Master's Thesis

The Price of Cryptocurrencies: An Empirical Analysis

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Abstract

In this paper, we analyze cryptocurrency price determinants suggested by literature using a panel of 17 cross-sections. We employ unit root and cointegration tests, and estimate the effects with Vector Error Correction Models, Dynamic OLS and Fully Modified OLS. Causality flows are examined by weak exogeneity and Granger causality tests. We confirm Metcalfe's Law, which identifies the value of a network to be proportional to the number of its nodes. We show that community factors and search engine queries have a cointegrating relationship with market capitalization. Our findings further suggest that the influence of innovation potential is heterogeneous across cross-sections. Moreover, we observe that the direction of causality often flows from market capitalization to the variable which is believed to be the determinant, but not vice versa.

Contents

Plagiatserklärung

Bern, July 6, 2018

Ich bezeuge mit meiner Unterschrift, dass meine Angaben über die bei der Abfassung meiner Arbeit benützten Hilfsmittel sowie über die mir zuteil gewordene Hilfe in jeder Hinsicht der Wahrheit entsprechen und vollständig sind. Ich habe das Merkblatt zu Plagiat und Betrug gelesen und bin mir der Konsequenzen eines solchen Handelns bewusst.

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1 Introduction

Since its introduction by Nakamoto (2008), Bitcoin has increasingly gained interest. The price rally in late 2013 attracted mainstream attention, not only towards Bitcoin specifically but also the underlying technology, Blockchain, due to its potential disruptive impact. Blockchain technology provides a cryptocraphically secure way of sending digital assets, without the need for trusted third parties like banks. Different features and innovations related to Blockchain are arising with a fast pace, such as smart contracts which promise to automate processes distributing contents of a will within the banking industry, compliance and claims processing, and possibly innovations in many other fields. A survey by the International Securities Association for Institutional Trade Communication, ISITC (2016), reveals that 55% of firms are monitoring, researching or already developing solutions for Blockchain technology. Amongst services only in the banking sector to be potentially disrupted by Blockchain are payments, clearance and settlement systems, securities, loans and credit as well as fundraising. The latter is called initial coin offering (ICO) and provide Blockchain companies with immediate access to liquidity, completely independent from traditional third party services. Consequently, a lot of cryptocurrencies and -assets[1] have emerged, providing innovative features related to the topics mentioned above. Most of the innovations are somehow related to improving speed, robustness and privacy. At this stage, it has to be mentioned that Bitcoin played a predominant role in the market and still is the largest issuer, if measured by market capitalization. However, its dominance decreased gradually over the past years. In the beginning of January 2014, Bitcoin had a market share (defined as market capitalization in percentage of total market capitalization) of 90%, which receded to current 36% according to CoinMarketCap (2018c). The second largest is the Ethereum network with 17%, followed by Rip-

[1] Hereinafter, we rely on the following definition according to Merriam-Webster (2018): Cryptocurrency is any form of currency that only exists digitally, that usually has no central issuing or regulating authority but instead uses a decentralized system to record transactions and manage the issuance of new units, and that relies on cryptography to prevent counterfeiting and fraudulent transactions. We use the term cryptoasset as a synonym in this thesis.

ple (7%) and Bitcoin Cash (6%). The market shares of the remaining currencies within the top ten move between 1% and 2%. In total, the 10 largest crypto-assets amount to 75% of total market capitalization, which leaves a considerable part to all other Altcoins[2]. Despite their rising relevance, research in the past years has focussed on Bitcoin. At the same time, existing studies for cryptocurrencies include three to five currencies and/or rather short time spans in their analysis. Thus, the motivation of this thesis is to shed light on the determinants of cryptocurrency prices from a empirical perspective, with a focus on the direction of causality flows. By construction, the supply side of the cryptocurrency market is fixed and consists of a predefined range of tokens or units which is announced in the act of an ICO. Thus, we are particularly interested in the question of what the determinants for demand are. In order to this, we look at research done so far in the field of cryptocurrencies and evaluate its results. Next, these insights are used and time series data is gathered in order to measure the relationship of these proxies and the price of a cryptocurrency. Due to the fact that cryptocurrencies have a predefined supply (which is often mined during a certain time period harwired in the source code) varying from one another, using price as dependent variable would lead to biased results. Consequently, this variable is standardized. The explanatory variables are derived from literature discussed in the subsequent chapters and are selected upon criteria related to Metcalfe's Law, development activity, community factors and search engine queries. The data is then grouped to a time series panel consisting of 17'299 daily observations. Next, we follow the standard procedure in the literature for non-stationary time series (which is a predominant property in our data) and test the series for cointegration. In order to measure the potential long-run relationship and short-term dynamics, we use a Vector Error Correction Model (VECM) as well as Fully Modified Least Squares (FMOLS) and Dynamic Least Squares (DOLS) to test the robustness of the estimates. It is tested for weak exogenity and Granger causality to further establish causalities amongst the variables. Finally, we discuss

[2]The term Altcoin is an abbreviation for alternative coin, which means any cryptocurrency other than Bitcoin

the outcome of the estimations. The remainder of the thesis is organised as follows: In Chapter 2, we review literature related to the topic and justify the research topic. In chapter 3, we discuss in detail the data selected for the analysis and the econometric approach and present the estimation results. Lastly, the results are discussed in chapter 4. Together with this thesis, we provide a broad database of estimation results for the different cryptocurrencies besides panel estimation results.

2 Review of literature

Before it is looked at literature linked specifically to cryptoassets, a brief digression may be allowed. As put out by White (2015), the cryptocurrency market is comparable to a market of competing private irredeemable monies in the sense of Hayek (1976). This market is characterized by financial institutions which create currencies that compete for acceptance, where stability in value is presumed to be the decisive factor for acceptance. Users will choose the currency they expect is the most competitive. However, there is big caveat: Hayek imagined that the issuer of a successful irredeemable currency would retain discretion to vary its quantity. The issuer would promise a stable purchasing power per unit, but this promise would appear to be time-inconsistent as the one-time profit of issuing new money would exceed the return of staying in business and as a result, the public would not believe the promise to begin with, hence giving money zero value in equilibrium. For a detailed discussion, see e.g. Taub (1985) or White (1989). In order to solve this problem, the privately issued money comes along with a money-back guarantee (a *price commitment*) such as gold given by the issuer as proposed in White (1989). The alternative solution to this problem identified by Coase (1972) is a *quantity commitment*, i.e. the issuer binds itself to produce only a limited amount of money. However, to make a credible promise not to exceed the self-imposed quantity limit is difficult if not impossible to put in place, resulting in the public not believing in the commitment. But the features of the crypto-market are different from what Hayek and other economists back in these days have imagined, i.e. the possibilities have changed with the introduction of Blockchain technology. As the issuer of a cryptoasset programs the quantity commitment into the source code, he provides a credible contractual promise not to exceed the limit defined in the first place. The source code is publicly available and the quantity limit defined therein is verified through a public ledger. Due to the availability of the source code, the Blockchain technology is basically accessible to everyone and therefore, the barriers to enter the crypto-market are low. Consequently, there was an tremendous increase of cryptoasset issuers in the past years: CoinMarketCap (2018b), an online price tracker for cryptocurrencies, currently lists 1600 issuers. As outlined in the first chapter, the competition has intensified within the past few years. Bitcoin has lost its predominant role, with a market share of roughly one third by today compared to 90% in the early years of Bitcoin. The subsequent questions is, obviously, by which factors users determine to buy these coins. For the sake of its dominance, a lot of research up to this date focused solely on Bitcoin. Nevertheless, there is a number of publications related to Altcoins and the cryptoasset market as a whole. White (1989) states in his analysis of the cryptocurrency market that Bitcoin was the first of its kind (decentralized peer-to-peer exchange, quantity commitment embedded in an open source code, and shared public ledger), but soon there were Altcoins coming alive with improved features, mostly in terms of speed, robustness and privacy. As there was demand for these new cryptocurrencies as well as subsequent rise in market capitalization, their value seemed justified. However, there were several coins which had an immense price rally after launch, eventually declining not long after that. This reminds of the dotcom collapse in the beginning of 2000, where the extreme growth in the usage and adaption of the internet caused excessive speculation and bubbles. Lansky (2016) analyses the price development of cryptocurrencies on a broad basis and puts together a database consisting of over 1200 currencies. Next, he was looking for the largest increases and drops as well as their respective causes. As reasons for the price drops, he names the burst of a bubble in late 2013 (without going into detail), the early sale of founders short after an ICO causing a demise and lastly the fact that some currencies introduced technical innovations, but were overcome quickly by other currencies in this regards. The author identifies the reasons for the largest price increases within the fact that a cryptocurrency either brought a significant technology innovation or if the cryptocurrency offered a decentralized service demanded by users, a team of people (which he calls foundation) managed the development and promotion amongst the community. These findings are interesting inasmuch as they are in line with the aforementioned characteristics of a market of competing currencies in the sense of Hayek, where technological innovation and the community base seem to be decisive factors for users. Farell (2015) is analysing the cryptocurrency industry and comes to the conclusion that major factors which affect growth are government regulations as well as public perception and retailers accepting coins. Similar to Lansky (2016), there is no quantitative support for the arguments. Ong et al. (2015) are evaluating the potential of alternative cryptocurrencies by a quantitative analysis of community support, developer activity and liquidity. However, there was very few data (less than two months of daily observations) available, thus making proper inference difficult if not impossible. S. Wang and Vergne (2017) show that innovation potential is positively associated with weekly returns for a panel of 5 cryptocurrencies and the time span of one year. They also find that public interest (measured as standardized metric consisting of bing search results and Alexa web traffic ranking) is negatively associated with weekly returns and negative publicity has no significant relationship. For the latter, the authors counted how many media articles were published with the cryptocurrency and a negatively associated keyword. Another strand in the literature for cryptocurrencies is to consider the Blockchain as a network which can be valued according to Metcalfe's Law. Four decades ago, Metcalfe (2013) suggested at the example of the ethernet that the value of a telecommunications network is proportional to the nodes of the network squared. This example has lately been tested for social networks such as Facebook as well as cryptocurrencies. Alabi (2017) shows that Bitcoin, Ethereum and Dash follow Metcalfe's Law. He states that this could be a potential identification scheme for bubbles, as it is shown that those price surges which are not accompanied by any commensurate increase in the number of participating users return to the path which is characterized by Metcalfe's Law. Finally, we also look at research which was done so far with regard to only the Bitcoin network. Ciaian, Rajcaniova, and Kancs (2016) summarize the three main determinants of the *Bitcoin* price identified in the literature up to now as follows: Market forces of supply and demand, attractiveness indicators and global macroeconomic and financial development. Most of the papers include a range of variables for the first determinant, supply and demand factors within the Bitcoin ecosystem, in their models. Kristoufek (2015) incorporates a broad range of such factors into a wavelet coherence analysis and finds that trade volume and trade transactions have significant relationships with changing signs over time, as well as that price is positively correlated in the long run with both hash rate and difficulty. Ciaian, Rajcaniova, and Kancs (2016) confirm the impact of such factors and find that demand side variables (such as number of transactions, number of addresses) appear to excert a more pronounced impact on Bitcoin price than the supply side drivers (e.g. number of Bitcoins). Bouoiyour and Selmi (2015) show by employing an ARDL bounds testing approach that the exchange-trade ratio and the estimated output volume affect positively and significantly the Bitcoin price, while monetary velocity and the hash rate have no impact. In the long-run, output volume bcomes statistically insignificant and the effect of exchange-trade ratio becomes less strong. On the other hand, hash rate becomes significant. When it comes to attractiveness indicators, it was foremost search engine queries that was used as a proxy. Kristoufek (2013) believes that the demand side of the market is not driven by an expected macroeconomic development of the underlying economy - as there is none - and its price is simply determined by expected profits of holding the currency and selling it later. The author therefore concludes that the currency price is solely driven by the investors' faith in the perpetual growth. To measure this faith, he uses Google and Wikipedia queries as a proxy for investors' sentiment. Ciaian, Rajcaniova, and Kancs (2016) confirm these findings and additionally show that "new members" and "new posts" on online Bitcoin forums have a significant impact on Bitcoin price. Lastly, macroeconomic variables where tested to have an impact on the Bitcoin price. Some papers, such as Bouoiyour and Selmi (2015) and Ciaian, Rajcaniova, and Kancs (2016) come to the conclusion that the inclusion of macroeconomic variables like oil price, Dow Jones index and exchange rates have no impact on the Bitcoin price. By contrast, J. Wang, Xue, and Liu (2016) show that the oil price and stock price index do have an influence. Smith (2016) claims Bitcoin to be digital gold and shows that nominal exchange rates implied by the Bitcoin price are highly cointegrated with the conventional exchange rates and that there is a unidirectional causality which flows from conventional exchange rates to Bitcoin implied rates, concluding that floating nominal exchange rates are a major source of price volatility in the Bitcoin market. As one can see, some results contradict each other and there does not seem to be a clear consensus yet upon what the determinants of the Bitcoin price are. Vockathaler (2015) discusses this issue and comes to the conclusion that some results are drastically different when they are re-tested after the results have been published. Moreover, he finds that unexpected shocks are the largest contributor to the price fluctuations of Bitcoin. In this thesis, we aim at testing factors which might influence the price of a cryptocurrency, not only the Bitcoin price. We thus rely on conclusions drawn from the analysis of the cryptocurrency market and combine these different strands of literature. First of all, results for proxies related to Metcalfe's Law seem to be quite robust across studies. Alabi (2017) shows a clear correlation between addresses squared and value for three currencies, but also daily trading volume and number of addresses in Bitcoin-only research shows evidence for this relationship. Secondly, White (2015) introduces the theoretical framework of a market where currencies compete amongst each other by introducing new, innovative features to convince users to choose their units above others. Lansky (2016) argues that the reason for failure of a cryptocurrency is to be overtaken by other currencies with superior innovations, while at the same time price surges are often due to significant technology innovation. In line with J. Wang, Xue, and Liu (2016), we include proxies for innovation potential in our analysis. Another factor which was confirmed to have an influence is the community behind a cryptocurrency, as put out by e.g. Lansky (2016). Moreover, we can motivate the inclusion of this factor by Metcalfe's Law: The larger and stronger its community, the higher should be a currency's adoption. Lastly, we include search engine queries in order to test if their relationship with a cryptocurrency price has the same character as in research done so far.

3 Empirical Evidence

3.1 Data

In the following chapter, the variables used for analysis are described in detail as well as how and where they were retrieved. Overall, we used market capitalization as dependent variable and 10 explanatory variables according to the factors outlined in the previous chapter.

Dependent variable: Market capitalization

A lot of studies mentioned in the literature review section use price as dependent variable. However, this would be misleading in our case as we aim at comparing different cryptocurrencies. Due to the fact that every currency has a pre-defined (maximum) supply of coins which is quite different from one another, we have to find a standardized figure which makes the currencies comparable. In order to do this, we use market capitalization (*marketcap*) as proxy for the value of a cryptocurrency. For the sake of data availability as well as the logic behind it, we rely on the definition provided by CoinMarketCap (2018a) which tracks market capitalization as product of circulating supply and price. Therein, price is calculated by taking the volume weighted average of all prices reported at each market. Circulating supply is defined as the number of coins that are circulating in the market and in the general public's hands. Therefore, coins that are locked, reserved, or not able to be sold on the public market can't affect the price and are thus not included in the calculation of market cap. The time series are retrieved from the aforementioned source. Within the context of cryptocurrencies, a recurrent behaviour of market participants is the formation of so called pump and dump groups. Holders of a (often, but not only a rather less-popular) token artificially inflate the price of this currency in hope that other investors will pick it up too as a result of their "fear of missing out". By the time the coin has reached a certain targed range, the initial buyers begin to sell and earn a quick profit. However, as there is no fundamental reason for the sudden price increase, the price of the cryptocurrency mostly decreases in price not a long time later. Consequently, one should correct for these outliers - which is obviously a rather difficult endeavour, as pump and dump groups don't reveal themselves. However, if the price increases with a very fast pace in a short time, there is a strong signal for possible pump and dump behaviour. For example, CoinCheckup.com (2018) tracks movements of cryptocurrencies which suddenly show a spike of 5% or more within 5 minutes. In this thesis, we use only daily data, hence such movements would not have a direct effect on market cap. We therefore use a different measure defined according to the following criteria:

$$
\begin{aligned}
&ln(marketcap)_{i,t} - ln(marketcap)_{i,t-1} \geq 0.3 \quad \text{and} \\
&ln(marketcap)_{i,t} - ln(marketcap)_{i,t+p} \geq 0.2, \; \max p = 5
\end{aligned}
$$

If marketcap increases by more than 30% from one day to the other and decreases again in the following period of up to 5 days, this could be signal that the price movement was caused artificially. The spike value is then deleted and the time series interpolated, removing the outlier. The estimations were pursued with the corrected series for marketcap and compared with the uncorrected estimation outputs. However, the results differed only slightly. Thus, we remain with the uncorrected series within this thesis. Nevertheless, it is interesting to compare the amount of spikes amongst currencies - hence, the results for the identified pump and dump moments are summarized in table 10 in the appendix.

Metcalfe's Law

Addresses squared [Abbr.: asquared]: The series incorporates the number of unique and active addresses per day. Data was retrieved from the web-scraping service BitInfoCharts (2018) and then squared. Obviously, we cannot assume that every address represents one individual, as one can easily have multiple addresses. Similar to Alabi (2017), we assume that given a large number of participating users, the ratio of the number of actual users to the number of unique addresses is roughly consistent.

Volume squared [volumesq]: The series were extracted from CoinMarketCap (2018b) from the historical data section of each currency and later squared. The number exhibits the last 24 hours trading volume on markets with fees. Markets with no fees are excluded, as it would be possible for traders or bots to trade back and forth with themselves, generating a lot of "fake" volume without penalty.

Development activity

All variables related to development activity are retrieved from GitHub. GitHub is a web-based hosting service which is used to host open-source software projects, including cryptocurrencies. The code is free for anyone to view and programmers worldwide are free to contribute to the code or copy the code to launch their own cryptocurrency. Besides the code, several metrics are shown in each GitHub repository. They measure the development activity in the repository, e.g. how many issues were raised by the community in order to scrutinize the source code. Therefore, these metrics serve as good proxies to measure and compare development activity amongst cryptocurrencies. The series were retrieved by using the official API from GitHub, web-scraping the different metrics. The data was kindly provided by CoinGecko, a website which provides a 360 degree overview of cryptocurrencies.

Open issues count [openissues] is a metric measuring the number of issues raised by the community with regard to the code. Coins which have attention of developers will see more issue requests. The issues raised incorporate improvements to the source code, bugs to be solved by the core team etc.

Closed issues count [closedissues] is the number of issues which were closed by the core development team.

Repository merged pull requests [mergedcount] is the number of proposals being merged into the core codebase. Pull requests are used by contributors to improve the source code, i.e. they scrutinize the code and send their proposal to the core development team, who merge these changes into the source code. Johnson (2018) explains in detail how a pull request is raised and approved.

Average commits in 4 weeks [commits] is the average number of times the source code has been updated. In GitHub, saved changes are called commits, each of them has got an associated commit message which captures the history of changes, so other contributors can understand what and why something was done. It can thus be concluded that the more commits are made on a GitHub Repository, the higher the developer activity.

Community factors

Data for the community factors is derived from Reddit. Reddit is a social news aggregation and discussion website which is frequented by programmers and a preferred discussion forum related to cryptocurrencies. Oviously, not all discussions about cryptocurrencys are taking place on this website, additionally its discussions are foremost in English, which might lead to a bias towards currencies in western countries. Nevertheless, it's the best forum where proxies can be derived to compare currencies, keeping in mind that results have to be interpreted with care due to the reasons mentioned. Another important issue when using community metrics is the possibility of community managers to manipulate scores. For a young cryptocurrency, there is an incentive to simulate a large community in order to attract new investors by e.g. buying likes. Thus, the choice of proxies has to be robust towards such manipulation, i.e. it is looked for activity-based metrics. Community metrics have again been extracted using web-scraping techniques and were also provided by CoinGecko.

Average accounts active in 48 hours [accounts] is the average count of online users at the coin's subreddit over the last 48 hour period. It might be easy to "buy" users, but it would be difficult to fake a community measured by how often individuals are online in a subreddit forum. Thus, this activity-based metrics reflects well how many individuals are interested in a cryptocurrency.

Average comments in 48 hours [comments] is the number of new comments over the last 48 hour period that appeared in posts which are on the front page of the subreddit site. In contrast to average accounts, this proxy goes further and measures the commitment of users in participating in a discussion. It is activity-based as well and thus quite robust to manipulation.

Search engines

Google search index [google] The search engine google provides a service named Google trends, which can be used to extract the popularity of a buzzword over a specified time range within the search engine. The search index is defined as number of queries for the buzzword divided by total google search queries. The index is then normalized to be within the range between zero and 100. Although google search index is a very powerful way of measuring the interest of people (As google is the most popular search engine), it comes with some caveats. The fact that its a relative measure could lead to wrong conclusions. If, for example, the interest for a keyword is increasing, but total google queries are increasing more (for unknown reasons), Google search index would drop. This is counter intuitive as we want to measure interest for our buzzword over a certain time period. Moreover, the normalization leads to imprecise data especially if there was a short time period with a very large interest. It can't be distinguished properly between changes in periods with less interest, since search index is on such a low level due to the relativization. Nevertheless, the data extracted gives useful hints. In addition, it is possible for buzzwords which might have a meaning besides the crypto world to allow only for results within a specified topic range such as finance. All data was retrieved from https://trends.google.com/trends. For the time range needed, only weekly data was available. Thus, the series were extracted as such and then interpolated linearly by use of EViews.

Bloomberg story count [storycount]: This is a measure which is extracted from Bloomberg terminal, a service to monitor and analyze real-time financial data and search financial data (amongst other features). Data is derived by the number of stories on the terminal (both by Bloomsberg News and other sources) which contain a certain buzzword in them. There are over 30'000 sources which feed into Bloomberg who are either ask to be added by Bloomberg or they are contacted. Opposed to Google's search index, storycount is an absolute measure which delivers the number of stories per day. The choice which sources are fed into the terminal is decided on editorial choice by Bloomberg. As Bloomberg is a service for a clientele in the finance area, these sources cover to a large extent stories from economic and financial news providers. It can thus be concluded that storycount might be a good proxy for (professional) investors interest, whereas Google search index measures rather mainstream interest.

In table 1, all currencies as well as the length of the time series are summarized. For each of the variables, we performed a log transformation in order to interprete the results as elasticities.

Summary of time series				
Full name	Abbr.	asquared	marketcap, volumesq, development & community factors, google	storycount
Bitcoin Cash	bch	Aug 17 - Jan 18	Aug 17 - Jan 18	Aug 17 - Jan 18
Bitcoin	btc	Jun 14 - Jan 18	Jun 14 - Jan 18	Jun 14 - Mar 18
Dash	dash	Jun 14 - Jan 18	Jun 14 - Jan 18	-
EOS	eos	-	Jul 17 - Jan 18	-
Ethereum Classic*	etc	-	Jul 16 - Jan 18	-
Ethereum	eth	Aug 15 - Jan 18	Aug 15 - Jan 18	Aug 15 - Mar 18
IOTA	iot	-	Jun 17 - Jan 18	-
Lisk	lsk	-	May 16 - Jan 18	-
Litecoin	ltc	Jun 14 - Jan 18	Jun 14 - Jan 18	Jun 14 - Mar 18
NEO	neo	-	Oct 16 - Jan 18	-
NEM	xem	-	Apr 15 - Jan 18	-
Stellar	xlm	-	Aug 14 - Jan 18	-
Monero	xmr	-	Jun 14 - Jan 18	Jun 14 - Mar 18
Nano	xrb	-	Jul 17 - Jan 18	-
Ripple	xrp	Jul 14 - Mar 18	Jul 14 - Jan 18	-
Verge	xvg	-	Dec 14 - Jan 18	-
Zcash	zec	-	Nov 16 - Jan 18	-

A few values were missing in some of the series during the web-scraping process, in this case these values were linearly interpolated.
*For Ethereum Classic, development factors were only available from Sep 17 to Jan 18.

Table 1: Data

3.2 Econometric Methodology

The econometric model contains marketcap as well as its explanatory variables outlined in the previous chapters. If we run a simple regression, we have to assume that marketcap depends on our explanatory variables but *not* vice versa. As proposed by Lütkepohl and Krätzig (2004), the estimation of non-linear interdependencies among interdependent time series in presence of mutually correlated variables is subject to the issue of endogeneity. This issue is circumvent by following the general approach in literature to analyze the causality between endogenous time series, the specification of a multivariate Vector Auto Regressive (VAR) model. Engle and Granger (1987) show that regressions of interdependent and *non-stationary* time series might lead to spurious results. If two variables are non-stationary, their combination might be stationary. In this case, the time series are considered to be cointegrated, which implies that there exists a long-run equilibrium relationship between them. This relationship can be estimated by application of a Vector Error Correction Model (VECM). Thus, we apply the following general procedure to both the panel data as well as individually to each cryptocurrency[3]: First, we test for stationarity of the time series by use of unit root tests. Second, we examine the optimal lag length in a VAR setup. In a third step, we employ Johansen's cointegration method to examine the long-run relationship between the series. For the panel, we additionally apply Pedroni's panel cointegration tests. If there is a cointegrating relationship, we estimate the VECM accordingly to quantify the long-run relationship between the variables as well as its error correction terms. It is also tested for autocorrelation of the residuals to avoid biased results. In the context of the panel, we also use Fully Modified OLS and Dynamic OLS to measure the long-run relationship, accounting for panel specific issues. Lastly, we examine if the variables are weakly exogenous and test for Granger causality. For all estimations, the EViews software package has been used and thus, we rely on the built-in methodology of the codes in the program. Details of how tests and estimations are conducted were retrieved from EViews (2018b).

Unit root tests

In order to check for stationarity of the variables, we employ a set of unit root tests. When we test the individual currencies, we carry out the standard Augmented Dickey-Fuller (ADF) test:

$$\Delta y_t = \alpha y_{t-1} + x_t' \delta + \epsilon_t \tag{1}$$

where y_t is the variable of interest, x_t' is a vector for optional exogenous regressors which may consist of a constant, or a constant and trend. α and δ are parameters to be estimated, and ϵ_t are assumed to be white noise. The null and alternative hypotheses may be written as $H_0 : \alpha = 0$ and $H_1 : \alpha < 0$ respectively. Thus, the null hypothesis states that the

[3]For the sake of visibility and ease, the majority of the results are presented only for the panel estimations. Nevertheless, all estimation results are grouped in a database and handed in together with the thesis.

series exhibits a unit root. All three cases are estimated and reported, from *i*) no constant, *ii*) constant to *iii*) constant and trend. In the context of the panel unit root test, the regression is slightly altered:

$$y_{it} = \rho_i y_{it-1} + X_{it}\delta_i + \epsilon_{it} \tag{2}$$

where $i = 1, 2, ..., N$ series, that are observed over periods $t = 1, 2, ..., T_i$. X_{it} represent the exogenuous variables in the model, including any fixed effects or individual trends, ρ_i are the autoregressive coefficients, and the errors ϵ_{it} are assumed to be mutually independent idiosyncratic disturbance. If $|\rho_i| < 1$, y_i is said to be weakly stationary. If $|\rho_i| = 1$, then y_i contains a unit root. For purposes of testing, there are two natural assumptions that we can make about ρ_i. First, one can assume that the persistence parameters are common across cross-sections so that $\rho_i = \rho$ for all i. The Levin, Lin and Chu (LLC) and Breitung test employ this assumption. Alternatively, one can allow ρ_i to vary freely across cross-sections. The Im, Pesaran and Shin (IPS), Fisher-ADF and Fisher-PP tests are of this form[4]. All tests exept the PP-Fisher test require a specification of the number of lags. They are chosen according to the optimal lag length determined by the Schwarz Information Criterion.

Cointegration tests

Given two non-stationary series, we may be interested in determining whether the series are cointegrated, and if they are, in identifying the cointegrating (long-run equilibrium) relationships. We adopt the methodology according to Johansen (1991) and Johansen (1995). Johansen's method is carried out by imposing restrictions on a VAR model. Consider a VAR of order ρ:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + Bx_t + \epsilon_t \tag{3}$$

where y_t is a k-dimensional vector of non-stationary I(1) variables, x_t is

[4]See EViews (2018a) for detailed discussion of the test properties. Results from all tests will be reported and discussed.

a d-dimensional vector of deterministic variables, and ϵ_t is a vector of innovations. We may rewrite this VAR as

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + Bx_t + \epsilon_t \tag{4}$$

where

$$\Pi = \sum_{i=1}^{p} A_i - I \quad \text{and} \quad \Gamma_i = -\sum_{j=i+1}^{p} A_j \tag{5}$$

Granger's representation theorem states that if the coefficient matrix Π has reduced rank $r < k$, then there exist $k \times r$ matrices α and β each with rank r such that $\Pi = \alpha\beta'$ and $\beta' y_t$ is I(0). r is the number of cointegrating relations (the *cointegrating rank*) and each column of β is the cointegrating vector. The elements of α are known as the adjustment parameters in the VEC model. Johansen's method is to estimate the Π matrix from an unrestricted VAR and to test whether we can reject the restrictions implied by the reduced rank of Π. An issue which arises is the specification of a trend. The series may have deterministic as well as stochastic trends. Similarly, the cointegrating equations may have intercepts and deterministic trends. Here, we need to make assumptions with respect to the underlying data. From a look at the series, almost all of them seem to exhibit a trend. We can therefore outrule the cases where no trend in levels is assumed. The question remains, however, if we allow for a linear deterministic trend in the data, i.e. whether we should estimate with or without trend assumption for the cointegrating equations. Thus, both cases are estimated and reported, which is in line with the so called Pantula principle. Based on Pantula (1989), the most restrictive model is first estimated and then moved on through all models to the least restrictive one. In our case, the less restrictive one is the model with trend, thus we test both cases and if trend is not significant, we will estimate without including a trend. We now move to the cointegration testing in the panel framework. The first two tests are based on the two-step method developed by Engle and Granger (1987), which is based on an examination of the residuals of a spurious regression performed using I(1) variables. If the variables are cointegrated, the residuals should be I(0) whereas in the case that they are not cointegrated, the residuals should be I(1). Pedroni (2004) and Kao (1999) extended this method to perform tests with panel data. Pedroni proposes several tests for cointegration that allow for heterogeneous intercepts and trend coefficients across cross-sections. When we consider the regression

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \cdots + \beta_{Mi} x_{Mi,t} + \epsilon_{i,t} \tag{6}$$

for $t = 1, ..., T$; $i = 1, ..., N$; $m = 1, ..., M$; where y and x are assumed to be integrated of order one, i.e. I(1). T constitutes the number of lags, N the number of cross-sections and M the number of explanatory variables. The parameters α_i and δ_i are individual and trend effects which may be set to zero if desired. Under der null hypothesis, the residuals $\epsilon_{i,t}$ will be I(1). The approach is to obtain the residuals from equation (6) and then test whether the residuals are I(1) by running the auxiliary regression

$$\epsilon_{it} = \rho_i \epsilon_{it-1} + u_{it} \tag{7}$$

or

$$\epsilon_{it} = \rho_i \epsilon_{it-1} + \sum_{j=1}^{p} \Psi_{ij} \Delta \epsilon_{it-j} + v_{it} \tag{8}$$

for each cross-section. Pedroni describes various methods of constructing statistics for testing the null hypothesis $\rho_i = 1$, which means no cointegration. There are two alternative hypotheses: First, we have the homogeneous alternative $(\rho_i = \rho) < 1$ for all i, which Pedroni terms the within-dimension test and obviously assumes common AR coefficients for all cross-sections. Second, we have the heterogeneous alternative $\rho_i < 1$ for all i termed the between-dimension and assuming individual AR coefficients. The Pedroni panel cointegration statistic is constructed from the residuals of equation (7) or (8). A total of eleven statistics with varying degree of properties (size and power for different N and T) are generated and reported in the section Results.

Kao (1999) follows the same logic as the Pedroni tests, but specifies cross-section specific intercepts and homogeneous coefficients on the first stage regressors. We have

$$y_{it} = \alpha_i + \beta x_{it} + \epsilon_{it} \tag{9}$$

for

$$y_{it} = y_{it-1} + u_{i,t} \tag{10}$$

$$x_{it} = x_{it-1} + \epsilon_{i,t} \tag{11}$$

for $t = 1, ..., T$; $i = 1, ..., N$. Kao then runs either the pooled auxiliary regression

$$\epsilon_{it} = \rho \epsilon_{it-1} + \upsilon_{it} \tag{12}$$

or the augmented version of the pooled specification

$$\epsilon_{it} = \rho_i \epsilon_{it-1} + \sum_{j=1}^{p_i} \Psi_{ij} \Delta \epsilon_{it-j} + \upsilon_{it} \tag{13}$$

Details regarding the estimation of the test statistics are provided in the original paper. Similar to Pedroni, the null hypothesis of no cointegration is tested.

Lastly, we report also results from a combined individual test based on the Johansen methodology. Maddala and Wu (1999) proposed an approach to test for cointegration in panel data by combining tests from individual cross-sections to obtain a test statistic for the full panel.

Estimation

We use a vector error correction model (VECM) once we established which series are known to be cointegrated from the tests before. The VECM is a restricted VAR with built-in specification so that it restricts the long-run behaviour of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. The cointegration term is known as the error correction term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments. We let $\mathbf{y_t}$ be a vector of time series[5]. The system is cointegrated if there exists some non-zero vector $\boldsymbol{\beta}$ such that $\boldsymbol{\beta}'\mathbf{y_t}$ is stationary. The system is said to be in equilibrium when $\boldsymbol{\beta}'\mathbf{y_t} = 0$ and out of equilibrium when $\boldsymbol{\beta}'\mathbf{y_t} \neq 0$. A deviation from equilibrium is defined as $\mathbf{z}_t = \boldsymbol{\beta}'\mathbf{y_t}$. If we consider a bivariate system

$$y_t + \alpha x_t = \epsilon_t, \qquad \epsilon_t = \epsilon_{t-1} + \xi_t \tag{14}$$

$$y_t + \beta x_t = \upsilon_t, \qquad \nu_t = \rho \nu_{t-1} + \zeta_t, \quad |\rho| < 1 \tag{15}$$

where ξ_t and ζ_t are white noise. Because ϵ_t is I(1), it must be the case that y_t and x_t are also I(1). Note that equation (15) is a linear combination of y_t and x_t. As ν_t is stationary, it must be the case that $y_t + \beta x_t$ is also stationary. Thus, y_t and x_t are cointegrated with a vector $\boldsymbol{\beta'} = (1, \beta)$. Following Engle and Granger (1987), the system can be rewritten as

$$\Delta y_t = \alpha \delta z_{t-1} + \eta_{1t} \tag{16}$$

$$\Delta x_t = -\delta z_{t-1} + \eta_{2t} \tag{17}$$

[5]We follow the setup applied by Smith (2016), who estimated a bivariate VECM for Bitcoin exchange rates and gold price.

where $\delta = (1-\rho)/(\beta-\alpha)$ and the η's are linear combinations of ϵ_t and ν_t. Since z_t represents deviations from equilibrium, equations (16) and (17) show how the series react to a disequilibrium. We consider $\boldsymbol{\beta}'\mathbf{y_t}$ to be a VAR(p) which can be extended to the VEC representation as follows:

$$\mathbf{\Delta y_t} = \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{y_{t-1}} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma_i}\mathbf{\Delta y_{t-i}} + \boldsymbol{\epsilon_t} \tag{18}$$

We will always apply the bivarate case, i.e. the first difference in the natural log of marketcap (Δy_t) as dependent variable and first difference in the natural log of one explanatory variable from the range outlined in the data section (Δx_t). Thus, $\mathbf{\Delta y_t}$ is a 2×1 vector $\begin{bmatrix} \Delta y_t \\ \Delta x_t \end{bmatrix}$. The vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are also 2×1 and contain the adjustment parameters and cointegrating vector respectively. The matrix $\boldsymbol{\Gamma_p}$ is a 2×2 matrix of lag parameters:

$$\boldsymbol{\Gamma_p} = \begin{bmatrix} \gamma_{yy,p} & \gamma_{yx,p} \\ \gamma_{xy,p} & \gamma_{xx,p} \end{bmatrix}$$

Following Johansen (1991) and Johansen (1995), we normalize β_1 to one for identification, as the amount of restrictions has to be equal to the amount of cointegrating relationships (which is the rank of of the coefficient matrix $\boldsymbol{\alpha}\boldsymbol{\beta}'$). This means that in our system, β_2 defines the equilibrium condition. Before we can estimate the VECM, the lag order of the underlying VAR has to be determined. In order to do this, we estimate an unrestricted VAR and determine the optimal lag length by minimizing some information criterion, i.e. Akaike Information Criterion (AIC), the Schwarz information criterion (SC) and Hannan-Quinn Information Criterion (HQ). The appropriate lag length is then selected (and substracted one lag length, since we work with differences in the VEC context) for the estimation of the VECM. Once the optimal lag lenght is determined, we first estimate the less restrictive model, i.e. with trend. If the trend coefficent is not significant on a 95% level, we re-estimate the model without trend. As we deal with daily financial data, the volatility is quite high and the issue of heteroskedasticity arises. We thus estimate using weighted least squares (WLS) to account for heteroskedasticity[6]. In order to find the weights, the EViews software carries out a first-stage estimation of the coefficients using no weighting matrix. Using starting values obtained from OLS, EViews then iterates the first-stage estimates until the coefficients converge. The residuals from this first-stage iteration are used to form a consistent estimate of the weighting matrix. In the second stage of the procedure, EViews uses the estimated weighting matrix in forming new estimates of the coefficients. Once the coefficients are estimated, we perform the Portmanteau Autocorrelation test which computes the multivarate Box-Pierce/Ljung-Box Q-Statistics for residual serial correlation up to the specified order. In case the estimated model exhibits autocorrelation, we repeat the procedure and choose higher lag orders. Finally, we perform weak exogeneity tests in order to investigate if the cointegrating relationship does not feed back onto one of the two variables involved. In order to do this, we restrict either α_1 or α_2 to zero and test if the restriction is binding ($= H_0$) by performing a Lagrange-Multiplier test. If we cannot reject the null, the underlying variable is said to be weakly exogenous.

The model outlined above is estimated for each pair of variables within each currency as well as for the panel. By doing the latter, however, there is a caveat. EViews estimates the VECM by simply taking into account the stacked data of the whole panel, but without letting lags go across cross-sections. It is, though, not possible to implement panel-style features such as fixed effects. Therefore, we additionally estimate the long-run relationship within the panel by employing the standard procedure in panel cointegration estimation, i.e. Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS). Although being regressions, both of these techniques can deal with endogeneity and serial correlation problems. Let's consider a cointegrated regression in the following general form:

$$y_{it} = \alpha_i + \beta X_{it} + \epsilon_{it} \tag{19}$$

[6]See e.g. Wooldridge (2015), chapter 8.4., for detailed discussion.

where $i = 1, 2, 3, ..., N$ cross-sections, $t = 1, 2, 3, ..., T$, ϵ_{it} are stationary residuals and X_{it} is a vector of regressors, each integrated of order one I(1) such that $X_{it} = X_{it-1} + \nu_{it}$. Phillips and Moon (1999), Pedroni (2001b) and Kao and Chiang (2001) extended the FMOLS approach proposed by Phillips and Hansen (1990) to panel settings. The FMOLS for panels can be written as[7]:

$$\hat{\beta}_{FM} = \left[\sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \bar{X}_i)(X_{it} - \bar{X}_i)' \right]^{-1} \left[\sum_{i=1}^{N} \left(\sum_{i=1}^{T} (X_{it} - \bar{X}_i) \hat{Y}_{it}^{+} - T \hat{\Delta}_{\epsilon u}^{+} \right) \right]$$

where $\hat{Y}_{it}^{+}$ is the endogeneity correction term while $\hat{\Delta}_{\epsilon u}^{+}$ is the serial correlation correction term. The DOLS estimator proposed by Stock and Watson (1993) was extended by Kao and Chiang (2001), Mark and Sul (2003) and Pedroni (2001a) for panel settings. To correct for endogeneity and serial correlation, the DOLS method expands the cointegrated equation by including leads and lags of the first difference of the regressors. The DOLS equation may be written as

$$Y_{it} = \alpha_i + \beta X_{it} + \sum_{j=-p1}^{p2} C_{ij} \Delta X_{it+j} + \nu_{it} \tag{20}$$

where ΔX_{it+j} asymptotically eliminates the effect of endogeneity of X_{it}, p_2 is the maximum lead length, p_1 is maximum lag length and ν_{it} is the error term. We perform both tests in two ways: On one hand, we perform a *pooled estimation* where cross-section specific deterministic components are removed prior to estimation. The pooled estimation accounts for heterogeneity by using cross-section specific estimates of the long-run covariances (in case of FMOLS) or the conditional long-run residual variances (in case of DOLS) to reweight the data prior to computing the estimator. On the other hand, we choose *grouped estimation* where each of the cross-sections are estimated and averaged, before being grouped together

[7]adopted from Kao, Chiang, and Chen (1999).

and performing the FMOLS or DOLS estimations. Pedroni (2001a) notes that in the presence of heterogeneity in the cointegrating relationships, the grouped-mean estimator offers the desirable property of providing consistent estimates of the sample mean of the cointegrating vectors, in contrast to the pooled estimator.

Granger Causality

To further examine causal relationships among the variables, we employ Granger causality tests. The Granger (1969) approach examines whether x causes y and to see how much of the current y can be explained by past values of y and then to see whether adding lagged values of x can improve the explanation. Obviously, the test is also done vice versa, and two-way causation is a frequent case. Note that the statement x Granger causes y does not imply that y is the effect of x, it simply measures precedence and information content. For our bivariate case, we run the following regressions:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_k y_{t-k} + \beta_1 x_{t-1} + ... + \beta_k x_{t-k} + \epsilon_t \quad (21)$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + ... + \alpha_k x_{t-k} + \beta_1 y_{t-1} + ... + \beta_k y_{t-k} + u_t \quad (22)$$

where y_t is marketcap and x_t is one of the explanatory variables. The reported F-statistics are Wald statistics for the joint hypothesis:

$$\beta_1 = \beta_2 = ... = \beta_k = 0$$

The null hypothesis is that x does *not* Granger-cause y in the first regression and vice versa and the second one. In the panel case, the above regressions are augmented with cross-sections i such that

$$y_{i,t} = \alpha_{0,i} + \alpha_{1,i} y_{i,t-1} + ... + \alpha_{k,i} y_{i,t-k} + \beta_{1,i} x_{i,t-1} + ... + \beta_{k,i} x_{i,t-k} + \epsilon_{i,t} \tag{23}$$

$$x_{i,t} = \alpha_{0,i} + \alpha_{1,i} x_{i,t-1} + ... + \alpha_{k,i} x_{i,t-k} + \beta_{1,i} y_{i,t-1} + ... + \beta_{k,i} y_{i,t-k} + u_{i,t} \tag{24}$$

There are two assumptions to test Granger causality in the panel context. The first is to treat the panel data as one large stacked set of data (similar to the approach when estimating the VECM), and then perform the Granger Causality test in the standard way, with the exception of not letting data from one cross-section enter the lagged values of data from the next cross-section. This method assumes that all coefficients are same across all cross-sections, i.e.:

$$\begin{aligned} \alpha_{0,i} = \alpha_{0,j}, \alpha_{1,i} = \alpha_{1,j}, ..., \alpha_{k,i} = \alpha_{k,j} \quad \forall i, j \\ \beta_{0,i} = \beta_{0,j}, \beta_{1,i} = \beta_{1,j}, ..., \beta_{k,i} = \beta_{k,j} \quad \forall i, j \end{aligned}$$

The second approach, introduced by Dumitrescu and Hurlin (2012), makes the opposite assumption, allowing all coefficients to be different across cross-sections:

$$\begin{aligned} \alpha_{0,i} \neq \alpha_{0,j}, \alpha_{1,i} \neq \alpha_{1,j}, ..., \alpha_{k,i} \neq \alpha_{k,j} \quad \forall i, j \\ \beta_{0,i} \neq \beta_{0,j}, \beta_{1,i} \neq \beta_{1,j}, ..., \beta_{k,i} \neq \beta_{k,j} \quad \forall i, j \end{aligned}$$

This test is performed by running standard Granger causality regressions for each cross-section individually. Next, the average for of the test statistics are taken. For all Granger causality tests outlined above, the number of lags corresponds to the optimal lag length determined according to the information criterions.

3.3 Results

In the following, we show our findings. With a few exeptions, only the panel results are presented in tables. However, results from the individual estimations are summarized in a database and delivered together with this thesis. Table 2 shows the unit root results. For ease of interpretation, all series which exhibit a unit root on a 95% significance level are marked in bold. The overall picture shows that almost all series exhibit a unit root, depending on the underlying assumptions.[8] This is especially true for marketcap, where the null hypothesis of a unit root is not rejected no matter which test is conducted. If no individual intercepts and trends are allowed (column "None"), the existence of a unit root is very robust across tests. However, this would be a very strong assumption and as one can see the picture looks different if we allow for individual fixed effects (column "Intercept") or individual effects and trends, which is the last column. Recall that LLC and Breitung tests assume common unit root processes across cross-sections, whereas ADF, PP and IPS assume individual processes. For the majority of the series, the series exhibit a unit root for both the common or individual processes assumption. The Breitung test relaxes the strong assumption of cross-sectional independence which is present in the other tests. The latter shows that all series except storycount are non-stationary even if we allow the cross-sections to be dependent. We can observe that a large block from the development factors, namely closedissues, mergedcount and commits reject the null hypothesis of no unit root for the majority of the tests if we allow for individual fixed effects and trends. If we don't allow individual effects, these series are clearly non-stationary, which indicates that there must be strong differences inbetween the currencies.

In the next step and based on the unit root test results, cointegration tests are employed. The results are summarized in table 3. We ruled out the exclusion of individual fixed effects and trends, as it seems to be an unrealistic assumption from the perspective of the unit root test results. Note that each variable was tested to be cointegrated with mar-

[8]All variables became stationary when transformed into the first difference form.

P-values panel unit root tests													
	None			Intercept				Intercept and trend					
Variable	LLC	ADF	PP	LLC	IPS	ADF	PP	LLC	Breitung	IPS	ADF	PP
marketcap	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**0.79**	**1.00**	**0.99**	**0.99**	**0.99**
asquared	**0.98**	**1.00**	**1.00**	**0.99**	**0.99**	**0.77**	0.00	**0.86**	**0.17**	**0.06**	0.00	0.00
volumesq	**1.00**	**1.00**	**1.00**	**0.99**	**0.97**	**0.96**	0.03	0.00	**0.37**	0.00	0.00	0.00
openissues	**1.00**	**1.00**	**1.00**	**0.06**	**0.44**	0.00	0.00	**0.49**	**1.00**	**0.11**	0.00	0.00
closedissues	**1.00**	**1.00**	**1.00**	0.01	**1.00**	0.01	0.00	0.00	**0.98**	**0.06**	0.00	0.00
mergedcount	**1.00**	**1.00**	**1.00**	0.00	0.00	0.00	0.00	0.00	**1.00**	0.00	0.00	0.00
commits	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.99**	0.00	0.00	0.00
accounts	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**0.97**	**0.52**	**0.45**
comments	**0.20**	**0.06**	0.00	**1.00**	**0.15**	0.01	0.00	**0.79**	**0.81**	0.00	0.00	0.00
google	**0.75**	**0.90**	**0.88**	**0.97**	**0.59**	**0.53**	0.00	0.02	**1.00**	0.00	0.00	0.00
storycount	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

The Levin, Lin & Chu (LLC) and Breitung tests have the null hypothesis of a unit root assuming common unit root processes, whereas the ADF-Fisher Chi-square (ADF), PP-Fisher Chi-square (PP) and Im, Pesaran and Shin W-stat (IPS) test assume individual unit root root processes. The tests requiring lag length specification were conducted with lag length selection according to the Schwarz Information Criterion. If the null hypothesis could not be rejected on a 95% significance level and the series thus exhibits a unit root, the result in the table is marked in bold.

Table 2: Unit root results

ketcap. Addresses squared, volume squared, comments and accounts show robust results towards cointegration across tests. Open issues is cointegrated with marketcap if one assumes common AR coefficients for the underlying tests (referred to as within-dimension) whereas the statistics for google show stronger signs for cointegration if individual AR coefficients are assumed (between-dimension). However, all of these series can be considered cointegrated with marketcap by the majority of the test statistics. Again, the aforementioned block consisting of closedissues, mergedcount and commits does not show any signs of cointegration, which is in line with the unit root test results, i.e. the series proven to be stationary are not cointegrated with market cap. The same goes for storycount, which was stationary across all unit root tests and is not cointegrated with market cap based on the majority of the tests. We will take a closer look at this variable later.

We move on and estimate the long-run relationship between marketcap and those variables where cointegration was detected in the previous step. For this matter, we leave out closedissues, mergedcount and commits as we could neither see non-stationarity within the series nor cointegration with marketcap. Table 4 reports the estimation results. For the sake of a better overview, we only show the results for the long-run parameters β

Summary cointegration tests										
	Pedroni				Kao	Johansen Fisher				
	Intercept		Intercept & trend				Intercept		Intercept & trend	
Variable	within	between	within	between	CI	Lags	No CI	CI	No CI	CI
asquared	4/8	3/3	4/8	2/3	0.08	15	0.00	0.37	0.01	0.62
volumesq	8/8	3/3	8/8	3/3	0.00	17	0.00	0.35	0.00	0.36
openissues	4/8	0/3	0/8	0/3	0.05	20	0.00	0.17	0.00	0.37
closedissues	0/8	0/3	0/8	0/3	0.15	6	0.00	0.59	0.00	0.23
mergedcount	0/8	0/3	0/8	0/3	0.00	15	0.00	0.50	0.00	0.83
commits	0/8	0/3	0/8	0/3	0.00	8	0.00	0.37	0.00	0.29
comments	6/8	3/3	6/8	3/3	0.00	17	0.00	0.11	0.00	0.19
accounts	4/8	3/3	6/8	3/3	0.00	10	0.00	0.13	0.00	0.47
google	3/8	3/3	3/8	3/3	0.19	20	0.00	0.10	0.00	0.66
storycount	4/8	2/3	5/8	2/3	0.48	12	0.00	0.51	0.00	0.27

The Pedroni Residual Cointegration Test output consists of 11 test statistics in total, 8 for the within-section and 3 for between. In this table, it is reported how many test statistics indicate a cointegrating relationship (Null hypothesis of *no* cointegration was rejected) on a 95% significance level. For the Kao Residual Cointegration Test, the p-value is reported. By construction, no trend is assumed. Like Pedroni, the null hypothesis of no cointegration is tested. For both the Pedroni and the Kao tests, the lag lenght is selected according to the Schwarz Information Criterion. For the Johansen Fisher Panel Cointegration Test, p-values are reported for the null of either "No Cointegration" (No CI) and "One Cointegration relationship" (CI). Lags for these tests were chosen according to optimal lag length examined in an unrestricted VAR, see table 11 in the appendix for details.

Table 3: Cointegration test results

and α. Parameters for the lagged values, though, are outlined in the electronic appendix. Note that we have to put in place one restriction in the context of one cointegrating relationship, hence β_1 is normalized to one following the standard procedure. By construction, each VECM consists of two variables and two equations. β_1 and α_1 are the parameters for the first equation with marketcap as the response variable. In the second equation, the other variable (shown in far left column) is the response variable with β_2 and α_2 being the corresponding parameters. Recall that in the bivariate system, β_2 defines the estimate of the relationship between marketcap and the second variable in equilibrium. We can see that this relationship is present and highly significant for for all variables. As we have a log-log model, this parameter can be interpreted as an elasticity. For example, if marketcap increases by 1%, addresses squared increase by 0.81% in equilibrium. The α parameters describe the way in which the corresponding series responds to disequilibrium. A first step towards causality in the relationship is the analysis of these parameters: While α_2 is significant in all VECM pairs, α_1 is only significant for volume squared, accounts and google. In other words, the second variable in the system responds in a disequilibrium and adjusts to restore balance. On the other hand, marketcap only responds for the three aforementioned cases, whereas for the other variables the same error correction dynamics are not present. A further illustration of this one-way causality can be found if we restrict α_1 to zero and test if this restriction is binding. For all variables where α_1 was insignificant, the null hypothesis of the Lagrange Multiplier test result could not be rejected, thus implying weak exogeneity. Put differently, we construct our model such that marketcap cannot be adjusted by the error correction term ($\alpha_1 = 0$) and check if this makes a difference compared to the normal model without restriction. If it does not, we can state that the marketcap is not affected by the respective variable in a disequilibrium, which is called weak exogeneity. This finding will further be confirmed by Granger causality tests, to which we come back later. First, we employ FMOLS and DOLS estimations, as these econometric techniques take into account panel-specific caveats, opposed to the VECM estimations. While the VECM simply estimates the stacked data, FMOLS and DOLS allow fixed effects but still correct for endogeneity and serial correlation in contrast to a simple OLS regression. Recall that *grouped* estimation takes the average of each cross-section and estimates in a second step, whereas *pooled* estimation removes cross-section specific components prior to estimation. As one can see, estimations for asquared, volumesq, comments, accounts and google are quite consistent with the VECM outcomes. In the case of openissues, the estimators vary more depending on the underlying assumptions, giving a hint that the currencies might be heterogeneous in their behaviour. This last finding is in line with the fact that the rest of the variables in the development factors block are not cointegrated in the panel context.

Finally, we turn to the panel Granger causality test results. Recall that one variable Granger causes the other if one adds lagged values of of the second variable (besides own past values) and these lags improve the explanation. For the variables asquared, volumesq, comments, accounts and google, there is strong evidence for a bidirectional Granger causal-

Estimation Results long-run relationship									
	VECM Parameters			Weak Exogeneity		FMOLS		DOLS	
Variable	β_2	α_1	α_2	$y_{i,t}$	$x_{i,t}$	β_{Pooled}	$\beta_{Grouped}$	β_{Pooled}	$\beta_{Grouped}$
asquared	0.81***	-0.0003	0.0080***	0.60	0.00	1.48***	1.03***	0.67***	0.87***
	(0.1728)	(0.0005)	(0.0026)			(0.0002)	(0.1068)	(0.0488)	(0.3312)
volumesq	0.42***	-0.0056***	0.0611***	0.00	0.00	0.43***	0.39***	0.33***	0.35***
	(0.0127)	(0.0008)	(0.0112)			(0.0019)	(0.0061)	(0.0060)	(0.0101)
openissues	2.09***	-0.0002	0.0009***	0.43	0.00	5.33***	4.89***	1.97***	4.82
	(0.4478)	(0.0003)	(0.0002)			(0.0005)	(0.1302)	(0.3032)	(12.83)
comments	2.30***	-0.0003	0.0041***	0.37	0.00	1.71***	2.39***	1.14***	1.54***
	(0.2540)	(0.0003)	(0.0008)			(0.0021)	(0.1239)	(0.0602)	(0.2165)
accounts	1.005***	-0.0009**	0.0039***	0.00	0.00	0.94***	1.09***	0.79***	0.82***
	(0.1400)	(0.0004)	(0.0008)			(0.0007)	(0.0643)	(0.0273)	(0.0706)
google	2.51***	-0.0007***	0.0005**	0.00	0.01	1.77***	3.94***	1.43***	2.40***
	(0.6732)	(0.0002)	(0.0002)			(0.0004)	(0.4573)	(0.0552)	(0.1439)

All VECM models were first estimated with trend, however, the trend was not significant for any of the pair of variables. Thus, trend was excluded for the VECM models as well as for FMOLS and DOLS. In oder to account for heteroskedasticity, pre-withening with lag specification according to AIC were employed for the calculation of the long-run covariance in FMOLS. For DOLS estimation, lags and leads were chosen according to Akaike and the long-run variance pre-whitened as mentioned above in the pooled case. In the grouped case, the covariance was estimated with HAC (Newey-West) standard errors as well as pre-whitened according to AIC. Stars denote the significance on a 90% (*), 95% (**) and 99% (****) significance level.

Table 4: Results Panel VECM, FMOLS and DOLS

ity: Both the stacked test and the Dumitrescu Hurlin results confirm this on a very high significance level. This is in line with the VECM results, making them more robust. As expected, we see different results for the development factor block. Openissues clearly exhibits unidirectional causality in the sense that marketcap Granger causes openissues but not vice versa, which is confirmed by both tests. In the case of closedissues, we see bidirectional, highly significant causality if we allow the test to consider individual coefficients. For mergedcount, the same applies only with a unidirectional causality if we allow for individual coefficients - here, mergedcount Granger causes marketcap but not vice versa. The outcome for commits further confirms the fact that commits might not be a series which seems to be related to marketcap: We cannot reject the null that one variable does *not* Granger causes the other in any case. Finally, storycount shows the expected results of a unidirectional causality from marketcap to storycount, but not vice versa.

Besides estimating the variables on a panel level, we employed the whole methodology on each currency's individual level too. As the findings were quite robust for the majority of the variables, we don't go into detail for

Panel Granger Causality Test Results					
		Stacked test (Common coefficients)		Dumitrescu Hurlin (Individual coefficients)	
Variable	Lags	y_t	x_t	y_t	x_t
asquared	16	0.00	0.00	0.00	0.00
volumesq	18	0.00	0.00	0.00	0.00
openissues	21	0.63	0.00	0.17	0.00
closedissues	7	0.72	0.00	0.00	0.00
mergedcount	16	0.45	0.12	0.00	0.42
commits	9	0.91	0.27	0.43	0.12
comments	18	0.00	0.00	0.00	0.00
accounts	11	0.00	0.00	0.00	0.00
google	21	0.00	0.00	0.00	0.00
storycount	21	0.33	0.00	0.31	0.00

The amount of lags corresponds to the optimal lag length determined for the VECM models + one additional lag. Reported numbers are p-values for the test "$x_{i,t}$ (the variable listed in the table) does not Granger cause marketcap ($y_{i,t}$)" for the first column and vice versa for the second column. For the Dumitrescu Hurlin case, the hypothesis is augmented to "$x_{i,t}$ does not homogeneously cause $y_{i,t}$".

Table 5: Results Granger Causality

the variables where the long-run relationship could be explained on the panel level. Nevertheless, all estimation outputs are available on the database and within the EViews files. It is interesting, though, to have a look at these variables where a cointegrating relationship was not present and unit root results would be mixed, namely closedissues, mergedcount and commits. We thus report the VECM results for these in tables 6, 7 and 8.[9] In the case of closedissues, cointegration is present within nine currencies. The results show a similar picture to what we have seen in the Panel VECM results: β_2 and α_2 is significant for all currencies, whereas α_1 is not significant exept for Dash, Lisk (lsk), Nem (xem) Nano (xrb). This is again further confirmed by the weak exogeneity tests. At this point, we also show the Granger causality tests in order to compare results with the rest of the estimations. They also confirm the findings of a rather unidirectional causality: The null of "closedissues (x_t) does

[9]Results for unit root and cointegration tests are not reported here, but they are outlined in the database and EViews files.

not Granger cause marketcap (y_t)" could not be rejected for almost all currencies (Dash is an exception), whereas marketcap Granger causes the respective variable in four cases. If we look at mergedcount, the overall picture looks the same. Mostly, α_2 is significant, with merged count being weakly exogenous and Granger caused by marketcap, but not vice versa. However, there are a few exceptions as well: For example, in the case of Litecoin (ltc), there is a unidirectional causality from mergedcount to marketcap, which is confirmed by both weak exogeneity and Granger causality test. The last variable in the block of development factors was commits. First of all, this variable seems to have another pattern compared to the other variables, as cointegration was detected for only five currencies. Here, most of the parameters are significant and for Stellar (xlm), Ripple (xrp), Verge (xvg) and Monero (xmr), the latter on a 90% significance level and with bidirectional causality according to weak exogeneity tests. However, taking into account the Granger causality test, the finding is put into perspective. Only Verge exhibits a bidirectional causality, while the other currencies show mixed results. Another variable which was tested on an individual level was storycount. The reason why only three currencies are outlined here is the fact that for other currencies, there was simply not enough data to rely on. Moreover, only those currencies where cointegration is present were estimated. The methodology was applied to Bitcoin Cash and Ethereum as well.[10] Once again, we can see that causality seems to be unidirectional: Besides β_2 being highly significant for all currencies, α_2 is the only significant error correction term. Tests for weak exogeneity and Granger causality confirm this finding.

[10] Only the largest and best-known currencies were tested. In order to compare the outcomes with a rather small, less-known currency, Zcash was tested as well. However, very little to no stories were published with this keyword. Thus, there was no sense to test this variable for all of the less known currencies.

Individual Estimation Results: Closed Issues Count									
		VECM Parameters			Weak Exogeneity		Granger Causality		
Currency	Lags	β_2	α_1	α_2	y_t	x_t	y_t	x_t
btc	6	8.02***	-0.0041	0.0017***	0.50	0.00	0.47	0.00
		(1.2807)	(0.0060)	(0.0004)				
dash	6	4.10***	-0.0019***	0.0012***	0.00	0.00	0.00	0.00
		(0.6407)	(0.0006)	(0.0004)				
lsk	0	4.90***	-0.0044**	0.0007***	0.05	0.00	0.14	0.00
		(0.7615)	(0.0023)	(0.0002)				
ltc	6	33.93***	0.0002	0.0004***	0.68	0.00	0.51	0.44
		(6.6117)	(0.0004)	(0.0001)				
neo	0	2.45***	0.0042	0.0046***	0.37	0.00	0.53	0.47
		(0.2703)	(0.0047)	(0.0008)				
xem	3	91.55***	-0.0023**	0.00009***	0.02	0.00	0.99	0.43
		(22.66)	(0.0009)	(0.00002)				
xmr	6	33.50***	-0.00006	0.0013***	0.92	0.00	0.08	0.13
		(5.78)	(0.0005)	(0.0013)				
xrb	2	14.61***	0.0478***	0.0025***	0.00	0.00	0.43	0.00
		(2.06)	(0.0109)	(0.0006)				
xvg	1	0.81**	0.0027	0.0027***	0.32	0.00	0.27	0.10
		(0.3676)	(0.0027)	(0.0006)				

Cointegration test results are not reported in this table, however, they are outlined in the database delivered together with this thesis. Lags were determined according to AIC, SC and HQ Information Criterion. The model was estimated with trend, if the trend component is significant. Granger Causality tests were employed with lag length in VECM + one lag. Stars denote the significance on a 90% (*), 95% (**) and 99% (****) significance level.

Table 6: Results Closed Issues Count

Individual Estimation Results: Merged Count								
		VECM Parameters			Weak Exogeneity		Granger Causality	
Currency	Lags	β_2	α_1	α_2	y_t	x_t	y_t	x_t
dash	8	0.87*	-0.0024***	0.0010***	0.00	0.00	0.09	0.00
		(0.5056)	(0.0008)	(0.0002)				
eos	1	0.80	-0.0110**	0.0072***	0.04	0.00	0.04	0.00
		(0.7589)	(0.0050)	(0.0013)				
ltc	1	4.79***	-0.0055***	-0.0002	0.00	0.14	0.01	0.80
		(0.6445)	(0.0015)	(0.0001)				
neo	2	3.87***	0.0056	0.0036***	0.24	0.00	0.09	0.44
		(0.8890)	(0.0042)	(0.0008)				
xem	2	383.68***	-0.0014***	0.00006***	0.00	0.00	0.78	0.23
		(44.7750)	(0.0004)	(0.00001)				
xlm	4	9.23***	-0.0002	0.0020***	0.87	0.00	0.00	0.00
		(1.1328)	(0.0012)	(0.0003)				
xmr	6	1.18***	-0.0040	0.0166***	0.26	0.00	0.00	0.33
		(0.0939)	(0.0033)	(0.0055)				
xrb	0	4.02***	0.0220*	0.0124***	0.09	0.00	0.12	0.00
		(0.4084)	(0.0131)	(0.0024)				

Cointegration test results are not reported in this table, however, they are outlined in the database delivered together with this thesis. Lags were determined according to AIC, SC and HQ Information Criterion. The model was estimated with trend, if the trend component is significant. Granger Causality tests were employed with lag length in VECM + one lag. Stars denote the significance on a 90% (*), 95% (**) and 99% (****) significance level.

Table 7: Results Merged Count

Individual Estimation Results: Commits								
		VECM Parameters			Weak Exogeneity		Granger Causality	
Currency	Lags	β_2	α_1	α_2	y_t	x_t	y_t	x_t
eth	1	1.93***	-0.0006*	0.0056***	0.52	0.00	0.19	0.00
		(0.5315)	(0.0009)	(0.0016)				
xlm	4	3.54***	-0.0033***	0.0015***	0.00	0.19	0.00	0.57
		(0.7436)	(0.0008)	(0.0010)				
xmr	1	4.00***	-0.0012*	0.0007***	0.09	0.00	0.34	0.00
		(0.3557)	(0.0007)	(0.0001)				
xrp	2	8.46***	0.0011**	-0.0045***	0.03	0.00	0.58	0.09
		(1.5345)	(0.0005)	(0.0009)				
xvg	2	2.99***	0.0056***	0.0060***	0.00	0.00	0.01	0.02
		(0.5559)	(0.0016)	(0.0015)				

Cointegration test results are not reported in this table, however, they are outlined in the database delivered together with this thesis. Lags were determined according to AIC, SC and HQ Information Criterion. The model was estimated with trend, if the trend component is significant. Granger Causality tests were employed with lag length in VECM + one lag. Stars denote the significance on a 90% (*), 95% (**) and 99% (****) significance level.

Table 8: Results Commits

Individual Estimation Results: Storycount								
		VECM Parameters			Weak Exogeneity		Granger Causality	
Currency	Lags	β_2	α_1	α_2	y_t	x_t	y_t	x_t
btc	5	0.74***	-0.0040	0.5965***	0.30	0.00	0.23	0.02
		(0.0469)	(0.0037)	(0.0675)				
ltc	5	4.03***	-0.0022	0.0414***	0.45	0.00	0.59	0.06
		(0.7015)	(0.0022)	(0.0092)				
xmr	7	5.43***	-0.0007	0.0325***	0.75	0.00	0.46	0.35
		(0.9232)	(0.0018)	(0.0061)				

Cointegration test results are not reported in this table, however, they are outlined in the database delivered together with this thesis. Lags were determined according to AIC, SC and HQ Information Criterion. The model was estimated with trend, if the trend component is significant. Granger Causality tests were employed with lag length in VECM + one lag. Stars denote the significance on a 90% (*), 95% (**) and 99% (****) significance level.

Table 9: Results Storycount

4 Discussion

In this thesis, we have estimated the relationship between cryptocurrency prices and different variables by using a set of panel data consisting of 17 cryptocurrencies. Our contribution is to examine Altcoins in a broad and empirical way, as academic literature mostly focussed on Bitcoin up to this date. This may be due to the fact that Bitcoin played a predominant role for many years since its appearance in 2008. However, as the dominance of Bitcoin decreased gradually in the past years, the question of what the determinants for the price of a cryptocurrency are is justified. Since supply is mostly predefined by the source code, we focussed on the demand side. We tested different factors which could play a role according to existing literature.

First, we tested the validity of Metcalfe's Law by using uniqe addresses squared as proxy and could confirm the findings of Alabi (2017) while extending it to more cryptocurrencies. In the long term, addresses squared increase by 0.82% if marketcap increases by 1% if estimated with a panel VECM. However, if we look at the short-term dynamics and causality, our results suggest that addresses squared respond to shocks of marketcap, but not vice versa. If we take daily volume squared as proxy variable, our results show that volume squared increases by 0.42% if marketcap increases by 1%. In this case, the causality is bidirectional, hence both respond variables react to a disequilibrium. The findings of were very robust, as they are in line with results from estimations using FMOLS and DOLS. Panel Granger causality tests suggested that both series are Granger causing one another no matter if we assume common or individual coefficents, which further confirms that there is a strong link between the series.

Based on the ideas of White (2015), S. Wang and Vergne (2017) and Lansky (2016), we tested if there is a relationship between the underlying technology of a cryptocurrency and marketcap. In order to do this, we used four proxies based on metrics from GitHub, the major hosting service for cryptocurrency software projects. Our results show that cryptocurrencies are quite heterogeneous when it comes to developers activity. First of all, only one variable, openissues, proved to be cointegrated with markecap on a panel level. The same conclusion as with addresses squared can be drawn: It is openissues which responds to shocks in marketcap, but not vice versa. This is confirmed by both weak exogeneity and Granger causality tests. Thus, we might draw the conclusion that if marketcap increases, programmers have more incentives to scrutinize the source code and suggest improvements to the core team. The rest of the proxies were not cointegrated with marketcap on the panel level. This is why we tested each currency individually, employing the same econometric methodology. For closedissues, nine cryptocurrencies proved to have a long-run relationship with marketcap. Dash, xem, xrb and lsk (the latter on a 90% significance level) exhibit a bidirectional causality within the VECM, while the other currencies behave the same way as openissues, i.e. the causality flows from marketcap to closedissues. Mergedcount looks similar, for eight currencies cointegration with marketcap is present. It is also dash, xem and xrb (the latter on a 90% significance level) which show bidrectional causality in VECM, and additionally eos. For the rest of the currencies, mergedcount is unidirectionaly caused by marketcap. An Exception is ltc, where the results are the other way round. The last variable, commits, has even less currencies with proof of cointegration and mixed results. From these outcomes, we can clearly see that is rather heterogeneous response behaviour when it comes to developers activity. However, for the majority of the currencies, some sort of long-run equilibrium could be observed. The mixed results are most certainly due to the fact that "technology" and "innovation" are very difficult to measure. It cannot be qualified whether one commit is more valuable than another, and most importantly, the cryptocurrencies are in different periods of their R&D life-cycle. While Bitcoin has been in place for many years, currencies such as eos or xrb exist since 2017. In the early stage, a contribution might be of much more value compared to a minor contribution (which is measured as to be equal) in the Bitcoin source code after many years of existence. Thus, results have certainly to be qualified on an individual level and it's probably not a good idea to compare them amongst each other (which is in line with our heterogeneous results). All in all, we observe a tendency towards more significant results for older currencies. Hence, it could also be the case that for younger currencies, there is simply not enough data to draw reliable results from, or, most probably, innovation is not measured well enough with the present variables. S. Wang and Vergne (2017) used similar variables to measure innovation potential in their paper and came to the conclusion that the proxy is positively correlated with weekly returns of the cryptocurrency's price for a panel of five cryptocurrencies (Bitcoin, Litecoin, Ripple, Stellar and Peercoin - the latter was not used in our analysis). These findings are in line with our results, however, the authors use a panel regression model and thus, the directions of causality could not be fully exploited. In our VECM model, which uses simultaneous equations, we were able to extend these results and found that the causality flows from marketcap towards the proxy measuring innovation potential, but not vice versa for the majority of the cryptocurrencies.

Within the community factors, we have a clearer picture on the panel level. There is a long-run equilibrium between marketcap and comments, which is characterized by a unidirectional causality from marketcap to comments. Granger causality tests, however, suggest a bidirectional causality. The first finding of comments being weakly exogenous could be explained by the fact that large movements in price tend to lead to more discussions in the reddit forum. When we look at accounts, causality is bidirectional for all estimation outcomes. If we put this into a Metcalfe's Law perspective, this makes sense: One could argue that reddit users interested in the underlying cryptocurrency might also invest in it. Thus, a rising number of accounts might be a proxy for adoption. Furthermore, an account corresponds to an individual opposed to unique addresses, where an individual potentially has more than one addresses (Recall that our variable only considers active reddit acounts, thus making it difficult due to its activity-based property). Alas, it could be the case that some currencies even use bots to automatically create discussion within a forum.

Lastly, we used google search queries as proxy for public interest or investors sentiment, which was often included in models for explaining the Bitcoin price. Our results are in line with findings by e.g. Kristoufek (2013). All results prove a bidirectional causality. The construction problem of the standardized google search index mentioned in the data section could certainly be mitigated by the fact that in late 2017, there was a very strong price rally which was accompanied by enormous public interest. It still would be interesting to see absolute measures of search queries and compare them for example with other time periods. Besides google search queries, we looked at a new variable which was, to our knowledge, never considered in research as a proxy for search engine queries. As search queries within the Bloomberg terminal might be more related to professional investors (whereas google covers mainstream), this could lead to more reliable results if we want to measure investors sentiment. First of all, it has to be mentioned that data is very rare for the majority of the cryptocurrencies discussed in this paper, which certainly proves that this asset class does not seem to be a broadly discussed topic within the investors press. However, cointegration is present for Bitcoin, Litecoin and Monero. Opposed to google search queries, causality is unidirectional. It seems that more articles are written about a cryptocurrency once there is an increase in marketcap. However, Granger causality results confirm this finding only for btc (on a 95% significance level) and ltc (on a 90% significance level).

Within our empirical analysis, we could show the nature of the relationships between a cryptocurrency price and its potential determinants. We extended existing literature insofar to include more cryptocurrencies and a larger time span, as well as by exploiting the direction of causality flows. It is the case quite frequently that marketcap is causing the explanatory variable, but not vice versa. This could give a hint that demand factors have not yet been examined enough. Furthermore, in face of the extreme price rally in late 2017, it could be the case that increasing prices created an incentive to develop innovations within the cryptocurrency market. For future research, it might be interesting to go into more details when it comes to measuring innovation potential and its influence on / relationship with the price of a cryptocurrency. From the estimations for the time series both on a panel level and each cryptocurrency's individual level, we created a broad database of results which might be used for this research.

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Appendix

All results outlined in the paper as well as intermediate results are handed in electronically together with this thesis.

	Summary statistics			
	>30%	p & d	share	time period
btc	-	-	-	Jun 14 - Jan 18
bch	7	3	43%	Aug 17 - Jan 18
dash	7	2	29%	Jun 14 - Jan 18
eos	5	2	40%	Jul 17 - Jan 18
etc	6	5	83%	Jul 16 - Jan 18
eth	5	3	60%	Aug 15 - Jan 18
iot	6	0	0%	Jun 17 - Jan 18
lsk	5	2	40%	May 16 - Jan 18
ltc	8	1	13%	Jun 14 - Jan 18
neo	17	3	18%	Oct 16 - Jan 18
xem	15	3	20%	Apr 15 - Jan 18
xlm	20	7	35%	Aug 14 - Jan 18
xmr	8	2	25%	Jun 14 - Jan 18
xrb	17	4	24%	Jul 17 - Jan 18
xrp	14	2	14%	Jul 14 - Jan 18
xvg	83	47	57%	Dez 14 - Jan 18
zec	6	1	17%	Nov 16 - Jan 18

The first column shows the number of times the market cap increased by at least 30%, whereas the second and third column show how often this was qualified as pump & dump case both as absolute number and percentage of 30%-spikes. If market cap depreciated by at least 20% up to 5 days following the 30%-increase, it is qualified a pump & dump case. Lastly, the underlying time period is outlined.

Table 10: Evaluation of pump & dump cases across currencies

	Optimal lag length			
Variable	AIC	SC	HQ	Choice
asquared	30	7	15	15
volumesq	30	7	21	17
openissues	29	15	27	20
closedissues	24	2	2	6
mergedcount	24	7	20	15
commits	29	2	4	8
comments	29	7	18	17
accounts	27	3	7	10
google	30	26	26	20
storycount	18	5	18	12

In order to determine the optimal lag length, an unrestricted bivariate VAR was estimated, each including marketcap and one of the variables outlined in this table. 30 lags were included in order to determine the optimal lag length. For the final choice of the VECM lags, a middle way of the three information criterions is chosen while making sure to include enough lags to account for possible autocorrelation of the residuals. One lag length is deducted for the cointegration test and the VECM, since we are running these models in the first difference.

Table 11: Lag length determination