The Cryptocurrency Market – An investment opportunity?

About the price mechanisms of cryptocurrencies

Master Thesis

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Study Program: Msc. in Finance and Strategic Management

Number of pages: 101 (78 Standard pages)

Number of characters: 165,576

Submitted in Copenhagen on the 14th of May 2018

Abstract

Cryptocurrencies are fascinating phenomena that went through incomparable price developments in the past years. This thesis investigates the price mechanisms in the cryptocurrency market and seeks to evaluate their properties as investment vehicles. While most research in this field is focused on Bitcoin only, I deliver a comprehensive analysis of multiple cryptocurrencies and the underlying market between the 9th of August 2015 and 31st of December 2017. I contribute to the existing research by adding new insights through tests on the weak form of the efficient market hypothesis (EMH) and the analysis of price formations for Bitcoin, Ether, Ripple, Litecoin, and Dash.

For the analysis of the EMH, I apply five robust test and find that Bitcoin, Ether, and Dash are efficient, whereas other cryptocurrencies appear inefficient. In the most representative subsample, results suggest that only prices of Bitcoin and Dash are efficient while other cryptocurrencies show long-range dependencies of returns and do not follow a random walk. Nevertheless, results of the overall market indicate an efficient market and contradict with most previous research. Furthermore, empirical results suggest that prices of smaller cryptocurrencies are rather influenced by the public media attention and their liquidity, while Bitcoin is affected by the developments on financial markets and macroeconomic factors.

Overall, I find that lower searching costs through an increased media attention as well as higher liquidities are significant drivers of prices and most likely, a reason for a higher market efficiency compared to previous research. Moreover, all results indicate a transition in this market towards efficiency and that prices are influenced by exogenous factors. Finally, the analysis demonstrates that cryptocurrencies are most likely used as a safe haven asset, speculation instrument and alternative investment vehicles by current investors. However, I find adequate investment opportunities only for the use as a diversification instrument and in some cases as a safe haven investment, due to a lack of fundamental value, high volatiles, and a low understanding of the price dynamics.

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List of Abbreviations

ADF	Augmented Dickey-Fuller
BTC	Bitcoin
CAGR	Compounded Average Growth Rate
CNY	Chinese Yuan Renminbi
EMH	Efficient Market Hypothesis
ETH	Ether
FTSE	Financial Times Stock Exchange
LB	Ljung-Box test
LTC	Litecoin
MSCI	Modern Index Strategy Index
REH	Rational Expectations Hypothesis
RWH	Random Walk Hypothesis
S&P500	Standard & Poor's 500 Index
VIF	Variance Inflation Factor
VR	Variance Ratio
XRP	Ripple

1. Introduction

Cryptocurrencies gained great popularity in the past years and moved gradually to the focus of society and investors within the context of a progressing digitization. Once demonized for the use of illegal purchases through the internet, cryptocurrencies became a multi-billion dollar industry and an accepted payment method at companies such as Microsoft. As one of the most searched words on the internet, cryptocurrencies gained momentum in 2017 and have arrived in the mainstream media as well as in the public awareness. The significant innovation behind them allow worldwide anonymous transactions as well as fast executions with low transaction costs, in the absence of any intermediaries and might change the traditional finance system (Halaburda and Sarvary, 2016). The disruptive potential of cryptocurrencies together with an increasing number of acceptance places, an easier access to cryptocurrencies and more liquid markets facilitated growth and popularity. The hype around cryptocurrencies led to an immense price rally and the emergence of over 1,500 cryptocurrencies with a total market valuation of 570 billion USD in 2017 (Coinmarketcap, 2017). These price developments raised awareness among investors, regulators and economists as well.

Critics argue that cryptocurrencies are not frequently used in retail transactions and that individuals rather store them instead of using them as a currency (Glaser *et al.*, 2014). Thus, many researchers claim that cryptocurrencies can be described as alternative investments and that they should be treated as an asset instead of a currency (Yermack, 2015; Hong, 2017; Baek and Elbeck, 2015; Baur, Hong, and Lee, 2017; Selgin, 2012). Furthermore, the increase of cryptocurrency prices, without a proportional change of transactions and real usage, raised the question about their valuation. Prominent economist such as Robert Shiller or Paul Krugman claim that cryptocurrencies do not have an intrinsic value and that the market is in a speculative bubble which will eventually burst (Krugman, 2018; Wearden, 2018). Without any dividends, interests or profits, questions about the reasons for an investment and the justification of the enormous price increases, seem legitimate. An understanding of the price formation is a fundamental aspect of finance and especially crucial for new assets (O'Hara, 1995). It allows to comprehend underlying economics, reveal potential risks and evaluate investment opportunities.

Hence, this theses explores the price mechanisms behind the cryptocurrency market and analyzes their adequacy as investment vehicles.

1.1 Theoretical background & Related Literature

The challenging questions about the economics and price determination of cryptocurrencies arouse interest from economic researchers since they emerged. In the financial theory, four main theories are usually used to explain stock price formations which are the efficient market hypothesis (EMH), the random walk hypothesis (RWH), the rational expectations hypothesis (REH) and the behavioral finance theory (Fama, 1965; Muth, 1961; Shiller, 1980).

The efficient market hypothesis is one of the major paradigms in the modern financial theory and is therefore often used as a starting point for the analysis of prices. The market efficiency provides valuable insights into the price mechanisms, and whether markets can incorporate external information into prices and reflect the true value (Fama, 1965). Furthermore, the EMH is used as an underlying assumption for most financial models and as an indicator for regulators. According to the EMH, prices in efficient markets reflect the true value of all assets at any time and wrong valuation of assets that might be caused by irrational decisions will cancel each other out or will be exploited by arbitrageurs instantly (Shleifer, 2000).

Louis Bachelier (1900) found that stock prices are random and cannot be predicted which led to the Random Walk Hypothesis (RWH). The RWH was economically explained by Fama (1965) through the EMH, which claims that current prices already incorporate all available information and that only new information that lead to a change of the intrinsic value drive the prices of stocks. Since new information and events are, unknown beforehand and random, future prices are also unknown and follow a random walk. This means that investors are not able to use historical prices to predict future prices. Fama (1970) acknowledged different forms of market efficiencies and categorized these into the weak form, semi-weak form and strong form of market efficiency:

- The *weak form* of market efficiency postulates that all information about past market prices are incorporated in the current prices, and it is not possible to earn higher profits by using information that is based on past prices. Therefore, the weak form of EMH assumes that prices follow a random walk.
- The *semi-strong* suggests that not only prices but also all publically available information play a role in the formation of prices.
- Under the *strong form* of the EMH, even insider information are included in current prices and cannot lead to abnormal returns (Fama, 1970).

The REH is also closely connected with the EMH and argues that investors are rational and make reasonable economic decisions by considering all information, whereby past mistakes are avoided by using their experiences (Muth, 1961). On the other hand, behavioral finance has opposing positions to EMH and assumes that people do not always make rational decisions. Hence, this theory combines psychological theories with traditional economics (Shiller, 1980).

The price mechanism and volatilities have been analyzed in financial markets extensively, but due to a fast emerging cryptocurrency market, research has only touched the surface in this market. The majority of the economic literature concentrates on the market efficiency and price drivers of Bitcoin, but there are many papers with different methodologies and opposing findings. Urquhart (2016) analyzes, as one of the first researchers, the market efficiency of Bitcoin by applying a wide range of tests and finds that the market is not weakly efficient, but shows a tendency towards efficiency in later subsamples. These findings were confirmed by Bariviera (2017) who used the Hurst exponent and detrended fluctuation analyses to measure the market efficiency. Contrary, Bartos (2015) find that the Bitcoin price is informational efficient and reacts to publically available information. Brauneis and Mestel (2018) underline the difficulty of testing the market efficiency due to a lack of knowledge about the price drivers and find that prices in the cryptocurrency market are efficient, whereby liquidity appears as one of the most critical factors for the development of markets. Overall, literature does not give clear evidence about the market efficiency of cryptocurrencies.

The other primary stream of literature investigates the price drivers of cryptocurrencies, as a better understanding of price drivers might deliver essential insights for investors and regulators. Ciaian, Rajcaniova, and Kancs (2016) argue that supply and demand factors are the significant determinants of prices and that microeconomic principles and the theory of prices can be used as a theoretical foundation for the price mechanisms.

Papers regarding price drivers are scarce, and many papers do not find any exogenous influences on the prices in the cryptocurrency (Baek and Elbeck, 2015). However, Kristoufek (2015) performs an extensive analysis of price drivers based on fundamental economic theories on currency formation and finds that the public interest in the form of Google and Wikipedia searches play an essential role for the price discovery. These findings were confirmed by Ciaian et al. (2016) and extended by size and velocity as price drivers.

1.2 Problem statement

Despite a range of research in this field, especially on Bitcoin, it stays still unclear whether the total cryptocurrencies market is efficient and which information determine prices. Contrary findings and different observation periods do not allow conclusive statements about this market. The drastic changes in market structures with an almost 80 times higher market capitalization in 2017 compared to 2015 suggest that previous findings might not apply to the new market conditions anymore. Furthermore, no research combines analyses on market efficiency and the price formations with the consideration of underlying economics. The analysis of price determinants strengthen findings on the weak form of the EMH and delivers insights about the market development and the decision-making of investors (Russel and Torbey, 2002).

I want to fill this research gap by providing an updated analysis and contribute to the existing stream of literature on the market efficiency as well as price drivers. Furthermore, I will use insights of the analysis to draw implications about cryptocurrencies as an investment vehicle and involved risks and chances for different investor groups.

1.3 Research Question

The fascinating development of cryptocurrencies and a somewhat unexplored price mechanism led to the research question of this thesis:

How do price mechanisms in the cryptocurrency market function?

To answer the research questions and give a comprehensive answer to the price mechanisms, I split the question into following two sub-questions:

Sub-question 1: Do prices follow the efficient market hypothesis?

Sub-question 2: What influences prices of cryptocurrencies?

1.4 Topic delimitation

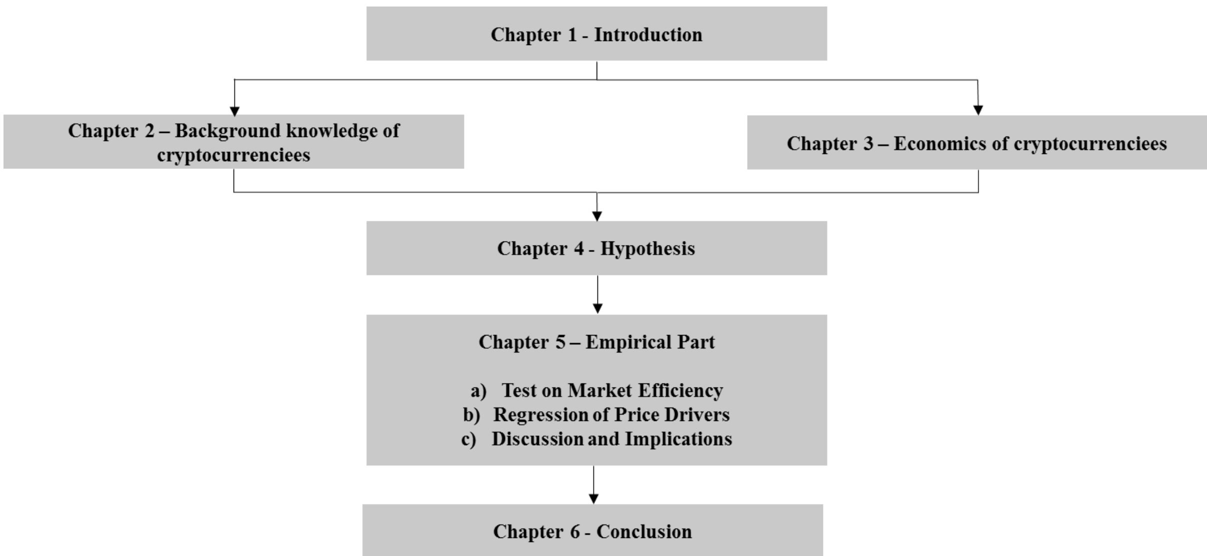
Many topics are essential for the analysis of cryptocurrencies as investments such as the volatility, analyses of potential speculation bubbles, fundamental economic research or the applicability of behavioral finance. However, I limit the scope of this thesis on tests on the weak form of the efficient market hypothesis and analyses of price drivers, as they form crucial elements for the analysis of prices and an understanding of this asset class. Data limitations and anonymous transactions make a more detailed analysis of the market efficiency rather difficult.

Furthermore, I limit the analysis on the period between August 2015 and December 2017 for the five most prominent cryptocurrencies, due to data availability. Finally, this thesis does not provide direct implications or suggestions for financial markets or regulators but will present properties of this asset class and evaluate potential investment opportunities.

1.5 Disposition & Research methodology

As Figure 1 illustrates, the thesis is structured in six chapters. In chapter 2, I give an introduction and background knowledge about cryptocurrencies, the market, and their classification among financial assets. In Chapter 3, I analyze the underlying economics of the market and describe the distinct characteristics of the supply and demand system. As the figure shows, I will use insides of previous sections to develop the hypothesis and define measurement methods in chapter 4. Similar to the research questions, the hypotheses are divided into market efficiency and price drivers. Chapter 5 builds on the previous analyses and forms the core of this thesis. Here, I perform the empirical test on the hypotheses, discuss findings and give implications about the price mechanisms and the investment opportunities. To answer stated research questions, I follow the methodology of Urquhart (2016) and apply multiple robust tests to determine the weak form of the EMH. Furthermore, I will use an autoregressive distributed lag model to reveal the factors that influence prices as performed by Bartos (2015) for the analysis of Bitcoin. Finally, I give an overall conclusion of my findings, emphasize the contribution to existing research, and suggest potential areas for further research.

Figure 1 - Structure of Thesis



2. Cryptocurrencies

This chapter provides the theoretical background of cryptocurrencies and introduces the major elements that define this market. Furthermore, I outline the development of the market and deliver a classification of cryptocurrencies that form the basis for further analyses.

2.1 Definition

Cryptocurrencies are virtual assets in decentralized systems that are secured by cryptography. The cryptography controls the transactions, prevents fraud and manages the supply of these assets. Unlike bank account balances, the ownership of these assets is not controlled by a third party (White, 2015). All confirmed transactions are stored digitally in a “blockchain” that serves as a public ledger or accounting system and is transparent to every user in the network (Gandal and Halaburda, 2014). The systems do not have any financial intermediaries or authorities that control transactions. They operate worldwide and can be used for any purchases (for virtual or physical goods) and are therefore competing against official currencies (European Central Bank, 2012). Transactions with cryptocurrencies have shared attributes such as low transaction costs, fast transactions (compared to traditional bank services), anonymity, transparency and no restrictions about the transfer amounts or the recipients (Halaburda and Sarvary, 2016).

2.2 History and Technology of Cryptocurrencies

Triggered by the eruption of the financial crisis in 2007, an unknown programmer with the pseudonym Satoshi Nakamoto published a paper about a “Peer-to-Peer Electronic Cash System” with the name Bitcoin.[1] His goal was to create a disconnected payment system that is not dependent on any financial institutions. Nakamoto (2008) criticizes specific properties of the existing electronic payment system such as the reversibility of payments and high transaction costs. He argues that electronic payments are prone to trust problems due to reversible transactions where merchants cannot entirely rely on payments. Further, he mentions that the financial intermediaries cause transaction costs that are limiting the minimum size of payments.

In 2009, he launched the Bitcoin network and created the first cryptocurrency with the same name, Bitcoin (BTC). The system allowed users to transfer Bitcoins directly between each

[1] The Whitepaper „Bitcoin: A-Peer-to-Peer Electronic Cash System" was released on the 1. November 2008 via a Cryptography Mailing List and was therefore only recognized by the Cryptography Community at the beginning.

other. Users that want to take part in the network were required to download a free open-source software which enabled them to store, receive and send Bitcoins via the network (European Central Bank, 2012). In the starting phase, users were not able to purchase Bitcoin with fiat money, and transactions were made mainly between developers and programmers.

In 2010, the first exchanges, such as “BitcoinMarket.com” and “Mt. Gox”, emerged and allowed users, without direct links to the cryptography community, to acquire Bitcoins in U.S. Dollars. The first real-world transaction was the purchase of two pizzas for 10.000 Bitcoins which was organized indirectly via a third person. This led to the first real valuation of around 0.01 USD per Bitcoin. The online marketplace "Silk Road", which gained public attention for selling illegal drugs online, used Bitcoin as a payment method and was once accounted for nearly 50% of all Bitcoin transactions. “Silk Road” was the first organization that made commercial use of the anonymity of Bitcoin and therefore helped to increase its popularity and demand, but also created skepticism about its use (Yermack, 2015).

Cryptocurrencies received first public attention in the mainstream media when WikiLeaks decided to accept donations in Bitcoin after all other payment providers refused to provide their service in 2011. Wikileaks encouraged other online service providers such as Baidu, the 5th most visited website, to accept Bitcoin as well (Halaburda and Sarvary, 2016). In the following years, many companies started to accept Bitcoin as a new payment method, and further exchanges in different countries simplified the purchase of Bitcoins for users.

At the end of 2017, Bitcoin became part of the international financial system when the world largest future and options exchange (CME) issued regulated futures on Bitcoins. This led, together with the extensive price development, to wide media attention and public awareness of cryptocurrencies (Hayter, 2017). Furthermore, many countries offer ATMs for Bitcoin, where people can withdraw money by selling their Bitcoin. The number of these ATMs rose from a few hundred in 2015 to over 2,500 in 2018 (see Appendix A).

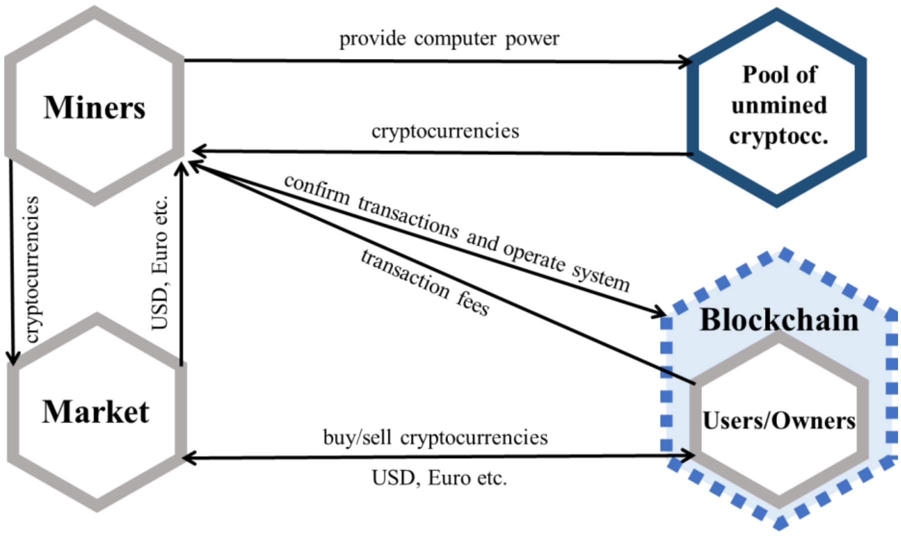
Due to the open-source protocol of Bitcoin, anyone can copy the original code and create an own cryptocurrency, what led to the emergence of many other cryptocurrencies. While some of those are simple copies, others deliver solutions for problems of the Bitcoin network such as faster transactions, lower electricity consumption, higher security or easier usage (Halaburda and Sarvary, 2016). The mechanisms of the cryptocurrency systems and the specific differences between them will be explained in the next sections.

2.2.1 Technology

Cryptocurrencies are mostly based on a peer-to-peer network, where single users appear as nodes that are interconnected by free open-source software.[2] This software allows to share information between nodes in the network. Additionally, it delivers an integrated digital wallet, comparable to an online banking account, where cryptocurrencies can be saved on a hard drive. Thus, the network and the wallet together allow to receive, send or store cryptocurrencies (Berentsen and Schaer, 2017).

The peer-to-peer network technology was also used by file sharing platforms such as “BitTorrent" before and is not the key innovation behind cryptocurrencies. There have been many attempts to use these decentralized networks for financial transactions, which failed due to the "double-spending problem”. Since virtual currencies are nothing else than electronic data that is sent between individuals, they can be copied. This leads to the problem that the same units can be spend multiple times (double-spending), what makes the use as a financial transaction medium senseless. Satoshi Nakamoto solved the double-spending problem in 2008 by the use of the “blockchain ledger technology” and cryptography (Nakamoto, 2008). A blockchain serves as a public ledger and is visible to every user of the network. It shows every transaction that has ever been made and lists the owners of cryptocurrencies.

Figure 2 - The cryptocurrency system



Source: own illustration.

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[2] Even though there are some differences, most cryptocurrencies are based on the same technology. Therefore, I will use the technology behind Bitcoin for this section.

The network can, therefore, ensure that units are spent only once. Furthermore, it confirms the validity of transactions and ensures that the cryptocurrency is not spent twice. The software uses cryptography to create pseudonyms, namely public keys, that serve as an account number, to keep the identity of user's anonym. Every user has a public key and a private key (similar to a pin code) that are used for the identification of the legitimate owner. The operators of the blockchain are called miners. They have two main tasks, which are the confirmation of transactions and the mining of new cryptocurrencies by providing computational power. Miners are comparable to gold mining companies that mine gold and sell it on markets. In contrast to gold mining companies, cryptocurrency mining works by providing computer power to the network with rewards in the form of cryptocurrency units. Figure 2 displays the underlying mechanisms of the system and shows the interaction between miners, users, and the market. It shows that miners play an essential role in operating the blockchain and supplying the market with new units. Further, the figure illustrates the flow from the “pool” of cryptocurrencies over miners through markets to the users or investors.

The total amount of unmined cryptocurrencies is usually limited, similar to the total amount of available gold. Furthermore, the system reduces the rewards for miners after a certain amount of cryptocurrencies are circulating, which makes it increasingly difficult to earn money with mining (Berentsen and Schaer, 2017). The roles of the three major parties in the cryptocurrency system, namely miners, users, and markets (exchanges) will be further discussed in the following sections.

2.3 Competition between Cryptocurrencies

Low barriers to entry in the form of publicly available algorithms and low capital requirements together with a highly profitable business led to an increasing number of alternative cryptocurrencies. Most cryptocurrencies are specialized in fixing specific problems to distinguish themselves from competing cryptocurrencies. Nevertheless, they operate all in the same market and compete against each other (Halaburda and Sarvary, 2016).

Bornholdt and Sneppen (2014) find that cryptocurrencies can gain a competitive advantage by having a better reputation, higher price stability, more media attraction, higher liquidity and market capitalization, faster transactions and a higher acceptance as a payment instrument. Despite its negative properties, Bitcoin's success is based on its first-mover advantage. It allowed Bitcoin to attract large followership and the most media attention.

While there are many different cryptocurrencies, I will focus on five of the most prominent and most popular cryptocurrencies. Following, I summarize the properties of four alternative cryptocurrencies (“Altcoins”) and point out differences to the original Bitcoin:

Ether (ETH). Ethereum was established in 2015 and is a network that completes certain tasks within the network. The underlying cryptocurrency that is based on this network technology is called Ether. Besides Bitcoin, Ether is seen as the most innovative cryptocurrency. Ethereum aims to offer more complex financial transaction than Bitcoin such as trading and settling of financial flows between banks. It allows the automatic administration, creation, and execution of decentralized contracts. Today, the innovative technology behind Ethereum, so-called "smart contracts," is used in the supply chain management of some industrial companies. However, the practical applications of Ethereum are based on its network technology and not the cryptocurrency itself (Popper, 2017).

Ripple (XRP). First traded in 2013, Ripple is a cryptocurrency issued by the company Ripple Labs. This is, therefore, among the first cryptocurrencies that are created by a professional profit-seeking company (White, 2015). The Ripple network needs only a few seconds to confirm transactions what makes it much faster than Bitcoin (Armknecht *et al.*, 2015). In contrast to Bitcoin, Ripple is focusing on banks as users (e.g., Morgan Stanley, Standard Chartered, Banco Santander) that are handling payments via the Ripple network. However, most of the banks are reluctant to roll out a large-scale application but instead test the technological capabilities of the network (Leising and Robinson, 2018)

Litecoin (LTC) and Dash. These two cryptocurrencies are very similar to Bitcoin and try to solve particular problems of the original code such as the speed or anonymity but do not deliver any significant innovation besides that.

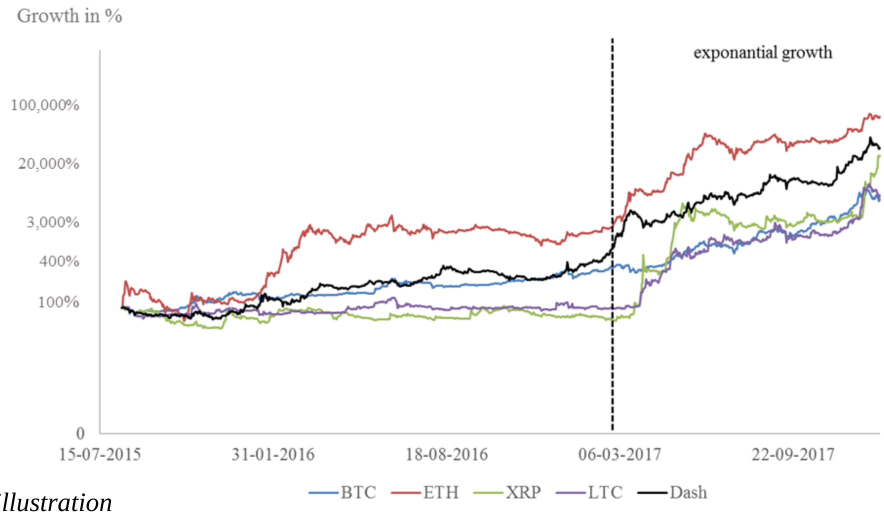
Litecoin was created in October 2011 as one of the first Altcoins. The primary goal was to provide a faster confirmation of transactions, which takes 10 minutes in the Bitcoin network and is reduced to 2.5 minutes in the Litecoin network

Similar to Litecoin, Dash was introduced to provide a faster confirmation of transactions. It can confirm transactions within seconds (instant confirmation) and provide a higher degree of anonymity (White, 2015).

Figure 3 shows the price development of these Altcoins and is a good representation of their history. Some cryptocurrencies such as XRP or LTC did not develop until 2017 and experienced an exponential price growth of around 20,000% and 5,700% within a year.

Figure 3 – Price Development of Cryptocurrencies

The graph shows the indexed logarithmic price development of five cryptocurrencies. The vertical axis shows the indexed growth between the 9.08.2015 and 31.12.2017. The prices are set at 100% on the 9.08.2015.



Source: own illustration

The economic reasoning for the competition and the development in the cryptocurrency market is delivered by Gandal and Halaburda (2014). They argue with two major effects that influence investment decisions in the cryptocurrency market, namely the reinforcement effect and the substitution effect. The reinforcement effect describes a situation in which investors believe that large cryptocurrencies will win the "winner-takes-all" race and demand more of the most popular cryptocurrencies. The contrary substitution effect explains a situation where, as cryptocurrencies get more popular and expensive, people believe that they might be overvalued and invest into alternative cryptocurrencies.

Interestingly, they find that the network effects and the popularity of cryptocurrencies where more important in the early stages of the market and hence the reinforcement effect more dominant. However, they also found that the substitution effect is stronger in later stages as more traders enter the market and see cryptocurrencies more as a financial asset than a medium of exchange. These effects can explain the choices of investors and the differences in growth as well as market shares between these cryptocurrencies. Figure 3 indicates a substitution effect in the current market, due to higher growth rates of Altcoins after 2017.

2.4 Market and Exchanges

"The cryptocurrency market is a market of competing private irredeemable monies" (White, 2015: 383). At the end of 2017, there were around 1,500 cryptocurrencies with a total market capitalization of 572 billion USD (Coinmarketcap, 2017). The market capitalization of crypto-currencies equals more than money supply of multiple countries such as India, Russia or Denmark in 2017 (Central Intelligence Agency, 2017).[3] However, compared to a traditional asset such as gold (14 times larger) or the equity markets (175 times larger), the cryptocurrencies market is still small.[4][5] The market grew significantly from 2013 to 2017 with a compounded annual growth rate (CAGR) of 175%, making cryptocurrencies the fastest growing asset class. For comparison, the S&P grew by 9.8% and gold by 1.8% in the same period.

The market composition experienced an immense change in 2017. As Figure 4 shows, Bitcoin's market share decreased drastically from 90% in 2015 to 39% in 2017. Bitcoin has still the lion share of the market, but direct competitors such as ETH or XRP as well as new cryptocurrencies managed to win market shares in the last year. Especially, Ripple gained high market shares and developed form 1% to 14% market share in 2017. However, the main reason for Bitcoin's market share decrease is the emergence of around 700 new cryptocurrencies in the market (Coinmarketcap, 2017). The total market share of the five cryptocurrencies that I will analyze sum up to 69%. Interestingly, the two cryptocurrencies LTC and DASH did not increase their market shares over the last two years even though they belong to the oldest cryptocurrencies. This might be explained by their lower innovation potential and network size compared to Bitcoin, Ether or Ripple.

Bitcoin is the most popular cryptocurrency for actual transactions to purchase goods, and by far the most accepted cryptocurrency (White, 2015). Out of all other cryptocurrencies, only ETH and LTC are accepted by some online merchants at the moment (Kariuki, 2017). Therefore, experts claim that the market will experience a phase where most of the cryptocurrencies without any significant technological value and low usage rates will disappear. Paycoin, for instance, was the 3rd largest cryptocurrency in 2014, but almost disappeared from the market in 2017 (Browne, 2018).

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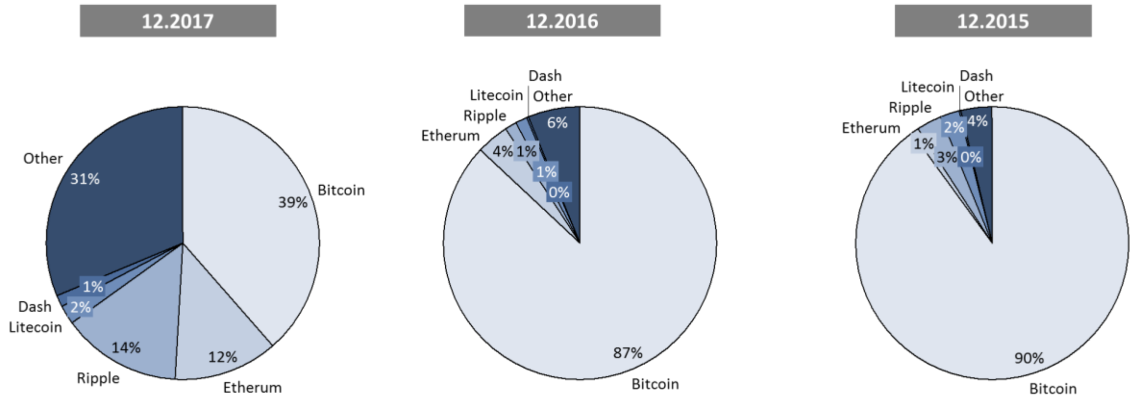
[3] Refers to M2 money supply which includes cash, checking deposits, saving deposits, money market securities and mutual funds.
[4] The gold market is estimated around 7 trillion USD (Bloomberg, 2018).
[5] The global equity market is estimated around 100 trillion USD (Bloomberg, 2018).

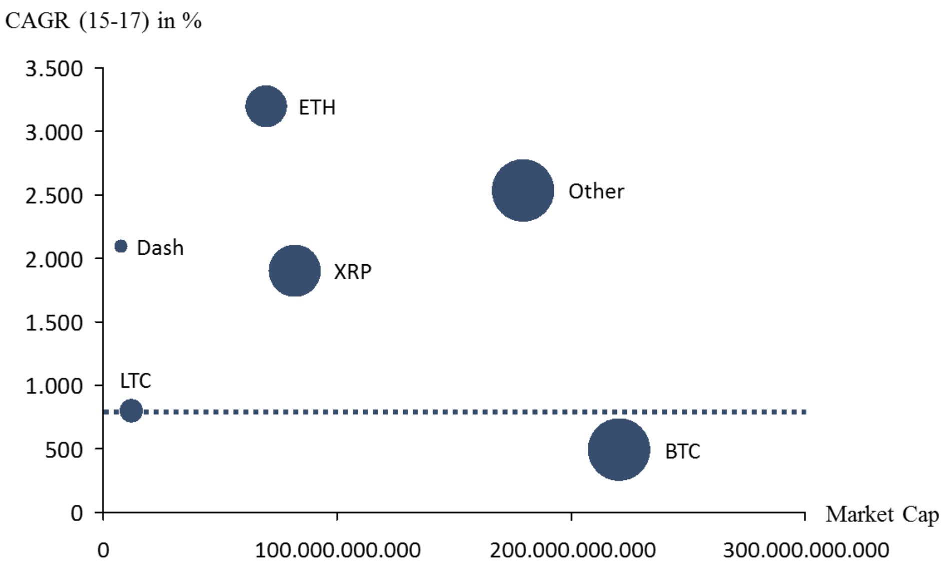
Figure 4 – Market Shares of Cryptocurrencies



Source: Own illustration with data from coinmarketcap.com

Figure 5 illustrates the growth in percent and market sizes in USD of the cryptocurrencies in the market, whereas the bubble size determines the market share and the dashed line depicts the average growth in the market. By comparing the growth rates, it can be seen, that Bitcoin has the lowest growth between 2015 and 2017 while LTC grew with the market (8-fold) and ETH, XRP and Dash grew between 18 to 30-fold. The fastest growing cryptocurrency was Ether (grew annually by 32-fold) and the second fastest growing group are other cryptocurrencies, which are driven by the cryptocurrencies Cardano, NEO and Stellar. Cardano, for instance, reached a market value of 600 million USD after its initial coin offer in 2016.

Figure 5 – Market Size and Growth



Source: Own illustration with data from coinmarketcap.com

2.4.1 Exchanges

As illustrated in Figure 2, cryptocurrency exchanges are the marketplaces where supply meets demand and thus play an important role in trading, price discovery and liquidity (Hileman and Rauchs, 2017). They allow exchanging cryptocurrencies for other cryptocurrencies or into traditional fiat currencies (Berentsen and Schaer, 2017). There are three categories of services offered at exchanges: order-book exchanges, trading platforms, and brokerage services. While smaller exchanges specialize in specific categories, larger exchanges provide the full range of services. With almost no barriers to entry and low regulations, many exchanges have been established since 2010 (Hileman and Rauchs, 2017). While all exchanges support Bitcoin, smaller cryptocurrencies are often only traded on specialized exchanges. In the early stages of cryptocurrency exchanges, there were major price differences between prices on exchanges in different countries which allowed the exploitation of arbitrage opportunities (Pieters and Vivanco, 2017). Nowadays it is increasingly difficult to exploit cross-country price differences due to a faster adaption of prices, transaction costs and regulations (Verhage, Choi, and Cho, 2018). It is very likely that exchanges will play a significant role when it comes to regulation of this market and taxation of cryptocurrencies. As the transfer of cryptocurrencies is anonymous and difficult to control, the regulation of purchase and sale might be the only option for authorities. The lax regulation of exchanges, lead to uncontrolled money transfers, hacking attacks and poses high risks for investors. Current regulations require exchanges in the U.S to register as "money transmitters" and to hold an official license. However, 85% of Asian and 57% of European exchanges do not hold a license (Hileman and Rauchs, 2017). Marian (2015) describes a framework of regulation and sees exchanges as a central element of future regulations.

2.5 Transaction Costs

As mentioned before, transaction costs are one of the main reasons for the emergence and usage of cryptocurrencies. Hence, I will give an overview of the costs for the most common online payment methods and compare them to Bitcoin.

Table 1 displays the average transaction fees for different payment methods. The fees refer to the total fees for the transactions. Bitcoin is the only payment method that charges the buyer exclusively, which should initially give an incentive for merchants to accept Bitcoin. Another interesting factor is the payment structure. Traditional payment methods are usually based on a combination of fixed and variable fees whereas Bitcoin has a fixed fee only. This makes Bitcoin a favorable payment method for more expensive purchases as shown in the table. However, a 10 USD purchase would lead to transaction fees of over 30% when Bitcoins are used. If we take the example of a 1,000 USD purchase via PayPal, the total transaction fees will be at 29.3 USD (1,000USD * 0.029 + 0.3USD). The total transaction fees for VISA and Mastercard are calculated by taking the mid-point between the transactions fee spread for buyers.

Table 1 – Cost Structure of payment providers

	FOR MERCHANT	FOR BUYER	FEES FOR 1000 USD PURCHASE
PAYPAL	2.9 % + 0.3$ per transaction	None	~29.3 USD
VISA	1.65% + 0.15$ per transaction	1.43% - 2.4%	~37.2 USD
MASTER	1.68% + 0.1$ per transaction	1.55% - 2.6%	~38.8 USD
BITCOIN[6]	None	3.33 USD (avg. 2017)	~3.33 USD

Source: Own illustration with data from company homepages and https://bitcoinfees.info/.

The transaction fees are also very volatile and depend on the number of requests. In December 2017, when the demand for Bitcoin increased immensely, the transaction costs rose to 36 USD per transaction and fall again to 0.17 USD in April 2018 (Bitcoinfees.info, 2018). Hence, fees are a major risks source for cryptocurrencies as they hinder their usage. Another problematic part about cryptocurrencies are their complex technologies that require additional intermediaries for the usage as a payment medium, for the average user at least. “Coinbase," one of the biggest providers of such services, requires a fee of 1.49% on every cryptocurrency purchase via their exchange. Even though there is no technical need for intermediaries, most people use these service providers (Cusumano, 2014). Nevertheless, it is not likely that that the total average transaction costs of Bitcoin or other cryptocurrencies would exceed those of traditional payment providers when the purchase amount is high enough.

Savings in transaction fees express the monetary value of cryptocurrencies and might explain prices of cryptocurrencies. A person that spends 20,000 USD a year can save 600 USD (~30 USD per 1000 USD) on transaction fees by using Bitcoin instead of credit cards. Savings in transaction costs result in a direct value of cryptocurrencies as a medium of exchange.

[6] This fee is payed to miners for the confirmation of the payment. It is not as fixed as traditional payments.

2.6 User groups

For a better understanding of the price mechanisms and the demanders of cryptocurrencies, I give an overview of investor groups and reveal their intentions behind their investments. The insights from this section form a basis for the development of hypotheses in Chapter 4 and for the interpretation of empirical results.

Most people that purchase cryptocurrencies can be classified in one of the following groups:

Active users

This group is using cryptocurrencies for real transactions and the purchase of goods or services. They often have a background in cryptography or programming and can be seen as tech-enthusiast and early adopters who use this form of payments for the sake of its technology (Glaser *et al.*, 2014). They keep the lowest balance of the three groups but make the highest amount of transactions. In terms of size, they are the smallest group of users (Baur *et al.*, 2017). A particular portion of this group sees cryptocurrencies as a protest against the existing centralized system that led to the financial crisis and buys them to disconnect with that system (Coindesk, 2015). Another part of this group uses cryptocurrencies for the purchase of illegal goods or money laundry. However, the illicit activities mark a small percentage of actual trades (Baur *et al.*, 2017).

As this group retain their utility from cryptocurrencies as a medium of exchange and therefore promote the acceptance of cryptocurrencies at merchants and in the society, they form the backbone of this market.

Long-term Inventors

This group of users can be divided into active and passive investors. Both are seeking to use cryptocurrencies as an investment vehicle and are rather long-term oriented. Active investors are buying and selling cryptocurrencies in large amounts whereas passive investors only buy them and keep them for a more extended period. Active investors are mainly miners or large investors that were early adaptors of cryptocurrencies and own a large portion of the market.

Passive investors may have similar intentions as gold investor's namely having an investment that is not related to the development of traditional assets, and that is disconnected to the political situation of any countries (Dyhrberg, 2016).

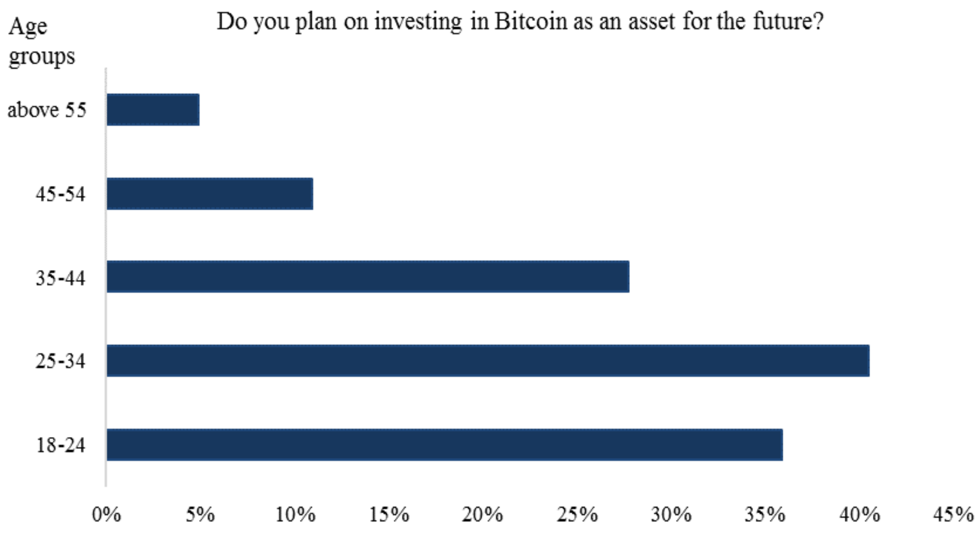
Short-term Investors

This user group is a somewhat new one and emerged with the massive media attention towards cryptocurrencies. They have a low-risk adversity and are willing to accept higher volatilities for higher returns. Glaser *et al.* (2014) find that this group of users tend to keep their cryptocurrencies on their exchange accounts and do not use them to purchase goods. They seek short-term profits and influence the price of cryptocurrencies by active trading. The limited supply of most cryptocurrencies creates deflationary effects which increase the price volatility and hence the speculation (Papadopoulos, 2015). As speculators benefit from volatilities, they favor the volatile environment of cryptocurrencies. However, some investors in this group help to make markets more efficient by exploiting arbitrage possibilities.

Demographics of investors

A survey about the plans to invest into Bitcoin in the future reveals that a high portion of younger adults between 18-34 years plans to purchase Bitcoin as an investment (see Figure 6). This unequal distribution is most likely caused by a higher technological affinity of younger investors. The high share of younger persons that are interested in Bitcoin might indicate a higher speculative behavior as it is likely that they are less experienced and do not take all risks into account. Furthermore, it might point a lower trust in traditional investments at younger age groups.

Figure 6 - Survey about the investments into Bitcoin in the U.S



Source: own illustration based on Statista (2017)

2.7 Classification

Economist, as well as authorities, are discussing the classification of cryptocurrencies since their emergence. Many researchers focus on the question whether cryptocurrencies can be categorized as a form of money or as an asset (Yermack, 2015; Baur *et al.*, 2017; Selgin, 2012). Thus, the literature uses different terminologies such as "Crypto-Assets," "Virtual Currencies" or "Virtual Assets." Despite its name, that suggests a definition as money, Yermack (2015) and most other researchers see cryptocurrencies rather as an alternative investment vehicle than a currency . The main arguments for this position are the high volatility and the detachment from the real economy that speaks against the economic definition of money.

To form a conclusive classification of cryptocurrencies, I give an overview of the functions of money and evaluate if cryptocurrencies fulfill these requirements.

Traditionally, money serves the three functions medium of exchange, store of value and unit of account (Krugman, 1984). Yet, the medium of exchange appears to be the major factor for all forms of money.

Medium of Exchange

Schlichter (2014) sees the ability to exchange money for goods as the most important function and the other functions as rather secondary. Cryptocurrencies are accepted by some online merchants but have limited applicability in physical stores (Acheson, 2018). Furthermore, most cryptocurrency transactions are not made to purchase any goods or services but for trading what means that only a small amount of the circulating cryptocurrencies are used as a medium of exchange (Rubin, 2018). When they are used as an exchange medium, they have some advantages compared to official currencies such as lower transaction costs, faster transaction times and high divisibility. However, they are not officially approved as a currency from any country, and there is no law that forces merchants to accept cryptocurrencies.

In addition to that, there are no goods that are actually expressed in cryptocurrency units, what makes them depended on traditional fiat currencies. Finally, the success of cryptocurrencies is tied to their network size and the number of people that use them for real transactions. Increased usage will increase the value as a medium of exchange (Berentsen and Schaer, 2017). I conclude that cryptocurrencies fulfill the function as an exchange medium in some cases and can be regarded as a limited medium of exchange.

Store of value

The ability to store value allows individuals to save and accumulate wealth or postpone consumption into future periods and is, therefore, an important element of money. The limited supply of cryptocurrencies is an interesting aspect, which imposes a natural scarcity. A scarce supply with an increasing demand can lead to deflationary effects and make objects more valuable. Yet, the most important factor of a good store of value is its stability, because individuals expect at least the same value in the future as today. In contrast to that, cryptocurrencies have high price volatilities and cannot ensure a steady value. Other options such as treasury bonds have not only lower volatilities but also a guaranteed repayment. Further, it seems difficult to control for changes in demand and the high volatility when there is no regulating central institution (Berentsen and Schaer, 2017). These arguments suggest that cryptocurrencies are not a good store of value.

Unit of account

High valuations and prices of cryptocurrencies require the use of fractional numbers, what makes purchases in the daily life more difficult due to less intuitive amounts. For example, one Dollar equals 0,000076 BTC on December 31, 2017, what makes the purchase of goods with smaller amounts less intuitive. In addition, high volatilities would lead to changing prices and lower comparability what induces a high risk for merchants and customers. However, in most cases, the unit of account will still be the fiat currency which is translated to the value of the cryptocurrency before the purchase. Thus, the unit of account is not as important as the other functions for cryptocurrencies.

Summarizing, high volatilities seem to be the main barrier for cryptocurrencies to become a currency seems to make them them to poor stores of values and units of account. Hence, people and merchants are reluctant to use them as a payment method. Regardless of these points, the European Central Bank acknowledged cryptocurrencies as “a digital representation of value, not issued by a central bank, credit institution or e-money institution, which, in some circumstances, can be used as an alternative to money” (European Central Bank, 2015: 25). Therefore, they formed an extensive classification of digital currency and formed a new group of currencies termed as “virtual currencies” which entail the subgroup of bidirectional virtual currencies, or cryptocurrencies, which is shown in Table 2.

The table shows that the difference of cryptocurrencies to other forms of digital currencies is the ability to transfer them into e-money and cash. It does also show the difference to money that individuals hold in their bank accounts, which is the direct availability of fiat currency.

Table 2 - Classification of Digital Currencies

Digital Currencies	**Virtual Currencies**	**Type 1**	Closed Systems (used in online games)	can only be used to purchase virtual goods
		Type 2	Unidirectional (Gift Cards, Token etc.)	can not be easily transfered to money
		Type 3	**Bidirectional (Cryptocurrenies)**	can be transfered back to cash
	E - money (Deposits)	is denoted in a fiat currency and can allways be converted into cash or another currency		

Source: own illustration following European Central Bank (2012)

Glaser *et al.* (2014) found that a majority of users are not acquiring cryptocurrencies for transactions but as a form of alternative investment vehicle. Similarly, Baur *et al.* (2017) and Selgin (2012) see them as a hybrid asset between currencies and commodities and propose a classification as “quasi-commodity money”. Furthermore, a federal judge in the USA classifies them as commodities and regards the Commodity Futures Trading Commission as responsible for their regulation (Bergman, 2018). A comparison with commodities such as gold or silver shows that they all have common features with no interests, a limited supply, increasing production costs, lower intrinsic value and are used as an investment vehicle. Hence, cryptocurrencies can also be regarded as commodities due to their mining process and similar properties to gold. Even if research finds that cryptocurrencies are rather used as investment vehicles, it is difficult to detach its currency abilities from it and classify them as alternative investments.

This overview shows that it is not possible to classify cryptocurrencies into one of the currently existing asset classes or as a typical currency. Cryptocurrencies open a new form of an asset class that lies between currencies and commodities. Due to their properties, I will follow Yermack (2015) and classify cryptocurrencies as an asset in the class of alternative investments, with commodity-like features. The following chapters will focus on cryptocurrencies as alternative investment vehicles, but will still relate to its use as currency. Thus, for the economic and empirical analyses, I will use and explain economic theories that are commonly applied on classical assets as well as for currencies.

2.8 Summary of Chapter 2

This chapter forms the foundation for a detailed economic analysis of cryptocurrencies and delivers essential insights for the next chapter as well as the empirical parts.

As described in this chapter, low transaction fees and the ability to transfer wealth without any state-regulated intermediary were the initial reasons for the demand of cryptocurrencies. These motives changed over time when people started to use them as investment vehicles instead of currencies. Higher public awareness and an increasing demand together with the development of many different cryptocurrencies led to the emergence of a market for cryptocurrencies. Further, I introduce the market structure that is composed of the three major players: users/investors, miners, and marketplaces. Users and investors demand cryptocurrencies and use them as a currency or investment vehicle. The second group, the miners, supply the market with cryptocurrencies and operate the system. Finally, the marketplaces, or exchanges, are the places where demand meets supply and prices are determined. Exchanges made cryptocurrencies accessible to a broad mass and played an important role in the emergence of this market.

Even though most people use cryptocurrencies as investment vehicles; it is not easy to classify them as a classical asset class. The most suitable comparisons to traditional assets would be gold, which is also used as an investment and was used as a form of currency for a long time. Therefore, the upcoming parts consider cryptocurrencies as an investment vehicle, but still relate to their function as currency. The following chapter examines the market structure and give an economic explanation for the emergence of this market that serves as a framework for the analysis of price determinants.

3 Economics of Cryptocurrencies

The cryptocurrency value is completely based on the dynamics of supply and demand and is determined on the markets (Brito and Castillo, 2013; Brière, Oosterlinck, and Szafarz, 2015). Hence, the standard microeconomic theory delivers a theoretical foundation for price determination and the development of price efficiencies. This chapter reviews existing literature on the price determination and applies the microeconomic theory on the cryptocurrency market to deliver an economic reasoning for the empirical analysis. First, I highlight the distinct supply system and describe the intentions behind the demand. Following, I describe the investment inentions analyze the price determination in the short- and long-run.

3.1 Supply

Most cryptocurrencies have a fixed total number of units, which are 21 million in the case of Bitcoin, 100 billion for Ripple, 84 million for Litecoin and 19 million for Dash (Coinmarketcap, 2017). ETH, on the other hand, does not have a maximum supply but allows a maximum of 18 million units to be created per year. The system behind ETH is supposed to lead to a status in which destroyed units are replaced, and the total supply is kept constant (Bovaird, 2016b).

Moreover, the algorithm behind most cryptocurrencies reduces the rewards progressively and makes it more difficult to mine cryptocurrencies (Brito and Castillo, 2013). The reward system is comparable to a gold mine, where mining companies need to dig deeper to get the gold over time. Thus, the supply system leads to a total supply curve that has high growth rates at the beginning, which diminish over time.

Since mining was a highly profitable business and had low capital requirements at the beginning, the number of miners increased very fast. An increasing number of miners led to lower rewards for each miner and high competition between those. The computers of the miners provide computational power to the system and solve specific tasks to get rewarded and those who solve a certain task as the first (which are in most cases the miners with the most computer power), will be rewarded with cryptocurrencies. Other miners, will not be rewarded and have to start solving a new problem. These problems are similar to riddles where computers guess answers as long as they get to the correct solution.

These problems were most likely implemented to incentivize miners and hence improve the supply system and foster faster confirmations of transactions.

The incentives behind this systems led to a digital arms race for better processors with higher computational power (Dwyer, 2015). Today, the mining business built up such high barriers to entry that it is not profitable for individuals or small miner groups to continue their activities. In China and Island, major miners made high investments into large facilities and fast processors leading to lower mining costs, due to lower electricity costs in those countries. To keep up with major mining companies, singles miners formed into pools to use their shared computer power and distribute the rewards in the pool (The Economist, 2015).
The main costs of mining are composed of electricity costs, hardware investments, maintenance and facility costs, where the electricity is the primary cost bucket (Berentsen and Schaer, 2017).

However, some cryptocurrencies have a different supply system. Ripple, for instance, does not have a mining process and the supply is controlled by the company RippleLabs, which owns around 50% of all coins. The other 50% is circulating in the market, but the company could flood the market with more units at any time. Therefore, Ripple is criticized for being a centralized system, which is not the purpose of cryptocurrencies (Levy, 2018).

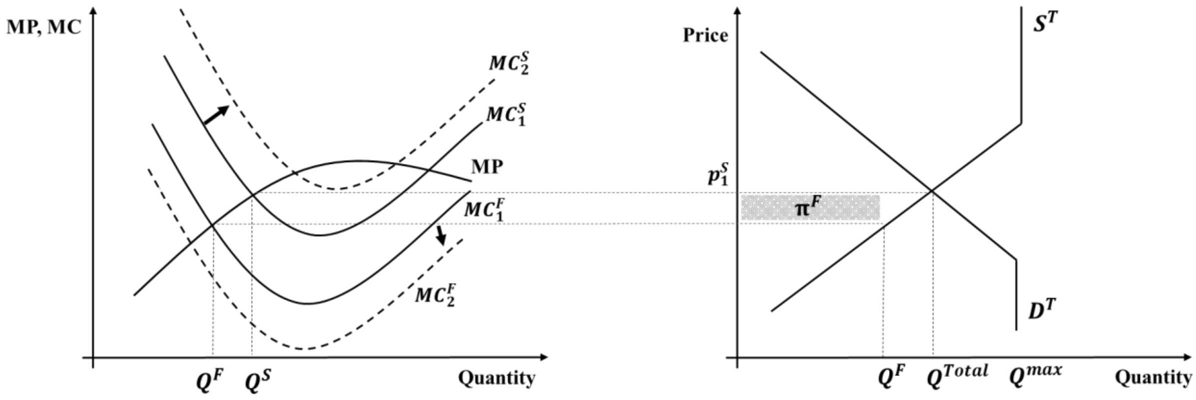
Following, I will describe the economic effects of this supply system with a simplified model that is shown in Figure 8. It explains how the competition between miners affect supply and prices as well as how smaller miners are pushed out of the market.

To understand the competitive forces on the supply side, I assume a simplified situation with two miners, one with faster and modern processors (F) and one with slower processors (S). Accordingly, miner F has lower marginal costs (MC) for the creation of cryptocurrencies than S due to more efficient processors, which lead to higher rewards. The marginal cost curves are expected to be u-shaped because rewards will be lowered over time and the competition will make it more difficult to get rewards. The marginal productivity (MP) is increasing but diminishing due to a limited supply and lower rewards and will decrease after a certain time. In this competitive situation, both sides have to decide on how much units they are going to sell since this will affect market price.

Wright (2017) finds that this situation leads to a Stackelberg competition. This is an economic model in which the market leader, here F, sets the optimal quantity first and the market follower, here S, adapts its quantity accordingly (Stackelberg, 2011). This form of competition usually applies to a market where one firm has a competitive advantage, which is the case in the supply system of cryptocurrencies.

Assuming a Stackelberg competition, F sets its supply amount, and S will react by offering a quantity that leads to a situation where MC = MP and the profits are almost zero (Sams, 2014). On the cryptocurrency market, this will lead to the price p_1^S what leaves the profit of π_1^F for F in the first period. If F uses these profits to reinvest into new processors, the marginal costs will further reduce to MC_2^F in the second period and the total amount of mined units will increase at the same time. Since S was not able to invest in faster processors, the rewards get even lower. With higher marginal costs for S and faster processors of F, this model predicts a situation where S will eventually be pushed out of the market, what leaves F as a monopolist.

Figure 7 – Competition on the supply side



Source: own illustration.

Even though this model is simplistic and neglects additional income from transaction fees or other factors that influence the marginal costs, there is a trend towards a monopoly on the supply at the moment. The cryptocurrency community recognized this development and is concerned of too much power in the hand of single miners (Huberman, Leshno, and Moallemi, 2017). However, there is an element that also keeps smaller players in the market, which are the transaction fees. They will play a more critical role in the future when it comes to incentivizing miners. Especially, when the majority of cryptocurrencies are mined there needs to be an incentive to operate the system, which will most likely be in the form of higher transaction fees (Kaskaloglu, 2014).

This analysis shows that prices of cryptocurrencies are highly dependent on strategic decisions of miners, which control the supply. Therefore, the real supply of cryptocurrencies is not easily predictable in the short-term and more comparable to the supply of commodities.

The insights of this analysis deliver direct implications about potential risks of cryptocurrencies and will be used to determine the price determination in section 3.3.

3.2 Demand

There is an increasing number of online and cashless payment systems in the last 10 to 15 years. The emergence of companies such as PayPal, ApplePay or Alipay indicates the increasing demand for alternative electronic payment systems, especially for the purchase of goods on the internet. The primary attributes of good payment systems are fast processing, high reliability, low transaction fees, trust, worldwide acceptance, easy usage and the ability to use them within a mobile application (Capgemini, 2017). Therefore, the function as innovative payment system was the initial reason for the demand of cryptocurrencies.

However, what influences the demand of cryptocurrencies as an investment? Dwyer (2015) finds that the demand depends highly on factors such as liquidity, price stability and the expectation of price appreciation in the future. He notes that the usage as a payment method does not determine demand. Furthermore, Luther and White (2014) find, in their analysis of Bitcoin, no general linkage between the usefulness and the demand and see it more as a speculation object. However, they acknowledge that if no one expected to make payments with cryptocurrencies in the future, they would be worthless today. Previous research finds that external factors do not play a significant role in the demand of cryptocurrencies and the public interest and awareness, as a proxy for information costs, are driving factors of the demand (Kristoufek, 2015; Ciaian *et al.).* Hence, it seems that the demand of cryptocurrencies is based on similar factors as the demand for high-tech companies. Investors buy cryptocurrencies with the expectation of future price increases when they become a widely accepted payment method.

Following, I give an overview of the main investment reasons and sources of demand for cryptocurrencies based on the report of the European Central Bank (2015):

Alternative investment vehicle

Cryptocurrencies have ideal prerequisites as speculative investment vehicles due to their high volatilities, which can hardly be compared to traditional financial products. Furthermore, arbitrageurs tried to benefit from inefficient markets and price differences, which became increasingly difficult over the years. On the other hand, the low-interest environment and the abundance of money in the market encouraged the search for alternatives with better returns and might be a reason for the growth of the cryptocurrency market (Bovaird, 2016a). Hence, the investment reasons are potentially driven by speculation and the lack of alternative investments.

Safe Haven

Cryptocurrencies are not linked to any economies, governments or authorities and are therefore not impacted by extreme events such as the financial crises. This property allows a particular group of people, who are afraid of economic or political instabilities, to shelter their wealth (Bouri *et al.*, 2017). These might be a similar group of investors that are invested in gold or currencies such as the Swiss Franc, due to its value stability.

Diversification/Hedging

Dyhrberg (2016) found that Bitcoin has clear hedging capabilities against the FTSE index and can be used to minimize specific market risks.[7] She suggests including Bitcoin as a hedging tool for portfolio managers. Brière *et al.* (2015) show that Bitcoin is a very good diversifier due to its low correlation with all other traditional assets. They argue that even a small portion of Bitcoin in a well-diversified portfolio could significantly improve the risk-return profile of portfolios. As more portfolio managers realized this property, funds started to invest in Bitcoin as well (Cheng, 2017).

Institutional problems

In addition to these major investment reasons, there are people in emerging markets that have a demand for cryptocurrencies due to unstable local currency and government, high inflation or capital restrictions. The demand of emerging countries is reflected in the amount of Google searches for cryptocurrencies where economically troubled countries such as Ukraine, Russia, Nigeria, Kazakhstan or Venezuela rank at the top of all countries (see Appendix B). Another example is China which has strict capital restrictions to prevent a capital outflow and limit the purchase of foreign currencies to 50,000 USD (Clover and Mitchell, 2017). Therefore, cryptocurrencies enabled the transfer of large amounts out of the country until regulation made it more difficult to acquire cryptocurrencies on Chinese exchanges.

The demand for cryptocurrencies plays an essential role in the price determination, what will be further analyzed in the following section. In the empirical part of this thesis, I will investigate the factors that influence the demand of cryptocurrencies as an investment and analyze which of these investment motivations are the driving force of the demand.

[7] The Financial Times Stock Exchange 100 Index lists the 100 largest companies at the London Stock Exchange.

3.3 Price Determination

This section forms the foundation for the empirical part and delivers essential insights to the price mechanism, what will be useful the analysis of market efficiency and price drivers. I mainly focus on the short and long-term price determination of cryptocurrencies as investment vehicles.

One of the most interesting parts of the economic analysis of cryptocurrencies is the emergence of the prices and liquidities in markets. There is a stream of research that focus on price determination of cryptocurrencies and tries to find explanations that are in line with economic theories (Kristoufek, 2015; Ciaian *et al.*, 2016; Dwyer, 2015). Even though there has been some research on the price determination and several papers have identified potential price drivers, it makes sense to perform a new analysis, due to mixed results and no clear evidence in existing literature. Furthermore, the driving factors might have changed over time as cryptocurrencies got more integrated into the financial systems and grew substantially. Research on other cryptocurrencies than Bitcoin might also reveal new insights or confirm previous findings. Especially, changed market structures after 2017 as shown in chapter 2 should be reflected in the price mechanisms and efficiencies.

From an economic perspective, the market value of a monetary object evolves from a combination of fundamental value, a promise to pay, a liquidity premium as well as a speculation premium (Berentsen and Schaer, 2017). Without any interest, dividends or industrial demand, cryptocurrencies cannot be valued similarly to assets or commodities with pricing models such as the CAPM.

An early attempt to create a fair price for Bitcoin was made by a miner, who calculated the average electricity consumption of the mining process and multiplied it with the electricity costs leading to an exchange rate of 1,392 BTC per USD (NewLibertyStandard, 2009). This cost-based approach delivers naturally the lower limit of a fair price. Luther and White (2014) used a different approach by comparing the market valuation of Bitcoin to the aggregated value of the U.S dollar. They showed that the market price of Bitcoin could vary between 0 USD and 98,462 USD when it replaces USD as a payment method. All previous approaches were rather approximations than theoretical based calculation, which indicate the difficulty of a price determination.

Economists argue that critical factors of the price formation are not present in cryptocurrency markets, what makes it challenging to determine prices. They criticize the detachment from the real economy, meaning that real goods, incomes or taxes are not expressed and paid in cryptocurrencies (Kristoufek, 2013; Dwyer, 2015; Ciaian *et al.*, 2016; Baek and Elbeck, 2015). Ciaian *et al.* (2016) argue that the demand side drivers will be the long-term drivers of prices. Thus, macroeconomic factors that affect the demand side might indirectly influence cryptocurrency prices in the future. For instance, low-interest rates in the past ten years led to high valuations on the equity and housing markets and enforced the demand for alternative investments and most likely cryptocurrencies as well (Bovaird, 2016a). Furthermore, the fear of a financial crisis or general economic downturn might also indirectly influence the valuation of cryptocurrencies.

Bouoiyour and Selmi (2015) find that the demand side or investors' attention towards Bitcoin, measured by the amount of Google searches, is the most important factor that influences prices (Bouoiyour and Selmi, 2015). They see Bitcoin therefore as a highly speculative instrument. In contrast, Kristoufek (2015) finds that indicators like the usage in trade, price level or the money supply play an important role in price determination of Bitcoin as well. He concludes that prices are in line with economic theories such as the quantity theory of money and that Bitcoin shows attributes of standard financial assets and speculative ones. Thus, it seems reasonable to include macroeconomic variables to describe the price development of cryptocurrencies and to account for cryptocurrencies' properties as an alternative investment, speculation object, safe haven or hedging tool. Even though prices are mainly driven by the market forces of demand and supply (Ciaian *et al.*, 2016).

As previous research finds, demand and supply factors are the most crucial price determinants of cryptocurrencies. Therefore, it makes sense to analyze the microeconomics behind the system and determine the price mechanism in short- and the long-term.

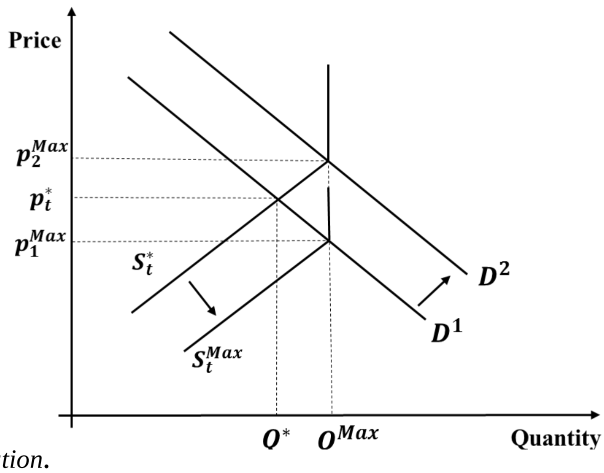
I will use the implications of section 3.1 and 3.2 to analyze the price determination with standard microeconomic theories based on supply and demand as recommended by Baek and Elbeck (2015) with a separation of the short-term and long-term price determination.

3.3.1 Short-term price determination

Miners will probably not directly sell-off all cryptocurrencies, but keep a specific portion to speculate themselves (Okonya, 2016). With this in mind, miners would store cryptocurrencies during phases of low prices and sell them when they believe that prices are high enough, similar to a profit-maximizing mining company. This leads to a dynamic market with an unpredictable total supply.

Figure 9 shows that the demand and the supply might influence prices in the short term. The supply curve is elastic and can shift right until the maximum amount of mined cryptocurrencies in the respective period is reached. The demand can shift to the left or the right. It is visible that prices might fluctuate between $\mathrm{p}_1^{\mathrm{Max}}$ and $\mathrm{p}_2^{\mathrm{Max}}$, when the supply shifts to $\mathrm{S}_\mathrm{t}^{\mathrm{Max}}$ or the demand to D^2. Most likely the circulating amount of cryptocurrencies Q^* will be below the total amount of mined units $\mathrm{Q}^{\mathrm{Max}}$.

Figure 8 – Short-term price



Source: own illustration.

This shows that the price mechanism is very dynamic in the short run and depends highly on miners. Since it is not possible to predict the exact supply and there are no fundamental valuation models, it is challenging to determine all influence factors of prices in the short-term.

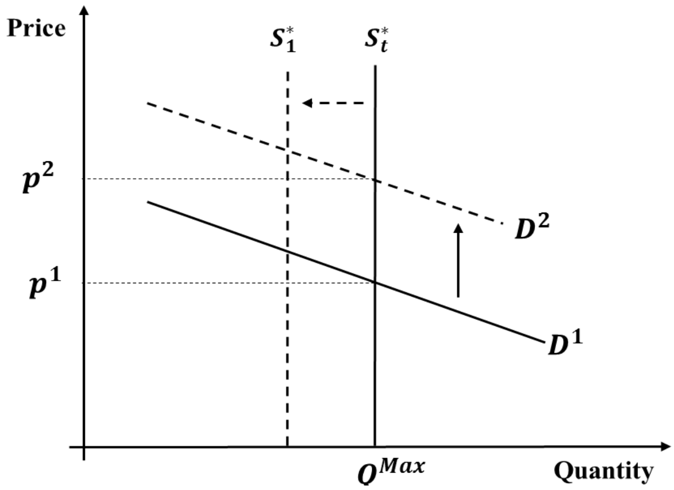
The power of miners and the control of supply in the hands of a relatively small group might also affect the market efficiency negatively since it is likely that there is asymmetric information, what would help miners to outperform regular investors in such an unregulated market. An explicit regulation of the supply side could help to make the supply more stable and markets more efficient in the sense of the strong form of the EMH.

3.3.2 Long-term price determination

In contrast to the short-term price, Figure 10 shows that the long-term prices of cryptocurrencies are not as dynamic. In the long-run, the total amount of cryptocurrencies are mined, and miners will eventually sell off their total cryptocurrencies. This leads to a fixed and inelastic supply of Q^{Max}, where only changes in demand will define the price levels of cryptocurrencies. However, cryptocurrencies with an absolute maximum supply have the risk that some of their units get destroyed or lost over time, comparable to diminishing oil or gold reserves. This would lead to a decreasing supply (shift of the supply curve S_t to the left) and a tendency towards increasing prices. Other cryptocurrencies such as Ether account for this problem and will more likely have a fixed total supply in the long-run. Nevertheless, this effect will be neglected in the further analysis.

Even though the factors that influence demand in the long-run are probably similar to those in the short-run, they will most likely have a higher influence on prices since miners do not play a role anymore. Compared to the short-term, prices might be less volatile as prices do not depend on a dynamic supply anymore.

Figure 9 – Long-term price



Source: own illustration.

I will use this long-run model for the hypothesis development and empirical tests of price drivers in following chapters because short-term prices depend on too many factors that are difficult to measure. Furthermore, there is no research or analysis on miners, and it is not clear what influences their decisions and how they may influence market prices.

3.4 Summary of Chapter 3

This chapter describes the economic mechanisms behind cryptocurrencies and reveals how their distinct functions influence the price determination. Interestingly, the competitive supply through miners affects prices in the short-run and makes the supply inelastic. Furthermore, the incentive structure of cryptocurrencies leads to a consolidation of miners and therefore to a concentration of market power. This might not only affect prices but also impact the efficiency of markets due to asymmetric information, which might allow excess returns for miners. However, as the supply is fixed in the long-run, only demand factors will determine prices. Previous research shows that the factors that influence demand are most likely the public awareness, a lack of alternative investments and the fear of financial crises.

This chapter delivers an economic reasoning for the price determination and will be used as a foundation for the development of hypotheses about market efficiency and price mechanisms in the next chapter. Moreover, I will come back to the economics of cryptocurrencies in the discussion of implications, since it delivers important implications about risks and potential regulations of the market.

4 Hypotheses and Measurements

In this chapter, I develop hypotheses that emerge from the research questions and will be empirically tested in the following chapters. The hypotheses are structured into propositions about the market efficiency, especially the weak form of the EMH, and into propositions about price drivers. As mentioned in Chapter 3, the determination of short-term prices is rather difficult due to the dynamic behavior of the market. Thus, I will focus on the demand side driver of prices. Empirical tests on these hypotheses will help to answer the questions about the prevalence of the weak form of informational efficiency in the market and about the price mechanisms in this market. Furthermore, they are supposed to give insides about the decision-making by investors and allow implications about investment opportunities.

4.1 Market Efficiency

The EMH and the RWH are closely related concepts but have essential differences. Stock prices that follow a random walk do not imply efficient markets per se. It will only allow implications about the independence of prices in time which is an indication for the weak form of efficient markets (Fama, 1991). Since it is difficult to measure the semi-strong and strong form of the EMH, I will focus on test for the weak form of the EMH, by assessing the random walk of cryptocurrency prices.

As mentioned in the literature review, previous research is primarily focused on Bitcoin due to its long range of data availability. Bartos (2015) analyzed the price behavior of Bitcoin from 2013 to 2014 and found that prices follow the efficient market hypotheses by testing the reaction to publicly announced information. Contrary, Urquhart (2016) found in the first extensive analysis of Bitcoin between 2010 and 2016 that prices are significantly inefficient. Despite, he acknowledges that some tests of later subsamples indicate a tendency towards an efficient market. Therefore, he concludes that Bitcoin was in a transition phase towards market efficiency between 2013 and 2016. These findings are confirmed by Bariviera (2017) who also found that Bitcoin exhibited more informational efficiency since 2014 and was inefficient before.

Financial theory and many types of research in the field of efficient markets suggest a strong relationship between the liquidity in the market and its efficiency. Higher liquidity allows arbitrageurs to act in the market, exploit price differences and align prices with their fundamental values at a low cost (Chordia, Roll, and Subrahmanyam, 2008; Chung and Hrazdil, 2010; Grosman and Miller, 1988). Hence, markets with higher liquidity are more likely to conform to the assumptions of the EMH.

Looking at the cryptocurrency market, it is easily noticeable that the market capitalization of Bitcoin grew in 2017 (by 14 times) and became much more liquid. If the market was in a transition phase towards efficiency as stated by Urquhart (2016) and Bariviera (2017), this suggests that Bitcoin prices might follow a random walk and are weakly efficient in 2017.

White (2015) was one of the first researchers to analyze the total cryptocurrency market and its competitive forces. He argues that most cryptocurrencies are based on very similar functionalities and are in direct competition with each other. Even though not all cryptocurrencies are made for the same purposes and might have different factors that influence them, he argues that they are in the same group of the asset class. This suggests that other cryptocurrencies might follow a similar path towards efficiency as Bitcoin. When the faster growth rates and the high market capitalization of Altcoins since 2015 are taken into consideration, it seems plausible that they might have reached market efficiency as well. Hence, I propose the following hypothesis:

H1: Returns in the cryptocurrency market (BTC, ETH, XRP, LTC, and DASH) follow a random walk and are weakly informational efficient.

4.2 Price determinants

Besides the efficiency of prices, it is also essential to understand which information investors mainly use to form their expectations about prices. This can deliver additional evidence about the market efficiency and give insights into the intentions of investors. A reaction on exogenous factors might also imply a higher efficiency in terms of the semi-strong form of the EMH. Furthermore, the development of market efficiencies and the reasons for high volatilities of prices might be revealed if the underlying price drivers are understood.

Following (2015) and Ciaian *et al.* (2016), I will group the price determinants into (1) attractiveness factors, (2) macroeconomic drivers and (3) financial market drivers and build hypotheses about the most important elements in each of these groups.

4.2.1 Attractiveness

This category refers to the factors that investors find appealing about cryptocurrencies and include the media attentions or the public awareness, liquidity and the network size. As there is no real intrinsic value, besides savings in form of transaction costs, this category might be essential for the price formation.

An important factor for the price determination of new assets that have not been valued before is the public interest, which can be used as an approximation for the real demand.

A changed of media attention has an impact on searching costs for alternative investments. Barber and Odean (2008) argue that the searching costs for information on new investments influence investors' behavior. Investors may, therefore, prefer investments that have high media attention to reducing their searching costs.

To account for this relationship, Kristoufek (2015) uses the total amount of search queries for the term "Bitcoin" on Google and Wikipedia as a proxy for the public interest and finds a significant correlation between the search queries and prices. However, he mentions that there is a bi-directional relationship and it is difficult to distinguish whether the information leads prices or vice versa. He finds that prices tend to lead to more public attention until 2012, which turns afterward. If the bi-directional relationship remains the same, the current research suggests that higher media attention for Bitcoin leads to higher prices (Kristoufek, 2015; Ciaian *et al.*, 2016). The media attention for Bitcoin increased exponentially in 2017 and spilled over to other cryptocurrencies as well. Most alternative cryptocurrencies were rarely mentioned in the mainstream media before the cryptocurrency market gained its momentum in the second half of 2017. In addition, it is not clear how long the positive relationship holds since they might diminish, as more people get more informed about cryptocurrencies over time. Therefore, the findings of Kristoufek (2015) and Ciaian *et al.* (2016) might only be applicable for a certain time span and need to be tested with an updated data sample. Therefore, I suggest the following for the cryptocurrency market:

H2a: Higher media attention leads to higher prices at early stages.

Following Kristoufek (2015), I will use the number of search request on Wikipedia and Google as a proxy for the media attention and information demands of investors.

As mentioned before, liquidity is a very important factor for the emergence of efficient markets. It also plays a major role in the price formation due to two main reasons. First, it is a crucial factor for the value as a medium of exchange. Without the ability to exchange cryptocurrencies into fiat currencies, they would be worthless. In other words, the utility of cryptocurrencies is higher when they are traded more frequently. Second, liquidity plays an important role in the standard asset pricing models and might be used by investors to form price expectations.

Yet, Kristoufek (2015) highlights two contradictory effects of liquidity and price. On the one hand, more transactions and trade volume increases the transactional value of Bitcoin. On the other, higher trade volumes might lead to increasing transaction fees due to overloaded systems and a higher demand for confirmations. I see the first effect as the stronger one, due to the young market and modest transactions compared to market capitalizations and suggest following:

H2b: Higher liquidity in the cryptocurrency market attracts more investors and influences prices positively.

Liquidity can be measured in terms of volume, market capitalization, transaction costs or market impact measures (Lybek and Sarr, 2002). Due to the date availability, I will apply I will apply the liquidity turnover ratio a measure of liquidity in the market.

$$LiquidityTurnover_{i,t} = \frac{Trading\ Volume_{i,t}}{Market\ Capitalization_{i,t}}$$

Another factor that is closely connected to the value as a medium of exchange is the network size of a cryptocurrency. The value of the network increases when more people use the same cryptocurrencies and transact with each other. Halaburda and Sarvary (2016) argue that the network size is essential for the transactional value of cryptocurrencies and their prices. Hence, I suggest following relationship:

H2c: Larger network sizes lead to higher prices

To measure the network size, I use the total transactions within a network, which describe the number of ownership changes and can also be used as a proxy for the popularity:

$$Transactions_{i,t} = \textit{number of confirmed transactions in the network}$$

4.2.2 Macroeconomic Drivers

Even though macroeconomic factors are also captured by the financial markets; it makes sense to have a detailed look to distinguish between different drivers. Previous research finds that factors such as inflation, GDP or the oil price are a good reflection of the economic development and have been applied on the analyses of Bitcoin before (Kristoufek, 2015; Ciaian *et al.*, 2016; van Wijk, 2013). However, the majority of previous research cannot find significant effects what leaves the relation of macroeconomic drivers and cryptocurrency prices still unclear. Bouoiyour and Selmi (2015) argue that favorable macroeconomic conditions could improve the use of Bitcoin and increase the demand which might have positive impacts on the price.

A general increase in price levels and inflation in the economy leads to higher investments in financial markets due to a depreciation of the money value (McClain and Nichols, 1993). If cryptocurrencies are seen as alternative investments and are linked to the real economy, investors might distribute a certain amount of their additional investments to cryptocurrencies. Ciaian *et al.* (2016) suggest that the oil price is a good measure of the cost pressure in the economy and can provide an early indication for the inflation development in the future. They used the oil price as a proxy for the changes in the price level and found a negative relationship with the Bitcoin price.

Following this approach, I apply a measure of the price level in the economy on the cryptocurrency market and suggest the following relationship.

H3a: Higher price levels lead to higher prices on the cryptocurrency markets.

To measure the price level, I follow Ciaian *et al.* (2016) and use the oil price as an approximation of the USD inflation.

$$Oil_t = Daily\ Brent\ Crude\ Oil\ price\ in\ USD$$

China is one of the most important countries in the ecosystem of cryptocurrencies. They have the largest community of cryptocurrency miners, the most exchanges and high demand in the population. It seems that some of the extreme events of Bitcoin prices coincide with events in China (Kristoufek, 2015). The market reacts sensitively to the increasing regulation from the Chinese government such as the ban of initial coin offers or tight controls of exchanges (Clark and Chen, 2018). Thus, the regulation in China plays an important role in cryptocurrency prices.

Kristoufek (2015) includes a measure to account for the Chinese influence on the cryptocurrency market and finds that the Chinese market is an important driver for the Bitcoin price in USD. Due to the dominance of China in nearly all other cryptocurrencies, I suggest following hypothesis:

H3b: The Chinese market is a driving force of cryptocurrency prices.

The Chinese government shut down many exchanges in China and made it difficult to purchase cryptocurrencies for Chinese people. Individuals can, however, buy cryptocurrencies at foreign exchanges and transfer them to their local wallets. To purchase them at a foreign exchange they will usually need to buy them in USD, what makes Chinese investors depended on the USD exchange rate. Furthermore, China has the largest miners that need to sell their cryptocurrencies in foreign currencies and transfer money back to local currencies.

Therefore, I will apply the CNY-USD exchange rate as a proxy for the Chinese influence as the Chinese demand depends on the currencies valuation towards the USD. I expect that cryptocurrencies will experience a price increase when the Chinese currency appreciates.

$$China = \frac{CNY}{USD}$$

4.2.3 Financial Market Drivers

Financial market indicators are supposed to capture the relationship between financial markets and the asset class of cryptocurrencies. They allow an indication of how investors see cryptocurrencies and how they are interrelated with the financial system.

Thus, these indicators may provide information to understand if investors use cryptocurrencies rather as alternative investments, speculation objects, safe haven or as hedging tools.

There are two potential effects of financial markets on cryptocurrencies. First, higher returns on financial markets might stimulate the demand for alternative investment vehicles and could therefore also increase the demand for cryptocurrencies (Bouoiyour and Selmi, 2015). Second, decreasing returns from traditional asset classes might evoke the fear of a potential downturn and increase the interests for alternatives, which could affect the prices of cryptocurrencies positively. This poses the question about the strength of the opposing effects and the real relationship between returns on stock exchanges and cryptocurrencies. The first effect is likely to be more dominant if cryptocurrencies are seen as an alternative investment and the second if they are rather used as a safe haven. Bouri *et al.* (2017) argue that Bitcoin has weak properties as a safe haven and serves as such only during certain times and in specific markets. This suggests that the first effect is more dominant than the second and that stock exchanges and cryptocurrency prices have a positive relationship.

Previous research on this topic found mixed results. In an analysis of Bitcoins' price drivers, van Wijk (2013) finds that the returns on the Dow Jones Index have a significantly positive influence on the Bitcoin price while Ciaian *et al.* (2016) and Baek and Elbeck (2015) do not find any significant influences of financial markets on prices.

The insignificant findings might be related to the circumstance that the Bitcoin market (between 2010 and 2014) was too small and isolated to be affected by the financial markets (Vockathaler, 2015). However, the market grew substantially, and cryptocurrency trading has become much more professional. In 2017, Bitcoin was even introduced to the future markets and got more integrated into the financial system. With the ability to buy futures on Bitcoin, investors are able to hedge their positions and manage their risk exposures what might also attract more risk-averse investors. Due to the major changes in the market and increasing integration of cryptocurrencies into financial markets, I propose following:

H4a: Higher returns on financial markets drive the prices of cryptocurrencies positively.

I use returns of the S&P 500 index (*SP500*) as well as the MSCI World Index (*MSCI*), to have a comprehensive measure of the international financial markets

Nevertheless, financial indices alone are not able to capture all effects of financial markets. To ascertain if investors are influenced by the hedging and safe haven properties of cryptocurrencies, previous research tested the relationship between the gold price or financial stress indicators and cryptocurrency prices (Bartos, 2015; Ciaian *et al.*, 2016; Kristoufek, 2015). A safe haven asset is generally insensitive to the changes on the financial markets or often negatively correlated to their returns. After financial crises in 2008, investors were more concerned and skeptical about the financial markets and invested strongly in gold, which is the most prominent form of safe haven. [8]

[8] The gold price rose from around 700$ in 2007 to over 1800$ in 2011 (https://www.bloomberg.com/quote/GC1:COM, accessed on the 26.03.18)

Even though it has a worse risk-return profile than treasury bonds, gold seems to attract investors especially in times of external shocks (Baur and McDermott, 2016). Similar to gold, cryptocurrencies are detached from the economic development and might, therefore, be used as a form of safe haven. Bouoiyour and Selmi (2015) argue that cryptocurrencies stand in competition with gold and that a fall in gold prices could drive the demand for alternative safe to havens. To test whether the gold price influence the cryptocurrency market, I formulate the following:

H4b: Cryptocurrency and Gold compete as a safe haven and have an inverse relationship.

In addition to the gold price, Kristoufek (2015) uses the Financial Stress Index from the Federal Reserve Bank of Cleveland to measure the effects of increased risk in the market on the Bitcoin price to determine its safe haven properties. According to his argumentation, investors might search for safe havens when the financial markets get more volatile, and the market expects a downturn. Following this argumentation about the safe haven properties of cryptocurrencies, I state the hypothesis as such:

H4c: Cryptocurrency prices increase when traditional financial markets get riskier.

Since the financial stress index is discontinued, I will use the CBOE Volatility Index (VIX) to measure the risk on financial markets. This index shows the market expectations of the 30-day volatility of the S&P 500 and is often uses as an indicator of uncertainty in the market.

$$RISK = CBOE\ Volatility\ Index\ (S\&P\ 500)$$

4.3 Summary of Chapter 4

In this chapter, I developed the hypothesis that I will test in the following chapter. Hypotheses are grouped into the market efficiency and price drivers, which is composed of the three categories attractiveness factors, macroeconomic drivers, and financial market drivers. Table 3 displays a summary of all hypotheses and respective measurement methods.

Empirical tests of these hypotheses will provide answers the research questions regarding the market efficient as well as price drivers and hence allow implications about cryptocurrencies as investments.

Table 3- Summary of hypotheses

The table shows a summary of all hypothesis and their measurement methods.

Hypothesis		**Measurement**
H1	Returns on the cryptocurrency market follow a random walk	Prices of BTC, ETH, XRP, LTC, and DASH
H2a	Higher media attention leads to higher prices	Google and Wikipedia searches
H2b	Higher liquidity in the market attracts more investors and influence prices positively.	Liquidity Turnover
H2c	Larger network sizes lead to higher prices	Transactions in the network
H3a	Higher price levels in the economy lead to higher prices on cryptocurrency markets	Oil price
H3b	The Chinese market is a driving force of cryptocurrency prices.	CNY/USD exchange rate
H4a	Higher prices on financial markets drive the prices of cryptocurrencies positively	S&P500 and MSCI World
H4b	Cryptocurrencies and Gold compete as a safe haven and have an inverse relationship	Gold price
H4c	Cryptocurrency prices increase when traditional financial markets get riskier	VIX index

5 Empirical Analysis & Results

The focus of this chapter is to test the hypotheses and to deliver a meaningful explanation of empirical results. The findings of this chapter will allow me to answer questions about the market efficiency and the appropriateness of cryptocurrencies as investment vehicles. First, I give an overview of the data sample and present descriptive statistics. Second, I present the methodology and empirical results of the market efficiency analyses and the price drivers. Third, I discuss findings and draw conclusions about the chances and risks of investments.

5.1 Data

The data sample consists of daily time series between 9th of August 2015 and 31st of December 2017. Data about prices, market capitalization and trading volume of cryptocurrencies are taken from coinmarketcap.com, which lists weighted average prices from many exchanges for almost all available cryptocurrencies. Since Ether is not listed before August 2015, I gathered all data starting from this date. This avoids an unbalanced data set and provides a better comparability. Nevertheless, I gathered 876 observations per cryptocurrency and 4380 observations in total. All macroeconomic and financial data such as the gold price, oil price, S&P 500, MSCI World, CNY/USD exchange rate and the VIX index are gathered from Thomson Reuters Eikon. The number of transactions in every respective network is taken from coinmetrics.io. Wikipedia searches are retrieved from their official analysis portal on tools.wmflabs.org/pageviews. Similar, Google searches are available on trends.google.com. However, the number of Google searches are shown in normalized numbers from zero to hundred, whereas Wikipedia shows absolute numbers. Furthermore, I divide the total sample into three subsamples to measure changes over time and capture the dynamics of the market. The first subsample is between 8.9.2015 and 31.12.2015; the second and third include the whole years of 2016 and 2017.

Data Interpolation. Different trading days are a major problem of the data sample. While most variables such as S&P500 or the gold price depend on working days and bank holidays, cryptocurrencies are traded every day. To overcome this problem, I decided to use the last data point on a working day (e.g., Friday) and apply it on non-working days (e.g., Saturday and Sunday). This might lead to biases in results, but as cryptocurrency prices are the most important variable in my analysis, I prefer this option to manipulation of price data. Another problem is posed by the Google trends data, which is only available on a weekly basis for periods over 90 days. To overcome this problem, I extracted the daily data in 90-day intervals for the total sample period and the weekly data for the same period. Since the data are percentage numbers, I rescaled daily values by using percentage changes of weekly data. Even though this is an approximation; it will be very close to the real daily search queries.

Index. To make implication regarding the total market, I created an index of the five crypto-currencies by calculating weights, which indicate the share on the cumulated market capitalizations. Following, I multiplied these weights with the prices of cryptocurrencies and summed those up, which creates a new time series. This index is used as a benchmark for single crypto-currencies and to make implications about the overall market in the discussion.

5.2 Descriptive Statistics

In this section, I display and briefly discuss the main variables of interest for the analysis and compare the characteristics of the price data between single cryptocurrencies. Subsequently, I draw first indications about the market and the hypotheses.

Table 4 presents the descriptive statistics of daily returns for cryptocurrency as well as financial data for the total sample. The average daily returns (Mean) of cryptocurrencies show high differences and range from 0.45% to 0.66%. Similar patterns are visible for the standard deviation (SD) which lay between 3.85% and 7.89%. High volatilities of cryptocurrencies are also conspicuous by extreme daily changes (Min and Max) which can range from daily losses of over 60% to gains of 100%. Looking at skewness and kurtosis of return distributions, Bitcoin is the only cryptocurrencies that has similar properties as traditional assets with a negatively skewed distribution and a kurtosis at nine. A negative skewness in the case of Bitcoin means that the majority of observations are on the left side of the distribution curve (see Appendix C). Other cryptocurrencies, with a positive skewness, have the majority of observations on the right side of the peak. Kurtosis is a measure for the occurrence of extreme returns at the tails of distributions and is especially high for XRP and LTC, whereas BTC, ETH, and DASH do not have as many extreme events. XRP seem especially risky, due to a high kurtosis and a wide range between the highest and the lowest value, that means that investors experience high gains and losses on single days. With these properties, XRP stands out in this list what I will consider in the results and discussion of empirical results.

Table 4 - Descriptive Statistics

This table provides descriptive statistics for the daily returns of 5 cryptocurrencies, the index, and macroeconomic as well as financial data between 08.09.2015 - 31. 12.2017. N describes the number of observations, Mean the average daily return, SD the average daily standard deviation and Min/Max the lowest and highest returns within one day.

Variables	N	Mean	SD	Min	Max	Skewness	Kurtosis
BTC	876	0.456%	3.85%	-21.8%	23.5%	-0.11	9.30
ETH	876	0.789%	7.29%	-31.5%	41.2%	0.59	7.63
XRP	876	0.639%	7.87%	-61.6%	102%	3.74	48.06
LTC	876	0.468%	5.79%	-39.5%	51.1%	1.63	19.03
DASH	876	0.666%	5.98%	-24.3%	43.8%	1.21	10.27
Index	876	0.559%	3.72%	-21.3%	20.7%	-0.09	8.16
SP500	876	0.029%	0.65%	-4.2%	3.8%	-0.51	10.51
Gold	876	0.019%	0.84%	-3.5%	7.6%	0.96	11.79
Oil	876	0.037%	1.9%	-8.1%	9.3%	0.11	6.05
MSCI	876	0.021%	0.59%	-5.1%	2.6%	-1.17	14.03
VIX	876	14.42	4.63	9.14	40.47	n/a	n/a
CNY/USD	876	0.005%	0.23%	-1.3%	1.9%	1.06	16.55

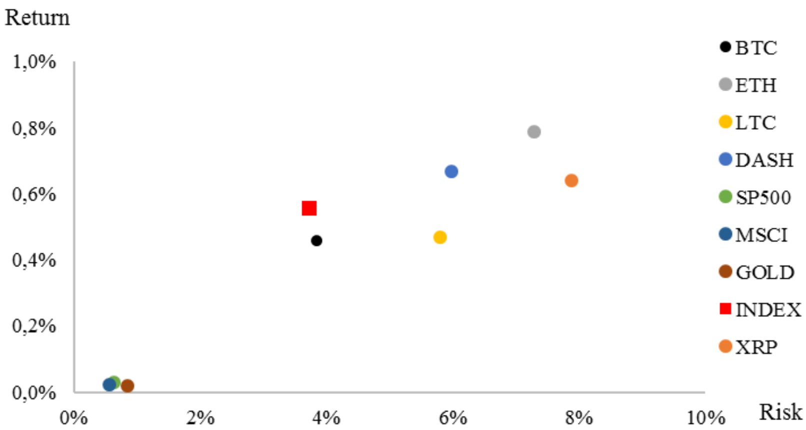
Interestingly, there seems to be a relationship between the volatility and the age of cryptocurrencies. BTC, LTC, and DASH show considerably lower volatilities than the XRP or ETH, which emerged later. A higher maturity is particularly visible in lower returns and standard deviations of BTC, which might be reflected in the market efficiency as well. Looking at the development of the market over time, the daily returns of the Index grew fourfold from 2015 to 2017, whereas the volatility grew only from 3.45% to 4.68% in the same period, what implies an improved risk-return profile (see Appendix D). Even though the extreme returns are higher in 2017 than in 2015, they occur less often what is indicated by a decreased kurtosis.

Financial markets, represented by the S&P 500 and MSCI World Index, experience a significant increase in returns in the same period from negative average returns in 2015 to daily returns of 0.048% (S&P 500) or 0.05% (MSCI). At the same time, the SD of S&P 500 and MSCI reduced to a third (Appendix D). A comparison of 10-day standard deviations indicates that the cryptocurrency market became highly volatile in 2017 and the difference to the volatilities of equities (S&P500) and commodities (gold) grew substantially (see Appendix E). Increasing volatilities and returns after the beginning of 2017, without similar patterns at traditional assets, might indicate a speculative bubble or a substantial change in the market.

For a better comparison of cryptocurrencies, I plot the price data in Figure 10. As this graph illustrates, it does not make sense to compare traditional assets with cryptocurrencies since they have significantly different risk-return profiles. Therefore, cryptocurrencies should probably not seen as alternatives to equities or commodities but rather as a new asset class. The graph indicates that the Index is dominating BTC and LTC and that DASH is superior to XRP, due to higher returns at lower risks. Furthermore, it is noticeable that the diversification effects à la Markowitz do also apply to the cryptocurrency market as the Index has the lowest volatility and still outperforms others. However, this does not display the optimal weights that lead to a minimum variance and the sample period is too short to imply the real risk-return profiles of this emerging market.

The graph illustrates that cryptocurrencies might be used to improve the risk-return profile of existing portfolios due to their extreme properties. Dyhrberg (2016) finds that it is actually possible to improve the risk-return profile of the global market portfolio by including around 2% cryptocurrencies in portfolios. Thus, it appears that classical portfolio theory might also apply to this market and should be considered in future research.

Figure 10 - Comparison of daily Risk/Return distributions



Correlations. Table 5 shows the correlations between the returns of cryptocurrencies and the financial data. There seems to be a high dependency between the single cryptocurrencies. Despite that, there is almost no correlation to traditional assets and the macroeconomic indicators. This might be another motivation for investors to use cryptocurrencies as diversification or hedging tool. Yet, correlations seem ambiguous as VIX has a negative correlation with all cryptocurrencies, which does not indicate safe haven properties as proposed in hypothesis *H4c*. Additionally, the correlation with gold is positive and does also not speak for a competition as a safe haven instrument. Further, the indicators of financial markets, SP500 and MSCI, do not show consistent correlations with cryptocurrencies. The correlation of macroeconomic indicators seems to coincide with stated hypotheses for the majority of cryptocurrencies.

Generally, it is not possible to draw implications from these simple correlations because they do not show significances and measure only direct relationships, but ignore multivariate influences. Nevertheless, it allows first indications for the later analyses and confirms that cryptocurrencies are most likely not strongly influenced by exogenous factors.

Table 5 - Correlation matrix

	Bitcoin	Ether	Ripple	Litecoin	Dash	Index	SP500	GOLD	Oil	MSCI	VIX	CNYUSD
Bitcoin	1											
Ether	0.2480	1										
Ripple	0.1478	0.1168	1									
Litecoin	0.5029	0.2413	0.2313	1								
Dash	0.2998	0.2492	0.0709	0.2813	1							
Index	0.9274	0.5313	0.2253	0.5141	0.3195	1						
SP500	0.0026	0.0197	0.0219	0.0128	0.0583	0.0013	1					
GOLD	0.0150	0.0426	0.0336	0.0040	-0.0078	0.0320	-0.1607	1				
Oil	0.0146	-0.0215	0.0062	0.0239	0.0506	0.0043	0.3572	0.0043	1			
MSCI	-0.0137	-0.0045	0.0350	0.0055	0.0564	-0.0214	0.9077	-0.1643	0.4008	1		
VIX	-0.0528	-0.0061	-0.0718	-0.0789	-0.0586	-0.0351	-0.1803	0.0421	-0.0541	-0.2065	1	
CNYUSD	-0.0266	0.0503	-0.0244	-0.0030	0.0290	0.0065	0.0135	0.0103	-0.0240	-0.0085	0.0250	1

Non-financial Variables**.** Table 6 displays the liquidity turnover, number of the transaction as well as the Google and Wikipedia searches for Bitcoin. The development of variables allows the first indication regarding hypotheses about price drivers. The table shows that the liquidity, public awareness as well as total transactions increased significantly after 2017, what is in line with the hypotheses. The public awareness shows a particular high change, with almost 10 times more Google searches in 2017. Interestingly, the number of the transaction does not show such a high change what indicates that cryptocurrencies are rather stored as assets than used for payments. The variables of other cryptocurrencies show similar patterns (see Appendix F).

Table 6 - Non-financial Variables of Bitcoin

Bitcoin	Liquidity		WIKI		Google		Transactions	
Period	>2017	<2017	>2017	<2017	>2017	<2017	>2017	<2017
Mean	2.7%	0.9%	41,174	9,822	10.8%	1.3%	285,034	204,171
Min	0.4%	0.04%	9,554	5,760	1.8%	0.7%	131,726	86,754
Max	8.5%	4.4%	344,686	88,391	100%	4.1%	490,459	329,565
Median	2.4%	0.8%	27,578	8,842	6.3%	1.2%	281,436	212,344

5.3 Market Efficiency

In this section, I will first give a detailed overview of the methodology and then present the test results on the random walk hypotheses. Further, I highlight the development in the past years and discuss the results.

5.3.1 Methodology

According to Cuthbertson and Nitzsche (2010), a random walk is determined as such:

$$p_t = p_{t-1} + \varepsilon_t + \delta \qquad E(\varepsilon_t) = 0,$$

where p_t describes the current price, p_{t-1} the price in the past period, ε_t an unknown random term and δ the drift, which is a constant that describes a price trend. There are three different forms of the RWH. The RW1 hypothesis assumes that the random term ε_t is independent and normal distributed and has an expected value of zero. Thus, if the condition to the right is fulfilled it is not possible to predict future prices with past prices and there is a random walk. The RW2 and RW3 loosen this assumption and more often used for the analysis of a random walk.

To test the RWH, I will follow the approach of Urquhart (2016) and apply a wide range of robust tests on the total data set and on subsamples to determine changes in the market structure. Tests about the randomness of returns can be divided into parametric and non-parametric tests. While parametric tests have a higher statistical power and can deal with skewed and non-normal distributed time series, non-parametric tests are better for smaller sample sized and samples with outliers (Hiremath, 2014). To capture all effects and benefit from the strengths of the parametric and non-parametric test, I apply five types of test that are testing the randomness and predictability of returns as well as their long-range dependencies. The combination of these tests delivers robust and detailed information about the randomness of returns what allows me to draw conclusions about the market efficiency. I apply these tests to the log returns that are calculated as such:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right),$$

where r_t is the return of cryptocurrencies and $\ln(P_t)$ the logarithms of cryptocurrency prices at time t and t – 1. Following, I give a detailed description of tests on serial correlation, run tests, the variance ratio test, unit root tests and long-term memory:

Serial Correlation. Serial correlation measures the correlation between two data points in a time series. In other words, it measures if the returns of yesterday are correlated with the returns of today. A high correlation indicates that prices can be predicted by using historical prices and implies that the time series does not follow a random walk. There are multiple ways to measure serial correlation, yet, I will focus on the Ljung-Box portmanteau Q-statistics which is one of the commonly used methods to analyze the market efficiency (Hiremath, 2014). The test is a weighted average of correlation coefficients that are calculated at different lags and is thus a good test to indicate a random walk (Brooks, 2014).

Run Tests. Run tests are nonparametric tests that are closely related to serial correlation tests. They give information about the randomness of returns, but do not rely on the assumption of normally distributed returns. Run tests measures if consecutive prices changes depend on each other, compares the number of runs, and analyzes repeating patterns. If these return patterns repeat over time, the tests indicate a non-random sequence in returns.

An example would be following return pattern: + + + - - - + + + -. This return pattern has four runs, or changes in returns, with the length of 3, 3, 3 and 1. If there are no significant return patterns, this test does indicate a random walk. Run tests are a good method to test the assumption about market efficiency, but are not suitable for detailed analyses and should be supported by additional methods (Campbell, Lo, and MacKinlay, 1997).

Variance Ratio Test. The absence of serial correlation is a necessary but not sufficient condition for the weak form of the EMH. Lo and MacKinlay (1988) propose the variance ratio (VR) test as a direct measure of market efficiency, which is widely used by researchers (Urquhart, 2016; Brauneis and Mestel, 2018). This test is mainly used for testing the RW_1 form, which is the strongest form of the RWH and will be tested in this work as well. It is superior to other methods when there is a large data sample over 256 observations (Chow and Denning, 1993). The assumption that the variances of an independent and identically distributed time series increase proportionally to the observation period makes this test possible. If the increments of the return variances are linear in all observation periods, the time series follows a random walk. The VR describes the relationship of two independent variance coefficients in a sample. To confirm a random walk, the relationship of variance increments has to be one. Larger VR's indicate a positive and smaller VR's a negative serial correlation (Brooks, 2014). The VR test of Lo and

MacKinlay (1988), also called individual VR test, is one of the most used forms of the VR test. It requires that the VR for each lag has to be one for a random walk (Charles and Darné, 2009).

Unit Root Test. A time series is called stationary when the mean and variances do not change over time. If they change, the time series contains a unit root. A stationary time series is predictable since mean and variance stay constant. Therefore, the presence of unit root is an indication for the random walk of returns. However, it does not imply a random walk and should not be used as a direct measure. To test the data on the unit root, I will use the Augmented Dickey-Fuller and apply it on the prices, which uses a lagged dependent variable and is an often used method in previous research (Brooks, 2014).

Long-term Memory. Following Urquhart (2016) and Bariviera (2017), I will apply a measure for long time memory of returns. In other words, this test measures the serial correlation with lags to measure if returns over longer periods depend on each other. A common way to measure long-term memory is the rescaled Hurst exponent, which provides an indicator for the long-range dependency of a time series (Couillard and Davison, 2005). The Hurst exponent H can range between zero and one, where values between 0.65 and 1 show strong persistence, meaning that positive returns will be followed by positive returns and the long-term returns will also tend to be positive. In the case of strong anti-persistence, for values between 0 and 0.45, indicating that positive returns are likely to be followed by negative ones. Hence, a Hurst exponent of 0.5 indicates no long-range dependencies between returns and a random walk (Urquhart, 2016).

While all these tests are helpful to determine the randomness of prices, the variance ratio seems superior to other tests due to its reliability, flexibility and the fact that it has been used by many previous types of research for a direct test on a random walk of time series (Charles and Darné, 2009). Hence, I will evaluate the results of the VR test with stronger emphasis. Further, I will use the Hurst exponent as a measure for the degree of market efficiency. Nevertheless, the application of a broad set of tests allows higher robustness of results.

5.3.2 Results & Discussion

Here, I present my empirical result and statistical tests based on the given data sample and subsamples. First, I present the results of all tests and determine whether hypotheses H1 holds for the index. Second, I present which cryptocurrencies are efficient and how they developed during the observation period. Third, I discuss all results and put them into perspective with the initial research questions. Furthermore, I give implications about the price adaption of prices to publically available information by analyzing the reactions to three distinct events.

Table 7 presents the results of all five test on the randomness of returns, whereby the figures in the columns refer to the p-values of respective tests. The first column displays the Ljung-Box (LB) test on serial correlation with the null hypotheses of serial correlation. Similarly, the column Run refers to the run tests on randomness. Column VR stands for the p-values of the variance ratio test with the null hypotheses of a random walk. The augmented Dickey-Fuller test (ADF) has the null hypothesis of a unit root, what means that a rejection shows stationary in variables. The last column displays the Hurst coefficients where a value of 0.5 implies no long-range dependencies between prices. Stars indicate the significances of variables at different levels. In this case, stars indicate the predictability of returns and that a variable is not following a random walk, whereas I reject a test at p-values of 0.05, or two stars.

Table 7 - Tests on Market Efficiency

The table presents results for the five cryptocurrencies and the created index from tests on return predictability. The columns report p-Values of the Ljung-Box test (LB), run tests, variance ratio tests (VR), augmented Dickey-Fuller Test (ADF and the rescaled Hurst exponent (Hurst).

Cryptocurrencies	**LB**	**Run**	**VR**	**ADF**	**Hurst**
BTC	0.79	0.59	0.61	0.99	0.54
ETH	0.26	0.46	0.29	0.99	0.64
XRP	0.00***	0.79	0.24	1.00	0.59
LTC	0.13	0.03**	0.00***	0.99	0.59
DASH	0.19	0.68	0.07*	0.99	0.54
Index	**0.63**	**0.18**	**0.16**	**0.96**	**0.56**

*** p<0.01, ** p<0.05, * p<0.1

The results show that the overall cryptocurrency market, represented by Index, follows a random walk over the total data sample. The p-values indicate that it is not possible to reject null hypotheses of no serial correlation, a random walk, stationary and long-range dependencies and therefore confirm a random walk. However, not every cryptocurrency is efficient, what is not reflected in the index due to the high representation of Bitcoin.

Following, an analysis of single cryptocurrencies:

- Tests on returns of BTC are insignificant and indicate randomness of returns and weakly efficient prices. A low Hurst value at 0.54 together with the high p-values indicate the highest efficiency among the cryptocurrencies. Contrary to previous findings, Bitcoin prices follow a RW and are weakly informational efficient.
- Results of ETH indicate a random walk of returns, but the Hurst exponent marks the highest value between all cryptocurrencies with 0.64. This value is under the threshold of 0.65, but can still be seen as a sign for long-term dependency. Thus, ETH prices seem to be efficient in the short term, but there are definite signs of long-range dependencies of prices. I assess the efficiency of ETH as unclear but rather efficient.
- For XRP, the LB test indicates a strongly significant serial correlation of returns, what means that returns on a given day can predict returns on the following day. Nevertheless, all other tests indicate a random walk and thus show signs of a weakly efficient market. The Hurst exponent of 0.59 indicates positive persistence in the long-term, which means that positive returns tend to follow on positive returns, which is less problematic according, to the definition of Urquhart (2016). Yet, the LB test indicates clearly that XRP does not follow a RW and is not efficient.
- LTC shows clear signs that speaks against a random walk. The run test as well as the variance ratio test reject the randomness of returns and imply that investors can use past prices to predict future prices. Further, the Hurst exponent (0.59) indicates a positive persistence for LTC as well. Altogether, the test results imply that prices of LTC are not random and do not follow the EMH.
- Dash prices do not reject any tests at 95% confidence level and follow therefore a random walk. Since the VR test is very powerful and is rejected at a level of 0.1, the results are not entirely conclusive. The Hurst exponent at 0.54 does not indicate a clear persistence and confirms the results of other tests. However, test results indicate efficient prices for Dash.

Summarizing these points, only Bitcoin and Dash show clear signs of efficient prices, whereas LTC and XRP prices are not random and probably predictable. ETH passes all tests and shows signs of efficiency in the short term, but the long-term price dependency indicates predictability to a certain degree. Nevertheless, I evaluate prices of ETH as rather efficient as the Hurst exponent is still under the suggested threshold.

Before jumping to a discussion of these findings, I want to highlight that these results depict the development over a period almost 2.5 years and do not necessarily reflect the prevailing situation on the market. As noticed before, this fast emerging market went through significant changes in the past years. Hence, it makes sense to look at the results of subsamples to investigate the changes in the market and have a more accurate statement about the current state of the market efficiency.

Development of the market efficiency

Table 8 presents the market efficiency of the subsamples between 2015 and 2017. The figures of the year 2017 are the most updated analysis of the market and should represent an accurate depiction of the market efficiency. The table shows that the total market follows a random walk in 2017 and 2015, but was inefficient in 2016, as the LB test indicates serial correlation and the Hurst exponent a strong positive persistence.

Contrary to the total sample, only LTC rejects the RWH in 2017 directly due to a strongly significant p-value of the variance ratio test. However, Hurst exponents of ETH and XRP show signs of strong persistence, what speaks against a random walk. Hence, I only recognize prices of BTC and Dash as efficient in 2017.

While BTC follows a RW during all subsamples, other cryptocurrencies show changing patterns. Interestingly, ETH and LTC returns were random in 2015, but strongly reject the run test on randomness in 2016, due to significant run tests. On the other hand, XRP and Dash show an evident development regarding market efficiency.

Nevertheless, high Hurst values in 2017 indicate a room for potential improvements. The strong persistence of returns, especially of ETH and XRP, occurs after 2016 and is most likely caused by the immense price developments. Thus, investors were able to predict returns by using the long-run trend variables. This speaks clearly against the assumptions of a random walk but is probably less problematic when price growth slows down in the future.

Table 8 - Tests on Market Efficiency between 2015 and 2017

Tests on Market Efficiency in 2017

The table presents results for the five cryptocurrencies and the index from tests on return predictability. The columns report p-Values of the Ljung-Box test (LB), run tests, variance ratio tests (VR), augmented Dickey-Fuller Test (ADF and the rescaled Hurst exponent (Hurst).

Cryptocurrencies	LB	Run	VR	ADF	Hurst
BTC	0.95	0.08*	0.71	0.99	0.50
ETH	0.96	0.43	0.48	0.99	0.67
XRP	0.12	0.19	0.44	1.00	0.69
LTC	0.93	0.79	0.00***	0.97	0.58
DASH	0.89	0.71	0.19	0.98	0.58
Index	**0.95**	**0.13**	**0.27**	**0.89**	**0.51**

Tests on Market Efficiency in 2016

Cryptocurrencies	LB	Run	VR	ADF	Hurst
BTC	0.07*	0.12	0.64	0.99	0.58
ETH	0.06*	0.00***	0.1	0.09*	0.62
XRP	0.99	0.21	0.61	0.11	0.46
LTC	0.85	0.01***	0.64	0.17	0.58
DASH	0.68	0.46	0.44	0.53	0.58
Index	**0.00*** **	**0.09***	**0.32**	**0.99**	**0.66**

Tests on Market Efficiency in 2015

Cryptocurrencies	LB	Run	VR	ADF	Hurst
BTC	0.63	0.56	0.47	0.93	0.57
ETH	0.55	0.80	0.39	0.17	0.63
XRP	0.14	0.36	0.02**	0.31	0.63
LTC	0.47	0.56	0.27	0.11	0.61
DASH	0.38	0.04**	0.21	0.18	0.46
Index	**0.93**	**0.45**	**0.47**	**0.94**	**0.49**

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Discussion of the market efficiency

Empirical evidence confirms the hypotheses H1 and a random walk of returns in the cryptocurrency market for the index. This implies that the market is weakly informational efficient and that investors are not able to use information of past prices to predict prices in the future and achieve abnormal returns. As there are, no fundamental values and the price determination is based on demand factors in the long-term, efficient markets might indicate that prices reflect the actual demand of cryptocurrencies.

Results speak against the findings of Urquhart (2016) and Bariviera (2017) but are in line with Nadarajah and Chu (2017) regarding the efficiency of Bitcoin. However, I am not able to prove the efficiency of all cryptocurrencies over the total sample. It is, moreover, not possible to draw definite conclusions about the reasons for the efficiency differences from this analysis, but the empirical tests on the random walk together with the descriptive statistics and economic analysis allow first interpretations and potential explanations of efficiency differences.

All test results show different values as Urqhart's (2016) analysis of Bitcoin and speak for a transition of the market as noticed by him in a subsample between 2013 and 2016. By assessing the subsamples, I do find a lower efficiency in 2015 and 2016. Hence, the results indicate a trend towards higher efficiency as markets get more liquid and cryptocurrencies more frequently traded, what is in line with the financial theories and findings of research on different markets (Chordia, Roll, and Subrahmanyam, 2008; Chung and Hrazdil, 2010; Grosman and Miller, 1988).

Differences in liquidity might also be an explanation for efficiency differences between cryptocurrencies and subsamples since the market capitalization and liquidity changed fundamentally in these two years. [9] The linkage of liquidity and market efficiency confirms the applicability of financial theories on the cryptocurrency market and indicates that they behave as standard financial assets.

Besides liquidity, information costs are another major element for the EMH and seems to play a crucial role for cryptocurrencies as well, since a less costly access to relevant information makes assets on average more efficient (Ippolito, 1989). Whereby an easier access to information allows the incorporating more relevant information into prices (Fama, 1970).

[9] Trading volumes of Bitcoin grew from 83 million USD to 13.5 billion USD in 2017 (coinmarketcap.com)

There seems to be a relationship between the information demand through Wikipedia as well as Google and the efficiency of cryptocurrencies since search queries increased exponentially after 2017 (Table 6). As cryptocurrencies do not have measurable fundamental values, there might be even increased importance of high information flows for investors. Whereby the information demand seems to be proxy for information that investors use for the price formation (Vlastakis and Markellos, 2012). Thus, higher availability and accessibility of information to all investors through the internet are probably important drivers of the increased efficiency in the market. However, it is not clear, if the higher information demand leads to more investments or if investors also incorporate more information into prices.

The Google searches for LTC in 2017 are below those of all other cryptocurrencies and might be a potential reason for the inefficiency as investors may find it more difficult to find price information. Furthermore, Wikipedia searches show a similar pattern with BTC and ETH as most searched, and LTC as a less popular search term (see Appendix G).

The market inefficiency in 2016 seems counterintuitive and might be caused by several factors, but I suppose that the numerous extreme events played a significant role. It is likely that the markets overreacted to those events what might explain the inefficiencies. Some of this major events were big hacking attacks in the Bitcoin attack or technical problems and a difficult mining process of ETH that led to disappointments and extreme price fluctuations in 2016 (Racine, 2016). Furthermore, there were some significant political events with unexpected results such as the “Brexit” referendum in the United Kingdom or the presidential elections in the USA. These events might have a significant effect on cryptocurrencies, due to an increased uncertainty.

A comparison between these findings and an analysis of the market efficiency in emerging countries by Mobarek and Mollah (2016), with an equal research method, indicates that cryptocurrency markets behave similar to emerging equity markets and have higher efficiencies than some developing stock markets. Even though this comparison is not entirely conclusive, it shows that market mechanisms of cryptocurrencies are not necessarily inferior to traditional markets and can include historical price information into present prices.

Following, I present the price reaction to some events that might be the reason for the inefficiency and major price fluctuations in 2016.

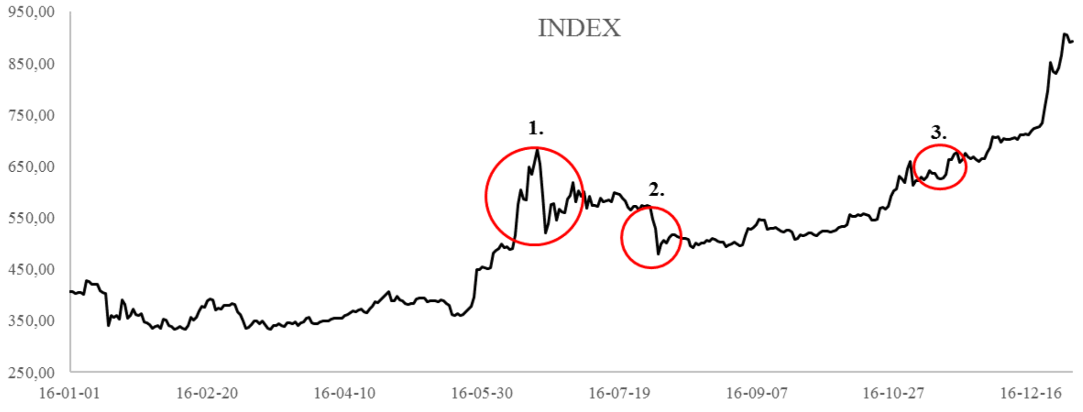
Reaction to Events

Figure 11 is an overview of price reactions to some of these extreme events that might explain the inefficiency in 2016. Even though the scope of this work are empirical tests on the weak-form of the efficient market hypotheses, the price reactions to extreme events strengthen my findingsn regarding the market efficiency and indicate an efficiency in terms of the strong from of the EMH.

The first distinct change of market prices in 2016 occurred at the same time as the Brexit referendum. It is visible that investors reacted to the referendum as well as to the polls before the final referendum and included this information into prices. The second substantial change of market prices lays together with a large hacking attack on an exchange, where the hackers managed to steal 120,000 Bitcoin or over 70 million USD. The third abrupt increase of prices occurred in November 2016 and was followed by an extended period of increasing returns, which might cohere with the presidential elections in the United States in the same period. It needs to be mentioned that these events are most likely the driving force of these price reactions, but there might be other unknown reasons that are also affecting these reactions.

This overview indicates that investors are reacting fast to publicly available information and adapt their expectations accordingly. I suppose that markets do incorporate public data to a certain degree, but overreact to some external events, what might an additional explanation for the market inefficiency in 2016.

Figure 11 - Price Development in 2016



Source: own illustration.

5.4 Price Determination

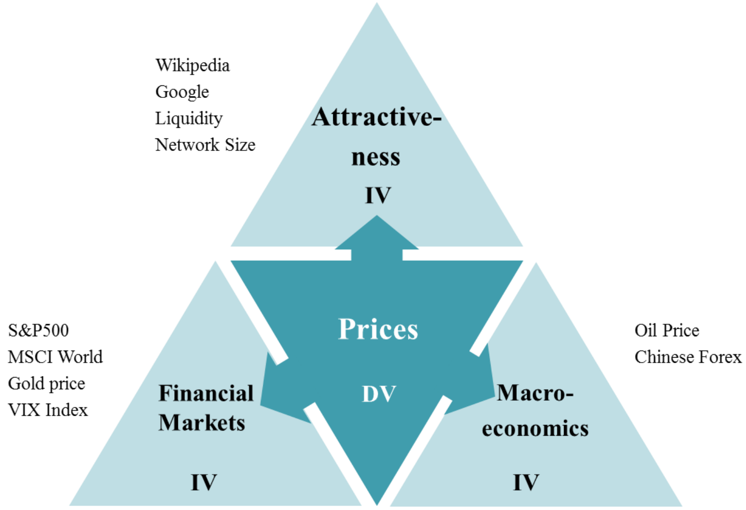
After the assessment of a random walk in the cryptocurrency market, I will derive which information influence the price determination and deliver insights about their properties as investment vehicles. First, I describe applied methods and models as well as robustness tests. Second, I present all regression results and determine if postulated causalities in the cryptocurrency market hold. Third, I discuss these results and give implications regarding the price mechanisms.

5.4.1 Methodology

For the estimation of the relationships between variables and returns, I follow the methodology of Bartos (2015) who applied an ordinary least square estimate (OLS). The OLS method allows estimation of the linear relationship between dependent (DV) and independent variables (IV). As discussed in Chapter 3, I determine the influence of the three categories attractiveness, financial markets and macroeconomics on the prices by using ten variables as shown in Figure 12.

Nevertheless, there are critical assumptions of an OLS such as the absence of heteroscedasticity, autocorrelation, multicollinearity, and stationary (Wooldridge, 2013). There might also be a bias due to omitted variables, which is likely due to the missing knowledge about price drivers. To prevent these biases in empirical results, I test the data and modify it to adapt to the assumptions of the model.

Figure 12 - Dependent and independent variables



Source: own illustration.

The heteroscedasticity of variables becomes a problem when residuals do not have a constant variance what might lead to insignificant coefficients. Similar, autocorrelation of error terms might lead to biased estimates. The problems with heteroscedasticity and autocorrelation are fixed by a logarithmic transformation of variables as applied by Bartos (2015).

Further, I deal with a potential bias of omitted variables by including ten variables that are based on economic theories and have been tested by previous research, what reduces a potential problem with omitted variables. To account for multicollinearity, I applied the variance inflation factor (VIF) test and did not find VIF values above 10 (see Appendix H) what indicates no problem with multicollinearity according to Wooldridge (2013).

Similar to the previous analysis, I will perform an analysis on the price effects on the index, on the differences between cryptocurrencies and on the evolution of price driver over the observation period.

5.4.2 Autoregressive Distributed Lag (ARDL) Model

The ARDL model is used to estimate the effects of current and lagged independent variables on independent variables in time series data and allows to determine effects over multiple periods (Pesaran and Shin, 1995). The application of lags makes sense because there might be a late response to new information and real purchases might occur a few days later. Additionally, the estimation of lags might help to correct overreactions to new information, which is a common tendency of financial markets (Bondt and Thaler, 1987).

The ARDL model has multiple advantages such as (Pesaran and Shin, 1995):

- No endogeneity problem, because there is no residual correlation.
- Cointegration can be handled with a modification to an error correction model
- The model can incorporate different lag structures.

Non-stationary of variables in time series data is a major problem that makes the application of statistical models more difficult. Therefore, it is critical to account for this property and to transform the data to adjust them to the assumptions of a normal distribution. As I find a unit root in some variables (see Appendix I), I use the first differences of all log variables to make them stationary as recommended by Granger and Engle (1987) and applied by Kristoufek (2013) and Bartos (2015) for the analysis of Bitcoin prices.

However, this leads to a loss of information and makes tests for long-run effects difficult (Granger and Engle, 1987). Furthermore, the log of all variables is taken to account for positive skewness, high kurtosis, and heteroscedasticity. Thus, logarithmic transformation allows a better estimation and interpretation of results in a linear model, since it comes closer to the normal distribution assumption of linear regression.

Granger and Engle (1987) suggest to test non-stationary data on cointegration, which occurs when two non-stationary time series depend on each other, which will give significant correlation even when they have no real relationship. In the case of cointegration, the model is usually transformed into an error correction model (Granger and Engle, 1987). The Engle-Granger test indicates a cointegration between variables for XRP, which makes the transformation of the ARDL model into an ECM necessary ECM can handle cointegration and can distinguish between short-run and long-run influences, whereby the ARDL reports only short-run influences. To have good comparability, I will present only the short-run results of the ECM for XRP. Furthermore, the Granger-causality test does not indicate a two sided causality, but prices seem to drive Google searches in the case of XRP (see Appendix J).

To determine the correct number of lags in this model the Hannan-Quinn information criterion (HQIC) is applied, which suggest a lag length of two (See Appendix K).

These modifications lead to following ARDL model:

$$\begin{aligned} \Delta \ln P_{t,t-1} = {} & \alpha + \phi_{1,2}\, \Delta\, (\ln P_{t-1;t-2}) + \beta_{0,1,2}\, \Delta\, (\ln WIKI_{t,t-1;t-2}) + \eta_{0,1,2}\, \Delta\, (\ln GOOGLE_{t,t-1;t-2}) \\ & + \gamma_{0,1,2}\, \Delta\, (\ln LiquidiyTurnover_{t,t-1;t-2}) + \delta_{0,1,2}\, \Delta\, (\ln Transactions_{t,t-1;t-2}) \\ & + \sigma_{0,1,2}\, \Delta\, (\ln Oil_{t,t-1;t-2}) + \chi_{0,1,2}\, \Delta\, (\ln China_{t,t-1;t-2}) + \tau_{0,1,2}\, \Delta(\ln SP500_{t,t-1;t-2}) \\ & + \mu_{0,1,2}\, \Delta\, (\ln MSCI_{t,t-1;t-2}) + \rho_{0,1,2}\, \Delta(\ln Gold_{t,t-1;t-2}) + \lambda_{0,1,2}\, \mathrm{l}\Delta(\ln Risk_{t,t-1;t-2}) + \varepsilon_t \end{aligned}$$

The model regresses first differences of log variables and its lags (t - 1 and t - 2) on the first differences of log returns in t. The term α stands for the constant term and ε_t for the error term. The independent variables such as $\beta_{0,1,2} \ln(\Delta WIKI_{t,t-1;t-2})$ reads as $\beta_0 \ln(\Delta WIKI_t) + \beta_1 \ln(\Delta WIKI_{t-1}) + \beta_2 \ln(\Delta WIKI_{t-2})$, where $\beta_{0,1,2}$ are the regression coefficients and Δ stands for the first differences of the variables. For the estimation of variables on the returns of the artificial index, I excluded the variable *Transactions* and *Google*, due to limited and ambiguous data. For the variable *Wiki*, the search term “Cryptocurrency” is used as a proxy for the total market.

5.4.3 Results & Discussion

In this section, I show empirical results of the multivariate regression model. First, I determine whether results confirm postulated hypotheses for the market in the total sample. Second, I will analyze the results of the three categories financial markets, macroeconomics, and attractiveness for single cryptocurrencies and describe the evolution of price drivers. Third, I will put these results in context with the findings of the market efficiency and discuss all findings.

Table 9 presents the regression results of given variables with two lags for the total observation period. Results for Index, or the overall market, indicate that the financial market drivers, the gold price, and the Chinese exchange rate have significant influences on prices. This delivers evidence for hypotheses *H3b*, *H4b* and partly *H4a*. These results are in line with the findings of Ciaian *et al.*, 2016, but contradict with findings of most other research, which could not find any significant influence of financial markets (Kristoufek, 2013; Bartos, 2015; Baek and Elbeck, 2015).

Other factors, such as liquidity turnover, the oil price, Wikipedia searches, and the risk on markets do not show significant effects on prices. Thus, I am not able to prove hypotheses *H2a, H2b, H3a* and *H4c* in the total sample.

Nevertheless, the price determination of individual cryptocurrencies shows interesting differences. ETH, XRP, LTX, and DASH are profoundly impacted by attractiveness factors whereas prices of BTC only incorporate financial market factors and the Chinese influence. Following, I will analyze the results of every category:

Financial Market Drivers

The S&P500 index has a strong positive significant influence on the cryptocurrency market. Interestingly, the returns of the MSCI World index show signs of a significant negative correlation. This means that a positive development of the stock market in the USA foster prices of cryptocurrencies, while the development of the worldwide stock exchanges, influences prices negatively. A potential explanation of these opposing effects might be the high share of developing countries in the MSCI index. Investors might see cryptocurrencies as an alternative to investments into emerging markets. However, this assumption is vague, and it is not possible to poof it with given data. Hence, the results do not fully support hypothesis *H4a*, but partly confirm it, as both indicators play a significant role.

Table 9 - Regression Results

Results of the ARDL- and EC model for the total observation period. L refers to a 1-day lag and L2 for a two-day lag. Values describe the regression coefficients and stars indicate significance level. The index does not incorporate Google and Transactions due to data limitations. Tables with standard errors can be found in Appendix L.

VARIABLES	INDEX	BTC	ETH	XRP	LTC	DASH
lnLiquidity_D1	-0.00042	-0.00246	-0.00927**	-0.0101***	-0.0316***	-0.00832***
L.lnLiquidity_D1	-0.00139	-0.00474	-0.0148***	-0.00327	-0.00733	-0.00687**
L2.lnLiquidity_D1	0.00755*	0.00575	-0.0120***	-0.00201	-0.00762*	-0.00377
lnWiki_D1	0.00541	0.00457	0.0208	0.00143	0.0586***	-0.00230
L.lnWiki_D1	-0.000922	0.00493	-0.0319**	-0.00929	0.0158	0.0139
L2.lnWiki_D1	0.000530	-0.00254	0.0155	-0.00683	0.0103	0.00312
lnGoogle_D1	n/a	0.00286	0.0254***	0.0307**	-0.00464	0.0124***
L.lnGoogle_D1	n/a	-0.00930	0.0155	-0.0421***	-0.00242	0.0117***
L2.lnGoogle_D1	n/a	-0.00387	0.0118	0.0240**	-0.00207	0.000704
lnTransactions_D1	n/a	0.00719	0.0409**	0.00673	-0.00451	0.118***
L.lnTransactions	n/a	0.00361	-0.00157	-0.00774	-0.0133	0.0385**
L2.lnTransactions	n/a	0.0115	0.00651	-0.000814	0.00973	0.0465***
SP500_D1	0.434	0.419	1.092	1.488	0.225	-0.347
L.SP500_D1	0.970**	0.852*	0.636	1.237	0.602	0.0500
L2.SP500_D1	1.428***	1.346***	1.135	0.399	1.386**	0.0742
Gold_D1	-0.185	-0.156	0.0724	-0.289	-0.121	-0.231
L.Gold_D1	-0.295*	-0.216	-0.106	0.0280	-0.226	-0.159
L2.Gold_D1	-0.410***	-0.384***	-0.0459	-0.251	-0.452**	-0.116
Oil_D1	0.0947	0.0814	0.0114	0.0203	0.146	-0.0681
L.Oil_D1	-0.0108	-0.00773	0.128	-0.229	0.0741	-0.0774
L2.Oil_D1	-0.0300	-0.0352	0.298**	-0.176	-0.0245	-0.0301
MSCI_D1	-0.937**	-0.797*	-1.580*	-1.994	-0.548	1.011
L.MSCI_D1	-1.263***	-1.069**	-0.391	-0.985	-1.267*	-0.227
L2.MSCI_D1	-0.986**	-0.904**	-1.099	-0.386	-1.103*	0.751
VIX_D1	-0.0236	-0.00831	-0.0412	-0.0488	0.0339	0.0279
L.VIX_D1	-0.0261	-0.0172	0.0196	-0.0368	-0.0359	0.00574
L2.VIX_D1	0.0268	0.0250	0.0719	0.0129	-0.0323	0.0319
CNYUSD_D1	-0.797	-0.827*	0.895	-1.595	-0.619	1.012
L.CNYUSD_D1	-0.566	-0.605	1.108	-1.162	-0.571	0.000798
L2.CNYUSD_D1	-1.452***	-1.363***	-0.704	-0.761	-2.052***	-2.434***
Constant	0.004***	0.00477**	0.00212*	-0.123*	0.00462**	0.00872***
Observations	873	873	874	912	912	694
R-squared	0.058	0.054	0.085	0.190	0.151	0.188

Further, the gold price shows a significant negative correlation at a lag of two days. This means that prices tend to decrease two days after an increase of gold prices, what supports hypotheses *H4b* about an inverse relationship between gold and prices. A negative correlation may indicate a competition between gold and cryptocurrencies as a safe haven instrument, but the insignificance of the VIX index shows that the uncertainty in the USA does most likely not affect the investment decisions.

Yet, the results show that not all cryptocurrencies are significantly impacted by variables in this category. Besides BTC, only LTC shows significant dependencies with the S&P500 and gold prices, what might be explained by its similarity to Bitcoin and a higher maturity compared to the rather young cryptocurrencies. Significant correlations with equity markets and gold prices indicate that BTC is more integrated into financial systems and is most likely seen as an investment vehicle. The differences in the price determination might also be the reason for the consistent higher market efficiency of Bitcoin.

Overall, findings do not deliver a clear answer for the intention of investors, but it is noticeable that some investors might indeed see cryptocurrencies as safe havens, alternatives to equities or speculation object what is in line with the findings of Baek and Elbeck (2015).

Macroeconomic Drivers

Results of Index support hypotheses *H3b* and a significant influence of China on the cryptocurrency market as the CNY-USD exchange rate shows an influence on prices. A negative coefficient means that the cryptocurrency market profits when the USD depreciates. This means that Chinese investors are likely to buy more cryptocurrencies when the exchange rate is favorable, what confirms my initial assumptions. This indicates that China has indeed a high influence on cryptocurrency prices, which is probably caused by a high demand and the large number of miners in the country. On a cryptocurrency level, only ETH and XRP do not show a significant impact on the Chinese influence, while BTC, Dash, and LTC show significant signs.

However, it is difficult to isolate the effects of the Chinese exchange rate on prices as it can capture multiple effects and might be biased by other factors.

Oil prices, as a proxy of the price levels in the economy, are not significant for cryptocurrency and seem to be irrelevant for the price determination, what contradicts findings of Ciaian *et al.*, 2016. Only ETH shows a significant positive influence, which seems rather coincidental as I cannot identify differences to other cryptocurrencies.

Attractiveness Driver

Table 9 shows that Wikipedia searches are not significant for the total market what contradicts findings of Kristoufek (2015) and Ciaian *et al.* (2016). The liquidity turnover shows a positive impact on prices at a lag at two days, which is not significant at a level of 95%. Hence, I cannot confirm any significant influences of this category on prices for Index.

It is interesting that BTC is the only cryptocurrency that is not impacted by the public awareness and network size or the liquidity. The high media attention in the last years and the vast availability of information might have led to a lower information demand compared to other cryptocurrencies. Further, BTC has already high liquidity and large network size. I suppose that Bitcoin as the first and largest cryptocurrency has already low searching costs for information and that further improvements do not affect prices.

As the index is biased towards BTC, it does not reflect that this category seems to be the most important factor for the price determination for all other cryptocurrencies. Results of Altcoins show significant values for liquidity turnover, public awareness in the form of Wikipedia or Google searches and the network size.

Google or Wikipedia searches are positive price drivers for the ETH, LTC and Dash, whereby ETH shows opposing influences for Google and Wikipedia. The results of XRP regarding Google searches are invalid and cannot be uses since the Granger-causality test shows that the higher public attention is caused in consequence of the price growth (Appendix J).

A positive significance of public awareness indicators could reflect a potential speculative behavior, as investors might be driven by the increased attached towards this asset class alone. On the other side, it could also reflect the information demand for investors that are interested in investing into the market and therefore be a proxy for the real demand of all investors (Kristoufek, 2013). Nevertheless, there might be various interpretations of these results as the number of search queries may capture multiple factors.

The negative correlation of liquidity turnover is counterintuitive and speaks against hypotheses *H2b*. The reason for this behavior remains unclear, but might be explained by investors who store their units instead of selling them to others as Baur *et al.* (2017) show in their analysis. Another potential reason for a negative influence might be due to increased transaction costs from overloaded systems as liquidity increases (Kristoufek, 2015).

Overall, results confirm hypotheses about the influence of the gold price and the Chinese influence clearly. Furthermore, I can partly confirm hypothesis *H4a*, the influence of financial markets, as S&P500 and MSCI World indices have both a significant but opposite influences on prices. All other drivers do not show significant signs and are therefore not able to confirm remaining hypotheses. If I do not consider Bitcoin, the results of other cryptocurrencies deliver evidence for, hypothesis *H2a*, the influence of the public awareness. Moreover, an analysis of Altcoins indicates that liquidity turnover is indeed a significant price driver, but has a negative impact on prices what speaks against hypotheses *H2b.* The network size affects only ETH and Dash, what speaks partly for hypotheses *H2c.*

It seems that the popularity together with an increased public awareness is more important for less liquid and smaller cryptocurrencies, whereas already popular ones react more to changes in financial markets.

Development of price drivers

To get an understanding of the evolution of the price determinants and the current status of price drivers, I analyze the price drivers within the subsamples. Table 10 shows the development of price drivers over 2.5 years, whereby the crosses indicate significant coefficients at a p-value below 0.05 at any lag. Detailed tables with coefficients, standard errors and lags are attached in Appendix L.

The results show that there were almost no measurable price determinants for the most cryptocurrencies in 2015, what is in line with the findings of previous research (Baek and Elbeck, 2015; Kristoufek, 2015; Ciaian *et al.*, 2016). By comparing that to results of 2017, it is noticeable that the price determination became much more affected by exogenous factors. This confirms the assumptions of a changed price determination in 2017, which is most likely related to the higher liquidity, easier trading opportunities, and higher public awareness. Furthermore, this could be an additional explanation for the higher market efficiency in 2017.

The distinct development of Bitcoin, from only one to five significant price drivers, might imply that investors started to include external information and especially financial information into their prices. Other cryptocurrencies are also dependent on more exogenous factors in 2017 than 2015, whereas these factors are mainly public awareness, Chinese influence, and the gold price. However, Dash seems to be an exception, due to the higher number of significant influence factors in 2015, which is not explainable with these results.

Table 10 - Evolution of price drivers

This table displays the significant factors at a p-Value < 0.05 for all cryptocurrencies. The exact tables with coefficients and standard errors can be find in Appendix L.

	2017						2016						2015					
	INDEX	BTC	ETH	XRP	LTC	DASH	INDEX	BTC	ETH	XRP	LTC	DASH	INDEX	BTC	ETH	XRP	LTC	DASH
Liquidity			x	x	x	x					x	x					x	x
Wiki	x	x			x					x		x						x
Google				x					x	x								
Transactions						x						x			x			x
SP500	x	x					x	x			x	x						x
MSCI	x	x					x	x		x	x	x						x
VIX													x	x			x	
Gold	x	x			x	x	x	x			x							
Oil				x				x										
CNYUSD	x	x			x	x	x	x	x									

The year 2016 appears to be a transition year for the price determination, as the prices are much more influenced by external factors for most cryptocurrencies. A potential reason could be that investors see them more as alternative investment and hence use more exogenous information to build their expectations about prices, whereas earlier investors saw cryptocurrencies as speculation objects. Results of 2017 show Bitcoin is affected by Wikipedia searches, what is in line with findings of Kristoufek (2015).

5.5 Overall Discussion & Implications

I analyzed the economic foundations, the market efficiency, and price mechanisms as well as potential uses of cryptocurrencies. Results show that their prices are efficient and they have properties of alternative investment vehicles. In this section, I want to merge findings on market efficiencies and price drivers to give implications about the appropriateness of cryptocurrencies as investments and highlight potential chances and risks for investors.

Even though there are multiple interesting overlaps of the findings of market efficiency and price drivers, I want to discuss the three most interesting findings:

First, information costs seem to be a crucial factor for the market efficiency and price determination, as cryptocurrencies with higher public attention and therefore less costly access to information tend to reach higher efficiency levels. Furthermore, investors seem to price in the public attention until a certain level of public awareness is reached since Bitcoin is not affected by the media attention in the overall sample.

Second, market efficiencies, as well as price determinants, indicate that Bitcoin has a unique position within the cryptocurrency market. Results indicate that Bitcoin is much more comparable to standard financial assets and can be regarded as an alternative investment vehicle, while other cryptocurrencies seem to be more speculative since they are only affected by attractiveness factors and the public attention.

Third, both analyses indicate a transition in the market, which is most likely induced by more capital, more transaction and ultimately higher liquidity in the market. Further, liquidity seems to be the crucial factor for the price formation and efficiency, what conforms with financial theories (Chung and Hrazdil, 2010; Grosman and Miller, 1988).

A higher relevance of the liquidity for Altcoins might indicate that Bitcoin has sufficient liquidity and prices do not appreciate after a further improvement of the liquidity.

Moreover, price drivers deliver insights about the decision-making and the intention of investors. The significant findings of financial market drivers indicate that Bitcoin might profit from a higher investment level in the economy and lower returns of other alternative investments. Furthermore, an inverse relationship to gold prices does indicate that some investors might see cryptocurrencies as an alternative safe haven instrument. Contrary, Altcoins seem to attract mainly speculators as most of them are only affected by higher public awareness, and tests indicate a high long-range dependency of returns. Finally, it seems that people in countries with capital constraint, here China, do have a higher interest in cryptocurrencies as they have a significant influence on prices.

Overall, results deliver evidence for the efficient market hypothesis and indicate that prices appear to incorporate also exogenous information in prices and changed price drivers might deliver a possible explanation for deviating findings with previous research (Urquhart, 2016; Bariviera, 2017). These findings imply that the asset class of cryptocurrencies follow with standard financial theories such as the EMH, the rational expectation hypothesis, microeconomic principles and classical portfolio theory. This supports previous research and indicates that the traditional economic theories also apply to this new market (Kristoufek, 2015; Ciaian *et al.*, 2016). Nevertheless, the economic analysis showed that these findings do only apply in the long-run as prices are also determined by a dynamic supply in the short-run.

Following, I describe the practical implication of this analysis for investors and evaluate the appropriateness of cryptocurrencies as alternative investments:

Chances

Empirical results suggest that the market developed very fast and Bitocin became weakly informational efficiency. If Altcoins follow the path of Bitcoin, there is a good chance that prices could include all information and reflect the real demand for cryptocurrencies, what could ultimately help to reduce the volatility in markets and establish cryptocurrencies as a payment method. This would also increase their utility as a store of value and safe haven instrument.

Based on my analysis and previous research, I see the most significant opportunities for the use as a diversification and hedging tool at the moment, since they have low correlations

with traditional markets and can, therefore, improve the risk-return profile of portfolios as shown by Dyhrberg (2016).
This might be interesting for professional investors with well-diversified portfolios. Especially the introduction of futures on Bitcoin that allows institutional investors to manage their risk might foster higher investments.

Furthermore, there are opportunities for investors that are looking for alternatives to gold, as cryptocurrencies do not have storage costs, lower transaction costs and are easier to trade. Empirical results suggest that there might be investors that see cryptocurrencies as a substitute for gold. However, a broad acceptance as an alternative to gold requires more stable prices and lower volatilities.

Additionally, people in economically troubled countries with unstable institutions and high inflation might benefit from cryptocurrencies. Investors in countries with capital restrictions and poor access to international capital markets might benefit from the anonymous transfers and wealth storages. Hereby, cryptocurrencies might be used to circumvent institutional failure and enable the access to international markets.

Risks

One of the major reasons that hold investors back from an investment into cryptocurrencies are high risks that arise from different areas. Here, I summarize the most relevant risks that investors should consider before an investment.

First, the volatilities are extremely high and can lead to price changes of more than 20% within one day. This uncertainty might be favorable for speculators, but not for the majority of risk-averse investors. Most important, high volatilities threaten the usage and implementation as a payment system since they become less practicable as a currency.

Second, low regulation and the anonymity within the network lead to potential risks of market manipulations. In fact, there are many claims about manipulations in markets that led to the immense price decreases in 2017. Some developers of the newly created cryptocurrencies reportedly use a “pump-and-dump” scheme. The founders started with a number of pre-mined cryptocurrencies, meaning that a portion is created before they are traded in the markets. After the initial coin offer at exchanges, the founders start to buy high portions of their own cryptocurrency and “pump-up” the price. As people seeing the fast price increase, many buy into them and create a price spiral. The founders then cash out ("dump") by selling the cryptocurrencies, what leads to a major price decreases (Gandal and Halaburda, 2014).

Third, I see the power of miners as high risk as described in chapter 3. They own high portions of the cryptocurrency market and are therefore able to manipulate prices on exchanges. With this development, the total network will be operated by a handful of miners, what incurs high risks for the viability of the system.

Forth, like any other technological innovation, there is a potential risk of new superior technologies. If superior technologies manage to attract a large user base and find higher acceptance by merchants, the value of cryptocurrencies could fall to zero.

Finally, there are risks from strict regulations. Countries such as China or South Korea banned exchanges, or initial coin offers what led to significant price decreases. In two countries, Thailand and Bolivia, Bitcoin became even wholly banned and illegal (Infante, 2014; Trotman, 2013). Nevertheless, regulations might also be able to lead to a safer investment environment and lower volatilities. Especially tighter supervision of exchanges and miners might help to overcome some of the listed risks.

Appropriateness as investment

When I assume that, the majority of investors live in areas with functioning institution there are not too many reasons that would speak for investment in cryptocurrencies. High volatilities and unpredictable prices, which are based on factors that we do not fully understand so, make cryptocurrencies too risky for average investors.

Even with efficient markets and a better understanding of price mechanisms, I see cryptocurrencies only as a potential diversification instrument due to their unique properties that can improve the risk-return profiles of already well-diversified portfolios. Additionally, they might be a real alternative to investments in commodities due to lower storage and transaction costs, but they are still too volatile for a frequent as a safe haven instrument.

Hence, cryptocurrencies as investment vehicles might only be appropriate for speculators that seek short-term profits and benefit from high volatilities.

Due to the volatilities and risks, supervisors need to set-up a regulatory framework that should focus on a clear control of exchanges as well as initial coin offers. Furthermore, antitrust authorities should monitor the impending danger of monopolization on the supply side to make investments into this asset class more appropriate.

5.6 Summary of results

Table 11 summarizes all findings for the total subsample as well as the subsamples and indicates if hypotheses can be confirmed, whereby partly confirmed hypotheses mean that the majority of cryptocurrencies support the statement. Overall, results show that prices follow a random walk and that markets can be regarded as weakly informational efficient. However, this needs to be analyzed in further research. Results support hypotheses regarding public awareness, gold prices and the Chinese influence as price drivers. The financial markets play an important, significant role but show contradicting directions. Thus, hypotheses *H4a* is marked as partly confirmed. Findings show that the network size, price levels in the economy as well as the uncertainty in markets are insignificant, and that I cannot prove the validity of these hypotheses. Finally, results regarding the liquidity turnover are significant but contradicts *H2b*.

Table 11 - Summary of findings

The table shows a summary of results and whether hypotheses can be confirmed. "Yes" means that the Index confirms the hypothesis, while "No" means that it is not significant or does not confirm the hypothesis. "Partly" is used when the majority of cryptocurrencies confirm the hypothesis.

Hypothesis		Total	2017	2016	2015
H1	Returns on the cryptocurrency market follow a random walk	**Yes**	**Yes**	**No**	**Yes**
H2a	Higher media attention leads to higher prices	**Partly**	**Yes**	**Partly**	**No**
H2b	Higher liquidity in the market attracts more investors and influence prices positively.	**No**	**No**	**No**	**No**
H2c	Larger network sizes lead to higher prices	**No**	**No**	**No**	**No**
H3a	Higher price levels in the economy lead to higher prices on cryptocurrency markets	**No**	**No**	**No**	**No**
H3b	The Chinese market is a driving force of cryptocurrency prices.	**Yes**	**Yes**	**Yes**	**No**
H4a	Higher prices on financial markets drive the prices of cryptocurrencies positively	**Partly**	**Partly**	**Partly**	**No**
H4b	Cryptocurrencies and Gold compete as a safe haven and have an inverse relationship	**Yes**	**Yes**	**Partly**	**No**
H4c	Cryptocurrency prices increase when traditional financial markets get riskier	**No**	**No**	**No**	**No**

5.7 Limitations

In this section, I want to list limitations of my analysis that might lead to biases and should be considered in future research. Central limitations emerge from the empirical analysis. Even though, I applied a wide range of tests and based the analyses on previous research there are some critical points that are mainly caused by data limitations and a low understanding of this new market.

Market Assumptions. I include five of the most popular cryptocurrencies which account for around 70% of the market and are therefore not wholly representing the full market. The remaining cryptocurrencies are often less liquid and have a smaller market capitalization. Thus it is very likely that they are less efficient than the considered cryptocurrencies. Including these cryptocurrencies might lead to a different picture regarding the efficiency. Furthermore, I assume that the market can be reflected by a weighted price index of these five cryptocurrencies what is disputable. The high share of Bitcoin until 2017 leads to a bias of the market results since other cryptocurrencies are almost not taken into account in 2015 and 2016. However, a weighted price index represents the returns and volatilites of the market better than an equal-weighted index, since investors are more likely to adapt their investments according to the market capitalization and buy a higher share of BTC than LTC for instance.

Comparability. It might be difficult to compare these cryptocurrencies as they have different purposes and different supply systems as analyzed in Chapter 3. Empirical results suggest that especially Bitcoin has different properties as other cryptocurrencies what makes a comparison questionable. Despite, I do not see a problem with the comparability between Altcoins, due to similar price drivers.

Sample size. A more general problem that affects the analysis of price drivers and market efficiency is the short observation period as well as the fast and distinct changes in the market. Other studies on the market efficiency of financial markets base their analysis usually on observation periods between 10 to 20 years, which is obviously not possible with cryptocurrencies (Lynch and Mendenhall, 1997; Chan, Gup, and Pan, 1997). A short observation period is prone to biases from certain events and may not reflect a correct picture of the real market efficiencies in the market. Nevertheless, the market changes very fast what makes it senseless to use all available data. As shown in the results, it is difficult to find a good observation period that is representative of the market and at the same time long enough to deliver robust results.

Data reliability. The data is based on a weighted average prices of all exchanges and is therefore not reflecting official prices because not all cryptocurrencies are traded on the same exchange. When some of these cryptocurrencies were mainly traded on less liquid exchanges during the observation period, it may bias the results of the price efficiency. In fact, Pisani (2017) finds that there are significant differences of Bitcoin prices at different exchanges due to liquidity differences. Additionally, interpolation of data might bias the results of the regression of price drivers as I manipulated data.

Emerging Market. Furthermore, it is a developing market, and my results are only able to show a snapshot of the market at the given time, which may have changed already. Consequently, a continuous analysis of the market in the future might be useful to confirm these findings or explain some of the counterintuitive results. However, it seems fair to assume that the results of the year 2017 are the most accurate estimate of price efficiency and drivers.

Neglected variables. Even though I can show significant influence factors; these results might not represent a full picture of the price determination as many other factors such as technical details, intentions of miners, transactions fees, and potentially unknown factors are not included in this regression model. To have a better approximation of significant price drivers, future research in this field is needed.

Regression model. There are also limitations regarding the used multivariate autoregressive model. A potential problem might lay in the causality of the results as statistical methods do not allow a full judgment about the cause-effect relationship (Gujarati and Porter, 2009). However, I limited potential causation problems by an economic reasoning of relationships and the reference to previous research in this field. Moreover, I want to stress out that some of my used proxies such as the oil price, Chinese exchange rate or the search engines queries, might not be entirely suitable to represent factors like the general price levels, Chinese influence or the public awareness.

6 Conclusion

Almost ten years after their inception, cryptocurrencies are more present in the public perception than ever. Hence, there is a growing interest in understanding the economics and the price mechanisms among investors and economists. The vast amount of economic literature has highlighted the importance of the efficient market hypothesis and the analysis of price drivers to investors and policymakers. This thesis contributes to the existing discussion about the price mechanisms in the cryptocurrency market and delivers findings for a better understanding of this new asset class. I investigated the factors that influence prices and whether prices follow a random walk by using the price data of the five most popular cryptocurrencies. Furthermore, I analyzed underlying economics with microeconomic principles and described the price determination in the market.

My findings contradict with most previous research and deliver new insights about the market. Empirical results confirm that the overall cryptocurrency market follows the weak form of the efficient market hypothesis and that the market efficiency improved over the last years. Interestingly, I find that there are differences in the market regarding the level of efficiency. While Bitcoin and Dash seem to have efficient prices, in terms of the random walk hypothesis, Litecoin, Ripple, and Ether appear rather inefficient. Thus, prices of Bitcoin and Dash reflect past price information in their current prices, and it is not possible to use previous prices to predict the future. In the second analysis, I find that the price determination is influenced by the public awareness or searching costs, financial markets, and the Chinese influence, whereby there are major differences between cryptocurrencies and in time. Bitcoin seems to be much more integrated into financial systems since it is the only cryptocurrencies that are significantly influenced by all financial indicators. Most other cryptocurrencies are mainly affected by the public awareness, liquidity and the gold prices. Furthermore, I describe the evolution of price drivers and find that the prices seem to be affected by more exogenous factors in 2017.

I conclude that the price mechanisms of cryptocurrencies are very dynamic and are changing over time. The market efficiency indicates liquid markets that are not predictable. Moreover, cryptocurrencies and prices seem to be partly explainable by exogenous factors and to follows standard economic models and financial theories as suggested by Kristoufek (2015).

Finally, the analysis of cryptocurrencies shows that they do not have a fundamental monetary value and that prices are driven by demand factors in the long-run. Especially, high volatilities, an unregulated market, and a problematic price determination do not indicate appropriate investment opportunities for private households at the moment. However, low correlations to traditional assets and interesting risk/return profiles might be interesting for professional investors with well-diversified portfolios. Moreover, cryptocurrencies might be reasonable safe haven instruments and alternatives to gold, when volatilities reduce, and markets get more regulated.

Despite my findings, there are limitations in the analysis. These relate mainly to the data availability and the short observation period. Additionally, results might be biased due to omitted variables and the absence of an asset pricing model. Therefore, I would like to address a long-run analysis of the market efficiency and underlying economics to future research. It would be interesting to consider factors that influence the supply side as well and determine if other cryptocurrencies follow the path of Bitcoin and are driven by the same factors in the future.

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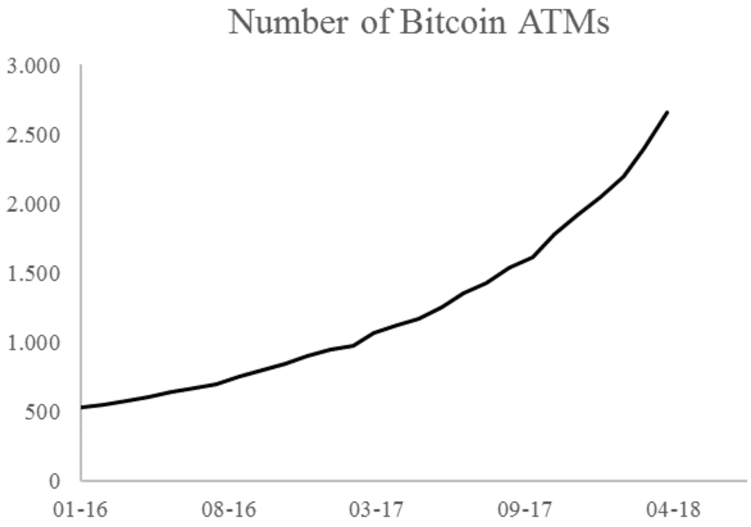
Appendices

Appendix A – Number of worldwide Bitcoin ATMs

The graph illustrates the number of Bitcoin ATMs between 01.2016 and 04.2018. The number grew in this time from 502 to 2662 ATMs.



Source: own illustration with data Statista (2018)

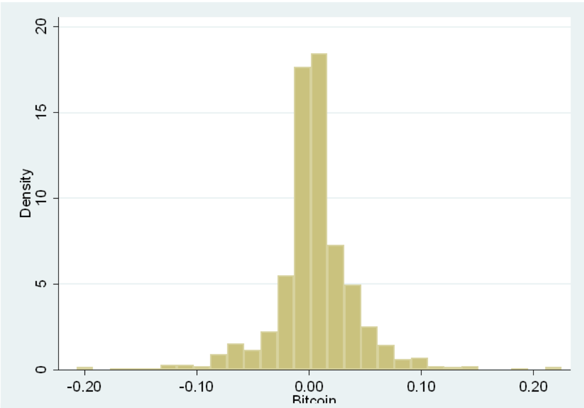
Appendix B – Google Trend Searches for Cryptocurrencies by Country

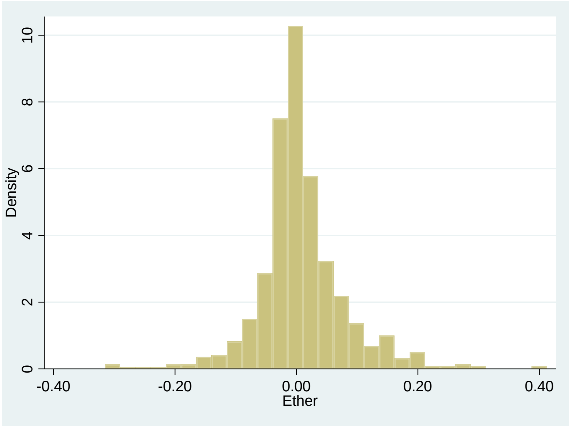
The world map shows the search queries by countries, whereby a darker color indicates a higher number of searches It can be seen that especially economic troubled countries such as Ukraine, Russia, Venezuela and some African countries have the most search queries, what indicates a higher demand for cryptocurrencies.

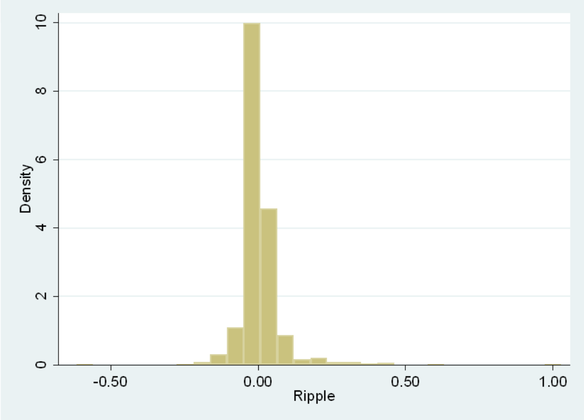
Source: https://goo.gl/Gtwrz1, retrieved on May 4, 2018

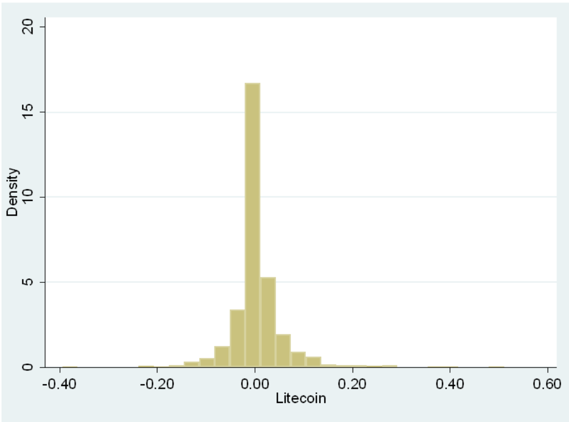
Appendix C – Histograms of return distributions

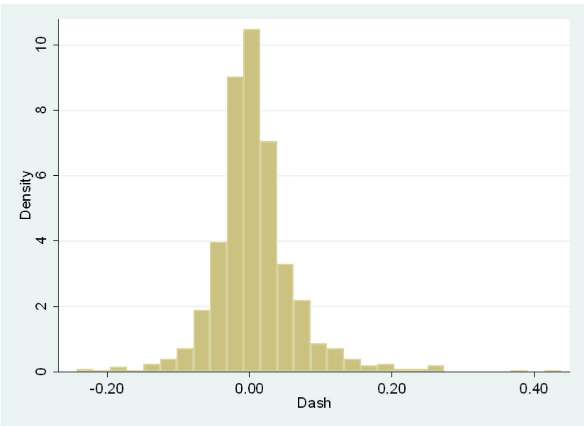
Following charts show the return distribution of BTC,ETH, XRP, LTC and Dash. While Bitcoin has a negative skewed distributions that comes close to a normal distribution, other cryptocurrencies the majority of observations on the right side of the mean.











Source: STATA output

Appendix D – Descriptive statistics of subsamples

The three tables in this Appendix show the descriptive statistics for the subsamples between 2015 and 2017.

Descriptive Statistics in 2015

Variables	N	Mean	SD	Min	Max	Skewness	Kurtosis
BTC	145	0.345%	3.54%	-20.1%	11.3%	-1.32	11.52
ETH	145	0.148%	8.97%	-26.9%	30.3%	1.23	8.24
XRP	145	-0.234%	4.81%	-14.2%	33,1%	0.87	8.65
LTC	145	-0.069%	4.02%	-13.7%	19.8%	0.46	7.84
DASH	145	0.041%	4.21%	-10.4%	14.1%	0.68	4.23
Index	145	0.244%	3.45%	-16.4%	9.3%	-0.58	7.12
SP500	145	-0.011%	1.03%	-4.0%	3.8%	-0.28	5.94
Gold	145	-0.021%	0.78%	-1.9%	3.1%	0.74	5.12
Oil	145	-0.118%	2.33%	-7.1%	8.0%	0.44	5.02
MSCI	145	-0.034%	0.85%	-3.8%	2.1%	-0.79	6.34
VIX	145	19.25	5.13	12.2	40.7	n/a	n/a
CNY/USD	145	0.031%	0.24%	-0.6%	1.9%	3.81	29.12

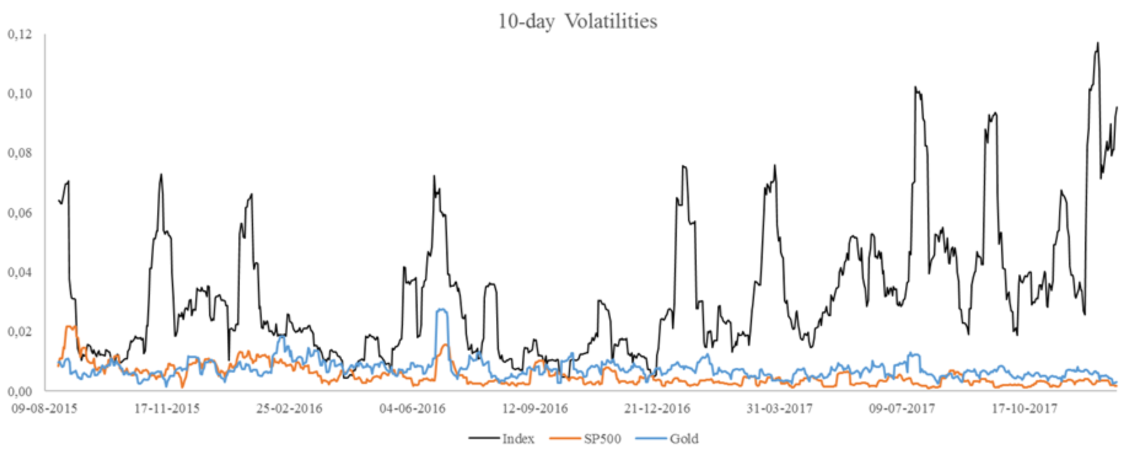
Descriptive Statistics in 2016

Variables	N	Mean	SD	Min	Max	Skewness	Kurtosis
BTC	366	0.220%	2.52%	-16.6%	11.3%	-0.71	12.92
ETH	366	0.56%	6.78%	-30.6%	30.3%	0.17	7.09
XRP	366	0.018%	3.49%	-10.9%	33,1%	3.41	29.11
LTC	366	0.059%	2.98%	-20.9%	22.8%	0.19	21.22
DASH	366	0.336%	4.41%	-16.4%	24.1%	0.97	8.13
Index	366	0.397%	2.55%	-10.6%	10.3%	0.11	7.95
SP500	366	0.025%	0.69%	-3.7%	2.4%	-0.47	7.74
Gold	366	0.019%	0.99%	-3.5%	7.6%	1.23	12.83
Oil	366	0.102%	2.31%	-8.1%	9.3%	0.14	4.93
MSCI	366	0.014%	0.68%	-5.1%	2.6%	-1.12	12.9
VIX	366	15.84	4.09	11.3	28.1	n/a	n/a
CNY/USD	366	0.018%	0.27%	-1.3%	1.7%	0.61	12.38

Descriptive Statistics in 2017							
Variables	**N**	**Mean**	**SD**	**Min**	**Max**	**Skewness**	**Kurtosis**
BTC	365	0.736%	4.93%	-20.8%	22.5%	0.04	6.24
ETH	365	1.25%	7.03%	-31.5%	29.0%	0.48	6.71
XRP	365	1.16%	11.22%	-61.6%	102%	2.75	26.66
LTC	365	1.09%	8.03%	-39.5	51.1%	1.24	11.33
DASH	365	1.24%	7.67%	-24.3%	43.8%	0.99	7.79
Index	365	0.848%	4.68%	-21.3%	20.7%	-0.15	6.29
SP500	365	0.048%	0.35%	-1.8%	1.3%	-0.37	8.36
Gold	365	0.036%	0.69%	-2.5%	3.4%	0.15	5.00
Oil	365	0.032%	1.32%	-5.5%	3.5%	-0.82	5.72
MSCI	365	0.050%	0.3%	-1.2%	1.6%	0.34	6.53
VIX	365	11.08	1.42	9.1	16.0	n/a	n/a
CNY/USD	365	-0.018%	0.18%	-1.0%	0.9%	-0.47	8.51

Appendix E – Volatilities of different assets

The graph shows the 10-day volatilities of the index, the S&P500 and gold between August 2015 and December 2017. It is visible that the volatilities of cryptocurrencies are remarkably higher than traditional assets and that the spread of volatilities increased after the end of 2016.



Source: own illustration.

Appendix F – Descriptive Statistics of Non-financial Variables

The following tables show the descriptive statistics for non-financial variables of ETH, XRP, LTC and DASH before and after 2017. It can be seen that all variables increased significantly after 2017.

Non-financial Variables of Ether

Ether	Liquidity		WIKI		Google		Transactions	
Period	>2017	<2017	>2017	<2017	>2017	<2017	>2017	<2017
Mean	3.2%	1.9%	6,115	1,319	16.7%	1.4%	377,382	28,513
Min	0.5%	0.00%	1,092	333	0.9%	0.07%	38,589	1,993
Max	14.9%	7.6%	21,580	7,939	100%	14.5%	1,318,300	68,241
Median	2.7%	1.3%	5,318	1,250	13.3%	1.1%	356,195	34,162

Non-financial Variables of Ripple

Ripple	Liquidity		WIKI		Google		Transactions	
Period	>2017	<2017	>2017	<2017	>2017	<2017	>2017	<2017
Mean	2.4%	0.4%	105	47	6.2%	1.1%	21,625	18,611
Min	0.0%	0.00%	30	18	0.7%	0.7%	751	469
Max	8.8%	7.5%	1607	164	100%	3.5%	114,645	47,979
Median	1.4%	0.3%	74	45	2.7%	1.1%	19,389	20,404

Non-financial Variables of Litecoin

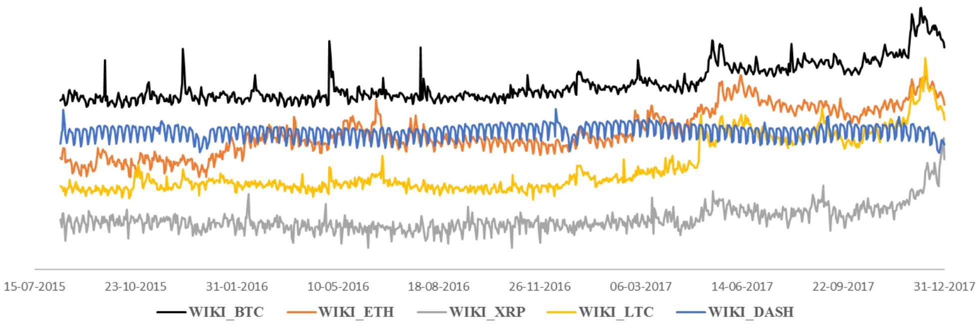
Litecoin	Liquidity		WIKI		Google		Transactions	
Period	>2017	<2017	>2017	<2017	>2017	<2017	>2017	<2017
Mean	11.5%	1.7%	2,426	236	2,82%	0.1%	22,178	4,361
Min	1.3%	0.00%	219	129	0.01%	0.01%	2,234	2,331
Max	92,7%	11.4%	44,211	785	100%	0.05%	162,372	11,574
Median	7.9%	1.3%	1,596	224	0.5%	0.09%	17,107	3,868

Non-financial Variables of Dash

Dash	Liquidity		WIKI		Google		Transactions	
Period	>2017	<2017	>2017	<2017	>2017	<2017	>2017	<2017
Mean	3.6%	0.8%	2,324	2134	15.6%	2.2%	5,725	1,329
Min	0.0%	0.00%	892	920	0%	0%	1,052	729
Max	24.0%	9.2%	3,162	5,443	100%	27.1%	20,701	2,922
Median	2.7%	0.05%	2,444	2,262	10.6%	1.6%	5,362	1,262

Appendix G – Wikipedia Searches over time

The graph illustrates the development of Wikipedia searches over time for all cryptocurrencies. To make them more comparable, the graph shows the logarithmic values. It is visible that Bitcoin is by far the most searched term, while Ripple is not often searched until the end of 2017.



Source: own illustration.

Appendix H – Test on Multicollinearity

The table shows the variance inflation factors for all cryptocurrencies. As values are below 10, there is no sign for multicollinearity between variables.

Variance inflation factors

Variables	INDEX	BTC	ETH	XRP	LTC	DASH
SP500	6.64	6.65	6.04	6.07	6.64	6.95
MSCI	5.23	5.25	4.96	4.92	5.14	5.55
Google	n/a	2.95	2.71	2.76	2.96	3.05
VIX	2.94	1.26	1.29	1.19	1.32	1.21
Oil	1.21	1.21	1.28	1.07	1.27	1.07
Gold	1.07	1.18	1.18	1.07	1.21	1.07
Wiki	1.03	1.17	1.16	1.06	1.16	1.07
Liquidity	1.02	1.08	1.10	1.06	1.07	1.02
Transactions	n/a	1.07	1.06	1.05	1.01	1.02
CNYUSD	1.01	1.01	1.02	1.02	1.01	1.01
MEAN VIF	**2.52**	**2.28**	**2.18**	**2.13**	**2.28**	**2.30**

Appendix I – Augmented Dickey-Fuller Test on Unit Root

The table shows the ADF test on unit root with the null hypothesis of unit root. Log refers to the logarithmic transformation of variables and FD to the first differences of the log variables. It can be seen that the FD does not have a unit root, while the log variables show a unit root for 4 variables.

Test on Unit Root

Variables	**Log**	**FD**
SP500	**0.8260**	0.0000
MSCI	**0.8260**	0.0000
lnGoogle	**0.0923**	0.0000
VIX	0.0001	0.0000
lnOil	0.1853	0.0000
lnGold	0.0900	0.0000
lnWiki	0.0001	0.0000
lnLiquidity	0.0000	0.0000
lnTransactions	0.0000	0.0000
CNYUSD	**0.1128**	0.0000

Appendix J – Engle/Granger Test on cointegration & Granger Causality

Test on Cointegration

The table shows the p-values for the Engle-Granger test on cointegration which indicates that XRP is cointegrated.1

	INDEX	BTC	ETH	XRP	LTC	DASH
p-Values	0.138	0.218	0.569	0.0000	0.240	0.830

Granger-Causality Test

The table presents results of the Granger Causality test on bi-directional relationships, whereas the top part shows if variables driver prices and the down part if prices drive variables. The results indicate that there is no two-sided Granger causality. A potential problem poses only XRP where Google searches seem to follow prices.

Variables on Prices	**BTC**	**ETH**	**XRP**	**LTC**	**Dash**
Liquidity	0.583	0.116	0.827	0.820	0.995
Wiki	0.623	0.374	0.855	0.620	0.819
Google	0.701	0.448	0.027	0.791	0.461
Transactions	0.957	0.914	0.925	0.335	0.377
Sp500	0.656	0.118	0.573	0.030**	0.809
Gold	0.162	0.719	0.072*	0.073*	0.437
Oil	0.812	0.022***	0.761	0.539	0.163
MSCI	0.971	0.198	0.923	0.047**	0.332
VIX	0.707	0.103	0.421	0.538	0.248
CNYUSD	0.001***	0.282	0.794	0.039	0.025
Prices on Variables	**BTC**	**ETH**	**XRP**	**LTC**	**Dash**
Liquidity	0.628	0.098	0.554	0.890	0.172
Wiki	0.348	0.807	0.375	0.614	0.188
Google	0.505	0.715	0.009***	0.338	0.576
Transactions	0.640	0.301	0.878	0.769	0.845
Sp500	0.333	0.706	0.852	0.572	0.969
Gold	0.176	0.559	0.754	0.099	0.406
Oil	0.504	0.559	0.621	0.561	0.242
MSCI	0.114	0.728	0.768	0.264	0.655
VIX	0.647	0.932	0.961	0.954	0.765
CNYUSD	0.640	0.015	0.694	0.674	0.544

Appendix K – Hannan-Quinn information criterion

The tables display the results of tests for the optimal leg length. The starts of HQIC show the optimal lag length for respective cryptocurrency.

Index

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	17890.1				1.2e-29	-41.0588	-41.04	-41.0096
1	18234	687.71	81	0.000	6.5e-30	-41.6624	-41.4738	-41.1696*
2	18424.2	380.41	81	0.000	5.1e-30	-41.9132	-41.5549*	-40.9768
3	18546.2	244.04	81	0.000	4.6e-30	-42.0074	-41.4794	-40.6274
4	18662.2	231.94*	81	0.000	4.3e-30*	-42.0876*	-41.39	-40.2641

Bitcoin

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	18684.6				6.6e-33	-42.8784	-42.8554	-42.8182
1	19108	846.85	121	0.000	3.3e-33	-43.5729	-43.2963	-42.85*
2	19351.7	487.35	121	0.000	2.5e-33	-43.8545	-43.3245*	-42.4691
3	19514.6	325.82	121	0.000	2.3e-33	-43.9508	-43.1672	-41.9027
4	19662.2	295.36*	121	0.000	2.1e-33*	-44.0121*	-42.9749	-41.3014

Ether

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	17877				2.5e-31	-39.266	-39.2438	-39.2078
1	18310.4	866.69	121	0.000	1.2e-31	-39.9525	-39.6859	-39.2543*
2	18556.2	491.72	121	0.000	9.4e-32	-40.2269	-39.716*	-38.8887
3	18706.8	301.02	121	0.000	8.8e-32	-40.2918	-39.5365	-38.3135
4	18839.7	265.9*	121	0.000	8.6e-32*	-40.318*	-39.3183	-37.6997

LTC

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	17877				2.5e-31	-39.266	-39.2438	-39.2078
1	18310.4	866.69	121	0.000	1.2e-31	-39.9525	-39.6859	-39.2543*
2	18556.2	491.72	121	0.000	9.4e-32	-40.2269	-39.716*	-38.8887
3	18706.8	301.02	121	0.000	8.8e-32	-40.2918	-39.5365	-38.3135
4	18839.7	265.9*	121	0.000	8.6e-32*	-40.318*	-39.3183	-37.6997

DASH

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	11528.1				2.6e-30	-36.9139	-36.8835	-36.8357
1	11919.2	782.2	121	0.000	1.1e-30	-37.7796	-37.4149	-36.8412*
2	12214.7	590.97	121	0.000	6.2e-31	-38.3388	-37.6399*	-36.5402
3	12340.6	251.72	121	0.000	6.1e-31	-38.3544	-37.3212	-35.6956
4	12582.2	483.34*	121	0.000	4.2e-31*	-38.7412*	-37.3737	-35.2221

Appendix L – Empirical Results per cryptocurrency for all periods

Regression Results for Index

Results of the ARDL- and EC model for the total observation period. L refers to a 1-day lag and L2 for a two-day lag. Values describe the regression coefficients and stars indicate significance level.

VARIABLES	Overall	2017	2016	2015
L.lnPrice_D1	0.101***	0.0775	0.0982*	0.0134
	(0.0341)	(0.0539)	(0.0527)	(0.0934)
L2.lnPrice_D1	-0.0529	-0.0436	-0.0529	-0.150
	(0.0346)	(0.0542)	(0.0528)	(0.0922)
lnLiquidity_D1	-0.000421	0.00795	-0.00219	-0.0172*
	(0.00415)	(0.00929)	(0.00378)	(0.00930)
L.lnLiquidity_D1	-0.00139	0.00773	-0.00650	-0.0184*
	(0.00429)	(0.00925)	(0.00407)	(0.00968)
L2.lnLiquidity_D1	0.00755*	0.00468	0.00640*	0.00908
	(0.00415)	(0.00924)	(0.00386)	(0.00970)
lnWiki_D1	0.00541	0.0582***	-0.00423	-0.0246
	(0.00692)	(0.0194)	(0.00570)	(0.0162)
L.lnWiki_D1	-0.000922	0.00235	-0.00356	-0.0122
	(0.00698)	(0.0191)	(0.00594)	(0.0159)
L2.lnWiki_D1	0.000530	0.00158	0.000402	0.00605
	(0.00690)	(0.0194)	(0.00566)	(0.0161)
SP500_D1	0.434	0.163	-0.113	1.492*
	(0.459)	(1.437)	(0.416)	(0.878)
L.SP500_D1	0.970**	4.327***	0.0764	-0.770
	(0.489)	(1.468)	(0.442)	(1.003)
L2.SP500_D1	1.428***	1.515	1.751***	-0.0540
	(0.460)	(1.452)	(0.408)	(0.922)
Gold_D1	-0.185	-0.754*	0.0932	-0.335
	(0.151)	(0.393)	(0.125)	(0.358)
L.Gold_D1	-0.295*	-0.942**	0.0214	-0.379
	(0.154)	(0.402)	(0.129)	(0.345)
L2.Gold_D1	-0.410***	-0.791*	-0.411***	-0.207
	(0.156)	(0.408)	(0.136)	(0.342)
Oil_D1	0.0947	0.129	0.100*	0.0173
	(0.0635)	(0.166)	(0.0533)	(0.141)
L.Oil_D1	-0.0108	-0.142	0.0470	-0.119
	(0.0642)	(0.166)	(0.0538)	(0.137)
L2.Oil_D1	-0.0300	-0.0595	-0.00654	-0.0772
	(0.0636)	(0.165)	(0.0535)	(0.141)
MSCI_D1	-0.937**	-2.120	-0.391	-0.877
	(0.469)	(1.453)	(0.391)	(0.963)
L.MSCI_D1	-1.263***	-5.306***	-0.481	0.451
	(0.483)	(1.535)	(0.397)	(1.005)
L2.MSCI_D1	-0.986**	-1.877	-1.341***	0.195
	(0.454)	(1.426)	(0.377)	(0.877)
VIX_D1	-0.0236	-0.0592	-0.0282	0.127*
	(0.0270)	(0.0583)	(0.0270)	(0.0672)
L.VIX_D1	-0.0261	0.00921	-0.0196	-0.139**
L2.VIX_D1	0.0268	0.0271	0.00518	-0.0223
	(0.0272)	(0.0588)	(0.0271)	(0.0711)
CNYUSD_D1	-0.797	-1.115	-0.892**	0.190
	(0.498)	(1.346)	(0.417)	(1.153)
L.CNYUSD_D1	-0.566	-1.736	-0.0712	-0.443
	(0.516)	(1.358)	(0.443)	(1.158)
L2.CNYUSD_D1	-1.452***	-5.712***	0.194	-1.530
	(0.487)	(1.294)	(0.400)	(1.152)
Constant	0.00402***	0.00665**	0.00202	0.00435
	(0.00141)	(0.00292)	(0.00135)	(0.00306)
Observations	873	365	366	142
R-squared	0.058	0.153	0.151	0.209

Regression Results for Bitcoin

Results of the ARDL model for the total observation period. L refers to a 1-day lag and L2 for a two-day lag. Values describe the regression coefficients and stars indicate significance level.

VARIABLES	Overall	2017	2016	2015
L.lnPrice_D1	0.0225	-0.00845	0.0405	0.0129
	(0.0345)	(0.0549)	(0.0531)	(0.0954)
L2.lnPrice_D1	-0.0498	-0.0544	-0.0419	-0.122
	(0.0347)	(0.0550)	(0.0528)	(0.0944)
lnLiquidity_D1	-0.00246	-0.00429	-0.000880	-0.00889
	(0.00431)	(0.00950)	(0.00418)	(0.00997)
L.lnLiquidity_D1	-0.00474	0.00388	-0.00502	-0.0142
	(0.00447)	(0.00974)	(0.00437)	(0.0105)
L2.lnLiquidity_D1	0.00575	0.00391	0.00616	0.0132
	(0.00426)	(0.00948)	(0.00412)	(0.0104)
lnWiki_D1	0.00457	0.0396**	-0.00623	-0.0139
	(0.00604)	(0.0159)	(0.00566)	(0.0123)
L.lnWiki_D1	0.00493	0.0170	0.000423	-0.00397
	(0.00618)	(0.0156)	(0.00609)	(0.0130)
L2.lnWiki_D1	-0.00254	0.00278	-0.00587	0.0165
	(0.00618)	(0.0157)	(0.00610)	(0.0125)
lnGoogle_D1	0.00286	-0.0138	0.0220*	0.0161
	(0.00732)	(0.0119)	(0.0120)	(0.0181)
L.lnGoogle_D1	-0.00930	-0.0122	0.00595	-0.0107
	(0.00735)	(0.0118)	(0.0119)	(0.0175)
L2.lnGoogle_D1	-0.00387	-0.00524	-0.000237	-0.0152
	(0.00731)	(0.0119)	(0.0118)	(0.0170)
lnTransactions_D1	0.00719	0.0166	0.00944	0.0135
	(0.0116)	(0.0204)	(0.0138)	(0.0296)
L.lnTransactions_D1	0.00361	0.0176	-0.0214	0.00565
	(0.0119)	(0.0214)	(0.0134)	(0.0302)
L2.lnTransactions_D1	0.0115	0.00432	0.0146	0.0222
	(0.0112)	(0.0197)	(0.0133)	(0.0293)
SP500_D1	0.419	-0.301	-0.206	1.450
	(0.430)	(1.341)	(0.400)	(0.916)
L.SP500_D1	0.852*	3.340**	0.130	-1.055
	(0.459)	(1.370)	(0.420)	(1.052)
L2.SP500_D1	1.346***	0.988	1.874***	0.169
	(0.431)	(1.352)	(0.390)	(0.971)
Gold_D1	-0.156	-0.691*	0.0842	-0.294
	(0.142)	(0.368)	(0.121)	(0.368)
L.Gold_D1	-0.216	-0.740*	-0.0136	-0.312
	(0.145)	(0.378)	(0.125)	(0.356)
L2.Gold_D1	-0.384***	-0.797**	-0.362***	-0.173
	(0.147)	(0.382)	(0.131)	(0.356)
Oil_D1	0.0814	0.00683	0.107**	0.0187
	(0.0594)	(0.154)	(0.0506)	(0.151)
L.Oil_D1	-0.00773	-0.0976	0.0548	-0.0608
	(0.0599)	(0.155)	(0.0511)	(0.143)
L2.Oil_D1	-0.0352	-0.0293	-0.0211	-0.00745
	(0.0593)	(0.153)	(0.0507)	(0.148)
MSCI_D1	-0.797*	-1.511	-0.278	-1.087
	(0.439)	(1.362)	(0.373)	(1.020)
L.MSCI_D1	-1.069**	-4.024***	-0.462	0.569
	(0.453)	(1.443)	(0.377)	(1.067)
L2.MSCI_D1	-0.904**	-1.216	-1.376***	-0.141
	(0.427)	(1.332)	(0.362)	(0.931)
VIX_D1	-0.00831	-0.0566	-0.0279	0.110
	(0.0252)	(0.0544)	(0.0260)	(0.0682)
L.VIX_D1	-0.0172	0.0209	-0.0131	-0.152**
	(0.0258)	(0.0558)	(0.0267)	(0.0690)
L2.VIX_D1	0.0250	0.0270	0.00981	-0.00745
	(0.0255)	(0.0554)	(0.0258)	(0.0726)
CNYUSD_D1	-0.827*	-1.049	-0.945**	0.109
	(0.466)	(1.254)	(0.398)	(1.197)
L.CNYUSD_D1	-0.605	-1.733	-0.253	-0.270
	(0.483)	(1.269)	(0.420)	(1.211)
L2.CNYUSD_D1	-1.363***	-5.046***	0.0472	-0.915
	(0.456)	(1.204)	(0.381)	(1.210)
Constant	0.00477***	0.00855***	0.00212*	0.00356
	(0.00132)	(0.00275)	(0.00127)	(0.00314)
Observations	873	365	366	142
R-squared	0.054	0.125	0.191	0.214

Regression Results for Ether

Results of the ARDL model for the total observation period. L refers to a 1-day lag and L2 for a two-day lag. Values describe the regression coefficients and stars indicate significance level.

VARIABLES	Overall	2017	2016	2015
L.lnPrice_D1	0.0378	0.0332	0.0346	0.188*
	(0.0348)	(0.0578)	(0.0544)	(0.0957)
L2.lnPrice_D1	0.0119	0.0175	-0.00477	0.0227
	(0.0349)	(0.0574)	(0.0552)	(0.0976)
lnLiquidity_D1	-0.00927**	-0.0343***	-0.00560	0.00647
	(0.00455)	(0.00999)	(0.00698)	(0.00959)
L.lnLiquidity_D1	-0.0148***	-0.0114	-0.00390	-0.0162
	(0.00490)	(0.0103)	(0.00789)	(0.0108)
L2.lnLiquidity_D1	-0.0120***	-0.0164*	0.00186	-0.0188*
	(0.00444)	(0.00960)	(0.00707)	(0.00990)
lnWiki_D1	0.0208	0.0232	0.0185	-0.0446
	(0.0145)	(0.0270)	(0.0193)	(0.0458)
L.lnWiki_D1	-0.0319**	-0.0247	-0.0332*	0.00684
	(0.0142)	(0.0264)	(0.0192)	(0.0439)
L2.lnWiki_D1	0.0155	-0.0117	0.0320*	-0.0339
	(0.0143)	(0.0256)	(0.0194)	(0.0446)
lnGoogle_D1	0.0254***	0.0150	0.0152	0.0301
	(0.00982)	(0.0168)	(0.0139)	(0.0329)
L.lnGoogle_D1	0.0155	0.0128	0.0371**	-0.0491
	(0.0103)	(0.0155)	(0.0172)	(0.0357)
L2.lnGoogle_D1	0.0118	0.0176	0.0508***	-0.0606*
	(0.00976)	(0.0139)	(0.0170)	(0.0327)
lnTransactions_D1	0.0409**	0.0665	-0.0120	0.110***
	(0.0183)	(0.0435)	(0.0263)	(0.0402)
L.lnTransactions_D1	-0.00157	0.00406	-0.0323	0.0238
	(0.0192)	(0.0438)	(0.0275)	(0.0438)
L2.lnTransactions_D1	0.00651	0.0254	-0.0349	0.0872*
	(0.0183)	(0.0441)	(0.0253)	(0.0450)
SP500_D1	1.092	-1.214	1.261	0.860
	(0.890)	(2.265)	(1.290)	(2.523)
L.SP500_D1	0.636	3.799	-1.150	-0.0387
	(1.110)	(2.741)	(1.578)	(3.292)
L2.SP500_D1	1.135	3.842*	-0.407	0.529
	(0.894)	(2.286)	(1.224)	(2.400)
Gold_D1	0.0724	0.577	-0.358	0.639
	(0.254)	(0.457)	(0.331)	(0.911)
L.Gold_D1	-0.106	0.562	-0.332	0.534
	(0.304)	(0.562)	(0.400)	(0.991)
L2.Gold_D1	-0.0459	-0.109	-0.105	0.348
	(0.257)	(0.469)	(0.334)	(0.883)
Oil_D1	0.0114	0.216	-0.129	0.153
	(0.118)	(0.233)	(0.155)	(0.365)
L.Oil_D1	0.128	0.134	0.0409	0.303
L2.Oil_D1	0.298**	0.250	0.0987	0.592
	(0.119)	(0.231)	(0.155)	(0.366)
MSCI_D1	-1.580*	3.671	-1.700	-1.034
	(0.920)	(2.320)	(1.199)	(2.630)
L.MSCI_D1	-0.391	-1.496	1.073	-1.468
	(1.111)	(2.715)	(1.422)	(3.161)
L2.MSCI_D1	-1.099	-2.329	0.272	-2.227
	(0.897)	(2.263)	(1.140)	(2.381)
VIX_D1	-0.0412	-0.0121	0.000801	0.0565
	(0.0541)	(0.0823)	(0.0842)	(0.189)
L.VIX_D1	0.0196	0.0934	-0.0208	-0.0892
	(0.0628)	(0.0961)	(0.0949)	(0.246)
L2.VIX_D1	0.0719	0.123	-0.00653	0.0489
	(0.0538)	(0.0838)	(0.0825)	(0.196)
CNYUSD_D1	0.895	-1.111	-0.227	3.017
	(0.931)	(1.792)	(1.170)	(3.322)
L.CNYUSD_D1	1.108	1.791	-1.959	4.262
	(1.113)	(2.024)	(1.475)	(3.511)
L2.CNYUSD_D1	-0.704	-2.216	-2.530**	5.998*
	(0.925)	(1.780)	(1.192)	(3.057)
Constant	0.00689***	0.0104***	0.00563	-0.00206
	(0.00245)	(0.00361)	(0.00350)	(0.00738)
Observations	874	365	366	143
R-squared	0.085	0.207	0.127	0.285

Regression Results for Ripple				
Results of the ECM model for the total observation period. L refers to a 1-day lag and L2 for a two-day lag. Values describe the regression coefficients and stars indicate significance level.				
VARIABLES	Overall	2017	2016	2015
LD.lnPrice_D1	-0.0705**	-0.132**	-0.00545	0.254***
	(0.0337)	(0.0545)	(0.0555)	(0.0861)
L2D.lnPrice_D1	0.151***	0.135**	0.00803	0.0307
	(0.0336)	(0.0538)	(0.0566)	(0.0915)
D.lnLiquidity_D1	-0.0101***	-0.0374***	-0.00216	-0.00348
	(0.00357)	(0.0104)	(0.00289)	(0.00439)
LD.lnLiquidity_D1	-0.00327	-0.0124	0.000286	-0.00328
	(0.00343)	(0.00986)	(0.00286)	(0.00392)
L2D.lnLiquidity_D1	-0.00201	-0.0123	-0.000884	-0.00412
	(0.00306)	(0.00928)	(0.00249)	(0.00332)
D.lnWiki_D1	0.00143	0.0374	-0.0110	-0.00782
	(0.0128)	(0.0291)	(0.0108)	(0.0214)
LD.lnWiki_D1	-0.00929	0.0130	-0.0116	-0.0148
	(0.0118)	(0.0272)	(0.00930)	(0.0196)
L2D.lnWiki_D1	-0.00683	0.0101	-0.0212***	-0.00277
	(0.0101)	(0.0230)	(0.00768)	(0.0167)
D.lnGoogle_D1	0.0307**	0.0224	0.0122	-0.00765
	(0.0127)	(0.0213)	(0.0170)	(0.0341)
LD.lnGoogle_D1	-0.0421***	-0.0603***	0.0151	0.0410
	(0.0121)	(0.0198)	(0.0184)	(0.0325)
L2D.lnGoogle_D1	0.0240**	0.0226	0.0340**	0.0266
	(0.0116)	(0.0191)	(0.0161)	(0.0270)
D.lnTransactions_D1	0.00673	0.00796	0.00578	-0.00766
	(0.00594)	(0.0177)	(0.00434)	(0.00887)
LD.lnTransactions_D1	-0.00774	-0.0297*	-0.000678	-0.00659
	(0.00570)	(0.0179)	(0.00405)	(0.00806)
L2D.lnTransactions_D1	-0.000814	-0.00683	-0.00111	-0.00567
	(0.00560)	(0.0184)	(0.00383)	(0.00772)
D.SP500_D1	1.488	7.560	-1.623	3.533
	(2.162)	(7.076)	(1.635)	(3.053)
LD.SP500_D1	1.237	6.983	-1.171	1.826
	(1.670)	(5.611)	(1.261)	(2.306)
L2D.SP500_D1	0.399	3.403	-1.493*	-0.136
	(1.038)	(3.673)	(0.760)	(1.348)
D.Gold_D1	-0.289	2.441	-0.701*	-0.207
	(0.579)	(1.694)	(0.405)	(0.885)
LD.Gold_D1	0.0280	1.608	-0.244	0.557
	(0.456)	(1.291)	(0.320)	(0.701)
L2D.Gold_D1	-0.251	0.0307	-0.209	-0.174
	(0.300)	(0.801)	(0.209)	(0.488)
D.Oil_D1	0.0203	-0.919	0.0788	0.0793
	(0.256)	(0.700)	(0.178)	(0.380)
LD.Oil_D1	-0.229	-1.202**	-0.0138	-0.0794
	(0.203)	(0.569)	(0.138)	(0.302)
L2D.Oil_D1	-0.176	-0.736*	-0.0334	-0.143
	(0.137)	(0.393)	(0.0925)	(0.196)
D.MSCI_D1	-1.994	-10.94	1.393	-1.695
	(2.030)	(7.605)	(1.375)	(2.774)
LD.MSCI_D1	-0.985	-8.050	1.328	-0.341
	(1.599)	(5.845)	(1.089)	(2.155)
L2D.MSCI_D1	-0.386	-6.012	1.419**	1.287
	(1.015)	(3.789)	(0.682)	(1.316)
D.VIX_D1	-0.0488	-0.342	-0.0166	0.238
	(0.111)	(0.246)	(0.0920)	(0.172)
LD.VIX_D1	-0.0368	-0.194	0.00549	0.151
	(0.0900)	(0.196)	(0.0734)	(0.144)
L2D.VIX_D1	0.0129	-0.124	0.0245	0.0966
	(0.0620)	(0.135)	(0.0513)	(0.0971)
D.CNYUSD_D1	-1.595	-5.689	0.971	2.001
	(2.174)	(5.866)	(1.717)	(2.755)
LD.CNYUSD_D1	-1.162	-3.585	0.348	1.928
	(1.684)	(4.384)	(1.279)	(2.338)
L2D.CNYUSD_D1	-0.761	-2.660	0.0663	2.234
	(1.090)	(2.893)	(0.756)	(1.738)
Constant	-0.123*	-0.129	-0.186*	-0.153
	(0.0674)	(0.150)	(0.111)	(0.176)
Observations	912	365	366	181
R-squared	0.190	0.391	0.149	0.273

Regression Results for Litecoin

Results of the ARDL model for the total observation period. L refers to a 1-day lag and L2 for a two-day lag. Values describe the regression coefficients and stars indicate significance level.

VARIABLES	Overall	2017	2016	2015
L.lnPrice_D1	0.00985	0.0308	0.00553	-0.128
	(0.0337)	(0.0554)	(0.0543)	(0.0778)
L2.lnPrice_D1	-0.0608*	0.00708	-0.0381	-0.244***
	(0.0338)	(0.0552)	(0.0554)	(0.0786)
lnLiquidity_D1	-0.0316***	-0.0458***	-0.0106***	-0.0403***
	(0.00457)	(0.00995)	(0.00361)	(0.0115)
L.lnLiquidity_D1	-0.00733	-0.0131	-0.00316	-0.0198
	(0.00483)	(0.0104)	(0.00380)	(0.0126)
L2.lnLiquidity_D1	-0.00762*	-0.0106	-0.00344	-0.0125
	(0.00457)	(0.00961)	(0.00359)	(0.0127)
lnWiki_D1	0.0586***	0.0892***	-0.00327	0.0439*
	(0.0106)	(0.0230)	(0.00946)	(0.0263)
L.lnWiki_D1	0.0158	0.0251	0.00471	-0.0128
	(0.0108)	(0.0234)	(0.00962)	(0.0266)
L2.lnWiki_D1	0.0103	0.00620	-0.000457	-0.00246
	(0.0109)	(0.0234)	(0.00972)	(0.0254)
lnGoogle_D1	-0.00464	-0.00404	-0.00400	0.00562
	(0.00435)	(0.00730)	(0.00421)	(0.0134)
L.lnGoogle_D1	-0.00242	-0.00846	0.00138	0.00884
	(0.00448)	(0.00740)	(0.00461)	(0.0143)
L2.lnGoogle_D1	-0.00207	-0.00371	0.00484	0.0145
	(0.00432)	(0.00743)	(0.00437)	(0.0133)
lnTransactions_D1	-0.00451	0.00126	0.00326	-0.0377
	(0.0125)	(0.0312)	(0.00976)	(0.0278)
L.lnTransactions_D1	-0.0133	-0.0318	-0.00637	-0.0354
	(0.0134)	(0.0322)	(0.0104)	(0.0316)
L2.lnTransactions_D1	0.00973	0.0363	-0.0120	-0.0145
	(0.0124)	(0.0312)	(0.00973)	(0.0274)
SP500_D1	0.225	-1.713	0.114	2.670*
	(0.638)	(1.982)	(0.483)	(1.446)
L.SP500_D1	0.602	0.523	0.0766	1.150
	(0.679)	(2.038)	(0.508)	(1.668)
L2.SP500_D1	1.386**	-0.133	1.132**	0.948
	(0.642)	(1.987)	(0.470)	(1.506)
Gold_D1	-0.121	-0.877	0.179	-0.0616
	(0.210)	(0.545)	(0.144)	(0.546)
L.Gold_D1	-0.226	-0.842	0.0479	-0.00683
	(0.214)	(0.557)	(0.151)	(0.536)
L2.Gold_D1	-0.452**	-1.249**	-0.330**	-0.470
	(0.217)	(0.560)	(0.158)	(0.529)
Oil_D1	0.146	0.204	0.103*	0.0705
	(0.0890)	(0.232)	(0.0620)	(0.233)
L.Oil_D1	0.0741	0.0636	0.00827	0.0177
L2.Oil_D1	-0.0245	-0.0991	-0.0421	0.107
	(0.0889)	(0.230)	(0.0623)	(0.234)
MSCI_D1	-0.548	2.131	-0.766*	-1.693
	(0.646)	(2.011)	(0.453)	(1.509)
L.MSCI_D1	-1.267*	-2.404	-0.345	-2.155
	(0.667)	(2.131)	(0.463)	(1.583)
L2.MSCI_D1	-1.103*	0.471	-1.036**	-1.872
	(0.629)	(1.973)	(0.441)	(1.404)
VIX_D1	0.0339	0.0511	-0.0305	0.296***
	(0.0377)	(0.0800)	(0.0318)	(0.104)
L.VIX_D1	-0.0359	-0.00261	-0.0347	-0.0519
	(0.0385)	(0.0815)	(0.0328)	(0.107)
L2.VIX_D1	-0.0323	-0.0169	-0.0156	-0.220**
	(0.0379)	(0.0814)	(0.0314)	(0.108)
CNYUSD_D1	-0.619	0.333	-0.846*	-1.423
	(0.707)	(1.857)	(0.490)	(1.975)
L.CNYUSD_D1	-0.571	-2.259	0.136	0.697
	(0.732)	(1.887)	(0.517)	(2.007)
L2.CNYUSD_D1	-2.052***	-7.117***	0.0445	-0.317
	(0.694)	(1.771)	(0.472)	(2.004)
Constant	0.00462**	0.00962**	0.000576	-0.00178
	(0.00194)	(0.00408)	(0.00155)	(0.00475)
Observations	912	365	366	181
R-squared	0.151	0.277	0.120	0.283

Regression Results for Dash

Results of the ARDL model for the total observation period. L refers to a 1-day lag and L2 for a two-day lag. Values describe the regression coefficients and stars indicate significance level.

VARIABLES	Overall	2017	2016	2015
L.lnPrice_D1	-0.0959**	-0.0320	-0.106	-0.124
	(0.0388)	(0.0561)	(0.0746)	(0.109)
L2.lnPrice_D1	-0.0799**	-0.0414	-0.193***	-0.0376
	(0.0381)	(0.0559)	(0.0712)	(0.119)
lnLiquidity_D1	-0.00832***	-0.0582***	-0.00343	-0.00624*
	(0.00286)	(0.0122)	(0.00325)	(0.00370)
L.lnLiquidity_D1	-0.00687**	-0.0210	-0.00339	-0.00804**
	(0.00322)	(0.0129)	(0.00373)	(0.00399)
L2.lnLiquidity_D1	-0.00377	-0.0205*	-0.00103	-0.00396
	(0.00292)	(0.0118)	(0.00328)	(0.00387)
lnWiki_D1	-0.00230	-0.00817	-0.00460	0.0187
	(0.00940)	(0.0153)	(0.0133)	(0.0190)
L.lnWiki_D1	0.0139	0.0131	0.0144	0.0207
	(0.00865)	(0.0142)	(0.0122)	(0.0178)
L2.lnWiki_D1	0.00312	-0.0188	0.0122	0.0381**
	(0.00898)	(0.0146)	(0.0129)	(0.0190)
lnGoogle_D1	0.0124***	0.0144*	0.0102**	0.00552
	(0.00384)	(0.00820)	(0.00456)	(0.00687)
L.lnGoogle_D1	0.0117***	0.00673	0.0191***	0.00446
	(0.00414)	(0.00891)	(0.00491)	(0.00735)
L2.lnGoogle_D1	0.000704	0.00911	0.00386	-0.0107*
	(0.00384)	(0.00820)	(0.00471)	(0.00640)
lnTransactions_D1	0.118***	0.0723**	0.0566**	0.0999***
	(0.0144)	(0.0306)	(0.0219)	(0.0282)
L.lnTransactions_D1	0.0385**	0.00771	0.0364	0.0353
	(0.0154)	(0.0322)	(0.0232)	(0.0293)
L2.lnTransactions_D1	0.0465***	0.0357	0.0515**	0.0102
	(0.0151)	(0.0302)	(0.0221)	(0.0285)
SP500_D1	-0.347	-1.064	0.162	-0.339
	(0.732)	(1.875)	(0.881)	(1.278)
L.SP500_D1	0.0500	-2.619	1.323	-2.115
	(0.781)	(1.904)	(0.956)	(1.431)
L2.SP500_D1	0.0742	-1.407	1.022	-2.893**
	(0.760)	(1.858)	(0.915)	(1.312)
Gold_D1	-0.231	-0.259	-0.332	-0.383
	(0.248)	(0.513)	(0.281)	(0.498)
L.Gold_D1	-0.159	-1.066**	-0.0580	0.313
	(0.258)	(0.526)	(0.290)	(0.504)
L2.Gold_D1	-0.116	-0.356	-0.196	0.788
	(0.266)	(0.539)	(0.318)	(0.522)
Oil_D1	-0.0681	-9.90e-05	0.0365	0.127
	(0.107)	(0.216)	(0.129)	(0.197)
L.Oil_D1	-0.0774	-0.0861	-0.219*	0.153
	(0.109)	(0.216)	(0.131)	(0.201)
L2.Oil_D1	-0.0301	-0.345	0.00892	-0.102
	(0.107)	(0.211)	(0.128)	(0.213)
MSCI_D1	1.011	3.283*	-0.473	0.407
	(0.771)	(1.913)	(0.872)	(1.558)
L.MSCI_D1	-0.227	0.491	-1.709*	3.524**
	(0.796)	(2.022)	(0.889)	(1.452)
L2.MSCI_D1	0.751	0.731	-0.721	3.431**
	(0.762)	(1.842)	(0.865)	(1.353)
VIX_D1	0.0279	0.108	-0.0244	-0.0137
	(0.0430)	(0.0753)	(0.0613)	(0.0911)
L.VIX_D1	0.00574	-0.0148	-0.0335	0.0497
	(0.0435)	(0.0776)	(0.0620)	(0.0916)
L2.VIX_D1	0.0319	0.00769	-0.0188	-0.0116
	(0.0436)	(0.0770)	(0.0614)	(0.0938)
CNYUSD_D1	1.012	2.265	0.0346	1.961
	(0.926)	(1.785)	(1.013)	(2.502)
L.CNYUSD_D1	0.000798	0.599	-0.356	0.246
	(0.960)	(1.808)	(1.069)	(2.870)
L2.CNYUSD_D1	-2.434***	-5.609***	-1.778*	-0.0571
	(0.888)	(1.693)	(0.967)	(2.567)
Constant	0.00872***	0.0122***	0.00787**	0.00161
	(0.00229)	(0.00380)	(0.00327)	(0.00411)
Observations	694	357	211	126
R-squared	0.188	0.322	0.258	0.339

Code of Conduct

I hereby declare that this thesis has been completed by me and is based on my individual work, unless indicated by a quote with references to their sources. No other person's work has been used without due acknowledgement in this thesis. The thesis complies with all regulations stated regarding size and form and all references, graphs, tables and data sets, have been specifically acknowledged.

Date: 14. May 2018

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