utilization of the blockchain technology, cryptocurrencies have experienced a significant price increase over the past few years. Following this, an influx of new investors speculating in the market have been observed. Critics are emphasizing the difficulties of estimating an objective fundamental value that justifies the current market prices of cryptocurrencies. Due to high price volatility carrying the risk of extreme losses, some financial experts advise against investing in the cryptocurrency market. Some critics point to bubble tendencies, while others, with Jamie Dimon (CEO of JPMorgan) in front, even condemn the market labeling it a fraud (Son et al. 2017). Although it is interesting to investigate the fundamental value, our thesis focuses on specific investment strategies within the cryptocurrency market, and how to achieve portfolio optimisation combining cryptocurrency with traditional assets.

Research topic: *An evaluation of the performance of momentum strategies in the cryptocurrency market and cryptocurrency's place in an optimized investment portfolio.*

Our motivation is to test if there are excess returns to actively trade based on technical analysis compared to a passive exposure to the cryptocurrency market. We also study how cryptocurrencies are weighted in optimized portfolios. The technical analysis is created to exploit momentum caused by the market psychology. Empirical studies reveal that the cryptocurrency market reacts quickly to news and rumors regarding regulations and adoption of the technology. Momentum investing aims to profit on the continuance of existing trends in the market, in other words; buying winners and selling losers. In this thesis, we define excess return as additional return compared to a passive buy and hold portfolio. To trade on changes in momentum, we create simple technical indicators to time the entry and exits of our investments. This is articulated well in this statement by Pring (1991, ss. 2-3):

The technical approach to investment is essentially a reflection of the idea that prices move in trends which are determined by the changing attitudes of investors toward a variety of economic, monetary, political and psychological forces. Since the technical approach is based on the theory that the price is a reflection of mass psychology ("the crowd") in action, it attempts to forecast future price movements on the assumption that crowd psychology moves between panic, fear, and pessimism on one hand and confidence, excessive optimism, and greed on the other.

The use of alternative investments for spreading risk and diversifying investments is widely seen in modern asset management. Examples of alternative investments are commodities, such as gold and oil, real estate, hedge funds, derivatives contracts and private equity. Investing in alternative asset classes is done mainly because they typically have low correlation with the more traditional asset classes like stocks, bonds, and currency, which creates a diversification benefit (Chueng et al. 2017). If cryptocurrency is classified as a new asset class, it is interesting to look at the benefits of including cryptocurrency as a part of a more traditional portfolio. We investigate this by including our passive portfolio with the other asset classes to see if this improves the risk-adjusted return through a variance-covariance optimization.

In this thesis, we present an overview of the cryptocurrency market, the blockchain technology and the cryptocurrencies we have included in our analysis. Furthermore, we present our strategies which are based on a time series model constructed of simple momentum indicators. The strategies have different formation periods and rapid rebalancing to efficiently react to new information and shifts in market sentiment and momentum. We present our findings and compare this new asset to the traditional assets and include all in optimized portfolios. Conclusively, we evaluate our findings and elaborate on the underlying risk, and the potential for a speculative bubble in the cryptocurrency market. Ultimately, we look at how an investor could utilize these findings when investing in cryptocurrency.

3. Background and literature

3.1 Blockchain Technology

A blockchain is defined as a digitized, decentralized, public ledger of all cryptocurrencies (Investopedia LLC, 2017). It eliminates the double-spending issue which was the problem with previous digital currencies, such as eCash (Gupta, 2017). Double spending is when a digital token can be spent more than once, due to duplication of the digital code. Blockchain facilitates the process of recording transactions in the public ledger and allows market participants to keep track without central recordkeeping.

The transactions are lumped into blocks, where the last line of each block is the first line in the next block, making it a chain that prevents tampering. This process is called cryptographic hashing. A hash is a fixed combination of numbers and letters for any transaction information. Any time the exact information is entered, the same hash will be produced. Any change will result in a different combination. With this method, it is not possible to change the history, only add to it (Gupta, 2017). According to Cam Harvey (2017) at the CFA Institute annual conference, "*To tamper with a blockchain by correctly guessing a hash would take roughly the same number of guesses as there are atoms in the known universe – and that is just for one block*."

Transactions are verified through a process called mining, where any individual with the computational power uses specific cryptographic software to generate the correct hash. "*Mining is the mechanism that underpins the decentralized clearinghouse, by which transactions are validated and cleared. Mining is the invention that makes bitcoin special, a decentralized security mechanism that is the basis for P2P digital cash. Mining secures the bitcoin system and enables the emergence of network-wide consensus without a central authority" (Antonopoulos, 2017)*.

When the right hash is generated, the transaction is validated, and is recorded on a global ledger – the block is then added to the blockchain. This process, which requires quadrillions of hashing operations per second across the entire network, is a global competition to find the solution first (Frydel, 2017). The miner who generates the correct hash, is rewarded by a given amount depending on the mined cryptocurrency.

Existing blockchain technology is continually being improved upon. When developers implement new technology into an already existing blockchain, it is done through a fork, which is an upgrade or a divergence from the old blockchain. An example is Bitcoin Cash which is a fork from Bitcoin. Cryptocurrencies that emerge through a fork or an initial coin offering (explained under 3.2.2) can be labeled as altcoins. Altcoins, or coins, is short for alternative cryptocurrencies launched after bitcoin.

3.2 The Cryptocurrency Market

Participation in the cryptocurrency market is done by buying coins or tokens at an exchange, or by receiving cryptocurrency through mining. This token or coin can be utilized for a variety of different activities, depending on the underlying technology of the different cryptocurrencies, but typical for all is that they are used for peer-to-peer transactions. An investor can exchange tokens directly to FIAT currencies or a variety of other tokens. FIAT money is an intrinsically worthless object, such as paper money, that is deemed to be money by law (Financial Times Lexicon, 2017). USD is categorized as FIAT money in the continuation of this thesis.

There are 1091 cryptocurrencies as of September 30th, 2017, with a total market capitalization of $147,653,000,000. The overall market cap has increased more than tenfold from January 1st to September 30th, 2017, where the market cap of January 1st, 2017, was at 17,735,500,000 USD (Coinmarketcap, 2017). This increase can be observed in Figure 1 below, which highlight our motivation to study this period in our thesis.

Figure 1: The increase in total market cap and 24-hour trading volume for all cryptocurrencies over the whole period (Coinmarketcap, 2017).

Underneath, in Figure 2, we see how the market cap in a percentage of the total market cap has changed for the top 10 biggest cryptocurrencies. Bitcoin, which have dominated 90% of the market the past years, has now decreased to around 50% as other cryptocurrencies have started getting traction.

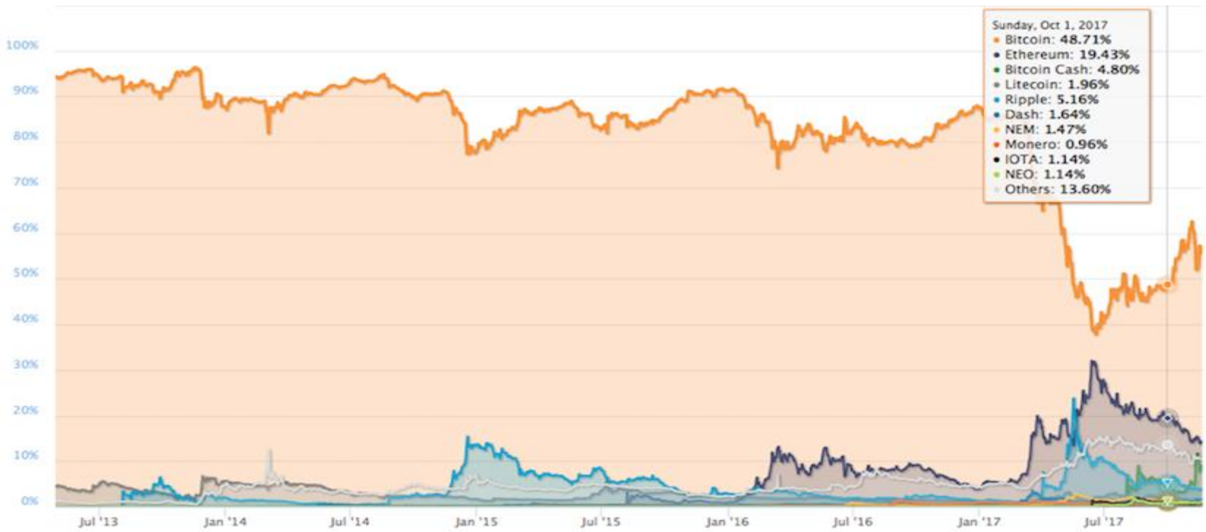

Figure 2: Shows the percentage market capitalization total of the 10 biggest cryptocurrencies and others from July 2013 until October 2017 (Coinmarketcap, 2017).

Panel A: Cryptocurrency	Mean	SD	Kurtosis	Skew	Minimum	Max
BTC	0.00448	0.03516	6.67046	0.09839	-0.18741	0.23936
ETH	0.00998	0.07367	3.50022	0.84318	-0.27055	0.35360
XRP	0.00747	0.09405	177.41825	10.00048	-0.46005	1.79367
LTC	0.00544	0.05749	30.05083	2.96330	-0.32642	0.66587
DASH	0.00823	0.05993	7.53881	1.52750	-0.21590	0.44645
XEM	0.01488	0.09923	12.07459	2.29341	-0.29753	0.78576
XMR	0.00986	0.08006	19.05780	2.71601	-0.25411	0.79434
DOGE	0.00501	0.06809	27.30686	2.93777	-0.38913	0.67925
BTS	0.00718	0.08508	15.86570	2.54850	-0.32409	0.68201
Panel B: Traditional Assets	Mean	SD	Kurtosis	Skew	Minimum	Max
S&P500	0.00053	0.00736	2.58561	-0.35279	-0.03592	0.02476
10y t-notes	0.00035	0.02119	2.37615	0.19977	-0.09201	0.11278
REIT	0.00055	0.00907	1.17353	-0.35287	-0.04008	0.02750
Olje	0.00064	0.02371	1.79538	0.42091	-0.07786	0.10978
Gold	0.00032	0.00869	3.63416	0.34784	-0.03319	0.04662
P/E	0.00012	0.01034	11.98343	-1.72810	-0.07423	0.04728

Table 1: The Mean daily return, Standard Deviation, Kurtosis, Skew, min and max return for the cryptocurrencies (Panel A), and traditional asset classes as S&P500, 10-year American treasury notes, Real Estate, Oil, Gold and Private Equity (Panel B).

As we can observe from Table 1, cryptocurrencies exhibit higher daily return, volatility, and considerably higher kurtosis and skew than other assets. Higher kurtosis and skew will, in turn, indicate extreme outcomes and risk of severe losses which will be discussed further.

3.2.1 Central banks and Cryptocurrency

Governments are controlling FIAT currencies by using central banks which operates monetary policy to exert economic influence. Governments can track currency movement, collect taxes and trace criminal activity, unless its cash. Control over currency can impact a nations fiscal policy, business environment and measures to control economic crime. Since governments purposely increase or restrict the amount of circulating money in an economy to stimulate investments, generate jobs, and adjust the inflation, control of currency is very important (Schwartz, 2008). The difficulties in regulating and tracking decentralized cryptocurrencies can, therefore, be an issue for central banks. Jens Weidmann, head of Germany´s Bundesbank, proclaimed that digital currencies have the potential to make a future financial crisis even worse, because digital currencies could increase the risk of bank runs in the future (Martin, 2017).

The way people interact with money and payment structures are rapidly changing. Several countries are moving towards a cashless society based on new technology. Physical cash in circulation has decreased 27% since 2011 in Sweden. Denmark wants to allow restaurants, shops, gas stations and clothing stores, to stop taking cash. The Bank of Korea is aiming for a cashless society by 2020; and physical cash is now used as a minority of transactions in the UK (Williams-Grut, 2017). Payment apps like Vipps and Mobilepay have increased in popularity in the Nordic countries and allow digital transactions without using an online bank.

The decline in the use of cash has led the Swedish Central bank, Sveriges Riksbank, to conduct an investigation into creating and using a digital currency and how this could be done in the best way possible. If the consensus is to create a digital currency, this is expected to happen at the end of 2019 (Sveriges Riksbank, 2017).

Sweden is not alone in this development. Lately, several central banks have announced growing interest. Ecuador, Tunisia, and Senegal have already created their own digital currency using blockchain technology (Mason, 2017). Japan wants to launch their digital currency in 2020, called J-Coin, at a 1:1 rate with Yen. Estonia, Russia, and Palestine are also looking to launch their cryptocurrency in the near future. Leading banks including HSBC, Barclays, UBS, and Santander, are developing a "Universal Settlement Coin” (USC) to make trades among themselves easier (Williams-Grut, 2017).

The president of the European Central Bank, Mario Draghi, stated that no member of the Eurozone could issue its digital currency, with the currency being Euro (Mason, 2017). The Bank of International Settlements (BIS) used their quarterly report to discuss cryptocurrency, specifying that central banks should consider whether or not to invent and use their own cryptocurrency in the near future (Martin, 2017). The fact that central banks are starting to partake in the technology could very well be a reliable indicator that the blockchain technology might have a future value.

3.2.2 Initial Coin Offerings (ICO’s)

Initial coin offerings (ICO´s) is a new way for start-ups to raise capital without selling stocks or going through venture capitalists. It is a new form of crowdfunding. These projects raise capital by issuing and selling their virtual token based on blockchain technology of the project.

This process is similar to an Initial Public Offering (IPO) in the stock market, but unlike an IPO, the new token does not give any ownership rights. Tokens, for some developers, are to be used within the underlying blockchain. An example is a blockchain-based company, GameCredits, which let gamers and developers purchase in-game items using the issued token (Gamecredits Inc, 2017). The majority of ICO's do not offer anything more but discounts on cryptocurrencies before they are available on exchanges (Nica et al. 2017). ICO´s regulatory uncertainty will be discussed under 3.2.3.

As of September 30, a total of 3.25 billion USD has been raised through ICO's in 2017 (Cryptocurrency ICO Stats, 2017). An ICO usually has a pre-sale to create awareness in the market with discounted prices. After the ICO is ended, the token can be traded on a variety of cryptocurrency exchanges. The token is usually traded on smaller exchanges until it gains enough credibility to be listed on the most popular. The funding through ICO's is highly controversial, and more than half of the offerings fail to reach their target (Risley, 2017).

Filecoin, a decentralized storage network, is currently the most successful ICO ever after the project raised $257 million this fall (Buntix, 2017). Of the more known cryptocurrencies, Ethereum, which is currently the second biggest cryptocurrency, raised $18.4 million in 2014 (Rowley, 2017). For comparison, the most significant IPO in history was the Alibaba Group, an online e-commerce company based in China, which raised a total of $25 billion in 2014 (Zucchi, 2017).

3.2.3 Risk of extreme losses

An essential aspect to consider when investing in cryptocurrencies is the risk of default – the risk of losing a significant amount of the initial investment. In other words, a price crash. Historically, we have observed several events that have led to a negative price shock. Bitcoin has suffered price drops of 71% and 49% due to hacking and the crash of the most prominent Bitcoin exchange, at that time, Mt. Gox. Ethereum and Ripple collapsed over 50% in the summer of 2017 to significant sales orders which triggered several stop-losses (Richter, 2017).

The surge in interest and the significantly increased prices have generated amplified interest and criticism. Regardless of the widespread lack of knowledge and technical understanding of the underlying technology, many of the characteristics of a speculative bubble are present (Zetzsche et al. 2017). Ron Insana (2017) has studied financial bubbles for 33 years and draws parallels between historical bubbles and cryptocurrency. He points to the rapid increase in the price, the high volatility and the growing speculation in Bitcoin. Insana states that "*When excessive optimism far outweighs normal rational expectations, crashes occur — and this will be the case with bitcoin".* An evaluation of a potential cryptocurrency bubble is included in the discussion in 7.3.

The value of a token during an ICO is only backed by the faith in the developers. Due to poor regulation, this has led to the creation of several fraudulent cryptocurrencies throughout the years, where people have invested in projects with a lack of business use-cases and lost their money (Kastelein, 2017). In early September 2017, Chinese authorities decided to ban the issuance of ICO', which resulted in a price drop of over 30% over the next weeks few weeks. (Shen, 2017). The reasoning behind the ban was the high amount of Chinese ICO´s that appeared to be fraudulent (Russel, 2017).

The price stability of the cryptocurrencies is a complex problem. Nica et al. (2017) survey the economic benefits and risk of cryptocurrencies, focusing on Bitcoin. They describe two possible scenarios that can destabilize the bitcoin. In the first scenario, a decrease in price generates a disequilibrium. We assume the miner´s primary incentives depend upon the rewards from the mining and the value of Bitcoin. If either of those two drops significantly, for example when Bitcoin reaches the maximum amount mined or there is significant negative news regarding Bitcoin, the interest in mining decreases. No mining puts the verifications on the Bitcoin blockchain at risk. Less mining will, in turn, lead to increased waiting time for transactions. Increased transaction times could lead to a loss of faith and subsequently a decrease in the value of the currency and further decrease the mining activity.

This death-spiral scenario has been observed several times, usually related to price changes. In November 2017, when the price of Bitcoin Cash increased, and the cryptocurrency became more profitable for miners, they changed from mining Bitcoin to Bitcoin Cash. The daily changes in Bitcoin Cash mining profitability can be seen in Figure A1 in the appendix. This change increased the transaction time of Bitcoin and amplified the initial price drop which ultimately resulted in a more than 20% drop in price. When Bitcoin Cash experienced an increase in difficulty, Bitcoin became more profitable again, and miners changed back. This

means that the threat of a death-spiral for every cryptocurrency that is based on proof-of-work (presented in 2.4.1) needs to be considered (Wong, 2017).

In the second scenario, a disequilibrium is generated by an increase in the price of Bitcoin. The limit of 21 million coins creates incentives to hoard Bitcoins as the value does not decrease over time. Due to this limit of supply, a growing economy will require falling prices if Bitcoin were to replace FIAT. If owners of Bitcoin expect the prices to increase further, investment projects are put on hold as long as possible, which causes depression in the economy and can in turn lead to Bitcoin falling into a deflationary spiral (Nica et al. 2017).

3.2.4 Classification of cryptocurrency

Cryptocurrency is the world`s fastest-growing asset class. As an emerging market, it is rapidly increasing in volume and area of application, and the potential and applications for cryptocurrencies and the blockchain technology seem to be endless. There is no global definition of what asset cryptocurrencies is classified as, besides the fact that it is a digital asset. Investopedia (2017) defines an asset class as a group of securities that exhibits similar characteristics, behaves similarly in the marketplace and is subject to the same laws and regulations. The main asset classes are stocks, bonds, cash (currency), real estate and commodities.

The Internal Revenue Service (IRS) as well as the U.S. Securities and Exchange Commission (SEC) classifies cryptocurrencies as property for tax purposes. Most ICO´s do not offer equity in venture start-ups, but only offers a discount on cryptocurrencies before listing on exchanges. Cryptocurrency does not have a rate of return, and there is no central entity in charge, which makes the digital asset hard to classify as security.

In September 2015, the Commodity Futures Trading Commission (CFTC) in the United States officially designated Bitcoin as a commodity (Hecht, 2017). A commodity is a basic good that’s easily tradable, such as gold, silver, and types of food. Like gold and silver, cryptocurrency can be a good option as a hedge to market risk in events such as financial crisis. Commodities work as a store of value because of the low correlation with the stock market (Chueng, Guo, & Wang, 2017). Gold, silver and even tobacco and tulips were used as means of payment in earlier days, pointing to that crypto can be a store of value and used as a mean of transaction at the same time.

The European Union, on the other hand, classifies cryptocurrency as currency (Lee, 2016). 80,000 merchants over the world were accepting Bitcoin payments in 2016. Some of these merchants are big corporations such as Amazon, Microsoft, Target and Home Depot. As cryptocurrency can be transferred anytime to anywhere without exchange cost when crossing borders, and does not require physical presence. The digital currency is also highly divisible, seen in Table 2. Cryptocurrency can also be a good asset for financially troubled countries like Zimbabwe and Venezuela, where the Bitcoin transactions have escalated. Zimbabwe does not have its own currency, with the government adopting the U.S. dollar and South African rand, among others, as legal tender in 2009 after hyperinflation rendered the local dollar worthless (Brand et al., 2017). Venezuela has, currently, the highest inflation rate in the world, and their currency, Bolivar, is almost worthless, which is why the users of Bitcoin has grown rapidly the past two years (Rands, 2017). Venezuela has the fourth highest growth of peer-to-peer transactions in the world from the beginning of 2017, until December 2nd. This is illustrated in Figure A2 in the appendix.

Cryptocurrency has hallmarks from several asset classes, at the same time it is somehow different. How cryptocurrencies are going to be globally classified remains to be seen. It is possible that different cryptocurrencies will be classified differently based on their applications. Currently, the extreme risk and high volatility make cryptocurrency challenging to use as anything else than an object of speculation. Even though some stores and companies accept it, the belief that the price will be higher tomorrow makes it harder to spend today.

Traits of Money	Gold	Fiat (US Dollar)	Crypto (Bitcoin)
Fungible *(Interchangeable)*	High	High	High
Non-Consumable	High	High	High
Portability	Moderate	High	High
Durable	High	Moderate	High
Highly Divisible	Moderate	Moderate	High
Secure *(Cannot be counterfeited)*	Moderate	Moderate	High
Easily Transactable	Low	High	High
Scarce *(Predictable Supply)*	Moderate	Low	High
Sovereign *(Government Issued)*	Low	High	Low
Decentralized	Low	Low	High
Smart *(Programmable)*	Low	Low	High

Table 3.0 *The degree to which gold, fiat, and cryptographic currencies fulfill the traditionally recognized traits of currency as well as the new traits made possible by the invention of the blockchain.*

Table 2: The differences between gold, FIAT, and cryptocurrency (Bitcoin).
Source: https://www.coindesk.com/origins-money-darwin-evolution-cryptocurrency/

3.3 Presentation of the Cryptocurrencies

In the following we will present the underlying technology behind the cryptocurrencies included in this thesis. The cryptocurrencies are presented in order of market capitalization.

3.3.1 Bitcoin (BTC)

Bitcoin was proposed by an unidentified programmer under the pseudonym Satoshi Nakamoto in 2008, with a publication of a paper titled "Bitcoin: A Peer-to-Peer Electronic Cash system" (Nakamoto, 2008). This invention was the world's first decentralized currency and was the introduction to blockchain technology (Antonopoulos, 2017).

The key concept was to use a “proof of work” algorithm (POW), which is a distributed computing system that allows the decentralized network to arrive at a consensus about the state of transactions. This POW-process is how Bitcoins are mined, thus created in this blockchain. According to Digiconomist (2017), a cryptocurrency data provider, Bitcoin mining is currently, on September 30th, 2017, consuming around 20 TWh per year. For comparison, the total Bitcoin mining electricity consumption is almost as high as for the country Ireland, and higher than most African countries. One Bitcoin transaction uses nearly 200KWh, which is 20,000 more energy than one Visa transaction (Martin, 2017).

On average, the correct hash is found every 10 minutes, and the winner is rewarded 12.5 BTC per block, which is $54,000 on October 1. 2017. Every 210,000 blocks (approximately every fourth year), the award will be halved as the amount of BTC mined are reaching the bitcoin protocol limit of 21 million (Antonopoulos, 2017). According to Coinmarketcap (2017), there are currently 16.6 million BTC in circulation. Because of this of this limitation, BTC cannot be inflated by “printing” new Bitcoins.

3.3.2 Ethereum (ETH)

Ethereum is a decentralized platform that enables developers to build and deploy applications. In the Ethereum blockchain, instead of mining for Bitcoin, the miners work to earn Ether, a token that fuels the network. Ethereum has a 14 seconds block time compared to Bitcoins 10 minutes, which is significantly faster. Beyond a tradable cryptocurrency, Ether can be used to pay for transaction fees and services on the Ethereum network (Ethereum Foundation, 2017).

Another interesting system is Proof-of-Stake (PoS), which the creator, Vitalik Buterin, wants to implement in Ethereum. Unlike PoW, no additional work is required under the PoS scheme, as the investors are rewarded based on the number of coins they hold. For example, a user holding 1% of the currency has the probability of mining 1% of that currency's blocks. In general, this system does not require a significant amount of computational work. It provides for higher currency security, and it is usually used in combination with other coins (Chuen, 2015).

3.3.3 Ripple (XRP)

Ripple is an open source, peer-to-peer payment network created by Chris Larsen and Jed McCaleb (Ripple, 2013). The cryptocurrency is built on similar principles as Bitcoin where the proof-of-work algorithm is used, but unlike Bitcoin, the source code of the technology is owned privately by the company, which means that anyone outside the organization can not verify it. Rather than competing with Bitcoin, Ripple positions itself as a compliment as it allows transfers of any currency, including Bitcoin (Brown, 2013).

3.3.4 Litecoin (LTC)

Litecoin was created by Charles Lee in 2011 and is a global, open-source, payment network that is based on the same principles as Bitcoin (Litecoin Project, 2011). The main difference for end-users that the block generation time is 2.5 minutes. Miners are currently rewarded 25 LTC per block, an amount that gets halved roughly every four years. The maximum limit of Litecoins is 84 million, where the circulation supply is $16.6 million (Coindesk, 2014).

3.3.5 Dash (DASH)

Dash, formerly known as XCoin and Darkcoin, is a peer-to-peer network also based on the Bitcoin software. Dash was launched in 2014 by Evan Duffield with an aim to be the most user-friendly and most on-chain-scalable cryptocurrency in the world. This coin allows anonymous transactions, similar to cash, which makes them untraceable. Like Bitcoin it uses proof-of-work, but it has a faster block time with 2.5 minutes compared to Bitcoins 10. Dash miners are rewarded 3.6 Dashes per block, which equals $1,168 at time of writing (The Dash Network, 2017).

3.3.6 NEM (XEM)

NEM is a peer-to-peer cryptocurrency and blockchain platform that was launched March 31, 2015 (NEM Foundation, 2014). Unlike the majority of cryptocurrencies, NEM has its personal source code. Where Bitcoin uses proof-of-work (POW), NEM uses proof-of-importance (POI). This means that the algorithm helps determine which user is going to calculate the next block. The process is called harvesting and is the equivalent of mining in this blockchain. NEM can validate more transactions in less time than Bitcoin with an average block time of 1 minute, compared to Bitcoins 10 minutes, and it has a maximum supply of 9 billion (Sayee, 2017).

3.3.7 Monero (XMR)

Monero (XMR) is an open source cryptocurrency launched in April 2014. Like Dash, Monero focuses on privacy where the transactions are untraceable, but it also allows to share information selectively by giving permits to the accounts view key. Similar to Bitcoin and other cryptocurrencies, Monero is created through mining using the proof-of-work algorithm. A block is made every two minutes compared to Bitcoins ten, and miners are rewarded approximately 7.46 XMR, which is $704 at the time of writing (Bovaird, 2017).

	BTC	**ETH**	**XRP**	**LTC**	**DASH**	**XEM**	**XMR**
Category	Value	Platform	Value	Value	Anonymity	Value	Anonymity
Market price	$4,318	$295	$0.1978	$54.41	$324.55	$0.234	$94.41
Market cap	$71.7bn	$28.4bn	$7.6bn	$2.9bn	$2.5bn	$2.1bn	$1.4bn
Avg. Yr. Return	673 %	2,304 %	736 %	264 %	19,767 %	21,926 %	1,329 %
Avg. Yr. Volatility	83 %	155 %	169 %	145 %	211 %	182 %	157 %
Mineable	Yes	Yes	No	Yes	Yes	No	Yes
Block time	10 min	14 secs	3.5 secs	2.5 min	2.5 min	1 min	2 min
Proof-type	POW	POW	POW	POW	POW	POI	POW
Untraceable	No	No	No	No	Yes	No	Yes

Table 3: The main differences between the currencies. Market price and market cap are retrieved from Coinmarketcap.com on September 30th, 2017. Average yearly return and average yearly volatility is calculated from the total existence period for the different cryptocurrencies.

4. Theory

4.1 Random Walk

A random walk is a non-stationary process which implies that price changes are independent of each other; thus, past prices cannot be used to predict future prices. A random walk indicates that today´s price is the best estimate of tomorrows price.

The formula is showed as:

$Y_t = Y_{t-1} + \varepsilon_t$

Where Y is the price at time t, and ε_t is white noise, which is a stationary process and without autocorrelation. Random walk assumes that the initial value Y is independent white noise with $t \geq 1$.

Movements in the currency prices are triggered by new, available information that influences the market expectations. According to a random walk, this information is impossible to anticipate.

If one can predict trend-patterns in a time-series based on historical information, this indicates that the error terms in the random walk-model are autocorrelated. This autocorrelation implies that period t affects the price evolvement in period t+1.

4.2 Market efficiency

A natural implication that the market efficiency hypothesis holds is that random walk is the best model for prediction of price change. A prerequisite for the market efficiency hypothesis to hold is that the investors are rational and risk neutral. Market efficiency set forth that all investors have equal available information, and their expectations of future evolvement are formed rationally and uniformly.

This model implies that momentum-strategies, which are based on trend patterns from historical information, will not be profitable. Speculation strategies that generate positive return are, therefore, an indication towards a non-efficient market. Investors who agree with this theory tends to buy passively managed index funds that track overall market performance.

4.3 Mean-reversion

A highly popular phenomenon to study is currencies´ tendency for ”mean-reversion.” Mean-reversion means that if there exists a coherence between the currency rate over a given period, this coherence can reflect a trend. The theory suggests that prices and returns eventually move back to the historical, or another relevant, mean or average.

The interpretation of mean-reversion is that the cryptocurrency prices can experience deviations from its fundamental value. There are difficulties in calculating an underlying fundamental value of the cryptocurrencies, but there might be mean-reversion effects where the prices tend to reverse to a historical price level.

4.4 Technical analysis

The technical analysis differs from fundamental analysis by design. A fundamental analysis evaluates a security by uncovering its fundamental intrinsic value using data from financial statements such as revenues, expenses, growth rates and qualitative measures like management and competition. The stock is bought if the price is below the intrinsic value. A technical analysis evaluates statistical data such as historical price and volume. Based on the technical analysis the stock is bought when it exhibits a positive trend based. A stock that shows strong technical indications, might be overvalued based on fundamentals. Conversely, a stock that technicians are selling based on their signals, might seem undervalued based on fundamentals (Kahn, 2010). Because of the difficulties connected to uncovering the fundamental value in cryptocurrencies, the technical approach can possibly work better than a fundamental approach in the cryptocurrency market.

When examining the profitability of technical trading historically, a study conducted by Park and Irvin (2007) categorize and review the evidence on the profitability of technical analysis. They find that early studies indicate that technical trading strategies generate a positive return in FOREX and futures markets, but negative returns in stock markets. Park and Irvin find that more recent, modern, studies indicate positive returns in several more speculative markets, but the inference of the empirical studies are subject to problems related to the testing. The study emphasizes on problems associated with ex-post selection of both data and investment strategies.

4.5 Momentum strategy

Momentum strategies aim to gain returns by analyzing trends in the market. The base for these strategies is that the market efficiency hypothesis does not always hold. The theory of market efficiency indicates that it is not possible to use historical information to predict future prices. Based on this theory, the observed price at time t will reflect all available information.

The existence of momentum in the cryptocurrency market indicates that the price evolvement does not follow the widely known theory about the random walk. Momentum theory determines that the best estimate for tomorrows currency price is today's price.

Several different versions of momentum strategies exist. The evaluation criteria vary for signal estimation, when to buy and sell, formation periods, and frequency of rebalancing. Based on the characteristics of momentum, one can conclude that momentum strategies are dependent on timing. An investment strategy based on momentum wants to identify and evaluate the trend patterns for a specific asset over different time periods. An investor wants to invest in assets that signalize a positive or negative trend based on a set of predetermined criteria. One highly used evaluation criteria is a comparison of a moving average over different time intervals. Moving averages smooth out price fluctuations that occur with each reporting period of price change, and reduces the possibility to misinterpret a change in the trend. A false signal or a misinterpretation is when it looks like a trend is about to reverse, but next period it is revealed it was just as a result of market fluctuations.

There are several approaches to create a moving average, where simple (MA), weighted, and exponentially weighted (EMWA) are the most common. Moving averages are by nature a lagging indicator, and often when moving average signals for either an exit- or an entry-trade it is in fact too late, and one might end up in an unfavorable trade. Given the high volatility and rapid fluctuations in the cryptocurrency prices, we use the exponentially weighted moving average. This variant gives a higher emphasis on the most recent observations, and a lesser emphasis on earlier observations, and will move more closely to the actual price, giving more accurate signals. If the generated signal changes from positive to negative, this means the low moving averages fall and breach down under the longer moving averages. The change from positive to negative shows that the shorter trend is more pessimistic than, the more extended trend. This change indicates a shift in momentum and signals that we should short the currency and the other way around if the signal goes from negative to positive.

An alternative approach is based on a filter-rule where the buy- and sell signals are given if the cryptocurrency appreciates or depreciate over a given percentage estimate.

Other approaches to momentum strategies also factor in the changes in trading volume or price pressure during a trading day. This is an approach we could have included in our thesis but chose not to focus on, due to the overall upward trend in the cryptocurrency markets.

4.6 Empirical studies

Momentum strategies are widespread and an accepted phenomenon in the financial markets. Empirical studies on momentum have revealed significant returns for exposure to assets that show trending tendencies based on technical analysis. Momentum investing aims to profit on the continuance of existing trends in the market. In other words; buying winners and selling losers.

Since cryptocurrencies are a relatively new asset, this market has naturally fewer empirical studies than the stock and FIAT currency market. As discussed, cryptocurrency might be classified as a currency, and studies from Burnside et al. (2011), Menkhoff et al. (2011) and Moskowitz et al. (2012) reveals the existence of significant momentum-prizes over time in the FIAT currency market, for both time-series and cross-sectional models.

The only other study we have found that investigates momentum in cryptocurrencies is the study by Osterrieder et al. (2017). They show that momentum-strategies exhibit higher Sharpe-ratio for the more volatile cryptocurrencies. The study indicates a substantial momentum factor in the cryptocurrency market, but there are difficulties tied to trading because of the high volatility. The high volatility is quantified in a study by Osterrieder et al. (2016). In this study

Osterrieder et al. studies statistical properties and extreme value behavior of cryptocurrency. They find that cryptocurrencies show risk characteristics that go above all the traditional asset classes. The currencies show evident clustering behaviors where extreme outcomes are likely to happen on consecutive days.

Momentum is based on the theory the market efficiency does not hold. Latif et al. (2017) test the weak form of efficient market efficiency in cryptocurrency using time series data for the cryptocurrencies Bitcoin and Litecoin. They find that the Bitcoin and Litecoin markets are inconsistent with a weak form of efficiency. Latif et al. conclude that cryptocurrency reacts instantly to new information, which is consistent with the study from Bartos (2015) on the efficient market hypothesis in Bitcoin. They conclude that cryptocurrency has a higher predictability power than the stock market due to this sensitivity to information.

A paper by Trimborn, Li, and Härdle (2017) examines the performance of portfolios composed of stocks from the American stock market by including S&P100, the German stock market by including DAX30, and from the Portuguese stock market when including cryptocurrencies. They also apply a liquidity constraint by using the LIBRO (Liquidity Bounded Risk-Return Optimization method). The study shows that by adding cryptocurrencies, they improve the risk-adjusted returns of the portfolio formation. This finding is substantiated by Chueng et al. (2017) which explores the risk and return characteristics of cryptocurrencies using a portfolio represented by a CRIX-index. They conclude that cryptocurrency can be a good diversification option in a portfolio containing different assets, as the correlation between the assets is low, and cryptocurrency gains a higher average return.

The empirical studies presented shows that there are positive prizes to momentum, and that there are diversification benefits to include cryptocurrencies in the traditional asset management. To our knowledge, the thesis by Osterrieder et al. (2017) is the only thesis investigating momentum within the cryptocurrency market. First of all, their thesis does not include Ethereum, which the second biggest cryptocurrency. Secondly, their thesis look at historical data until February, 2017, and thus does not look at the rapidly expanding period from April, 2017. Their thesis is limited to one exponentially moving avarage strategy. The thesis by (Trimborn, Li, & Härdle, 2017) is based on datasets that ends the 20th of March 2017. We want to expand upon this thesis by including several other cryptocurrencies and by expanding the time horizon to include the evolution so far this year. The studies generally look at historical data of Bitcoin and other cryptocurrencies, but not the implications and outlook on future prices. Our paper include a discussion of the alternative risk by including cryptocurrencies as an asset and the risk for extreme losses and potentially default.

5. Data

All data for cryptocurrency is collected from Coinmarketcap.com and was retrieved on September 30th, 2017. Coinmarketcap reports the volume weighted average of all the prices quoted on the different exchanges in the market. Datasets for traditional assets are collected from Yahoo Finance and Investing.com on September 30th, 2017.

We test our strategies on cryptocurrencies that have a minimum of two years of available price data. This restriction made several of the most significant coins ineligible, excluding them from this analysis. Of the top ten measured by market capitalization, seven were included. These cryptocurrencies are Bitcoin, Ethereum, Ripple, Litecoin, Dash, NEM, and Monero.

An alternative data selection is offered, where we define the portfolio to include the top seven cryptocurrencies measured in market capitalization at the beginning of our testing period. This alternative selection is made for comparison reasons. By doing this, NEM and Monero are substituted with Dogecoin and Bitshares, which are respectively ranked as number 36 and 25 today.

Market capitalization is one way to rank the relative size of a cryptocurrency. It is calculated by multiplying the price by the circulating supply, where the circulating supply is the number of coins that are currently in circulation in the market and can be obtained through trade.

For the traditional assets, we have retrieved data for the S&P500 index and CBOE 10-year interest rate treasury notes. For the more non-traditional hedging investment classes, we have chosen to include, Dow Jones REIT (Real estate Investment trust), futures on Brent Oil, Gold futures and ETF's on Pro Shares Global Listed Private Equity fund. We do this to analyze how cryptocurrency can be included in different portfolios with other assets, and observe if we can create diversification effects by doing this.

We specifically use the closing-price for all assets throughout this thesis. Cryptocurrency is traded at all hours throughout the day, every day, unlike the traditional asset classes. The term closing-price is in that regards futile for the cryptocurrency, but refers to the price recorded at midnight UTC. The only assets that trade on the same days are S&P500, T-notes, and the REITs. All the different classes close on various holidays. The quoted prices are all daily prices. When comparing cryptocurrency with other assets, we leave out the observations on weekends and holidays where the traditional assets are not traded. This is done to get the correct correlation between the assets.

We assume the quoted price is the mid-price, meaning the average of the bid and ask. Thus, our calculations do not directly consider the transaction cost from the bid/ask-spread. We discuss the implications of this prerequisite further under 7.2, transaction costs and returns.

The choice of data length is further commented upon in the explanation of the different strategies. To create a momentum trading signal today, one needs to calculate a signal looking backward at the price history. This requires our strategy to include a formation period to generate the signal, and this formation period is not included in the rest of the analysis.

Our observation period starts September 9th, 2015 and ends September 30th, 2017. Of the seven currencies, Ethereum has the fewest total observations. Therefore, after calculating our strategies with exponentially moving averages, September 9th, 2015, is the first day we can trade Ethereum. To include an equal amount of observations for the different currencies, we set this exact date as the start of our observation period.

5.1 Skewness and Kurtosis

The most known measurement of risk and return in financial theory, like Sharpe-ratio and volatility, is based on the distribution to be normally distributed. In cases where the return distribution deviates from a classic normal distribution, it is essential to analyze the implications of risk and return.

For distributions where the values of skewness and kurtosis deviate from the normal distribution, measurements like standard deviation will not represent the potential risk to the underlying asset. For the evaluation to give a more precise picture of the risk, we have to consider the size and frequency of extreme outcomes.

A normal distribution has per definition skewness = 0 and kurtosis = 3. Kurtosis is often standardized by subtracting three and gives us another alternative measure of kurtosis called “excess kurtosis,” which is what we use when referring to kurtosis in this thesis.

Skewness is a term in statistics used to describe asymmetry from the normal distribution in a set of statistical data (Investopedia LLC, 2017). It is often used to analyze the direction of extreme outcomes of the return distribution. Skewness is defined as the third aspect of the return distribution and indicates the frequency of the returns relative to the mean. The distribution can have a negative, positive, or normal skew.

A positive skewness indicates a right tail to the distribution. The interpretation of a positive skewness is that the frequency of returns larger than the average is higher than the frequency of returns below average. This implies that the possibility to achieve returns above average is higher than the possibility to achieve returns below average. A positive skewness for an investor implies that the possibility for extreme, positive values is larger than the normal distribution. If there is positive skewness, the mean is larger than the median as seen in Figure 3.

A negative skewness indicates a left tail to the distribution. The interpretation of a negative skewness, conversely to positive skewness, is that the frequency of returns below average is higher than the frequency of returns above average. This implies that the possibility to achieve returns below average is higher than the possibility to achieve returns above average. A negative skewness for an investor implies that the possibility for extremely negative outcomes is larger than the normal distribution. If there is negative skewness, the mean is lower than the median, as seen in Figure 3.

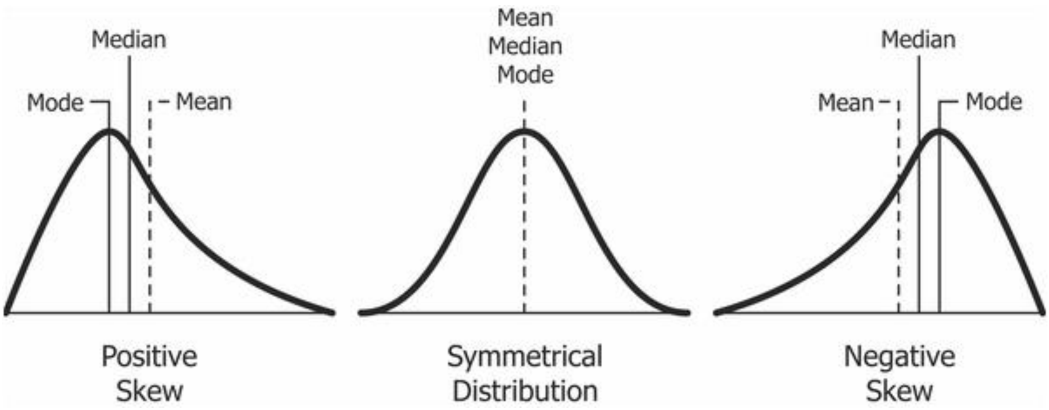

Figure 3: The coefficient of Skewness is a measure for the degree of symmetry in the variable distribution.

Source:https://www.safaribooksonline.com/library/view/clojure-for-data/9781784397180/ch01s13.html.

The formula for sample skewness, where n is the number of observations and S = σ_S is the standard deviation:

$$S = \frac{n}{(n-1)(n-2)} \frac{\sum_{i=1}^{n}(X_i - X_{avg})^3}{s^3}$$

Source: http://www.macroption.com/skewness-formula/

Kurtosis calculates the peak of the distribution, and is often referred to the volatility of "volatility." It is a measure of the combined weight of a distribution´s tails relative to the rest of the distribution (Investopedia LLC, 2017). Kurtosis signalizes where the volatility is centered and hence the possibility of extreme outcomes. Where skewness is the third moment of the distribution, kurtosis is the fourth.

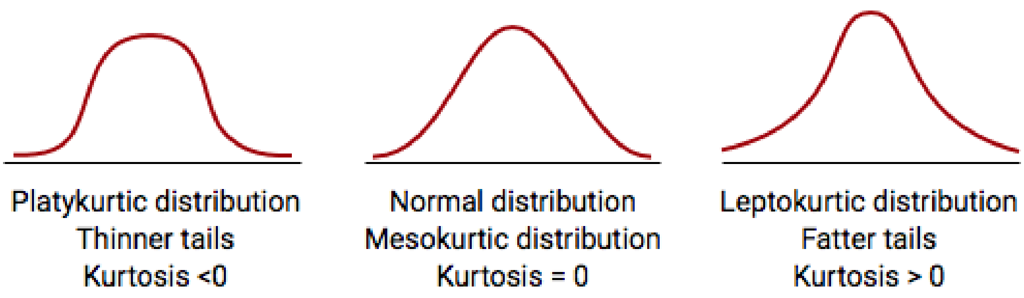

Figure 4: The different types of kurtosis.
Source: https://www.medcalc.org/manual/skewnesskurtosis.php

If a distribution has a positive kurtosis, the tail will be "fatter" compared to the normal distribution as seen in Figure 4. This means that changes in the observations are less frequent than in the normal distribution; thus, the observations are more centered around the mean, but there is a more significant possibility of extreme outcomes. A fat tail is therefore associated with a significant volatility.

If a distribution has a negative kurtosis, the tail will be "thinner" compared to the normal distribution as seen in Figure 4. This means that changes in the observations are more frequent than in the normal distribution; thus, the observations are more scattered around the mean, which implies that there is a smaller possibility of extreme outcomes.

Sample (excess) kurtosis formula:

$$K = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \frac{\sum_{i=1}^{n}(X_i - X_{avg})^4}{s^4} - \frac{3(n-1)^2}{(n-2)(n-3)}$$

Where n is the number of observations, and $S = \sigma$ is the standard deviation. The last part of the formula is where kurtosis is standardized to excess kurtosis by subtracting 3 as mentioned above.

If the distribution of a speculation theory is asymmetrical, the possibility of extreme outcomes is more significant compared to the normal distribution. Different investors have different preferences and risk aversion. A common assumption is that investors dislike negative skewness because it represents a larger possibility of an extremely negative outcome. A higher kurtosis will also signalize a larger possibility of extreme outcomes, which is assumed that investors dislike.

6. Method

All prices are quoted in USD to cryptocurrency, making the currency pair XXX/USD. Common for all strategies is to not utilize leveraging, meaning that this thesis does not consider cost of interest rate. Each approach has different criteria regarding buy and sell, but common for all is that they are normalized to 1 USD in T=0. The initial value of each portfolio equals the normalized amount invested, which means that net value per definition is 1 USD.

We assume that the risk-free investment alternative is represented by the ten-year t-notes issued by the Chicago Board Options Exchange (CBOE), which averages 2.06 % annually. We simplify this by using 2% annually. This is shown in Table A1 in the appendix.

6.1.1 Weights

Equally-weighted

Every portfolio from the different momentum-strategies is equally-weighted. We do this to simplify the comparison between the active and passive strategies. This weighting means, in short, that every currency included in the portfolio for each strategy contributes to an equal amount of the initial value. The interpretation is that an investor can expose a given amount (normalized to 1 USD) against the underlying strategy, equivalent to the investment in an index, which is the buy & hold in this thesis. The investor´s equity will always be dependent on the return of the portfolio to the underlying strategy. The investor`s equity balance will change in the following manner:

$EQ_t = EQ_0 * \{1 + \left\{\sum_{i=1}^{n} w_{i,t} * r_{i,t}\}\right\}$, where $\sum_{i=1}^{n} w_{i,t} * r_{i,t}\}\}$ is the cumulative return to the portfolio i in period t, where $w_{i,t}$ equals the weight for currency i, at time t. In an equally-weighted portfolio, the weight for each cryptocurrency will be: $w_{i,t} = \frac{1}{\sum_{i=1}^{n} n_i}$

The implications of the above mean that the total amount is allocated equally between the different currencies. $\sum_{i=1}^{n} n_i$ is the total number of currencies included in the portfolio. If we have, as in the momentum-strategies, 7 currencies included in the portfolio at all times, each currency will be weighted $\frac{1}{7}$.

Optimized weights

As a supplement to the equally-weighted portfolios, we have analyzed alternative constructions with buy and hold and traditional assets, that maximizes the Sharpe-ratio.
Sharpe ratio= (Return of the portfolio – risk-free rate) / The standard deviation of the portfolio.

$$= max \left\{ \frac{E[r_p] - r_f}{\sigma_p} \right\} \quad .$$

When maximizing the Sharpe-ratio of the portfolio, the different assets will contribute with dissimilar weights to the selected strategy.

Minimum-variance

On the other hand, an investor might be looking for the safest investment opportunity without focusing about the expected returns, and wants to minimize his total risk.

When minimizing the volatility of the portfolio, the different assets will contribute with different weights to the selected strategy.

6.1.2 Rebalancing

A simple investment strategy will be a strategy where an investor at a specific time, based on a set of evaluation criteria, takes a long position and holds this position. This is a buy and hold strategy. The problem with this kind of strategy is that it does not take into account new information available under the investment period, and which would have had an impact on the original position.

Rebalancing is an essential aspect of our evaluation of which cryptocurrencies are included in the portfolio for each of the momentum strategies. Based on the evaluation criteria for each strategy, daily rebalancing means that we continuously update the buy- and sell decisions according to new information. The position we take in a given day reflects the new information according to the evaluation criteria. The results of the different strategies will be measured and compared up against the passive buy and hold strategy. As Latif et al. (2017) finds, Bitcoin and Litecoin is inconsistent with the weak form of efficiency. By considering the high volatility, and increased amount of news regarding cryptocurrency, we want to frequently capture the price fluctuations. Therefore, we chose to rebalance daily, which is the most frequent observation we can observe from our dataset.

The challenges related to daily rebalancing is mainly connected to the liquidity in the cryptocurrency market. In periods of relatively high volatility, there can be problems with rebalancing the positions. If many investors close their positions at the same time, a possible implication will be higher transaction costs. In this thesis, we assume no rebalancing cost. Whether this is a realistic assumption will be evaluated further under 6.2 – Transaction costs and returns.

6.2 Time-series

The majority of the few empirical analyses connected to cryptocurrencies focus on both time-series and cross-sectional approaches. In this thesis, we concentrate on time-series only. If we had chosen a cross-sectional model, we would have had to buy and sell three coins by every rebalancing period, which means that we could buy (sell) coins with a sell (buy)-signal if the signal were among the highest (lowest). As presented earlier, the growth in this market has been enormous, and we assume that a cross-sectional approach to this market will be inefficient, because of the significant bull trend.

Since the market is relatively new, the possibility to short the cryptocurrencies is limited. To short a cryptocurrency, collateral in either Bitcoin or USD is needed. At the current state of the market, a time-series approach is more realistic, where we start with an amount normalized to 1 USD and always buy or sell $\frac{1}{7}$ of every cryptocurrency. This means that the portfolio will be 100% equity-financed.

The fundamental aspect of the time-series model is a rating of the different cryptocurrencies against each other, based on the historical return over a given period. When the signals are unveiled, we buy the currencies with positive signals and sell the currencies with negative signals. Our approach constructs the portfolio with all seven coins, which means that by every rebalancing period, we identify the signals for every coin and either buy or sell each coin based on the generated signal. If the signal at one point is zero, we buy this coin.

In our time-series model, the buy- and sell signals for a specific cryptocurrency are therefore independent of the other currencies` price change over the same period. As the portfolio is equally-weighed, we always buy or sell each currency every day. Selling different currencies means that we will have the amount in USD as collateral.

6.2.1 Momentum strategies

A momentum strategy is based on short-term trends in price changes for a specific coin. One of the reasons why trends exist is because of the investor's sentiment, or behavioral bias, and is an indication of non-rational behavior based on an expectation of future change in price.

The momentum strategy is based on revealing and signaling shifts in price trends for the different cryptocurrencies. In this thesis, all cryptocurrencies are bilateral and quoted in USD per unit crypto, at the form XXX/USD.

Momentum strategies in the cryptocurrency market is untried waters, and the empirical results are limited. This means that there is no insight into what the optimal momentum strategy could be. As mentioned (Osterrieder, Rorhbach, & Suremann, 2017) create a momentum strategy based on an avarage of three EWMA-differences. Because of the limited empirical results, we decide to create a few different simple strategies, instead of one technical strategy. The strategies we create are; one strategy based on a percentage difference in the exponential moving avarage, called the Percentage Price Oscillator (PPO), and three different filter strategies created from the avarage return over three different time windows. The chosen strategies will be explained in the following subchapters.

Strategies created by techincal oscillator like the Relative Strenght Index, Stochastic indicator or Money Flow Index discovers oversold and overbought areas. These are interesting indicators, but based on the historical returns, we know that the market has had extreme price growth. This price growth would, in these strategies, give many signals indicating overbought areas which in turn signals a short position. We assume this would lead to very negative results, and we do not include them in our thesis.

Percentage Price Oscillator (PPO)

In this strategy, we use an exponential moving average (EMA) over two time-intervals to identify the trends in the different cryptocurrencies. The PPO is the percentage difference between the intervals. Compared to an ordinary moving average strategy, this difference as a percentage allows us to compare cryptocurrencies to each other more easily.

The formula for the PPO strategy is:

$$PPO = \frac{12\ day\ EMA - 26\ day\ EMA}{26\ day\ EMA}$$

The interpretation of this is that we buy a currency if the shorter moving average is above the longer moving average, which reflects a convincing upwards momentum. This is shown as EMWA(m,n) $\geq$ 0. If the shorter moving average is below the longer moving average, we believe in a downwards momentum and sell the coin, shown as EMWA(m,n) < 0.

In our PPO strategy, we focus on 12-day and 26-day EMAs, which are the most commonly used values for short-term averages. A trader can use several different combinations where the parameters can be adjusted to higher or lower the sensitivity.

Filter strategies

The filter rule strategy is the simplest of the momentum strategies examined in this thesis. This strategy relies on buying winners and selling losers based on their average return over a given formation period t. The strategy is an equal-weighted strategy where every day, we rebalance and place a trade, either long or short, depending on the signal generated by the average return over period T-t. This position is held until we have a new signal to trade upon, which is the following day at the same time. If the signal at t=0 equals the signal of the previous period, we will technically rebalance to create the same portfolio. In practice, this will be the same as holding the very same portfolio and not rebalancing.

The formula for the filter strategy is:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$$

Where $\bar{x}$ is the average, x_i is the observation and n is the number of observations.
We can observe the performance of the different filters and compare these against each other over the observation period. There are several different filters we could include in this strategy which would have given different results, but we have chosen three different filters. One day, one week, and one month. The performance and comparison of the different filters can be seen in Table XXXX under results.

7. Results and evaluation

It has been observed several times that impactful news, such as regulations and bans on cryptocurrency services, affects the cryptocurrency market. It is also natural to assume that coin specific factors will drive the price in the long run. An investment in a coin is exposure to the qualities and factors behind the development of the coin, as well as exposure to the cryptocurrency market. Some of the unique qualities could be underlying technology, the market sentiment, and the development team behind the cryptocurrency.

	BTC	*ETH*	*XRP*	*LTC*	*DASH*	*XEM*	*XMR*	*DOGE*	*BTS*
BTC	1								
ETH	0.2614***	1							
XRP	0.1603***	0.0576	1						
LTC	0.5077***	0.1676***	0.2081***	1					
DASH	0.3674***	0.2392***	0.0182	0.244***	1				
XEM	0.341***	0.1405***	0.098***	0.2231***	0.214***	1			
XMR	0.332***	0.2391***	0.101***	0.2383***	0.2916***	0.1582***	1		
DOGE	0.3974***	0.241***	0.3713***	0.4085***	0.2167***	0.2548***	0.1895***	1	
BTS	0.3045***	0.2764***	0.3661***	0.2822***	0.1987***	0.2448***	0.1763***	0.4649***	1

Table 4: Correlation matrix. Significant at the 0.1-level (*), Significant at the 0.05-level (**), Significant at the 0.01-level (***).

The correlation for all currency pairs is below one and significant, except for XRP/ETH and XRP/DASH, as seen in Table 4. This means that we can benefit by combining several cryptocurrencies to a portfolio. The portfolio creation will reduce the exposure to idiosyncratic risk, and according to simple diversification theory, improve the risk-adjusted returns. The most commonly used risk-adjusted measure is the Sharpe Ratio, which has become an industry standard and will be used throughout this thesis. The Sharpe Ratio assumes normally distributed returns and might be misleading otherwise, which will be evaluated under 7.

Our buy and hold-portfolio include the same cryptocurrencies as our active momentum portfolios. The active strategies create a trading signal based on shifts in momentum. When we examine the return from the momentum portfolios, we expect that excess return, compared to the buy and hold strategy, is caused by successfully identifying the momentum shifts, which creates the trading signal to take a favorable long or short position.

It is evident from our analysis that cryptocurrencies are highly volatile. Even compared to the volatility of stocks during the financial crisis of 2008, the volatility of cryptocurrency is enormous. Equity and fiat currency volatility only reached volatilities in the 60-70% range over short periods during the peak of the crisis (Schwert, 2010). From Figure 5, we can observe from the 30-day rolling volatility, that there are periods where the cryptocurrencies exhibit substantially higher volatility than 60-70%.

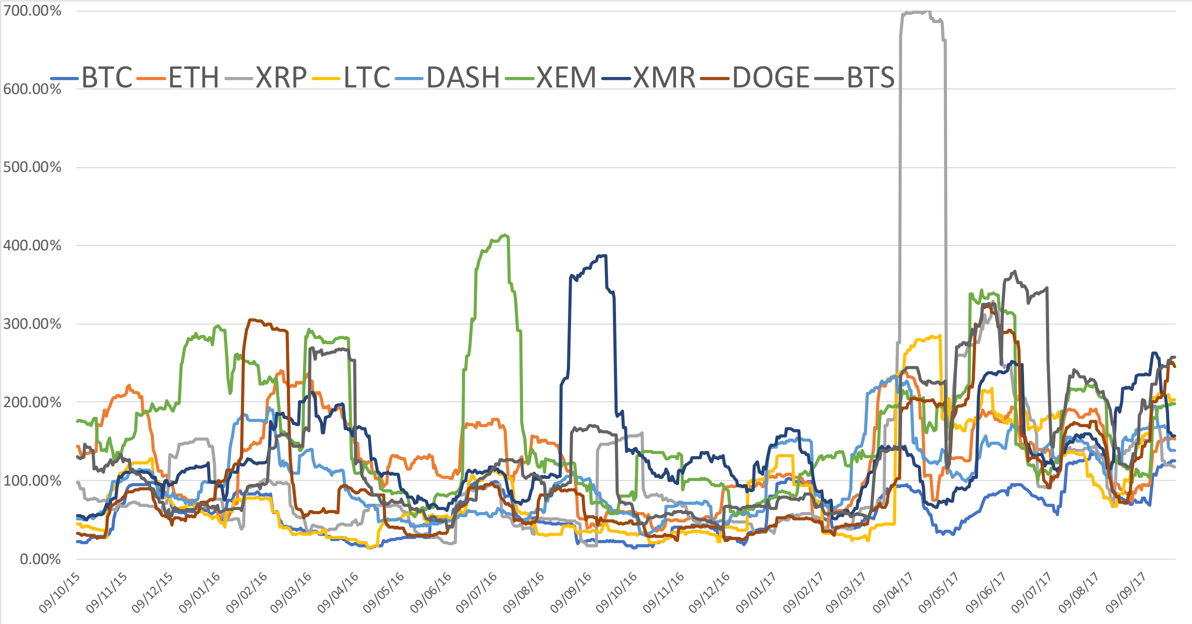

Figure 5: 30-day rolling volatility of the included cryptocurrencies over our investment horizon from September 9th, 2015 to September 30th, 2017.

7.1 Buy and hold

The conservative buy and hold-portfolio buy an equally weighted portfolio where the investor invests a normalized amount of $1 spread across the seven included cryptocurrencies. The investor buys at time zero and holds without rebalancing the portfolio. The investor also holds without rebalancing in the event of price movements. This strategy is entirely passive and will become our benchmark for determining whether our active strategies gives better return based on trading signals generated from our technical momentum indicators. All strategies include all seven cryptocurrencies over the whole investment horizon. The return generated by the buy and hold strategy is caused by the exposure to long-term trends in the cryptocurrency market.

	Return	Std.dev	Sharpe	Skewness	Kurtosis
BTC	835.66%	67.17%	12.41	0.098	6.67
ETH	12044.05%	140.75%	85.55	0.843	3.5
XRP	1200.16%	179.67%	6.67	10	177.418
LTC	868.02%	109.84%	7.88	2.963	30.051
DASH	6459.03%	114.50%	56.39	1.527	7.539
XEM	126774.94%	189.57%	668.74	2.293	12.075
XMR	9136.89%	152.96%	59.72	2.716	19.058
Portfolio	22474.11%	76.28%	294.61	0.409	5.29

Table 5: Average yearly return, average yearly standard deviation, Sharpe ratio, Skewness and Kurtosis of the ***buy-and-hold portfolio*** *in the period of September 9th, 2015 to September 30th, 2017.*

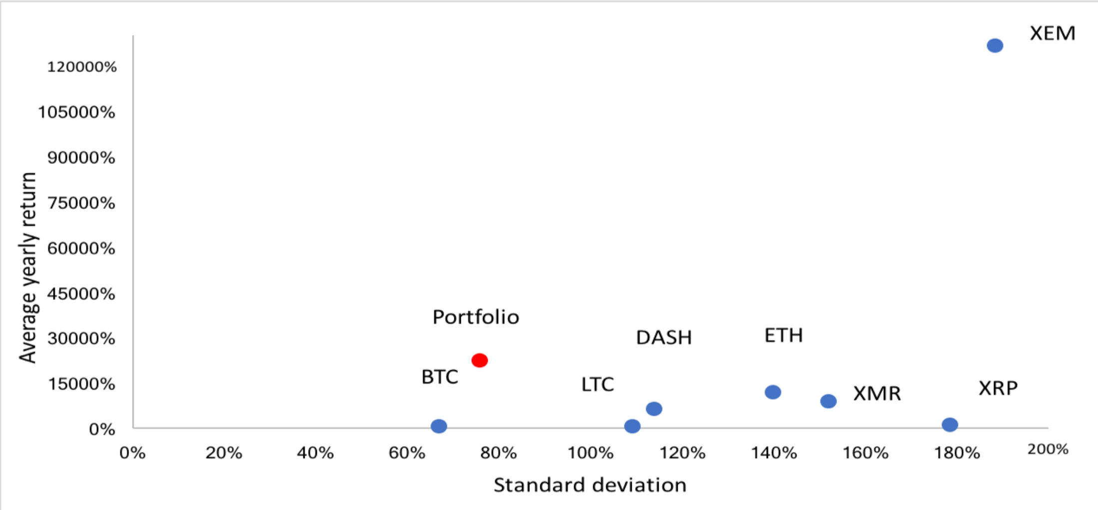

Figure 6: An illustration of the average yearly return in relation to the yearly standard deviation of the individual cryptocurrencies, and the buy-and-hold portfolio over the period of September 9th, 2015 to September 30th, 2017.

As we can see from Table 5 and Figure 6, the buy and hold portfolio gains an annualized return of 22,474.11%, and a Sharpe ratio of 294.61, which reflects the strong upwards trend in the cryptocurrency market over the observation period. All included cryptocurrencies yield a positive return, where XEM drives a lot of the portfolio's performance with an annualized return of 126,774.94%. XRP exhibits a higher return than both BTC and LTC but has a lower Sharpe ratio due to the volatility. The standard deviation depicts the high volatility connected to the different cryptocurrencies included in our thesis. All cryptocurrencies, except BTC, has a standard deviation of a 100%. From Figure 6, we see that by combining the coins in an equally-weighted portfolio, we gain a diversification effect in the form of reduced volatility.

This effect depends on the correlation between the cryptocurrencies and will vary over time, illustrated in the rolling correlation with traditional assets in 6.4.

This strategy performs no active trades over the investment horizon. No active trades mean that trading fees, currency risk and other transaction fees like the cost of the bid/ask-spread are avoided. This cost is minimal in the active strategies but non-existent in this very approach. The presence of transaction costs is something we will elaborate further on in the evaluation. With the buy and hold-strategy, one does not consider new information. Information such as shifting price trends or impactful news is not considered. Rebalancing could potentially result in higher returns if the timing is correct, which is the goal of our active strategies.

Our alternative selection of the included cryptocurrencies for the buy-and-hold portfolio might give an extra insight. This selection removes two cryptocurrencies that have had phenomenal growth over the past two years, namely XEM and XMR. They are replaced with the two cryptocurrencies DOGE and BTS. This alternative selection is made for comparison reasons and because they fit our selection criteria at the start of our data period. Our other portfolios are based on the biggest currencies today and might be suffering from a selection bias. The data selection is satisfactory when we look at the passive vs. active trading aspect, but when expecting past returns will reflect future expected returns, we expect this not to be representative of the cryptocurrency population. This alternative selection might be a more representative selection when assessing the expected future return.

	Return	Std.dev	Sharpe
BTC	824%	67%	12.241
ETH	11879%	141%	84.382
XRP	1184%	180%	6.577
LTC	856%	110%	7.776
DASH	6371%	115%	55.620
DOGE	374%	130%	2.858
BTS	868%	163%	5.328
Portfolio	3194%	79%	40.345

Table 6: Average yearly return, average yearly standard deviation, Sharpe ratio, Skewness and Kurtosis of the ***alternative buy-and-hold portfolio****, in the period of September 9th, 2015 to September 30th, 2017.*

Table 6 shows that we get a drastically lower return compared to the other buy and hold portfolio, but we still have excess return compared to traditional assets over the holding period. We achieve a 3,194% yearly average return with a standard deviation of 79%.

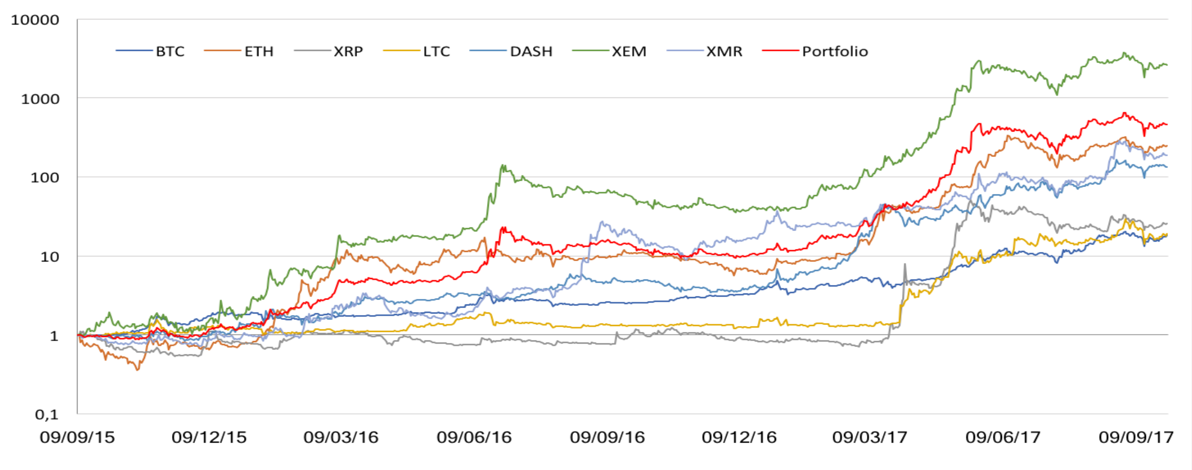

Figure 7: Log scale of the cumulative returns for every cryptocurrency, and of the portfolio over the observation period.

Figure 7 is a log scale of the cumulative returns, and consists of buy and hold indexes for every cryptocurrency, and the equally-weighted portfolio. This cumulative return shows an investor´s account balance at a given time, when passively investing.

7.2 Filter Strategy

As mentioned under 5.3.1, we create the trading signal based on the average return over the formation period. The difference in formation periods between the three filter strategies is the number of days included in the calculation of the average. We create the strategies based on averages over one day, one week and one month.

	Return	St.dev	Sharpe	Skewness	Kurtosis
BTC	-7.98%	67.71%	-0.147	-0.187	6.517
ETH	64.27%	141.85%	0.439	0.477	3.739
XRP	1068.40%	179.69%	5.935	9.916	177.426
LTC	113.36%	110.17%	1.011	2.802	30.194
DASH	-37.14%	115.58%	-0.339	-0.176	8.073
XEM	-46.35%	191.69%	-0.252	1.109	12.851
XMR	-16.19%	154.05%	-0.118	2.015	19.583
Portfolio	162.62%	66.96%	2.399	1.105	11.376

*Table 7: Average yearly return, average yearly standard deviation, the Sharpe-ratio, Skewness, and Kurtosis of the of the **one-day filter portfolio** in the period of September 9th, 2015 to September 30th, 2017.*

We observe from Table 7 that the one-day filter portfolio gives an annualized return of 162.62% and a Sharpe-ratio of 2.399. The individual performance of each currency pair in this strategy is variable, where four of the seven cryptocurrencies, give a negative return. The standard deviation is similar compared to the buy-and-hold strategy, but the Sharpe-ratios are significantly lower due to lower returns.

In the different filter-strategies, the number and timing of long and short positions vary. This gives a different contribution towards the portfolio's returns. From Table A2 in the appendix, the number of long and short positions is summarized for every cryptocurrency. In the one-day filter portfolio, 48.80% of the total trades are short positions. Over the included time frame there has been a steady upward trend. If the momentum signals are accurate, we should benefit by being long in the upwards trend, but also benefit from our short positions. In the one-day filter strategy, XRP is the cryptocurrency which contributes the most to the return of this portfolio with a return of 1068.40%. 56% of the total trades on XRP are short positions. The total average of short positions in this strategy is 49%.

Currency	Return	Std.dev	Sharpe	Skewness	Kurtosis
BTC	58.72 %	67.64 %	0.839	-0.193	6.574
ETH	3,878.17 %	141.10 %	27.472	0.512	3.683
XRP	1,657.96 %	179.60 %	9.220	9.831	177.573
LTC	51.83 %	110.23 %	0.452	3.444	30.145
DASH	259.77 %	115.30 %	2.236	1.294	7.789
XEM	1,205.87 %	190.93 %	6.305	1.928	12.385
XMR	292.26 %	153.76 %	1.888	2.600	19.266
Portfolio	1,057.80 %	67.60 %	15.617	0.894	11.177

*Table 8: Average yearly return, average yearly standard deviation, Sharpe-ratio, Skewness, and Kurtosis of the **one-week filter portfolio** in the period of September 9th, 2015 to September 30th, 2017.*

We observe that the one-week filter portfolio gives an annualized return of 1057.80%, and a Sharpe-ratio of 15.617. Compared to the one-day filter portfolio, the returns are significantly higher in this filter-strategy. Due to similar volatility, the Sharpe-ratios are therefore also higher. All cryptocurrencies included in this strategy give a positive return, with ETH contributing the most with an annualized return of 3878.17%. At the same time, the annualized return is significantly lower compared to the buy and hold portfolio, meaning we are better off holding the equally weighted passive long position.

As with the one-day filter strategy, the contribution of XRP is greater in the active portfolio than in the passive portfolio. All other cryptocurrencies perform worse when compared to the passive portfolio. From Table A2 in the appendix, we see that XRP is shorted 55.32% of the investment period in this strategy. Total amount of short positions for the overall strategy is for comparison 43.18%

	Return	St.dev	Sharpe	Skewness	Kurtosis
BTC	156.78%	67.54%	2.292	-0.580	6.745
ETH	1693.01%	141.32%	11.966	0.554	3.671
XRP	194.52%	179.94%	1.070	9.699	177.291
LTC	65.19%	110.21%	0.573	2.792	30.237
DASH	297.70%	115.27%	2.565	1.281	7.786
XEM	57.14%	191.38%	0.288	1.873	12.526
XMR	1658.63%	153.42%	10.798	2.594	19.164
Portfolio	589.00%	66.37%	8.845	0.296	5.968

Table 9: Average yearly return, average yearly standard deviation, Sharpe ratio, Skewness and Kurtosis of the ***one-month filter portfolio****, over the period of September 9th, 2015 to September 30th, 2017.*

The one-month filter strategy averages an annualized return of 589.00%, which is a higher return than the one-day filter portfolio, but a lower return than the one-week filter portfolio. All included cryptocurrencies have a positive return in this strategy. BTC and LTC perform better in the one-month filter strategy than in the two filter strategies, giving a higher Sharpe ratio. ETH and XMR are the coins with the highest annualized return in this strategy. XRP is shorted 51% of the trades, as seen in Table A2 in the appendix. This is similar statistics to the other filter strategies, but in this filter strategy, it does not perform as well, with an annualized return of 194.52%.

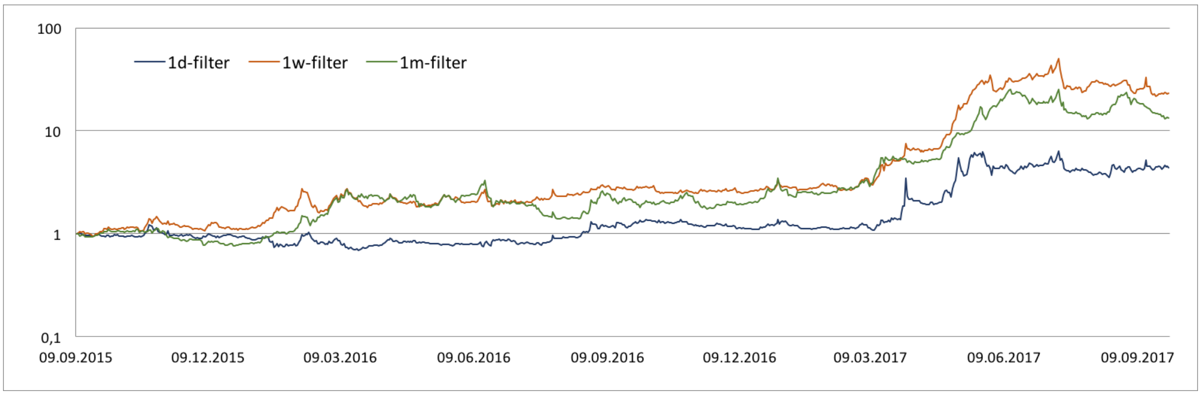

Figure 8: Plots the log scale of cumulative return of the three filter strategies over the period September 9th, 2015 to September 30th, 2017.

As we observe in Figure 8, the one-week filter strategy is superior to the two other filter strategies. Because of this, we chose to focus on aspects of the return distribution for this portfolio, and not evaluate the results of the other two filter strategies.

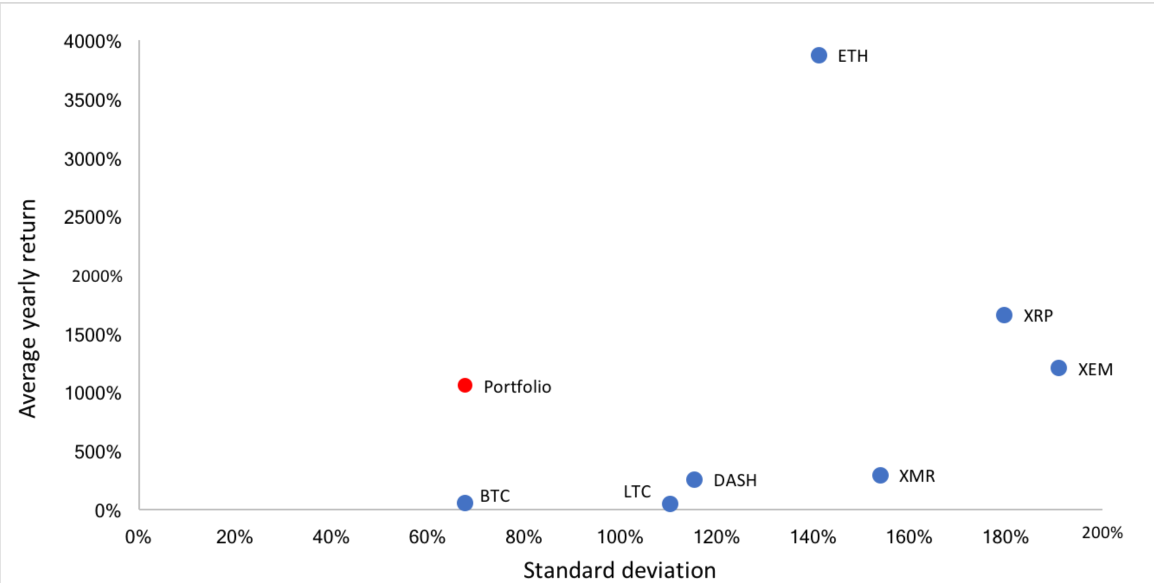

Figure 9: The standard deviation and the annualized return of the cryptocurrencies and the ***one-week filter portfolio*** *marked red, over the period from September 9th, 2015 to September 30th, 2017.*

From Figure 9, we can observe the diversification benefits by combining the currencies into the portfolio, where the volatility of the portfolio is 67.60%. Combined with an annualized return of 1,057.80%, this results in a Sharpe-ratio of 15.617.

The return distribution contains essential information about the risk of the investment not directly shown in the risk-metric that is the standard deviation. When assessing the return distribution, it is interesting to look at the kurtosis and skewness of the return distribution of the portfolio and compare this to the properties of the individual currencies.

The skewness for the 1-week portfolio is 0.894, as shown in Table 9, which is moderately skewed according to (Bulmer, 1979)'s rule of thumb. This number is lower than most of the individual coins except for BTC and ETH, which have a skewness of -0.193 and 0.512 respectively. The corresponding kurtosis is 11.177 which is higher than BTC, ETH, and DASH, but smaller than LTC, XEM, XMR and significantly lower than XRP that has a kurtosis of 177.573. The fact that the portfolio has positive skewness means there is a higher than average probability of achieving positive returns.

The kurtosis and skewness of the portfolio are both lower than the average skewness and kurtosis of all the individual cryptocurrencies. The fact that the skewness and kurtosis is lower than average means the distribution of returns has thinner tails and indicates that the probability of extreme returns is lowered in the portfolio.

Lower skewness in conjunction with kurtosis indicates that we will have less extremely negative returns, but that we also lose some of the incredibly positive returns compared to each currency. At the same time, both skewness and kurtosis are positive. Thus the possibility of achieving returns higher than average is greater than achieving returns lower than average. The latter can be seen through the low return from the currency NEM(XEM) which is the primary driver in the buy-and-hold strategy and might explain much of the lower return.

Considering the risk of such markets, we calculate the drawdown which is the percentage between the peak and the subsequent trough (Investopedia LLC, 2017). We elaborate on the presence downside risk in the evaluation in 7.1.

From Table 15 in the discussion, we see that the drawdown of the portfolio is lower (relative value, closer to 0) than the drawdown for all currencies, except DASH, which is 6% lower. This implies that the drawdown of the portfolio is lower than the average drawdown for the currencies.

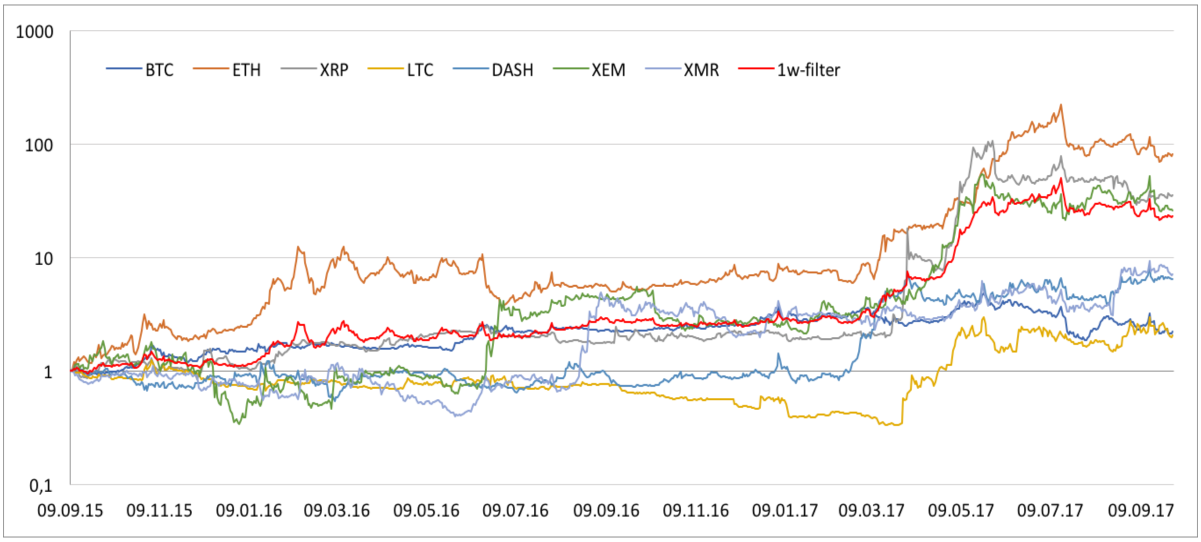

Figure 10: The log scale return of the included currencies in the one-week filter strategy over the period September 9th, 2015 to September 30th, 2017.

We observe that the performance of the 1-week momentum strategy is time-varying. The fact that performances of momentum-strategies vary over time is not surprising. It is natural that, over time, it will be impossible for a specific window to catch all effects of all the factors which influence currency movements. In the period from July 2016 to February 2017, we can observe a relatively small return, before it picks up and increases from March 2017. This can also indicate that the currencies trends in some periods, but follow a random walk-process in other periods.

To summarize our results, we see that our filter strategies do not generate an excess return over the observation period compared to the passive portfolio. Each cryptocurrency performed better in the passive portfolio, except for XRP, which performed better only in the one-week filter strategy. When comparing the different filter strategies, we see that the one-week filter strategy performs best, dominating the other filter strategies. We have based our strategies on daily rebalancing and testing on daily close prices. Implications of this will be evaluated in chapter 7.

7.3 Percentage Price Oscillator (PPO)

The other active strategy we have created is the Percentage Price Oscillator. This is based on the exponential moving average difference. This means we go long when the two differences cross and stay long whenever this difference is positive, and we go short when the difference crosses down and is negative.

	Return	St.dev	Sharpe	Skewness	Kurtosis
BTC	154%	67.54%	2.244	-0.898	6.836
ETH	690%	141.32%	4.872	0.421	3.729
XRP	628%	179.94%	3.479	9.622	177.424
LTC	122%	110.21%	1.086	2.773	30.195
DASH	535%	115.27%	4.625	1.287	7.754
XEM	6557%	191.38%	34.251	1.976	12.308
XMR	785%	153.42%	5.101	2.451	19.250
Portfolio	1352.95%	66.98%	20.170	0.271	8.241

Table 10: Average yearly return, average yearly standard deviation, Sharpe ratio, Skewness and Kurtosis of the ***PPO-portfolio*** *in the period of September 9th, 2015 to September 30th, 2017.*

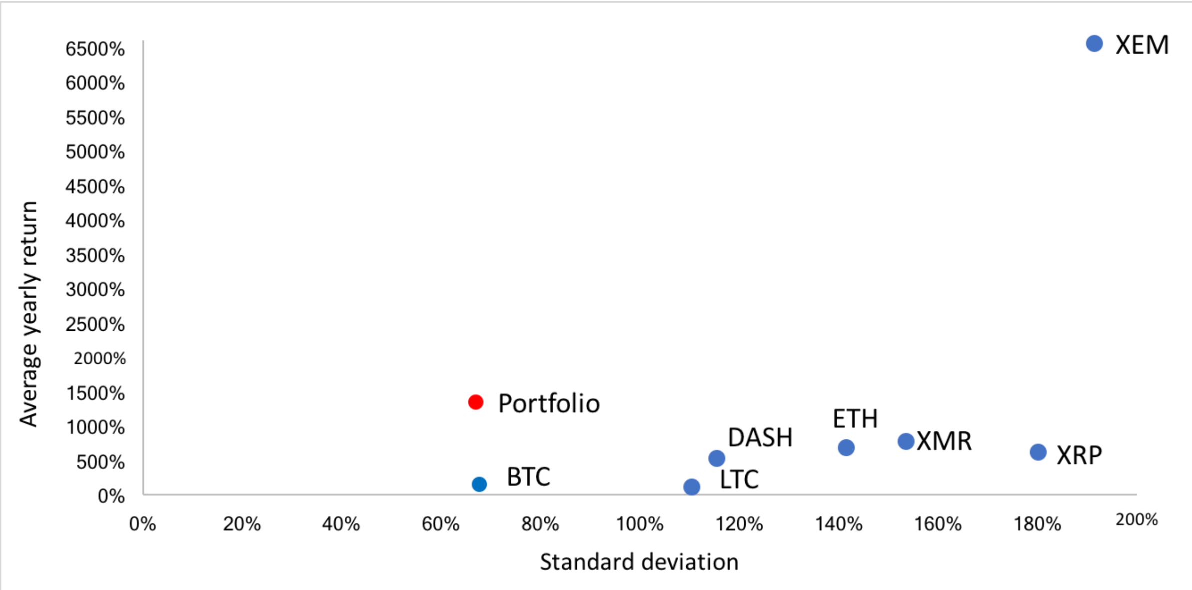

Figure 11 Risk and return for the different currencies (XXX/USD) over the observation period.

As we can see from Table 10, the PPO strategy gives an annualized average return of 1,352.95% and a Sharpe ratio of 20.17. All the included coins yield a positive return. Some of the currencies perform better than others, where XEM is an outstanding example with an annualized return of 6,557% and a Sharpe ratio of 34.251 over the observation period.

Looking at the distribution of returns can reveal information about a potential crash-risk and extreme outcomes. It will be interesting to observe if the portfolio also diversifies away some of this skewness and kurtosis as the individual cryptocurrencies have.

The skewness of the portfolio, seen in Table 10, is lower than six of the seven currencies. BTC has a skewness of -0.898 and is the only coin with negative skewness. At the same time, the kurtosis value of 8.241 is higher than three coins and lower than four. The skewness of the portfolio is thereby lower than the average skewness among the currencies, and the kurtosis is lower than the average currency, where XRP (177.424) has a significant effect on this average. This implies that the currencies drag the portfolio in the direction of lower frequency of extremely positive returns than looking at the currencies isolated.

The kurtosis indicates that the possibility of extreme outcomes is lower than the currencies isolated. A positive kurtosis combined with a positive skewness implies that there is a higher possibility of extreme positive outcomes than extreme negative outcomes. Watching the drawdown values in Table 15 in the discussion, we see that an equally-weighted portfolio generates a slightly higher (relative number, further from 0) drawdown than the average, which is -68.89%. Here we observe that the drawdown of the portfolio is higher than for BTC, LTC, and DASH, and lower than for ETH, XRP, XEM, and XMR.

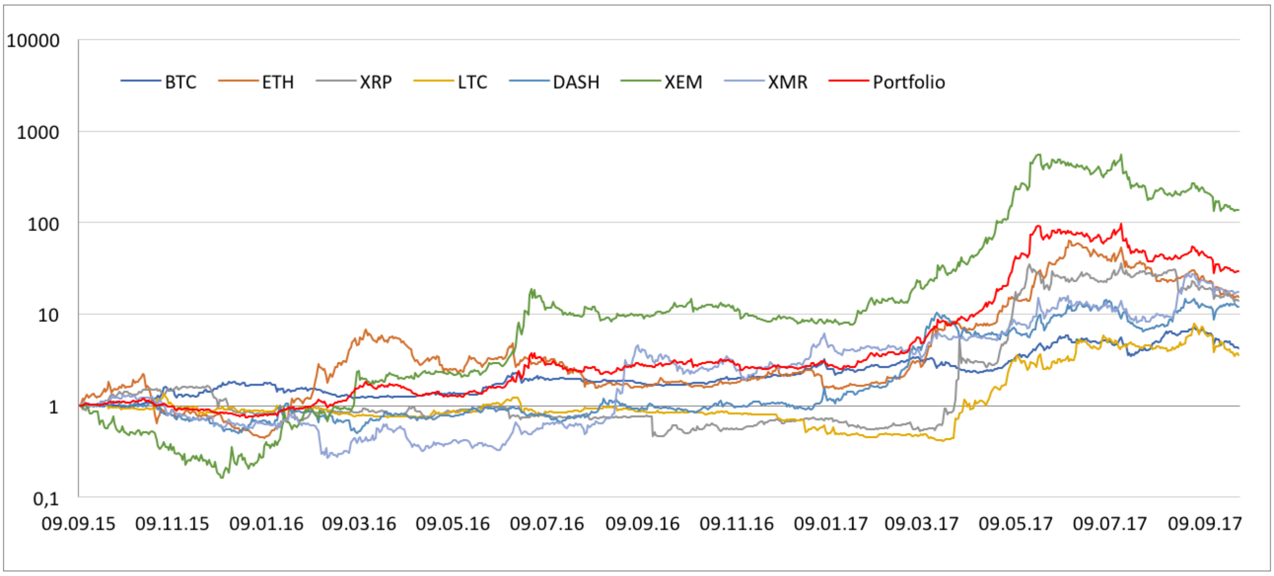

Figure 12: Log scale of the cumulative returns generated by the PPO strategy from September 9th, 2015 to September 30th, 2017.

As in the other strategies, we observe in Figure 12 that the performance of the currencies is time-varying. It is natural that, over time, it will be impossible for a specific window to catch all effects of all the factors which influence the currency movements. This can also indicate that the currencies trends in some periods, but act accordingly to a random walk-process in other periods.

7.4 Portfolio optimization combining cryptocurrency and traditional assets

As a supplement to the decision between active versus passive trading strategies, we investigate if there are positive benefits to include cryptocurrencies to a more traditional portfolio. Cryptocurrencies trade the entire day, every day throughout the whole year unlike the other asset classes included. The only assets that trade on the same days are S&P500, T-notes and the REITs. All the different classes close on various holidays. To get the correct correlations, we look at the trading days where all assets trade at the same time. Because this is an extension to the buy-and-hold portfolio, the returns are holding period returns, calculated as the yearly average. The creation of the optimized portfolios is based on a correlation matrix where the relationship is between the days all the assets have open markets. There will be price changes in the cryptocurrencies in days where the regular markets are closed. The result of this is that our findings on the optimal portfolio will be slightly inaccurate, but it still gives insight into what allocation the cryptocurrencies would have in this regard.

	BTC	ETH	XRP	LTC	DASH	XEM	XMR	DOGE	BTS	Buy/hold
S&P500	-0.033	0.038	0.024	-0.028	0.0783*	-0.046	0.047	0.019	0.062	0.017
T-Bonds	-0.021	-0.040	0.000	0.012	0.050	-0.063	0.014	-0.037	0.003	-0.020
REIT	-0.019	-0.029	0.011	-0.016	0.004	-0.010	0.067	0.051	0.058	0.004
Oil	-0.043	0.004	-0.0724*	0.013	-0.0832*	-0.013	-0.026	-0.057	-0.040	-0.049
Gold	0.040	0.038	0.005	-0.046	-0.060	0.000	0.029	0.057	-0.029	0.002
P/E	-0.064	-0.061	0.016	-0.005	-0.001	-0.1716***	0.016	-0.003	-0.037	-0.0769*

Table 11: Summary of the correlations between the seven included cryptocurrencies and the equal-weighted buy and hold portfolio with traditional asset classes. Six conventional asset classes are included; S&P500, T-bonds, REITs, Oil, Gold and Private Equity. The sample

consists of the period from September 9th, 2015 to September 30th, 2017, where some trading days are removed.

From Table 11, we can see that the correlations between the traditional financial assets and the cryptocurrencies are low, and some are negative. The correlations are not significant, and as shown in Figure 13, time-varying. The problems with significance could make inference from these findings valid. We still choose to look at the results from combining cryptocurrencies and traditional assets. Correlations different from one improves upon the assumption that including a portion of cryptocurrency in an investor's portfolio will enhance the risk-adjusted return. We expand upon our simple buy and hold portfolio to find the optimal portfolio by comparing cryptocurrencies with traditional asset classes over the holding period from September 9th, 2015 to September 30th, 2017. The portfolios presented first are restricted not to include short-selling of any of the assets, and we will include short-selling in the next portfolio creation.

	Optimal portfolio	Optimal portfolio no crypto	Optimal constrained portfolio (1)	*Optimal constrained portfolio (2)*
Weight crypto	0.7087	0.00	0.0700	0.1601
Returns	15928.79%	12.27%	1582.42%	3604.15%
Standard dev	55.29%	9.83%	9.83%	14.43%
Sharpe	288.05	1.04	160.72	249.65

Table 12: Shows the weights of the cryptocurrency, the yearly average holding period returns, yearly standard deviation and Sharpe ratio for the optimized portfolio over the observation period. The constrained portfolio number (1) is constrained to have the same standard deviation as the optimal portfolio with no crypto. Optimal constrained portfolio (2) is constrained to have the same standard deviation as S&P500.

When running a variance-covariance portfolio optimization, as seen in Table 12, with traditional assets and cryptocurrency we see that the weights shift in favor of the equally-weighted cryptocurrency portfolio, but we get positive diversification effects. The diversification effects are mainly from Private Equity and Gold, but also from Bonds and Real Estate. S&P and Oil are dominated by other asset classes and are not included in the final portfolio.

The optimal portfolio restricted to exclude cryptocurrencies, gives a yearly average return of 12.27% and consist mainly of S&P500 (63%), Gold (29%) and REITs (8%). The portfolios can be seen in Tables A3-A7 in the appendix. In the optimal constrained portfolio (1), we restrict the portfolio to have the same yearly standard deviation, so to be equal to that of the optimal portfolio without cryptocurrencies. This restriction is done to directly see how that could affect the results regarding risk-adjusted return through the diversification effects. The average holding period return for the cryptocurrency portfolio is very high, and by weighing in 7.39% of cryptocurrency we obtain the same volatility as before, but tremendously increase our return. The portfolios average yearly return is increased from 12.27% to 1,582.42%. Conversely, if we keep the weights and standard deviation equal, and instead calculate the same return with the data from the alternative cryptocurrency selection, where DOGE and BTS are included in place of XEM and XMR, we get an increase from 12.27% return to 232.07% for the same standard deviation.

The second constrained portfolio is constrained to have the same standard deviation as stocks, which in our thesis is reflected in the S&P500 index. The yearly average return of the S&P500-index over the observation period is 14.43%. The portfolio we create that replicates the same level of standard deviation gives a yearly return of 3,604.15% return. Conversely, with the alternative cryptocurrency selection, with the same weights, the return would have been 518.18%. The benefits of including a portion of cryptocurrencies in a traditional portfolio are apparent, through the increase in yearly return and Sharpe Ratio. The total risk of doing so is evaluated further in 7.1.

	Optimal portfolio	Optimal portfolio no crypto	Optimal constrained portfolio (1)	*Optimal constrained portfolio (2)*
Weight crypto	0.7939	0.00	0.0739	0.1628
Returns	17838.25%	16.53%	1669.83%	3665.23%
Standard dev	61.62%	12.24%	9.83%	14.43%
Sharpe	289.44	1.19	169.60	253.88

Table 13: Weights of cryptocurrency, yearly average holding period returns, yearly standard deviation and Sharpe ratio for optimized portfolios with allowing short-selling, over our observation period. The constrained portfolio number (1) is constrained to have the same standard deviation as the optimal portfolio with no crypto. Optimal constrained portfolio (2) is constrained to have the same standard deviation as S&P500.

By including the possibility to short-sell any of the assets in this portfolio we see that the optimal allocation will change slightly, to generally include more cryptocurrency, which has the highest Sharpe ratio. The full allocation can be seen in Table A3-A7 in the appendix. The results are that we short-sell S&P500 and Oil to get an increased weight in the other asset classes that are dominating. This is mainly P/E and Gold, but also some in cryptocurrency, REITs, and T-notes.

The cryptocurrencies are highly volatile and carry high risk. In Table 14, we investigate a minimum variance portfolio showing which combination of assets that will return the lowest standard deviation. This is the least risky portfolio measured in standard deviation. We look at the idiosyncratic risk connected to the included cryptocurrencies and systematic risk connected to the cryptocurrency market, that might change the intuition to these findings.

	Weight	Returns	Standard dev	Sharpe
buy hold	0.01	22474.11%	78.33%	286.87
S&P500	0.30	14.43%	13.80%	0.90
T-bonds	0.08	2.92%	40.56%	0.02
REITs	0.11	13.88%	17.04%	0.70
Oil	0.00	7.86%	44.65%	0.13
Gold	0.43	7.12%	16.48%	0.31
Private EQ	0.07	1.52%	19.75%	-0.02
Portfolio	1	332.19%	8.81%	37.47

Table 14: Weights, average yearly holding period returns, yearly standard deviation and Sharpe ratio for the minimum variance portfolio. Data from September 9th, 2015 to September 30th, 2017.

From Table 14, we can see that by minimizing our standard deviation we only include 1% of the cryptocurrency portfolio, but the portfolio still returns 332.19% yearly average return and a Sharpe Ratio of 37.47. As a result, we know that even the portfolio which minimizes the standard deviation includes some cryptocurrency.

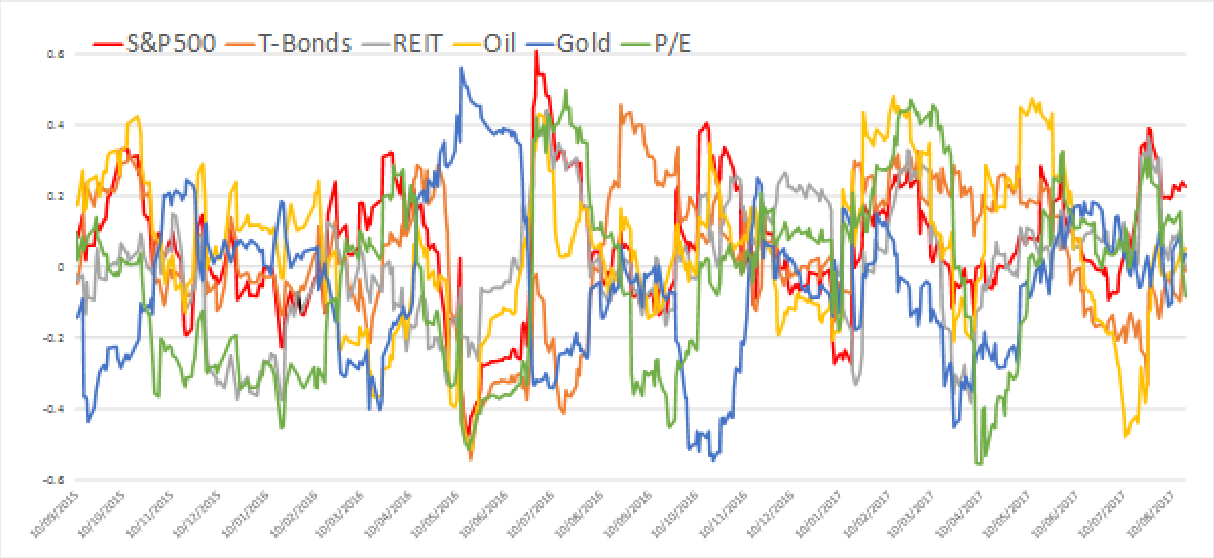

Figure 13: A 30-day moving correlation between the buy and hold-cryptocurrency portfolio and the six traditional assets, S&P500, T-bonds, REIT, Oil, Gold and P/E.

This asset allocation between the cryptocurrencies and the more traditional investment alternatives relies on the covariance of the assets. From Figure 13, we can see that the 30-day correlation between the assets is highly variable and does not follow a clear trend. Based on this finding, it is hard to predict how the relationship between the assets will move in the future. There is no clear indication or trend on how the different assets will move compared to cryptocurrencies in the future.

The creation of the optimal portfolio is an evaluation of what combination of weights will return the highest amount of return for the lowest corresponding standard deviation. Over our observation period, the return of the cryptocurrencies has been phenomenal, and there are reasons to believe that the this might not continue at the same pace, as we discuss in 7.0. As a supplement to the optimal allocation, we have plotted weight of cryptocurrencies included for different levels of return of the cryptocurrency portfolio.

The portfolio is constructed based on the same covariance that is used in the previous optimization. In this scenario, we change the weights with the declining returns and keep all else equal. The standard deviation is set to be 78.33%.

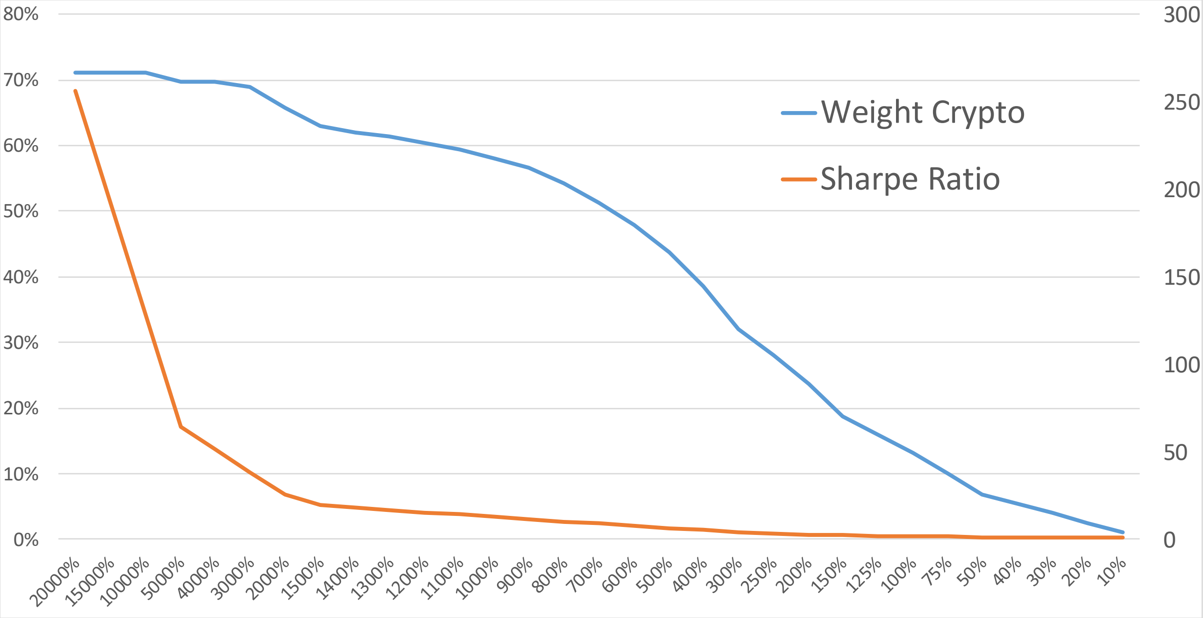

Figure 14: Illustrates the change in weight of the optimal portfolio dominated by the cryptocurrency portfolio (left axis) and the resulting Sharpe Ratio of the optimal portfolio (right axis) when looking at different returns from the cryptocurrency portfolio, all other things equal.

From Figure 14, we observe that even at a yearly average return of 75%, which is almost five times higher than the return of the S&P500 index, we would only want to include 10.04% of the cryptocurrency portfolio. This is based on the volatility, but also the correlation with the assets. From this, we can see that the justification for including a significant portion of cryptocurrency is the extremely high historical return. Weights of every level of return can be observed in Table A9 in the appendix.

8. Discussion

The passive portfolio outperforms the active momentum strategies created in this thesis. In this section, we present and discuss alternative explanations related to the observed performance of the strategy. We also address idiosyncratic and systematic risks with the cryptocurrency market and the included cryptocurrencies. Furthermore, we give a topical assessment of the bubble tendencies in the cryptocurrency market, and how this could affect the results in this thesis, and future implications of this risk aspect.

8.1 Alternative explanations to the performance of the active strategies

With a significantly higher return on the buy & hold portfolio, we know that the signals do not function well enough. When implementing a momentum strategy, there are mainly four matters to contemplate to achieve the best results; The formation period, the rebalancing aspect, the holding period, and the chosen weights.

The historical data on cryptocurrencies is limited. The overall transparency for the cryptocurrencies has historically been low. In the early stages, the data was mainly limited to daily closing prices. As a result of the limited historical data available on cryptocurrencies, the strategies in our thesis are created using the daily close prices. As observed in figure 5, the volatility in the included cryptocurrencies are high, and during one intraday there is a lot of price action we might miss out on with this approach.

A dataset with an increased frequency of observations could pick up more of the information, making our signals more accurate and positively impact the strategies. According to Latif et al. (2017) and Bartos (2015), the cryptocurrency market reacts instantly to new information. They argue that cryptocurrencies are more sensitive to new information compared to stocks and commodities, because commodities and stocks are backed in intrinsic value, but cryptocurrencies are not. This makes the reactions in the cryptocurrencies stronger. Since the market reflects new information so quickly, they point to that spikes in the market price could increase the level of speculation in the currencies. One implication for this is that our signals are created without the consideration of all the available information. Strategies created based on more frequent observations could potentially be interesting to look at in future research. If the thesis was based on more frequent observations, we would have been able to rebalance our portfolio more often, to capitalize on the price movements and recent news that could indicate a price change. By looking at table XXX in the appendix, we see that there are days with extreme outcomes during one day. By rebalancing daily in a market with extremely positive and negative values, we might miss out on some significant increases in price if out signals do not pick up this information.

Menkhoff et al. (2011) evaluate possible reasons to explain return in momentum-strategies. He explains that momentum-strategies are variable, and can give extended periods with a negative return. This intensifies the importance of timing to profit from different trend patterns. For an investor a with a short horizon, momentum strategies represents a significant risk to experience significant losses due to bad timing. The risk of short-term losses might prevent investors with a short horizon to use this strategy. His explanation of the importance of timing can help in making an alternative explanation for why the speculation strategies make lower returns than the buy & hold.

The maximum drawdown can be seen in Table 15 under alternative risk measures. Drawdown is quoted as the percentage decrease between a peak and the subsequent low. The maximum drawdown is the highest drop an investor can expect to receive before it turns and moves upwards. If our signals are not accurate, there is a possibility to hit one of these extreme negative returns while missing out on extreme positive returns, which affects the return of the portfolio negatively.

We select seven of the largest coins measured by market cap today. There is a reason why they have a large market cap, and that is because of positive growth. If we had chosen seven of the largest coins at the beginning of our observation period (September 9th, 2015), Dogecoin and Bitshares would substitute XEM and XMR, which are respectively ranked as number 36 and 25 today. Dogecoin and Bitshares have had a positive return over the observation period, but significantly lower then XEM and XMR. This would have impacted all our portfolios. The buy & hold portfolio would be impacted the most because it would be without the enormous return XEM. Conversely, we try to exploit momentum by buying and selling cryptocurrencies based on signals. If our strategies were accurate and the market had a weak form of efficiency, we should still be able to generate higher returns.

8.2 Alternative risk measures

Sharpe ratio is the conventional and one of the most used risk metrics for evaluating the risk-adjusted returns of investments and portfolio performance. The Sharpe ratio makes comparing different equities, currencies, and portfolios easier. This metric is used throughout our thesis when comparing the cryptocurrencies and the various momentum strategies. The Sharpe ratio expresses the excess return compared to the risk-free asset controlled for the investments standard deviation from the return distributions.

Sharpe ratio= (Return of the portfolio – risk-free rate) / The standard deviation of the portfolio.

$$= max\left\{\frac{E\left[r_p\right] - r_f}{\sigma_p}\right\} \quad .$$

The use of Sharpe Ratio for comparison for our portfolios and cryptocurrencies might, however, be the wrong risk metric to apply. It can give inaccurate results when applied to portfolios and assets that do not have a symmetrical or normalized return distribution, which is the case for our strategies and cryptocurrencies.

The problems with using the Sharpe Ratio as a performance indicator is that it relies on controlling for the risk from the standard deviation. The standard deviation measures the differences in return compared to the return distributions average. This means that it penalizes up-side volatility equally to down-side volatility. Standard deviation does not consider that the contribution to volatility comes from both positive and negative returns.

To enrichen our evaluation of the risk with the cryptocurrencies and the portfolios, we include alternative performance metrics to supplement the Sharpe Ratio. These risk metrics consider the asymmetry in the return distribution. The drawdown for some of the currencies are high, and we also want to quantify the losses that occur in extreme events when investing in cryptocurrency. By including the alternative metrics, we get a distinction between the upside and downside volatility of the cryptocurrencies. This distinction will give a better indication of the magnitude of the downside risk.

Studying the long and fat tails of the return distribution, another aspect of risk is present. The presence of skewness and kurtosis indicates the probability of achieving extreme returns, both negative and positive. Both skewness and kurtosis are positive in all our strategies, which suggests a higher probability of positive outcomes than negative outcomes. We know from traditional risk aversion theory that investors tend to be distinctly more sensitive to losses than to gains.

The alternative risk is substantiated by Osterrieder and Lorenz (2016). They assess the volatility of Bitcoin and the risk from Bitcoins extreme tail behaviour. They compare the risk of Bitcoin compared to G10 currencies and find that the volatility is six to seven times larger. They can quantify that extreme events can lead to losses that are eight times higher compared to the G10 currencies.

Estimating the value at risk (VaR) and expected shortfall (CVaR) for the different portfolios is performed to give a better understanding and visualization of the extreme losses, which leads to increased downside-risk, one can expect to receive with investing in cryptocurrencies.

The definition of Value at Risk as the most prominent loss an investor can expect from the portfolio over a specified time interval, for a given probability. We calculate the daily value at risk at the 5% level, meaning we have a 5% chance of losing the VaR-value or more of our portfolio any given day. VaR provides useful information on how much capital an investor must keep covering potential losses on a day-to-day basis.

The expected shortfall, or Conditional Value at risk (CVaR), is an extension of VAR. Expected Shortfall calculates the average of the losses that occur beyond the VaR cut-off point. Compared to VAR, shortfall gives a clearer picture of the size of the losses because it returns an average expected loss, where VaR gives a range of potential losses.

Panel A	Buy and hold	PPO	1dFilter	1wFilter	1mFilter	
Return	22,474.00 %	1,352.95 %	162.62 %	1,057.80 %	589.00 %	
Std.dev.	76.28 %	66.98 %	66.96 %	67.60 %	66.37 %	
Sharpe-ratio	29,461.00 %	2,017.00 %	239.90 %	1,561.70 %	884.50 %	
Max.drawd.	-59.64 %	-70.95 %	-45.79 %	-57.25 %	-57.69 %	
VaR	-4.98 %	-4.37 %	-4.37 %	-3.88 %	-4.63 %	
CVaR	-7.96 %	-7.33 %	-7.15 %	-7.20 %	-7.63 %	
Skewness	0.409	0.271	1.105	0.894	0.296	
Kurtosis	5.290	8.241	11.376	11.177	5.968	
Panel B	**S&P500**	**10-year bond**	**REIT**	**Oil**	**Gold**	**P/E**
VaR	-0.941%	-0.787%	-1.242%	-3.381%	-1.112%	-1.241%
CVaR	-1.799%	-4.429%	-2.080%	-4.841%	-1.912%	-2.795%

Table 15: Performance of the strategies.

Table 15 above, shows an overview of the various performance metrics over our observation period, where return, standard deviation, and Sharpe-ratio are quoted in yearly performance.

The value at risk (VaR) is negative for all the portfolios in the range of -3.88% (for the 1-week filter portfolio) to -4.98% (for the buy-and-hold portfolio). The buy and hold portfolio, which has the highest Sharpe ratio, also has the highest (relative value) VaR and expected shortfall. From the traditional assets, we observe the opposite, where S&P500 yields the highest Sharpe ratio, but lowest VaR and shortfall. The same patterns cannot be observed in the active strategies, where VaR of the one-month filter strategy is higher than the other active strategies, even though the one-month filter only performs third best of the active strategies. The one-week filter exhibits the highest return of the filter-strategies, but lowest VaR.

These findings implicate reduced tail-risk in the active portfolios, compared to the passive buy-and-hold portfolio. VaR means that you can expect to have a 5% chance of losing between 3.88% and 4.98% or more of the total portfolio value in one day. Value at risk might lead to an under-estimation of the potential losses because it only calculates the minimum percentage one can lose and ignores negative returns beyond this given level.

CVaR, or expected shortfall, returns the average expected loss for our 5% worst returns. Implications for our portfolios is that we will have an average loss of -7.96% (for the buy-and-hold) to -7.15% (for the 1-day filter) for our 5% worst returns over the investment horizon. Oil has the highest volatility amongst the traditional assets, and exhibits higher VaR and shortfall compared to the others, but have the second highest return. We observe that the numbers for cryptocurrencies are significantly higher than for traditional assets.

The results indicate that both the value at risk and expected shortfall show substantial risk to experience significantly negative returns, which is consistent with the findings of Osterrieder and Lorenz (2016). By investing in cryptocurrency for shorter periods of time, especially with leverage, timing is essential, as an investor can stand to lose substantial values by missing the mark.

8.3 Bitcoin bubble?

"*Bitcoin is a dangerous speculative bubble with a lack of underlying intrinsic value to the concept."* Stephen Roach, Chief Economist at Morgan Stanley on December 5th, 2017.

As we have mentioned under 3.2.3, many prominent economists have pointed to the bubble tendencies in the cryptocurrency market. These statements are substantiated by several well-known investors and Nobel Prize-winning economists, such as Warren Buffet, Jamie Dimon, Joseph Stiglitz, Ray Dalio and Robert Shiller, all declaring that cryptocurrencies probably are in a bubble (Kottasovà, 2017).

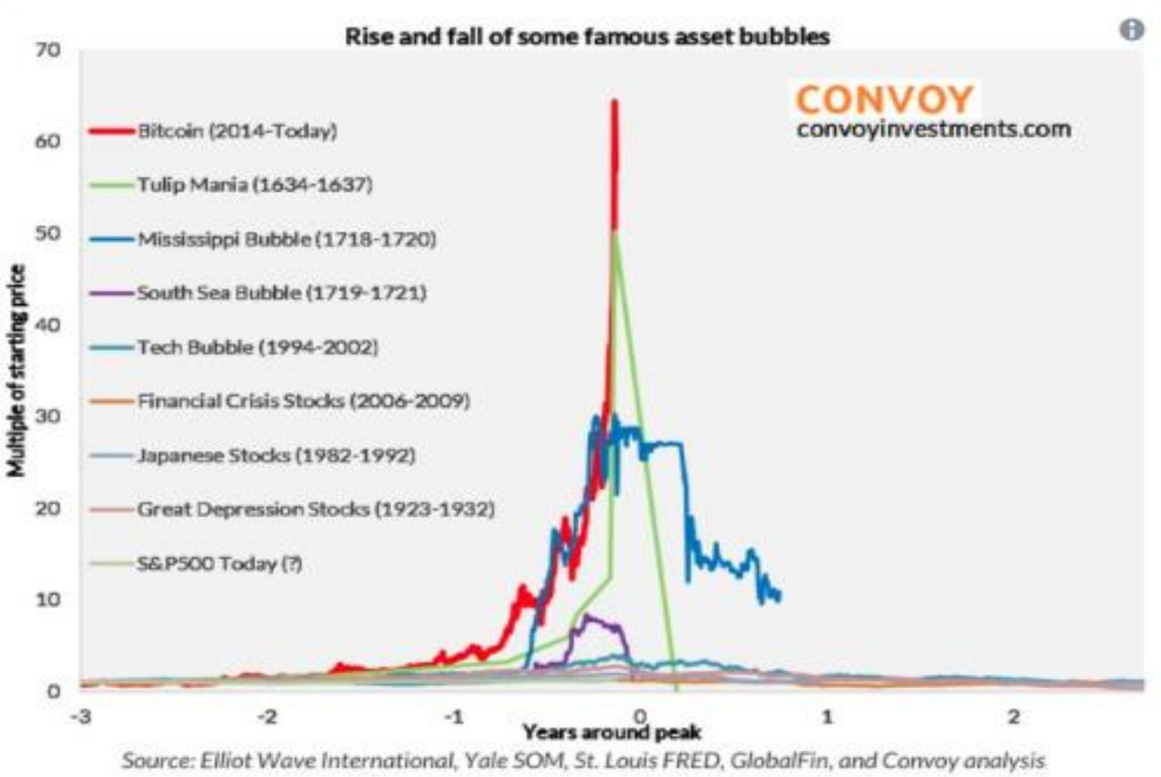

Figure 15: Shows Bitcoin (in red) and well known historical asset bubbles in other colours.The X-axis show numbers of years around the peak of the bubbles, where bitcoin is placed in year 0 for comparison. The Y-axis shows the mutiple of the starting price. "Today" is the 12th of December, 2017. Source: https://www.rt.com/business/412944-bitcoin-biggest-bubble-ever/

The parallels between the recent cryptocurrency market and historical asset bubbles are striking, as we observe in Figure 15. Bitcoin has surpassed every all-time high of the asset bubbles. The question is, however, are we classifying cryptocurrencies as assets and are they used as such. The validity of a direct comparison, depends on how cryptocurrency is classified and used.

With the historic bubbles, speculation drove the value to levels far beyond the intrinsic value, much like we observe in Bitcoin today. For cryptocurrencies, a belief in the underlying technology could be an explanation for the massive increase, but a more plausible explanation of the enormous growth is the fear of missing out on the vast price climb. People are buying with expectations of selling at a higher price. This situation is what describes the greater fool theory, where the last seller is the greatest fool (Buttonwood, 2017).

Investors and amateurs invest in Bitcoin, altcoins, and all sorts of ICO´s with various levels of background information, making the trading volume higher than ever, driving the prices up. The number of cryptocurrencies has increased from 66 in December 2013 to 1364 in December 2017, and the total market cap has increased from $10.5 billion to $590 billion over the same period (Coinmarketcap, 2017). By observing our results, we see the significant upturn the included cryptocurrencies have had over our observation period. Prices have further increased since the end of our dataset. On December 17th, one Bitcoin is worth $19,000, a $15,000 increase from September 30th, 2017 (Coinmarketcap, 2017).

There could be uncertainties as we approach a time where futures are entering the market. The CBOE Futures Exchange (CFE) opened for Bitcoin futures on December 10th, 2017, followed by the Chicago Mercantile Exchange (CME) on December 18th. Futures will improve the transparency, and will also invite hedge funds into the market (Pisani, 2017). As we know, the Dutch market issued futures for tulips just before the crash.

Like tulips, cryptocurrency has no rate of return. Stocks have the dividend, real-estate has rent, bonds have coupons, but cryptocurrency has nothing, the coins have zero intrinsic value, creating zero income, but are based on the expectation of adaption. A zero rate of return implies that if a potential bubble burst, nothing supports cryptocurrencies, and they can drop to a value of zero.

8.4 Impact of transaction costs

We base our active strategies on rebalancing daily. The frequent rebalancing raises the question of transaction costs and fees and how this will affect the profitability. The challenges related to daily rebalancing is connected to the liquidity in the cryptocurrency market which might cause “slippage.” Slippage occurs in the event of significant price movements during the rebalancing causing either the orders not to execute or execute at an unfavorable price. In periods of high volatility, there can be problems with rebalancing our positions. If many investors want to rebalance their portfolio based on new information at the same time, a possible implication will be higher prices due to liquidity pressure.

In this thesis, we have assumed no transaction costs to simplify the strategies. The transaction fees are directly dependent on the value of the trade. It is still interesting to analyse the impact of transaction fees on our portfolios. There are different fees connected to investing in cryptocurrency.

The first step to investing in the cryptocurrency space is to receive funds in the exchange. The transfer of FIAT currency to the exchange might impose an initial fee, depending on the currency and the policies of the bank in the home country. Some countries may allow transfers of FIAT-currencies to an exchange without fees; one example is EURO-payments from countries within the EU/EEA-area to the exchange kraken.com.

Initially, the cryptocurrency structure was based on the idea of having transactions that had very low or even zero transaction fees and costs. There were several exchanges offering trades with zero transaction fees in China, in early 2017, but were forced by Chinese regulators to enforce a flat 0.2% trading fee a few months later. Transaction fees for the different cryptocurrencies vary from the exchange and currency pairs within the exchanges.

Bithumb, which has the highest 24-hour trading volume today, as of November 19th, 2017, has a flat 0.15% fee both for the market maker and taker. They also give traders the opportunity to reduce the transaction fees by buying coupons for a fixed amount. Bithumb's main volume is trades of XXX/KRW currency pairs. Bitfinex, which has the second highest trading volume ranked by 24-hour trading volume measured USD, has fees ranging from 0.1%-0.0% maker fees and 0.2%-0.1% taker fees, depending on the transaction volume of the trades.

When we enter a trade, either long or short, there will, as we see in Figure 16, be a difference in the asking price and the bidding price. The spread means that when we enter the trade, we are already exposed to a risk of losing the bid-ask-spread if we enter the trade with a loss. If we enter a long trade and receive a signal to short it at a later stage, we will ultimately pay the bid-ask-spread if the price did not move in any direction during this trade. This means that we are subject to extra risk due to the bid-ask spread. Data on historical bid-ask spreads the included cryptocurrenices over our investment period does to our knowledge not exist, except for Bitcoin. For future research, this is interesting to investigate.

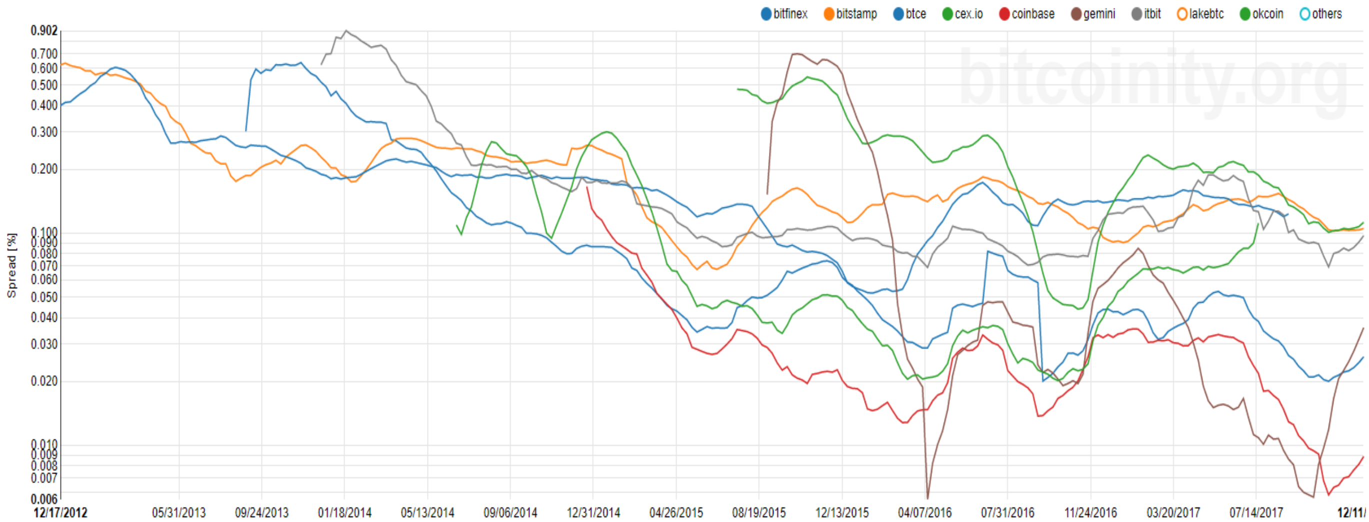

Figure 16: Bid/ask-spread in Bitcoin trades on the exchanges Bitfinex, Bitstamp, btce, cex.io, coinbase, gemeni, itbit, and okcoin.

Some exchanges offer the possibility to margin trade, which is the closest we get to shorting cryptocurrency. To be allowed to margin trade, you need to have bitcoin or the actual currency we want to short as collateral. By holding this currency as collateral, we miss out on the alternative risk-free investment.

The fees derived from trading cryptocurrencies are relatively small when compared to regular fees to trade stocks, and may get quite close to zero if the transaction amount is high enough. In our portfolio construction, we change our position only when the signal shifts from a buy-signal to sell-signal for a given currency. This way we only rebalance some coins every day, causing our active portfolios to take on fewer transaction costs.

9. Concluding remarks and recommendations

In the first part of this thesis, we characterize Blockchain, Bitcoin and other cryptocurrencies, and the status quo in the cryptocurrency market. Anecdotal evidence based on empirical studies suggest that the market is in an early stage with an extreme state of innovative and speculative growth. In the second part of our thesis, we examine the possibility and the performance of active trading strategies based on momentum indicators. The active strategies are compared to a passive, equally-weighted buy-and-hold portfolio. Furthermore, we compare the return characteristics of cryptocurrencies to traditional investment assets, specifically stocks, bonds, real estate, oil, gold and private equity. We look at how cryptocurrencies and the traditional assets could be combined in optimal portfolios. We broaden this evaluation by assessing the possibilities of cryptocurrencies being a speculative bubble and the implications this might have for an investor.

Our results show that the active strategies give a positive return over the period, but not better than the passive portfolio. The passive portfolio has a Sharpe ratio of 295 over the investment period compared to the best performing active strategy, which is the percentage price oscillator, with a Sharpe ratio of 20. In principle, there can be two main reasons for poor performance. First, this thesis is limited by the data to use daily closing prices, and misses out on critical information when generating the trading signal before rebalancing. The holding period of minimum one day might also explain the poorer performance, where the position is locked over the duration of an intraday in an extremely volatile market. Second, the signals generated by the trading strategies created in the thesis could be inaccurate. To outperform the strong positive trend in the market, the signals are required to be precise. Our methodology could be extended in several ways, for example, to account for transaction costs and fees as well as optimizing signal frequencies and rebalancing.

We show that based on a variance-covariance optimization, a traditional portfolio would be significantly improved by including cryptocurrencies as a portion of the total portfolio. The portfolio optimization suggests including a weight of 71% cryptocurrency. On the other hand, the results imply that there is no statistically significant correlation between cryptocurrencies and traditional assets over the observed period, making inference difficult. Our findings show that there is considerably higher value at risk and expected shortfall in the cryptocurrencies compared to the traditional assets. This piece of evidence is amplified by the potential of a speculative bubble in the cryptocurrency market.

From an academic research and investment perspective, the corollary of our findings is that it is advisable to include a portion of cryptocurrencies to a diversified portfolio because of the increase in risk-adjusted returns. This portion should be considerably lower than the optimal portfolio suggests, based on the underlying risk factors.

Throughout the work with this thesis, we have encountered three alternative approaches to investigate for further research. The first, most contiguous research topic would be to examine momentum strategies with the use of more frequent observations and optimized strategy creation. The second approach is to investigate the changes in correlation over time and how this affects the portfolio optimization in the tradition asset management aspect. The last and highly topical aspect to investigate is the fundamental value of the cryptocurrencies and compare this value to the value reflected in the highly speculative current prices. We expect to see these questions investigated in future research.

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11. Appendix

11.1 Introduction

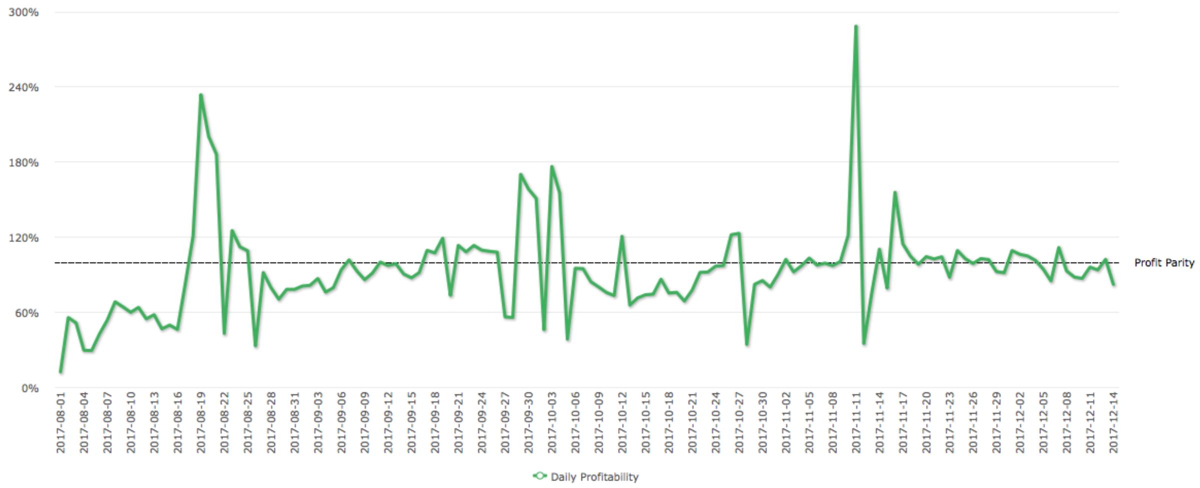

Figure A1: The profitability of mining Bitcoin Cash vs Bitcoin

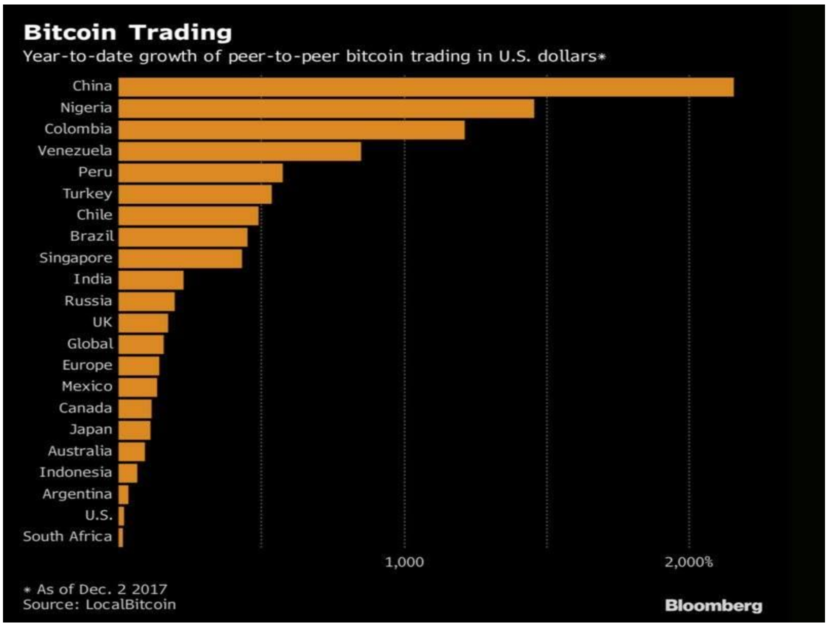

Figure A2: Peer-to-peer transactions measured in USD year to date as of December 2nd , 2017.

11.2 Methods and data

CBOE Interest Rate 10 Year T No (^TNX)	
Mean	2.060645192
Standard error	0.013551356
Median	2.157
Mode	2.225
Standard dev	0.309018472
Kurtosis	-1.076558716
Skewness	-0.348747735
Minimum	1.366
Maximum	2.608
Observations	520

Table A1: Descriptive statistics for T-bonds.

11.3 Results and evaluation

	PPO		1 day filter		1 week filter		1 month filter	
Currency	% Long	% Short	% Long	% Short	% Long	% Short	% Long	% Short
BTC	80.72 %	19.28 %	58.64 %	41.36 %	65.69 %	34.31 %	78.46 %	21.54 %
ETH	62.10 %	37.90 %	50.66 %	49.34 %	56.91 %	43.09 %	65.43 %	34.57 %
XRP	44.55 %	55.45 %	43.62 %	56.38 %	43.09 %	56.91 %	48.80 %	51.20 %
LTC	58.24 %	41.76 %	52.13 %	47.87 %	59.71 %	40.29 %	66.36 %	33.64 %
DASH	72.74 %	27.26 %	52.13 %	47.87 %	61.57 %	38.43 %	71.14 %	28.86 %
XEM	65.03 %	34.97 %	50.53 %	49.47 %	59.57 %	40.43 %	72.07 %	27.93 %
XMR	72.21 %	27.79 %	50.66 %	49.34 %	55.98 %	44.02 %	72.61 %	27.39 %
Portfolio	65.08 %	34.92 %	51.20 %	48.80 %	57.50 %	42.50 %	67.84 %	32.16 %

Table A2: Percentage of long and short positions in the active strategies.

	Weight	Returns	Standard dev	Sharpe
buy hold	0.71	22,474.11 %	78.33 %	205.11
S&P500	0.00	14.43 %	13.80 %	0.90
T-bonds	0.01	2.92 %	40.56 %	0.02
REITs	0.00	13.88 %	17.04 %	0.70
Oil	0.00	7.86 %	44.65 %	0.13
Gold	0.06	7.12 %	16.48 %	0.31
Private EQ	0.21	1.52 %	19.75 %	-0.02
Portfolio	1	15,928.79 %	55.35 %	288.05

Table A3: Optimal portfolio with all assets. No short selling allowed.

	Weight	Returns	Standard dev	Sharpe
buy hold	0.00	22,474.11 %	78.33 %	205.11
S&P500	0.63	14.43 %	13.80 %	0.90
T-bonds	0.00	2.92 %	40.56 %	0.02
REITs	0.08	13.88 %	17.04 %	0.70
Oil	0.00	7.86 %	44.65 %	0.13
Gold	0.29	7.12 %	16.48 %	0.31
Private EQ	0.00	1.52 %	19.75 %	-0.02
Portfolio	1	12.27 %	9.83 %	1.04

Table A4: Optimal portfolio without cryptocurrency. No short selling allowed.

	Weight	Returns	Standard dev	Sharpe
buy hold	0.07	22,474.11 %	78.33 %	205.11
S&P500	0.25	14.43 %	13.80 %	0.90
T-bonds	0.08	2.92 %	40.56 %	0.02
REITs	0.11	13.88 %	17.04 %	0.70
Oil	0.00	7.86 %	44.65 %	0.13
Gold	0.40	7.12 %	16.48 %	0.31
Private EQ	0.09	1.52 %	19.75 %	-0.02
Portfolio	1	1,582.42 %	9.83 %	160.72

Table A5: Optimal portfolio restricted to 9.83% volatility. No short selling allowed.

	Weight	Returns	Standard dev	Sharpe
buy hold	0.79	22,474.11 %	78.33 %	205.11
S&P500	-0.42	14.43 %	13.80 %	0.90
T-bonds	0.10	2.92 %	40.56 %	0.02
REITs	0.15	13.88 %	17.04 %	0.70
Oil	-0.10	7.86 %	44.65 %	0.13
Gold	0.09	7.12 %	16.48 %	0.31
Private EQ	0.39	1.52 %	19.75 %	-0.02
Portfolio	1	17,838.25 %	61.62 %	289.44

Table A6: Optimal portfolio allowing short selling.

	Weight	Returns	Standard dev	Sharpe
buy hold	0.00	22,474.11 %	78.33 %	205.11
S&P500	0.97	14.43 %	13.80 %	0.90
T-bonds	-0.02	2.92 %	40.56 %	0.02
REITs	0.07	13.88 %	17.04 %	0.70
Oil	-0.03	7.86 %	44.65 %	0.13
Gold	0.31	7.12 %	16.48 %	0.31
Private EQ	-0.31	1.52 %	19.75 %	-0.02
Portfolio	1	16.53 %	12.24 %	1.19

Table A7: Optimal portfolio without cryptocurrency, allowing short selling.

	Weight	Returns	Standard dev	Sharpe
buy hold	0.07	22,474.11 %	78.33 %	205.11
S&P500	0.25	14.43 %	13.80 %	0.90
T-bonds	0.08	2.92 %	40.56 %	0.02
REITs	0.11	13.88 %	17.04 %	0.70
Oil	-0.04	7.86 %	44.65 %	0.13
Gold	0.44	7.12 %	16.48 %	0.31
Private EQ	0.09	1,52 %	19.75 %	-0.02
Portfolio	1	1,669.83 %	9.83 %	169.60

Table A7: Optimal portfolio restricted to 9.83% volatility. Short selling allowed.

	Weight	Returns	Standard dev	Sharpe
buy hold	0.00	22,474.11 %	78.33 %	205.11
S&P500	0.33	14.43 %	13.80 %	0.90
T-bonds	0.09	2.92 %	40.56 %	0.02
REITs	0.10	13.88 %	17.04 %	0.70
Oil	-0.04	7.86 %	44.65 %	0.13
Gold	0.44	7.12 %	16.48 %	0.31
Private EQ	0.08	1.52 %	19.75 %	-0.02
Portfolio	1	9.37 %	8.72 %	0.85

Table A8: Minimum variance portfolio. Short selling allowed.

Return of crypto portfolio	Weight	Sharpe
20000 %	71 %	256,34
15000 %	71 %	192,25
10000 %	71 %	128,16
5000 %	70 %	64,07
4000 %	70 %	51,25
3000 %	69 %	38,43
2000 %	66 %	25,62
1500 %	63 %	19,21
1400 %	62 %	17,93
1300 %	61 %	16,65
1200 %	60 %	15,37
1100 %	59 %	14,09
1000 %	58 %	12,81
900 %	57 %	11,53
800 %	54 %	10,25
700 %	51 %	8,98
600 %	48 %	7,71
500 %	44 %	6,44
400 %	39 %	5,18
300 %	32 %	3,94
250 %	28 %	3,32
200 %	24 %	2,72
150 %	19 %	2,15
125 %	16 %	1,88
100 %	13 %	1,62
75 %	10 %	1,39
50 %	7 %	1,20
40 %	5 %	1,15
30 %	4 %	1,10
20 %	3 %	1,07
10 %	1 %	1,05

Table A9: Weight of cryptocurrency in a portfolio with traditional assets, based on declining level of return.

11.4 Discussion

Panel A: Positive	BTC	ETH	XRP	LTC	DASH	XEM	XMR
1	23.94%	35.36%	179.37%	66.59%	44.64%	78.58%	79.43%
2	15.47%	33.66%	57.34%	33.78%	30.85%	65.35%	57.09%
3	15.30%	32.20%	44.94%	33.47%	29.26%	64.55%	53.77%
4	13.46%	31.33%	39.82%	32.41%	28.72%	55.51%	42.24%
5	12.33%	30.97%	39.29%	26.52%	27.25%	47.11%	31.70%
6	11.95%	27.04%	39.27%	25.61%	26.58%	46.58%	31.32%
7	11.69%	26.91%	35.31%	21.94%	23.86%	45.24%	27.63%
8	10.99%	24.83%	31.43%	21.92%	23.26%	37.78%	27.52%
9	10.89%	22.92%	30.46%	21.08%	21.39%	37.45%	26.79%
10	10.62%	22.37%	29.23%	19.17%	21.16%	35.32%	26.44%
Panel B: Negative	**BTC**	**ETH**	**XRP**	**LTC**	**DASH**	**XEM**	**XMR**
1	-18.74%	-27.06%	-46.00%	-32.64%	-21.59%	-29.75%	-25.41%
2	-15.33%	-26.33%	-21.80%	-20.57%	-17.29%	-25.10%	-21.65%
3	-14.31%	-25.30%	-19.24%	-18.88%	-16.81%	-24.81%	-18.41%
4	-12.24%	-22.81%	-18.23%	-16.12%	-16.34%	-22.77%	-17.33%
5	-11.49%	-19.65%	-16.84%	-15.14%	-15.10%	-21.34%	-15.74%
6	-11.42%	-19.14%	-13.33%	-13.62%	-13.00%	-20.96%	-14.75%
7	-10.97%	-18.34%	-13.27%	-13.54%	-12.95%	-20.62%	-14.50%
8	-10.58%	-16.08%	-13.22%	-13.21%	-12.48%	-18.92%	-13.69%
9	-10.50%	-15.98%	-13.21%	-12.20%	-12.17%	-18.72%	-13.34%
10	-10.09%	-15.25%	-12.96%	-12.18%	-11.72%	-18.61%	-13.07%

Table A10: The 10 most positive daily returns in panel A, and the 10 most negative daily returns in panel B, over our observation period for the seven included cryptocurrencies.