Cryptocurrencies: Price Determinants and Similarities to the Stock Market

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Abstract:

In this thesis I partly replicate earlier research on cryptocurrencies and its return drivers. As the cryptocurrency market is relatively new and no stable equilibrium has been found, the factors of interest to returns are buzz and innovation. The buzz-factors are shown to significantly influence weekly returns. Search trends affect returns positively while Wikipedia page view numbers affect returns positiviely in one week and negatively the week thereafter, signaling investor overreactions. Innovation is an important factor in the technological development of a cryptocurrency but the measure used is not sufficiently capturing the full development and is thus insignificantly affecting weekly returns. Supply growth and liquidity drive returns negatively as they do in traditional financial instruments. Furthermore, unlike the traditional stock market, no particular trading days show above average returns. The findings on momentum in returns show signs of inexperienced investors through patters of over- and under-reaction to price actions of up to thirteen days.

JEL-codes: G11, G12

Keywords: Cryptocurrency returns, buzz-factors, momentum

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Introduction:

In the recent cryptocurrency craze, people have been investing in the large amounts of different cryptocurrencies in the hopes of making very profitable returns. 2017 saw the total market capitalization of cryptocurrencies grow from $18 billion to over $600 billion in December of 2017. Most of the growth came in the last 3 months of 2017, as the market capitalization grew fourfold. News articles and national television networks reported of the impressive Bitcoin value increase and the so-called Bitcoin millionaires. This piqued the average person's curiosity and motivated many into entering the crytocurrency market. More and more money flowed into the markets and by January 7 of 2018 the market capitalization came to its peak of over $800 billion, after which a subsequent crash was inevitable, slashing this figure to under $300 billion a month later.

The cryptocurrency market is relatively new compared to the stock market. The earliest iteration of Bitcoin was launched in 2009, and trading Bitcoin at the time was not as easy as it is nowadays with the numerous of exchanges available to trade on and the possibilities of converting traditional currencies. As more cryptocurrencies saw their inception, knowledge regarding the possibilities of trading and buying them at launch increased as well. As these are new financial products, research on cryptocurrencies is new as well and while they are called currencies, their characteristics do not always compare to traditional money. Much of the research can be improved by taking into account a longer time-period, newer findings, and a more stable market behavior. Many of the previous findings might be giving a twisted image on this market as the results have been mostly taken for the period before January 2018.

This thesis aims to further develop the understanding of some of the return drivers of cryptocurrencies on the basis of (Wang and Vergne, 2017) and (Décourt et al, 2017), by investigating whether investor interest or fundamental values are more important in determining cryptocurrency prices. In addition, it aims to possibly find the existence of a price momentum. The methodology of (Wang and Vergne, 2017) and (Décourt et al, 2017) will be partly replicated and applied in the context of a market crash. This is done by choosing research periods in which the market crash of January 2018 is included.

The thesis is laid out as follows. Earlier research is compiled and summarized in a literature review. An overview of the data and methodology used and the analysis done is given. The results section provides regression results and an analysis. Finally, the main findings will be summarized.

Literature Review:

This section starts with a minor introduction of cryptocurrency and Bitcoin. The coin overview in the data and methodology part expands on this. An overview of the research done on cryptocurrencies is then mentioned. First, the studies on what type of financial instrument a cryptocurrency is, and whether it can be useful in an investor's portfolio will be put forth. Findings on the efficiency of Bitcoin and the cryptocurrency market follow. Finally, the studies on the return drivers of cryptocurrencies are summarized.

Cryptocurrencies

The phenomenon of cryptocurrencies started with the paper of (Satoshi Nakamoto, 2008) in which the writer proposed a decentralized electronic currency, Bitcoin. This currency was to be safe from influences from the mediation of financial institutions, making the reversal of transactions impossible and decreasing transaction costs. More importantly, the need for trust in transactions when using the newly proposed Bitcoin was removed as the payment system was based on the cryptographic proof in the validation of transactions as opposed to verification by institutions. Since the creation of Bitcoin the amount of cryptocurrencies in existence and the amount of markets in which these currencies were to be traded have exploded. At the time of writing (21-4-2019) www.coinmarketcap.com reports 2129 unique cryptocurrencies.

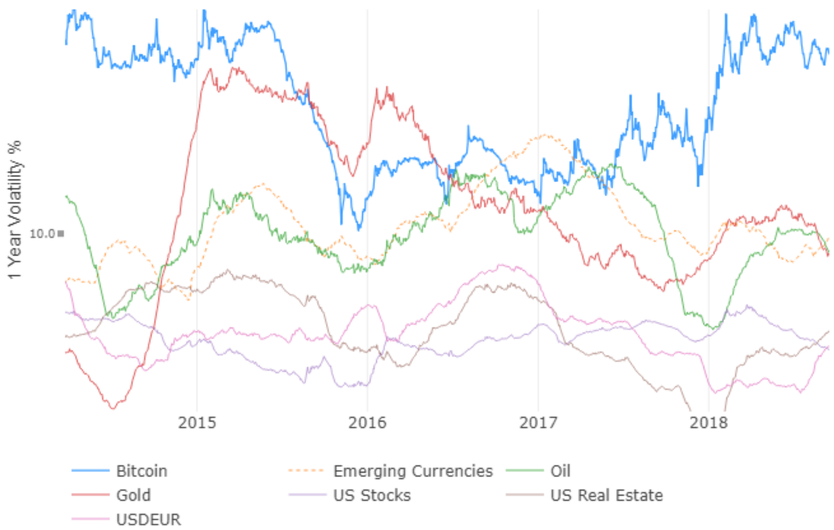

Figure 1: 1-Year Volatilities

Bitcoin and its place in portfolios

As a new financial instrument, research on cryptocurrencies has been focused towards their properties and its place it can have in an investor's portfolio. A 2016 analysis of Bitcoin by Dyrhberg shows similarities to gold in terms of the volatility of its return, as the return is more affected by the demand than by temporary price shocks, and its response to exchange rates (Dyhrberg, 2016a). Figure 1 shows the one year return volatilities for Bitcoin, gold, and other securities for comparison.

Coefficients for the influence of the USD-EUR (0,05) and USD-GBP (-0,07) exchange rates on the Bitcoin return show the presence of regional specific effects. A similarity to currencies and exchange rates is also suggested in that an increased federal fund rate leads to an increased demand of Bitcoin. Furthermore, Dyrhberg shows that a positive volatility shock to several variables studied (federal fund rate, USD-GBP exchange rate, FTSE index and gold futures) indicates a decrease of the volatility of returns on Bitcoin. These findings suggest a use for Bitcoin in portfolio management, risk analysis and market sentiment analysis, which is further explained in (Dyhrberg, 2016b), in which is found that Bitcoin returns, on average, are uncorrelated with stocks in the Financial Times Stock Exchange Index. This means that Bitcoin can be used as a hedging instrument. Less conclusive findings on the possibility of hedging against the dollar were found. Similarities to gold are also found by (Ciaian et al, 2016) as Bitcoin price formation in the long run is unrelated to global macro-financial developments, but rather driven by market forces and attractiveness to investors.

On the other hand, Krystoufek finds Bitcoin's price to be influenced by its usage in trade, money supply and price level in the long run. This study also researches safe haven properties and shows no consistently significant and positive correlations of Bitcoin prices with the Financial Stress Index, which would indicate Bitcoin could be a safe haven, and no correlations at all with the gold price. These findings are more in line with the volatility of Bitcoin prices (Krystoufek, 2015). A study replicating Dyrhberg's (2016a) analysis of Bitcoin's similarities with gold using alternative econometric analysis methods provides different results. These show Bitcoin having unique risk-return characteristics and Bitcoin to be a highly speculative asset unlike gold or currency (Baur et al, 2018). Other research includes Bouri et al's (2017a) analysis of Bitcoin in which is found that, depending on the use of daily or weekly time horizons, Bitcoin can act as either a safe haven or a hedging instrument, but can mostly be used for diversification purposes for Japanese, Chinese and Asia-pacific stocks.

Further study uses implied volatility indexes as a global uncertainty measure (Bouri et al, 2017b). An analysis is done on the correlation between Bitcoin returns and the global uncertainty to find possible hedging capabilities. 14 developed and developing equity markets' volatility indexes were used with quantile regressions, as opposed to OLS regressions, and Bouri et al show Bitcoin to act as a hedge against low and high uncertainty, especially for short term investments at higher quantiles of uncertainty in bear and bull markets. In general the correlation between Bitcoin returns and uncertainty is negative. Demir et al make use of the Economic Political Uncertainty (EPU) index constructed by (Baker et al, 2016) in order to look at the correlation between economic political uncertainty and Bitcoin returns (Demir et al, 2018). The EPU index is a measure of the frequency of newspaper articles which contain words about uncertainty in politics and legislation. In lower and higher quintiles of EPU the correlation with Bitcoin returns was found to be positive, indicating the possibility that Bitcoin can serve as a hedge against extreme uncertainty during bull markets, or as a portfolio diversification in a bear market. Similar to (Bouri et al, 2017b) a negative correlation between uncertainty and returns was found outside of the extreme quintiles.

Efficiency

Recent research includes studies on the (in)efficiency of Bitcoin in terms of the Efficient Market Hypothesis (EMH), altcoins (coins other than Bitcoin) and informational efficiency. Urquhart examines Bitcoin by testing for the weak form of the EMH, which states that a market is efficient if prices reflect historical price information (Fama, Malkiel, 1970). Urquhart's findings reject the weak form of the EMH which indicates informational inefficiency (Urquhart, 2016). After splitting the sample, some tests do not reject the EMH in the later sample (the period of 1st of August 2013- 31st of July 2016), which might suggest an increasing efficiency over time. A follow-up study follows the same methodology but efficiency testing is done using an odd integer power of Bitcoin returns as opposed to Bitcoin returns. This resulted in most tests not rejecting the weak EMH form and finds Bitcoin returns to be incorporating price information reflecting efficiency (Nadarajah and Chu, 2017). The use of a sliding window and De-trended Fluctuation Analysis shows two separate Bitcoin return regimes. EMH efficiency is found for the period of 2011-2014, but not thereafter due to unknown reasons (Bariviera, 2017). In a further study an efficiency index is constructed, and in combination with robust estimator tests Tiwari et al (2018) show that Bitcoin prices are efficient with the exception of 2 periods in 2013 and 2016.

Research on altcoins is done in which market liquidity is incorporated as a factor. This study follows the approach of (Urquhart, 2016) and uses the Amihud illiquidity ratio as a proxy for market liquidity. In line with the findings of (Urquhart, 2016) most of the cryptocurrencies examined show evidence of anti-persistence in illiquid markets. A strong correlation between liquidity and volatility is found, which suggests an increased efficiency with higher liquidity. In contrast with traditional financial assets, no illiquidity premium (a premium for holding illiquid assets) is found among cryptocurrencies. Furthermore, altcoins are mostly inefficient as they show significant signs of autocorrelation and non-independence since their valuation is tied to Bitcoin. The more established and more liquid cryptocurrencies show an improvement in efficiency over time (Wei, 2018).

Brauneis and Mestel (2018) criticize the testing of efficiency on the basis of the EMH as this theory states that prices are solely driven by relevant information and investors are assumed to behave rationally. They subsequently test Bitcoin efficiency with regards to the random walk hypothesis. (Dyrhberg, 2016) previously suggests that Bitcoin prices show a random-walk behavior. Tests are done on efficiency together with market capitalization as a proxy for size, and with liquidity measured on the basis of the log-dollar volume, the turnover ratio, the Amihud illiquidity ratio and the bid-ask estimate. Cryptocurrencies are found to be increasing in the efficiency of returns with market capitalization and with the turnover ratio. The bid-ask rate shows a negative effect relating to efficiency. Out of the 73 cryptocurrencies tested, Bitcoin is found to be the most efficient.

Return drivers

Research on the drivers of cryptocurrency returns is still in its infancy. The Monday effect anomaly, which occurs in the stock market due to the closing of the markets in the weekends, is researched for Bitcoin. As Bitcoin is traded every day, the non-existence of this phenomenon is a logical hypothesis. The results in (Décourt et al, 2017), however, show a difference in returns for different weekdays. An above-average return of 1,18% on Mondays for Bitcoin is found and the regression only returns statistically significant coefficients for Mondays and Thursdays. This is in contrast with a below-average return on Mondays in stock markets.

Focus on the volume and volatility predicting Bitcoin returns is done with a causality-in-quantiles approach. Volume is taken after de-trending the natural log of trading volume. Trading volume is shown to be correlated with returns over the quantile range of 0,25 to 0,75 of the return distribution, but is uncorrelated with volatility. This indicates that volume can predict returns in non-bear and non-bull market times (normal market) so that volume-return trading strategies can be constructed. Volume information is irrelevant in predicting returns outside of the market functioning around the median (Balcilar et al, 2017).

Earlier research suggests that cryptocurrencies miss fundamentals for valuation and that prices are solely driven by investor sentiment. Krystoufek (2013) regresses Bitcoin prices on a proxy of investor sentiment taken by analyzing Google Trends and Wikipedia searches. A strong causal relation is found between Bitcoin prices and investor sentiment. This correlation is also bidirectional, meaning that Bitcoin prices influence searches on Google Trends and Wikipedia as well. Furthermore, with above-trend prices an increased amount of searches pushes the price even higher, while with below-trend prices an increased investor attention decreases the price even more, leading to frequent bubble behavior. This is also suggested by Bouoiyour et al (2015), who find Bitcoin volatility to be more influenced by negative than by positive expectations and the market to be driven by self-fulfilling expectations, and by Krystoufek (2015), who finds investor interest pushing up prices even further during rapid increases, and the opposite for rapid declines. Furthermore, Krystoufek (2015) finds Bitcoin to appreciate in price in the long run with increased real economic Bitcoin transactions, and in the difficulty of mining, which decreases the Bitcoin supply growth.

Research on what causes the increased investor attention towards Bitcoin is done in (Urquhart, 2018). Attention is measured with the amount of searches on Google Trends for the term 'Bitcoin' and is then standardized. Investor attention is found to be significantly correlated with previous day volatility and volume (factor coefficients of 0,6 and 0,09 respectively), and with returns two days prior (coefficient of -0,05). This is in line with Bouoiyour's (2015) self-fulfilling expectations theory and Krystoufek's (2013) finding of a bi-directional correlation between Bitcoin prices and investor attention.

For five major cryptocurrencies, Wang and Vergne (2017) research the impact of innovation potential and media buzz on the returns of cryptocurrency. The innovation potential measure is developed by looking at technological developments in terms of changes to the underlying code of a cryptocurrency. Media buzz is constructed with two factors, negative publicity and public interest, and is taken from social media and internet searches. After controlling for liquidity and supply growth, they find innovation potential to be significantly and positively related to weekly cryptocurrency returns (coefficient of 1,96). Media buzz, in contrast with other findings, is found to strongly and negatively impact returns. Surprisingly, this negative relation comes from public interest and not negative media publicity, as seen by a change of the coefficients for public interest from -4,92 to -4,66 after removing negative publicity. They also find that an increased supply leads to increased returns, which contradicts the Quantity Theory of Money (Fisher, 1911) and means that cryptocurrencies do not behave like currencies. This is also in contrast with the findings of (Krystoufek, 2015), who finds the long-run price formation of Bitcoin to be influenced similar to traditional currencies. The findings by Wang and Vergne may be explained by the demand-side effects dominating the supply-side effects. An increase in supply may be the result of a spike in mining-intensity, which speeds up the creation of coins, and might signal a cryptocurrency's increasing potential together with current investors choosing to reinforce their position which in turn spikes demand.

On the other hand research has been done towards more fundamental aspects' impacting cryptocurrency returns. Corbet et al (2018) make use of a sentiment index from GDP, unemployment, CPI and durable goods to find a link between macroeconomic news announcements and Bitcoin returns. Positive news relating to unemployment rates and durable goods is found to decrease Bitcoin returns, while the opposite is found for negative news regarding these macroeconomic factors. This suggests a possible diversification opportunity, as traditional equity returns typically follow increased and decreased return patterns respectively. In an earlier paper, Van Wijk finds the euro-dollar exchange-rates, the oil price, and the Dow Jones index to significantly impact Bitcoin prices in the long run (van Wijk, 2013). A recent study finds that financial openness and inflation factors do not seem to impact Bitcoin transactions and subsequently neither its valuation (Vadepalli and Antoney, 2018).

This thesis aims to develop a better understanding of the factors that drive the returns of cryptocurrency, whether actual trading is based on fundamental values or on short-term price information, and to find whether the market may be moving towards a more stable investor behavior, in the context of a market crash.

Data and Methodology:

In this section the set-up of the research is explained first. Following this, the observation periods for the different analyses are mentioned, along with the corresponding amount of data points. Then a quick overview of the cryptocurrencies used in this research is given, after which the variables and data used are explained, and the sources of the data mentioned. Finally, the methodology is covered.

Set-up

The main part of this research is based on a journal article by Wang and Vergne (2017) in which the weekly returns of five major cryptocurrencies are analyzed over the period September 2014 – August 2015. This research will take six cryptocurrencies, the five that were used by Wang and Vergne, Bitcoin (BTC), Litecoin (LTC), Ripple (XRP), Stellar (XLM), Peercoin (PPC), in addition to Ethereum (ETH), and analyze weekly returns over a different period: September 2015 – May 2018. Ethereum is added due to its large influence on the general cryptocurrency space. It is an important platform coin of which its network has allowed many other coins to have launched in the year 2017. As of 22-7-2018, over 500 active coins based on the Ethereum Network are reported by https://etherscan.io/tokens. Ethereum has had a place in the top 10 in terms of market capitalization of cryptocurrencies since its launch. Out of the all coins only Peercoin is currently not in that top 10.

The second part of this thesis concerns return patterns. As opposed to traditional stock markets, trading of cryptocurrencies occurs around the clock. The stock market's more traditional trading times lead to well-known anomalies such as the Monday effect, also called the weekend effect (French, 1980). This anomaly states that returns on Mondays are positive when returns on the previous Friday are positive, and that returns are negative on Mondays when they are negative on the previous Friday. I aim to find the possible existence of a Monday effect like Décourt et al (2017), who find daily Bitcoin returns on Mondays to be above-average, and extend the analysis to find possible return patterns on other days.

Finally, I look at the possible existence of a price momentum. As cryptocurrencies became more prominent in the news, more people were exposed to their existence and the possible return opportunities. It might be then, that Bitcoin's abnormal positive or negative returns are continuing to show positive or negative returns as investors are spurred on by news, a so called price momentum. Price momentum in the stock market refers to the continuation of positive and negative abnormal returns in a short-to-medium term period. Jegadeesh and Titman find abnormal returns by taking long positions in winner stocks and short positions in loser stocks of the past three to twelve months (Jegadeesh and Titman, 1993). Since (Dyrhberg, 2016b) finds a lagged variable of price to be significantly correlated with returns, and (Wang and Verne, 2017) find significant effects of media buzz in cryptocurrencies' returns I hypothesize the existence of a price momentum for Bitcoin.

Observation period

The period over which the main analysis is done is split in two. The first period starts on the 1st of September 2015. This starting date is chosen due to ETH being launched at the end of July 2015 and pricing history being available from August 7, 2015. By choosing to start in September 2015 the influence of the launch on pricing is minimized. The analysis ends on the 30th of April 2018, resulting in a research period of 2 years and 9 month. This period includes the January 2018 cryptocurrency-market crash. All of the chosen cryptocurrencies were in existence for the total duration of the analysis. Like Wang and Vergne (2017), weekly returns are used as the independent variable, because of the unavailability of daily data for some of the dependent variables; Trend and WRC. This gives a total of 834 observation points, 139 for each cryptocurrency. The second period comprises of 51 weekly observations starting in the week of 17-24 July 2017 ending in the week 9-16 July 2018. This is due to earlier data on the amount of github commits not being available before this period.

For the second part of this research on weekday effects, daily Bitcoin returns are taken for the period of the 1st of May 2013 - 1st of May 2018. Décourt's findings are for the period January 2013 - October 2017. The starting date for this research is due to unavailability of data for the first four months of

2013. The choice of this period results in 1826 observations. This comes out to 261 observations for each weekday. Again, by extending the period to May 2018, the January 2018 crash is taken into account.

For the analysis of price momentum Bitcoin's return is taken for the same observation period as for the analysis of the weekday effects: the 1st of May 2013- 1st of May 2018. 2 Lag variables for the daily, weekly and monthly returns have to be taken. This gives 1824 daily, 259 weekly, and 58 monthly return observations.

Coins

Bitcoin: The first cryptocurrency, launched in 2009. It is a peer-to-peer payment network on which transactions are validated not through an intermediary but through a proof-of-work system (www.bitcoin.org). This is a system for which transactions need work, in the form of computing power. This is called mining. While it validates the transactions, it also is the basis of the creation of new supply of Bitcoin, as a reward to the miner for the validation. Bitcoin currently (22-7-2018) has a circulating supply of just under 17.2 million coins and is capped at 21 million coins (www.coinmarketcap.com). It is the largest coin by market capitalization, having 43% of total cryptocurrency market capitalization, and is ranked at number 1 for trading volume, with almost 32% of all cryptocurrency trading volume. Built into the Bitcoin code is an an automatic bi-weekly change in the difficulty of mining which prevents the supply of Bitcoin to increase rapidly. By the year 2040 all Bitcoins will have been created.

Litecoin: This is a decentralized coin that was created in 2011 for use in a payment system and designed to improve on the technical aspects of Bitcoin. Its aim is to allow faster and cheaper transactions through quicker verification than Bitcoin does and to improve the scalability of the amount of possible transactions per second, together with improved storage efficiency (www.litecoin.info). Like Bitcoin it uses a proof-of-work system. The supply is capped at 84 million coins.

Ripple: Ripple developed the cryptocurrency XRP for banks in payment systems to source liquidity with lower transaction costs than in traditional banking. XRP was designed to allow for very fast verification of transactions and thus high scalability together with very low transaction costs (www.ripple.com). The coin is distributed by the creators of the technology behind it, which means it is pre-mined and the total supply of 100 billion XRP will not change. Even though XRP is designed to work with Ripple's payment system xRapid as an intermediary currency, it is, however, not necessary to for banks to use XRP in order to use xRapid. This is the most centralized cryptocurrency in this research as XRP is un-mineable and 60% of the supply is in the hands of the distributors.

Stellar: The Stellar network is a decentralized, very low-cost payment system, created by the non-profit stellar.org and was designed to create accessibility to financial systems all over the world. The cryptocurrency Stellar Lumens (XLM) was pre-mined with a total supply of 100 billion XLM and has an inflation rate of 1% per year. Every transaction uses a fraction of XLM. Built into the Stellar network, XLM was designed to offer liquidity by facilitating trading between (crypto) currencies for which there is no liquid market (www.stellar.org).

Peercoin: The first cryptocurrency to use a combination of proof-of-work and proof-of-stake. The proof-of-stake system rewards owners of the coins to hold them and validate the transactions. It aims to be a more energy-efficient and more secure decentralized payment system than Bitcoin (www.peercoin.net). The proof-of-stake system increases security in that one party would need to acquire a majority of all coins in order to have control of the network, which is very costly and highly unlikely.

Ethereum: This is a decentralized platform for running smart contracts. The coin Ether (ETH) is used to run and validate these contracts or transactions on the ethereum network. 60 million coins were pre-mined for the creators and to fund development. 18 million coins will be created each year in a proof-of-work validation system, although the system is expected to change into a proof-of-stake algorithm (www.ethereum.org). The current supply is almost 101 million coins (www.coinmarketcap.com). Ethereum is a platform on which many other tokens (cryptocurrencies without their own network) have been created through a smart contract. This explains Ether's rapid increase in price and Ethereum's importance in the cryptocurrency market.

	01-09-2015	**09-07-2017**	**30-04-2018**	**16-7-2018**
BTC	$3,352bn	$42,3bn	$160,3bn	$109bn
LTC	$120mln	$2,7bn	$8,6bn	$4,5bn
XRP	$256mln	$9bn	$34,1bn	$17,5bn
XLM	$12mln	$228mln	$8,5bn	$4,1bn
PPC	$8mln	$58mln	$64mln	$37mln
ETH	$98mln	$23,5bn	$68,4bn	$45,4bn

Table 1: Market capitalizations

Table 1 shows an overview of the coins with their market capitalization at the end of the starting and ending weeks of the two research periods. At the time of writing (22-7-2018) these six cryptocurrencies together account for 71,2% of total cryptocurrency market capitalization.

Variables, data sources and regressions

The independent variable for each analysis is a form of the returns, *Ri*. Daily, weekly and monthly returns are calculated as follows: $\frac{(Pi,t - Pi,t-1)}{Pi,t-1}$, with 'P' denoting the average price , and 't', denoting a period of a day, week, or month. Prices used for the calculation of returns are taken as an average of the open and close prices because of the fact that cryptocurrencies are being traded around the clock. By taking the average, the influences of very short-lived highs and lows on returns are reduced.

The variable *trend* is composed of search term trend data, taken from trends.google.com/trends. This is a standardized value from 0-100 that represents search interest relative to the highest point on the chart for the chosen region (worldwide) and time period of the research. A value of 100 represents peak popularity of the search term. The search terms for which the values are taken are: 'bitcoin', 'litecoin', 'ethereum', 'stellar lumen', and 'ripple coin'. The search terms for Stellar and Ripple are modified to avoid capturing searches unrelated to the cryptocurrencies.

The variable website rank change, *WRC*, is the weekly change in the global Alexa Traffic Rank of the official website for each cryptocurrency. The Alexa Traffic Rank is an estimate of a site's popularity based on its average daily visitors and pageviews over 3 months. Ranked number 1 is the most popular website, which means that a negative weekly change in rank is an indicator of increased popularity. The highest (most decreased popularity) and lowest (most increased popularity) change in weekly rank observed in the test period is 114038 and -100026 for Litecoin and Stellar respectively. The data is taken from www.alexa.com.

Wikipedia page views*, WPV,* is a variable denoting the weekly amount of views of a cryptocurrency's en.wikipedia.org page taken from https://tools.wmflabs.org/pageviews. Unlike the *trend* data, this data is not standardized.

The variable *Supply* denotes the circulating supply. It is the amount of coins of a cryptocurrency that have been created. For minable cryptocurrencies, this is the sum of all coins that have been mined. For un-mineable coins, this is the sum of all coins that have been released on the market. Both these figures include coins that have been lost as it is possible that devices that coins were stored on were lost or damaged. It is impossible to take lost coins into account as this is an unknown figure.

Iliquidity is measured using the Amihud illiquidity ratio (Amihud, 2002) calculated with this formula:

$$\text{ILLIQiy} = \frac{1}{Diy}\sum_{t=1}^{Diy}|Riyd|/VOLDivyd$$

It denotes the average ratio of the absolute return to the trading volume for a particular time frame. Diy denotes the number of days over which the illiquidity ratio is measured, Riyd denotes the return of cryptocurrency, VOLD denotes the daily trading volume. The availability of daily price and volume data allows for the calculation of a weekly illiquidity ratio.

Data on price history, trading volume and circulating supply are taken from www.coinmarketcap.com. As opposed to data from www.coingecko.com used by Wang and Vergne, this website gives data for these variables that is easier to work with.

Innovation is modeled by the amount of weekly github commits in the cryptocurrencies' underlying code. These are changes made to the code which reflect development updates. It is taken as a proxy variable for the involvement of the developers and community in the technological development of a cryptocurrency. Table 2 shows the total amount of github commits to the main chain of the cryptocurrencies' code in the period 23-7-2017 until 16-7-2018. While Bitcoin and Ethereum, ranked number 1 and 2 in terms of market capitalization, show the most changes in the code, there does not seem to be a clear correlation to size, as rank number 3 coin, Ripple, only had 234 commits over this period, as opposed to Peercoin with 253 commits while being outside of the top 100 coins. The data for this is taken from the pages of each respective cryptocurrency on www.github.com.

To research price momentum lag variables of the return are taken. These are simply returns from one and two periods prior.

Cryptocurrency	**Commits 23-7-2017 until 16-7-2018**
BTC	1763
LTC	807
XRP	234
XLM	631
PPC	253
ETH	849

Table 2: Total github commit amount

Like Wang and Vergne, the first part of the main analysis will make use of weekly returns as the dependent variable. The independent variables will be: *trend*, *website rank change*, *Wikipedia page views*, *supply,* and *liquidity*. For the second part the *innovation* variable is added. Control variables are the supply, and liquidity. Exact replication of the variables studied by Wang and Vergne is impossible due to data unavailability. Their variable for media buzz is comprised of public interest and negative publicity. The public interest part for this research is modeled by three variables: the Google search trend, the Alexa website world rank change, and the Wikipedia page views amount. This means that the media buzz only considers public interest factors. The effect of dropping negative publicity by Wang and Vergne, however, does not affect the public interest factor substantially and negative publicity is not found to be significantly associated with returns. As such, dropping this part of the buzz factor is not a problem.

The innovation variable for Wang and Vergne's study makes use of technological indicators for which only the Github commit data is available for the last year. The second part of the main analysis is therefore done over the period 24 July 2017 - 16 July 2018. The regression models for the main part of the analysis are as follows:

$$Ri = \alpha + \beta 1 * Trend + \beta 2 * WRC + \beta 3 * WPV + \beta 4 * Supply + \beta 5 * Liquidity + \varepsilon$$

$$Ri = \alpha + \beta 1 * Trend + \beta 2 * WRC + \beta 3 * WPV + \beta 4 * Supply + \beta 5 * Liquidity + \beta 6 * Innovation + \varepsilon$$

For the second part of the analysis average daily Bitcoin returns are calculated and histograms are made to discover the properties of returns on different weekdays. Daily returns, calculated with the use of the average of the daily open and close prices, are then regressed on dummy variables for each weekday, with Monday being the base. The regression is as follows:

$$Ri = \alpha + \beta 1 * Tue + \beta 2 * Wed + \beta 3 * Thu + \beta 4 * Fri + \beta 5 * Sat + \beta 6 * Sun + \varepsilon$$

For the analysis on price momentum, again, only Bitcoin returns will be used, while Jegadeesh and Titman select stocks based on returns of the past 1, 2, 3 or 4 quarters and construct portfolios to hold for 1, 2 ,3 or 4 quarters. This research is simplified a lot by only taking Bitcoin into account and not including holding periods. The price momentum regression is done like Jegadeesh and Titman, who follow (Lo and MacKinlay, 1990), with Ri t-1 being the lagged value of either daily, weekly or monthly returns, and Ri t-2 being a secondary lag variable to determine whether an overreaction effect takes place. The regressions follow an AR(2) model and look like this:

$$Ri = \alpha + \beta 1 * Ri\, t - 1 + \beta 2 * Ri\, t - 2$$

A Hausmann test with the Sargan-Hansen statistic is done to check whether a fixed-effects model is appropriate (Woolridge, 2010). Testing for autocorrelation is done using the Woolridge test (Drukker, 2003), and a LLC test is done to check for stationarity (Levin et al, 2002).

Analysis: Dependent variable	Analysis 1a: Weekly returns	Analysis 1b: Weekly returns	Analysis 2: Daily returns	Analysis 3a: Daily returns	Analysis 3b: Weekly returns	Analysis 3c: Monthly returns
Independent variables	Trend	Trend	Tuesday	1-Lag return	1-Lag return	1-Lag return
	WRC	WRC	Wednesday	2-Lag return	2-Lag return	2-Lag return
	WPV	WPV	Thursday			
	Supply	Supply	Friday			
	Liquidity	Liquidity	Saturday			
		Innovation	Sunday			

Table 3: Overview of the regression models

Results:

This section is split up into parts for each of the regressions. Regression 1A deals with the influence of public interest variables on weekly returns. In regression 1B, an innovation variable is added and the research period is changed. An effect of different weekdays on daily Bitcoin returns is looked at in the Monday effect part. Finally, a regression of daily, weekly, and monthly Bitcoin returns on their respective lags is done for research on price momentum.

Regression 1A: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Weeklyreturn	834	0,0494376	0,3421166	-0,3855296	7,328527
WRC	834	-787,9448	12425,13	-100026	114038
WPV	834	37207,93	109720,9	111	1662094
Trend	834	9,647482	16,43591	0	100
Log Illiquidity	834	-19,7572	3,590898	-27,07.877	-11,19146
Supply Growth	834	0,0026818	0,0192794	-0,00772	0,4323527

Table 4: Summary statistics for the Variables of Regression 1A

The summary statistics (Table 4) show that over the observation period the average weekly return is 4,94%. A maximum of 732,85% is observed. This value is attributed to XLM in the week of 8-5-2017. Why the price jumped so high and so fast is speculated to be the result of a distribution of XLM to holders of BTC as seen by an increase in the circulating supply seen a month earlier ("We're distributing", 2017). The price increase corresponds to the finding of increased returns with supply growth (Wang & Vergne, 2017). While weekly returns in the two months following the jump show a correction in the price suggesting an overreaction, with 5 out of 8 weekly return values being negative, the price in the weeks after the spike never returns to its pre-spike value. The WRC, WPV and Trend variables for the week of 8-5-2017 show a substantial increase in the public interest of XLM that slowly decreases in the following weeks but stays above the public interest pre-spike. The most negative weekly returns are for XRP in the week of 5-2-2018 with -38,55%. An overreaction is observed in the prices and returns in the two weeks thereafter. The interest variables WPV and Trend show a continuing decrease in popularity that started in the week of 15-1-2018. The variable WRC shows a declining improvement in page rank until 19-2-2018. The highest weekly return for XRP is 389% in the week of 3-4-2017. This is after announcing that MUFG joins Ripples GPSG interbank group ("MUFG joins", 2017).

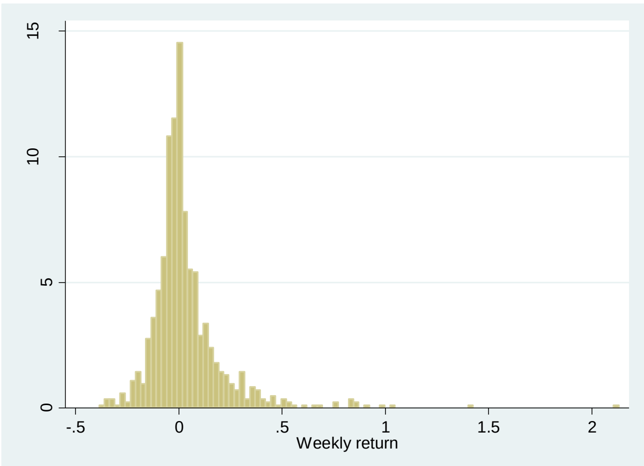

Figure 2: Histogram of Weekly Returns Regression 1A

A histogram of the weekly returns (Figure 2) shows a right-skewed distribution as is to be expected with positive average weekly returns and strong outliers. A more detailed summary of weekly returns (Table 3) shows the four highest values to be substantially further from zero than the four smallest (negative) values and a skewness with a value of 13,82. When dropping the two highest weekly returns (XRP's 389% and XLM's 733%), the skewness falls to 3,48. While extreme, these two observations will not be dropped from the dataset, however, as they seem to be explainable with the previously mentioned sources. Due to the values for the Illiquidity variable being very small, the logarithms are taken to create the LogIll variable.

Weekly Return				
	Percentiles	**Smallest 4**	**Obs**	834
1%	-0,28253	-0,38553		
5%	-0,16495	-0,340274	**Mean**	0,049438
10%	-0,12036	-0,338828	**Std. Dev.**	0,342117
25%	-0,05249	-0,337607		
			Variance	0,117044
50%	0,002694		**Skewness**	13,817
		Largest 4	**Kurtosis**	267,908
75%	0,07957	1,407		
90%	0,222222	2,131		
95%	0,364579	3,890		
99%	0,848452	7,329		

Table 3: Detailed Statistics Weekly Returns

When looking at the statistics of weekly returns for each cryptocurrency individually (Table 4), we see that all coins exhibit a positive weekly return on average, with the lowest and highest values for BTC (2,56%) and XLM (8,21%) respectively. The exceptionally high average weekly return for XLM is due to the highest value of weekly returns observed and when dropped, since when dropped would fall to 2,96%.

Variable	Obs	Mean	Std. Dev.	Min	Max
RweekBTC	139	0,025637	0,097786	-0,28895	0,371225
RweekLTC	139	0,034891	0,169776	-0,22343	0,921021
RweekPPC	139	0,026862	0,171757	-0,33761	0,975807
RweekETH	139	0,052951	0,188793	-0,34027	0,828246
RweekXLM	139	0,082103	0,648866	-0,33883	7,32853
RweekXRP	139	0,074182	0,42302	-0,38553	3,8902

Table 4: Weekly Returns for each cryptocurrency

	Weeklyreturn	WRC	WPV	Trend	LogIll	SGrowth
Weeklyreturn	1					
WRC	-0,2717	1				
WPV	0,0193	0,0102	1			
Trend	0,145	-0,0532	0,4615	1		
LogIll	-0,034	0,0007	-0,4503	-0,3726	1	
SGrowth	-0,0212	-0,0144	-0,0309	-0,0476	0,0393	1

Table 5: Correlation Matrix for Variables Regression 1A

The negative mean for the variable WRC indicates an increase in popularity of cryptocurrency overall. This cannot be be concluded from the WPV data, however. When plotting the sum of the six cryptocurrencies' WPV over the research period we see a strong increase and a strong fall before and after the January 2018 crash. WPV is however strongly correlated (corr=0,73) with market capitalization, also seen when viewing the graphs side by side (Figure 2).

The correlation matrix (Table 5) shows weekly returns to be positively correlated with WPV and Trend, as also found in (Krystoufek, 2013). The negative correlation with WRC is expected, as this variable indicates an increase in popularity for negative values. Negative correlation with Illiquidity is no surprise since no illiquidity premium is found in earlier research (Urquhart, 2016). A negative correlation with Supply Growth is seen, while the opposite is found in (Wang and Vergne, 2017). Surprisingly, WRC is not strongly correlated (-0,05) with Trend, even though www.alexa.com reports an average of 43% of visits to the cryptocurrencies' websites come from web-searches.

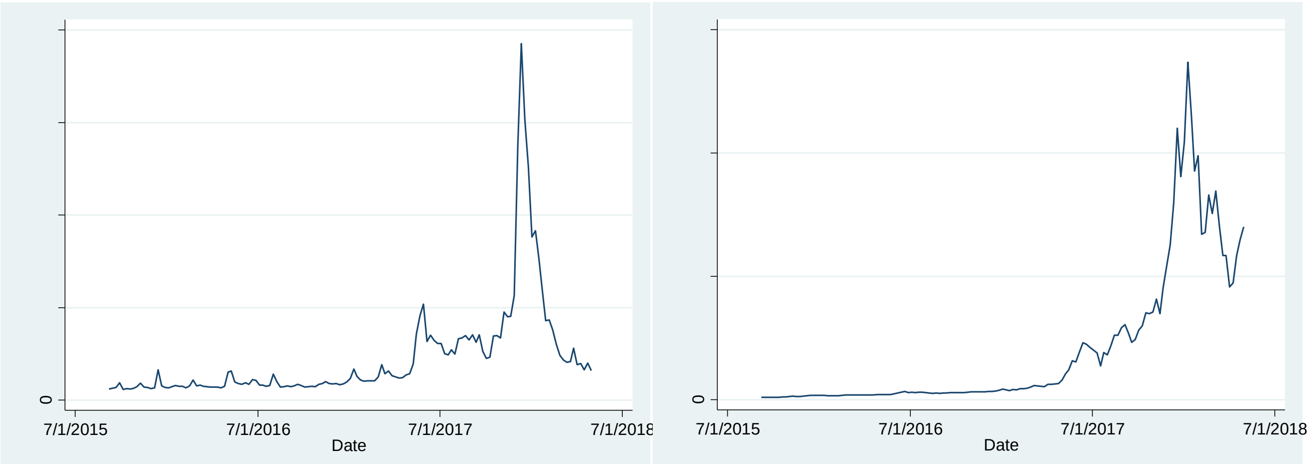

Figure 3: Sum of WPV and sum of Market Capitalization over time

Regression 1A: models

The regression of panel data can be done with a fixed-effects or random-effects regression model. A fixed-effects model allows for the unobserved cryptocurrency effects to be correlated with the research variables (Greene, 2012), which violates the independency assumption of standard OLS regression. We can assume that the developer team behind each cryptocurrency has influence on the variables Trend and Supply Growth, through things such as marketing efforts and promises of holding and using supply for future developments, which would make a random-effects regression biased. A fixed-effects regression is also applicable to use when only considering time-varying variables, like the ones in this research.

	(1)
VARIABLES	**FE Driscoll-Kraay**
WRC	-7.25e-06
	(5.50e-06)
WPV	-1.99e-07**
	(8.51e-08)
Trend	0.00418***
	(0.000731)
LogIll	0.00793
	(0.0120)
SGrowth	-0.463
	(0.377)
Week	0.000174
	(0.000696)
Constant	-0.346
	(1.870)
Observations	834
Within or adjusted R-squared	0.0984
Number of CC	6

Robust standard errors in parentheses

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

Table 6: Model 1 for Regression 1A

The Hausman test does not reject the hypothesis of no random effects being present (p=0,1682). The Wooldridge test for panel data fails to reject the notion of no autocorrelation being present (p=0,2452). Finally, the LLC test rejects non-stationarity for all cryptocurrencies for all dependent variables (p=0,003 for Trend, p=0,000 for all other variables). Running a modified Wald-test for heteroskedasticity rejects the notion of homoscedasticity (p=0,000). Following Wang and Vergne's procedure, a model with Driscoll-Kraay standard errors is chosen. Table 6 provides the regression results, where a week-trend variable is added. This is done to take out the effect of the rising popularity of cryptocurrencies in general.

Regression 1A: Findings

Of the variables concerning the public perception of cryptocurrencies, WRC is not found to be significantly associated with weekly returns. WPV and Trend are negatively and positively correlated (significant). A one standard deviation increase in WPV leads to a 2,2% lower weekly return (109720,9*-1,99e-07), and a one standard deviation increase in Trend increases weekly returns by 6,9% (16,43*0,004). The coefficients for the Illiquidity and Supply Growth variables are not significant. Adding a lag of WPV to the model (2) (Table 7) shows that the lag is negatively correlated with weekly returns and the coefficient for WPV changes sign. It could thus be that increased interest in cryptocurrencies influences weekly returns through increased demand, and that the dying down of that demand negatively influences returns of the following week. This would show in increased trading volume and so to test this, a variable for weekly trading volume is added (3). The volume is summed for the week of the corresponding returns and the logarithms are taken. The model improves a lot in terms of the significance of the coefficients and the within R-squared value (0,1885) after adding volume as an explanatory variable. Both the Illiquidity and Supply Growth coefficients are now significant, associating positively and negatively with weekly returns respectively. The finding of Supply Growth negatively affecting returns is in contrast with Wang and Vergne's finding, but is consistent with standard economic laws. The positive coefficient for Illiquidity corresponds to Wang and Vergne's findings, and suggests that the price impact of trading given higher trading volumes (more liquidity), is smaller. Liquidity is thus positive for weekly returns. Volume is also positively and significantly associated with weekly returns. The coefficients for WPV and its lag do not change much, however, after adding Volume.

VARIABLES	(2) Driscoll-Kraay WPV-Lag	(3) Driscoll-Kraay WPV-Lag Vol	(4) Driscoll-Kraay WPV-Lag Vol No Ill
WRC	-7.24e-06	-5.24e-06	-6.15e-06
	(5.50e-06)	(4.47e-06)	(4.85e-06)
WPV	2.51e-07*	2.02e-07**	3.50e-07**
	(1.33e-07)	(9.52e-08)	(1.44e-07)
WPV_L1	-5.16e-07***	-5.02e-07***	-5.23e-07***
	(1.45e-07)	(1.12e-07)	(1.38e-07)
Trend	0.00424***	0.00271***	0.00213
	(0.000719)	(0.00103)	(0.00135)
LogIll	0.00775	0.121***	
	(0.0120)	(0.0452)	
SGrowth	-0.467	-0.623*	-0.587
	(0.377)	(0.348)	(0.379)
LogVol		0.121***	0.0474**
		(0.0461)	(0.0224)
Week	0.000197	-0.000876	-0.00256**
	(0.000698)	(0.000642)	(0.00102)
Constant	-0.416	3.092*	6.856**
	(1.875)	(1.816)	(2.719)
Observations	833	833	833
Within or adjusted R-squared	0.1023	0.1885	0.1324
Number of groups	6	6	6

Standard errors in parentheses

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

Table 7: Models 2, 3 and 4 for Regression 1A

Adding Volume to the model does however create a problem of multicollinearity with the Illiquidity factor, meaning the estimators of that model are biased. Removing Illiquidity from the model but leaving Volume results in model (4). This is an improved model as compared to (1) and (2) in terms of the within R-squared. Volume is positively and significantly correlated with weekly returns and the coefficient for Trend is not significant anymore, as Volume seems to take over its effect. Interesting is the significant negative sign of the Week variable. It indicates that the impact of the January 2018 crash is large enough to substantially impact returns over the time of the research period negatively.

Regression 1B: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Weeklyreturn	312	0,032096	0,203574	-0,38553	1,407
WRC	312	1.612,567	6.831,107	-15166	59512
WPV	312	67303,62	166107,9	474	15,80586
Trend	312	19,86058	21,84704	0	100
LogIll	312	-22,48846	3,107176	-27	-15,4787
SGrowth	312	0,002696	0,024888	-0,004529	0,432353
Innovation	312	14,54167	14,25824	0	66

Table 8: Summary statistics for Variables Regression 1B

The summary statistics of the data for research period 2 are shown in table 8. Again, the logarithms of liquidity are taken. Looking at the weekly returns, the maximum value (140,7%) belongs to XRP for the week of 18 December 2017. While being drastically lower than in period 1, it is still very large compared to traditional financial assets. The positive weekly XRP returns continue until the week of January 8, 2018. The minimum value for weekly returns (-38,55%) is the same as in period 1, also belonging to XRP. The average weekly return is a positive 3,2%, even though the market crash is included. This further indicates an incredible market growth in the last quarter of 2017. The added variable of Innovation shows a maximum value of 66 weekly github commits, belonging to BTC. BTC also has the highest average of weekly github commits (33,9), twice as much as the second highest average (ETH with 16,3). The sign of the correlation between Innovation and Weekly Return is positive (Table 9), as also found by Wang and Vergne. The signs of the correlations between the rest of the variables and Weekly returns have not changed from period 1. A histogram of the returns (Figure 4) shows, like in period 1, a right-skewed distribution but with smaller extremes and a substantially smaller skewness of 2,19.

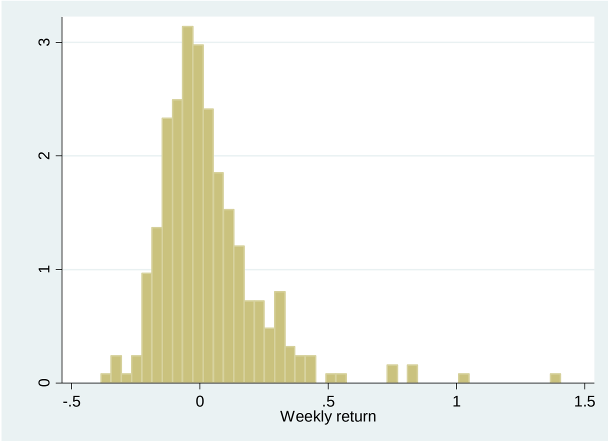

Figure 4: Histogram Weekly Returns Regression 1B

	Weeklyreturn	WRC	WPV	Trend	LogIll	SGrowth	Innovation
Weeklyreturn	1						
WRC	-0,226	1					
WPV	0,0821	-0,1075	1				
Trend	0,2462	-0,2876	0,4483	1			
LogIll	-0,0255	0,3137	-0,3989	-0,1534	1		
SGrowth	-0,028	0,01	-0,0315	-0,0602	0,0794	1	
Innovation	0,0685	-0,2695	0,3905	0,139	-0,4575	-0,0342	1

Table 9: Correlation Matrix for Variables Regression 1B

Regression 1B: Findings

Like for period 1, regressions are done with Driscoll-Kraay standard errors, and a Week variable is added to control for the time-trend. The results are shown in table 10. The additional variable Innovation is not significant in explaining weekly returns. The difference in this finding compared to that of Wang and Vergne may be explained by the factors taken into account when creating the Innovation variable. Their variable consists of a number of data representing technological updates to the code of a cryptocurrency. One part of that data is the average number of github commits in the last four weeks, which only needs to increase by 7,6% in order to increase their Technological development variable by one standard deviation. This suggests that the amount of github commits is an important factor, even though the Innovation variable is insignificant in the regression.

The only significant regression coefficient is for Trend, and is positive. An increase in Trend by one standard deviation is found to increase weekly returns by 5% on average (21,847*0,00233).

Since weekly volume was found to explain part of the weekly returns in the first period, and captured the impact of the Trend variable, a second regression is done (model 2) with a variable denoting the logarithms of weekly volume. This variable replaces the illiquidity variable in order to prevent multicollinearity. Volume does not significantly explain weekly returns. While it increases the significance of Trend (alpha level of p=0,01), it impacts the coefficient only slightly. After adding volume, the coefficient for WRC is now significant at an alpha level of 0,10.

	(1)	(2)
VARIABLES	**Driscoll-Kraay**	**Driscoll-Kraay Volume**
WRC	-3.90e-06	-3.90e-06*
	(2.49e-06)	(2.13e-06)
WPV	-1.18e-08	1.23e-08
	(7.82e-08)	(7.43e-08)
Trend	0.00233*	0.00235**
	(0.00126)	(0.000931)
LogIll	-0.00125	
	(0.0268)	
SGrowth	-0.213	-0.217
	(0.208)	(0.167)
Innovation	0.00101	0.00102
	(0.00111)	(0.000983)
Week	-0.000426	-0.00376
	(0.00139)	(0.000989)
LogVol		0.000287
		(0.00810)
Constant	1.238	1.106
	(3.805)	(3.019)
Observations	312	312
Within R-squared	0.1037	0.1037
Number of groups	6	6

Standard errors in parentheses

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

Table 10: Models for Regression 1B

Monday effect

A histogram of the daily returns (Figure 5) used to find weekday effects, shows us that they follow a normal distribution, although there are some outliers. Table (11) shows the average daily return for each weekday, with Tuesday showing the highest average daily return (0,58%), and Wednesday the lowest (0,125%). The average for the main day of interest, Monday, is 0,488%. This is much lower than the findings in (Décourt et al, 2017) where the average Monday return is 1,18%.

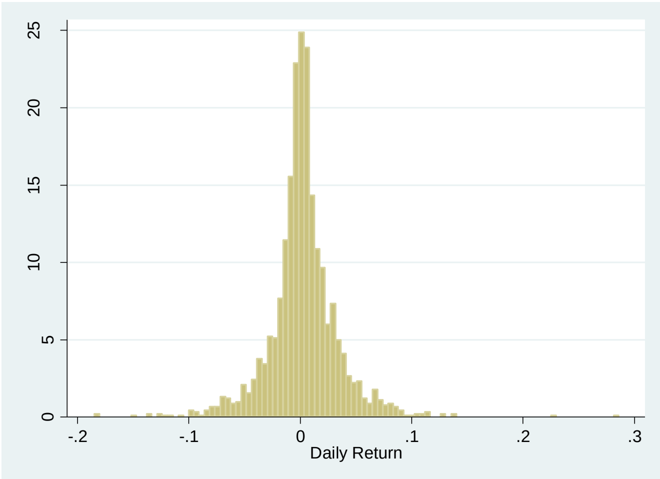

Figure 5: Histogram of Daily BTC Returns

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Average Daily Return	0,488%	0,580%	0,125%	0,0770%	0,177%	0,206%	0,217%

Table 11: Average Daily Returns per Weekday

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Monday	1	0.7399	0.1567	0.1531	0.2727	0.2913	0.2571
Tuesday		1	0.0821	0.0811	0.1565	0.1631	0.1303
Wednesday			1	0.9668	0.7629	0.6720	0.6046
Thursday				1	0.7362	0.6473	0.5811
Friday					1	0.9175	0.8719
Saturday						1	0.9602
Sunday							1

Table 12: P-values for T-tests on the Differences between Weekday Returns

T-tests on the difference between weekday returns (p-values shown in Table 12) do not produce significant outcomes that indicate differences between daily returns for different weekdays. Performing a one-way ANOVA further disproves the notion of a difference in average daily returns between weekdays (p=0,4321). A regression is therefore not necessary.

Price Momentum

To do the regressions for the price momentum, lag variables are created for daily, weekly and monthly returns. The results of the regressions are shown in table 13. The first and second lags of daily return variables are significantly influencing daily returns, positively and negatively respectively. It seems there is a one-day momentum of returns, with a reversal after 2 days indicating an overreaction to price information. The regression of weekly returns on its first and second lags shows that the first lag is significantly and positively influencing weekly returns. The coefficient of the second lag is not significant. Since the findings suggest a one-week price momentum, that possibly continues beyond one week, a regression of daily returns on 14 lag variables is run, for which the result is shown in table 14. The coefficients are monotonically decreasing with lag length and the influence of previous daily returns is significant up to 12 days at an alpha level of 0,05 . The coefficients show an interesting pattern where a positive coefficient of a lag is followed by a negative coefficient for the next lag, like in the regression with only 2 daily return lags. There seems to be a trend of a swing between the market over- and under-reacting to return information which clearly has a big impact in the buying and selling decisions of investors in this young market, most likely due to inexperienced traders. The monthly returns also show a price momentum. The coefficient of the first lag is significant and positive. The second lag does not influence monthly returns significantly.

Price momentum in the cryptocurrency market seems to be limited to a short time period. Inexperienced traders and highly volatile prices result in a lot of trading being based on recent returns, news, and hype rather than being based on long-term fundamentals. Fundamentals, however, might be hard to find and put into figures given this new financial product of which valuable trading knowledge could be limited to industry-insiders.

	(1)	(2)	(3)
VARIABLES	**DailyReturn**	**Weeklyreturn**	**Monthlyreturn**
DailyLag1	0.653***		
	(0.0445)		
DailyLag2	-0.340***		
	(0.0474)		
WeeklyLag1		0.239**	
		(0.102)	
WeeklyLag2		0.0579	
		(0.106)	
MonthlyLag1			0.252***
			(0.0874)
MonthlyLag2			-0.0509
			(0.0577)
Constant	0.00173***	0.0155**	0.0926**
	(0.000595)	(0.00761)	(0.0452)
Observations	1,885	237	59
R-squared	0.325	0.066	0.060

Robust standard errors in parentheses

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

Table 13: Regressions for price momentum

VARIABLES	DailyReturn
DailyLag1	0.865***
	(0.0480)
DailyLag2	-0.771***
	(0.0628)
DailyLag3	0.664***
	(0.0605)
DailyLag4	-0.540***
	(0.0593)
DailyLag5	0.513***
	(0.0603)
DailyLag6	-0.377***
	(0.0630)
DailyLag7	0.299***
	(0.0619)
DailyLag8	-0.257***
	(0.0599)
DailyLag9	0.225***
	(0.0604)
DailyLag10	-0.136**
	(0.0594)
DailyLag11	0.163***
	(0.0534)
DailyLag12	-0.116**
	(0.0516)
DailyLag13	0.0768*
	(0.0420)
DailyLag14	-0.0253
	(0.0324)
Constant	0.00104*
	(0.000534)
Observations	1,897
R-squared	0.442

Robust standard errors in parentheses

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

Table 14: Daily return regression with 14 lag variables

Conclusion:

Main findings

Two of the variables concerning public perception are found to be significantly affecting weekly cryptocurrency returns. These are Wikipedia Page Views (negatively) and Trend (positively). The negative correlation between Wikipedia Page Views and weekly returns changes to positive after adding a lag of Wikipedia Page Views to the regression. This lag takes over the negative coefficient. An increased interest in a cryptocurrency pushes up the weekly returns and in the week thereafter this interest dies down and decreases the returns. This looks to be an overreaction to positive news which influences the demand and subsequently the returns. In the following week this attention dies down and even turns into negative attention as the returns come back down more than they went up. The negative coefficient of the Wikipedia Page Views lag is twice as large as the positive coefficient of Wikipedia Page Views. These findings correspond to the positive coefficient of the Trend variable.

Supply growth affects returns negatively as is consistent with standard economics and the positive coefficient for Illiquidity shows that higher illiquidity increases the weekly returns. The lower the liquidity, the higher the price impact of trading. This corresponds to Wang and Vergne's findings.

The Innovation variable is insignificant in the regressions. While the underlying factor, the number of github comments, is important for a cryptocurrency's development, the insignificance can be attributed to the fact that this factor only makes up a small portion of a cryptocurrency's total technological development.

The data does not point to certain days within the week having higher than average returns. As the cryptocurrency market is open for trading around the clock worldwide, investor trading decisions can be executed without delay. This is unlike the traditional stock market that is closed for trading in the weekends and certain periods of the year. Further research on stock market anomalies like the January effect, Halloween effect, or on returns around the Christmas period could be interesting for cryptocurrencies, however, they cannot be done yet given the amount of data available.

Daily, weekly and monthly momentum in returns is found for cryptocurrencies. The regressions show an interesting pattern which could be due to an over-reaction being followed by an under-reaction most likely caused by inexperienced traders. As the newness of the market fades away along with hype-based trading, and as more institutional investors take part in this market the fluctuation patterns might decrease and altogether stop. Again, this can be researched in time as more data becomes available.

Limitations

The main limitation to this study is the amount of data available. Cryptocurrencies as instruments in the financial market, or as currencies for that matter, have not found long-term relative stability and this can be retraced to the fact that this is a new product in the market of which financial institutions and governments have little overview in terms of regulation, and to many people, their real world use case is still questionable. This results in a highly volatile market and periods of extreme returns, both positive and negative. Besides, many beginner-investors and the general public have little knowledge regarding the technology behind these cryptocurrencies and whether these are merely speculative assets or actual currencies to be used in the near-future for real world transactions.

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