UNIVERSITEIT GENT

FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION

UNIVERSITY OF GHENT

FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION

ACADEMIC YEAR 2015 – 2016

The Evolution of Bitcoin Price Drivers: Moving Towards Stability?

Thesis submitted in fulfillment of the requirements for the degree of

Master of Science in Commercial Sciences

Jens Seys
Kjartan Decaestecker

Under the supervision of

Prof. Dr. Koen Inghelbrecht

UNIVERSITEIT GENT

FACULTY OF ECONOMICS
AND BUSINESS ADMINISTRATION

UNIVERSITY OF GHENT

FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION

ACADEMIC YEAR 2015 – 2016

The Evolution of Bitcoin Price Drivers: Moving Towards Stability?

Thesis submitted in fulfillment of the requirements for the degree of

Master of Science in Commercial Sciences

Jens Seys
Kjartan Decaestecker

Under the supervision of

Prof. Dr. Koen Inghelbrecht

Nederlandstalige samenvatting

Bitcoin is de bekendste en meest gebruikte digitale munt tot op heden. Een digitale munt, of cryptovaluta, laat toe om geldtransacties uit te voeren zonder de tussenkomst van een centrale instantie. De munt werd gecreëerd vlak na het ontstaan van de financiële crisis als reactie op de gebleken mankementen in ons huidig financieel systeem. Dat systeem is vandaag louter gebaseerd op vertrouwen. De productiekost van een geldmunt of –biljet is immers verwaarloosbaar waardoor zijn toegekende waarde intrinsiek een illusie is. Niet tegenstaande een dergelijk digitaal alternatief heel aantrekkelijk lijkt, kende Bitcoin in zijn jonge geschiedenis al heel wat problemen. Naast het gebruik voor illegale praktijken zoals drugs- en wapenhandel, is de prijs ook zeer volatiel. Dit is de hoofdreden waarom de munt tot op heden nog maar in weinig verkooppunten wordt geaccepteerd. Een onderzoek naar de drijfveren achter deze prijsveranderingen is dus een absolute meerwaarde voor de bestaande literatuur.

In ons onderzoek vertrekken we vanuit vijf hypotheses, gebaseerd op eerder wetenschappelijk onderzoek. Door het gebruik van een verschillende statistische methode, een langere onderzoeksperiode en een toegevoegd onderzoek over de impact van specifieke evenementen op de prijs, onderscheiden we ons van deze literatuur.

De wisselkoers van Bitcoin tegenover de Amerikaanse dollar wordt in eerste instantie getoetst aan het aantal dagdagelijkse betalingen, het aantal zoektermen op de online encyclopedie Wikipedia, de onzekerheid op de financiële markten, de goudprijs, de prijs voor ruwe olie en de Chinese markt. Over het algemeen blijken enkel de laatste twee factoren een significante invloed te hebben gehad op de prijs van bitcoin. Toch kan gesteld worden dat een algemene kijk op de drijfveren van de prijs leidt tot weinig accurate conclusies, gezien de nog premature staat van de digitale munt.

Daarom werd ook de invloed van Bitcoin-gerelateerde evenementen op de prijs onderzocht. Door de hoge frequentie van deze evenementen was dergelijk onderzoek geen evidentie. Toch werden in totaal 8 significante evenementen gevonden, waaronder de Cypriotische crisis begin 2013. Slecht nieuws blijkt daarbij een grotere en meer directe impact te hebben op de prijs dan goed nieuws.

Tot slot werd ons onderzoek opgesplitst per jaar, om zo een idee te krijgen van de evolutie van invloedrijke factoren. Daaruit blijkt dat er wel degelijk geen consistentie heerst in de drijfveren. Van midden 2011 tot eind 2015 was er dus vooral een wisselend klimaat, gekenmerkt door korte termijnschokken veroorzaakt door de onderzochte evenementen. Dit volatiel prijsverloop is vooral te wijten aan de grote groep speculanten die Bitcoin enkel beschouwd als een interessante investering. Een stijging in het gebruik voor dagdagelijkse aankopen lijkt de enige oplossing tot stabiliteit.

Preface

This Master's thesis was written in order to obtain the degree of Master of Science in Commercial Sciences, with specialization in Finance and Risk Management. At first, we want to express our gratitude to the entire Faculty of Economics and Business Administration of the University of Ghent to give us the opportunity to conduct this research with the proper assistance.

As we were both fascinated by the concept of cryptocurrencies and its distributed ledger technology, this subject had our preference. Additionally, its increasing media coverage makes a compelling research on the matter highly relevant. Academic research on Bitcoin is scarce and still has potential for improvement.

In the months leading towards this end result, our mentor, Prof. Hannes Stieperaere, offered a tremendous amount of support. His useful insights and enthusiasm throughout this process were of utter importance. Hence, we want to explicitly thank him for his great assistance.

At last, we want to thank both Mr. Jelle Cappelle and Mr. Jasper Vynckier for reviewing our thesis and therefore contributing to the quality of this paper.

Content

List of abbreviations

ADL	Augmented Distributed Lag
ATM	Automated Teller Machine
AR	Abnormal Return
AVG	Average
BIC	Schwarz Bayesian Criterion
BPI	Bitcoin Price Index
BTC	Bitcoin
CAR	Cumulative Abnormal Return
CEO	Chief Executive Officer
CFSI	Cleveland Financial Stress Index
CNY	Chinese Yuan
CNN	Cable News Network
ECM	Error Correction Model
EUR	Euro
FINCEN	Financial Crimes Enforcement Network
GBP	British Pound
HAC	Heteroscedasticity and Autocorrelation standard errors
HQC	Hannan-Quinn Criterion
IMF	International Monetary Fund
IRS	Internal Revenue Service
JPY	Japanese Yen
MSCI	Morgan Stanley Capital International
OLS	Ordinary Least Squares
PBOC	People’s Bank Of China
S&P	Standard & Poor’s
SE	Standard Errors
SEC	Securities and Exchange Commission
USA	United States of America
USD	United States Dollar(s)
VAR	Vector Autoregression
VIF	Variance Inflation Factors
VIX	Chicago Board Options Exchange Volatility Index

List of figures

List of tables

List of annexes

The Evolution of Bitcoin Price Drivers: Moving Towards Stability?

Decaestecker Kjartan and Seys Jens

University of Ghent

Abstract

The digital currency Bitcoin has now been around for more than half a decade but still has not been used in a significant amount of day-to-day transactions. The main reason for that lies in its volatile price behaviour. This forces retailers into a rather sceptic mindset for accepting the cryptocurrency. Understanding those price fluctuations would mean a great deal to both academic research and the Bitcoin community. After an existence of more than 7 years, the time has come for an in-depth research on the matter. Previous studies from Ladislav Kristoufek formed the basis for our five hypotheses. Aside from a general approach on the compelling price drivers, a separate event study gave insights into the specific event-driven impact on the bitcoin price. Within these events, bad news had a greater and more direct impact. Looking at macro-economic events, only the Cypriot crisis in early 2013 seems to have significantly moved the price up. Finally, dividing our dataset into a year-by-year price study showed an ever-changing atmosphere. Especially the Chinese market has shown significant influence, together with the recent price trend of crude oil. It is safe to say that stability has not yet been achieved. A more mature user base that is not characterized by an investment purpose has to take the lead in order to reduce the volatility issue. As Bitcoin evangelists continue their quest, the cryptocurrency still has a long way to go in order to obtain mainstream usage.

1. Introduction

1.1. What is Bitcoin?

"Money is too important to be left to central bankers" (Friedman, 1962, p.219)

August 5th, 1971. That was the date US president at the time, Richard Nixon, announced that gold would no longer be exchangeable for US dollars[1], ending the so called 'gold standard'. The US dollar had till then, always been backed by the supply of the commodity. As of that date, the value of the US dollar was solely based on trust. That trust should be guaranteed by the US government. A couple of recessions later, trust has crumbled. If citizens lose trust in their currency, they look for alternatives that are believed to be more trustworthy. The value of the currency declines, forcing the central bank to up the pace of money-printing. As one dollar continues to be worth less, inflation reaches a peak. Several extreme examples exist, from the Argentinian Peso[2] to the former Zimbabwean Dollar[3]. Alternatives rise to the occasion, making Bitcoin one of them (Casey & Vigna, 2015).

Bitcoin is a digital decentralized currency that allows its users to make transactions directly, without the need of a trusted third party. In 2008, Satoshi Nakamoto published a paper that offered a solution to the double-spending problem that caused the failure of Bitcoin's digital predecessors. Until then, digital currencies could easily be duplicated and spent more than once unless a central authority verified every transaction. Nakamoto wanted to create a decentralized currency and tackled this problem by implementing a peer-to-peer network to store and verify transactions. This ensures that bitcoins cannot be spent twice while removing the third trusted party from the trading process. However, Karame, Androulaki & Capkun (2012) found that the double-spending problem can still occur when dealing with fast transactions since Bitcoin's proof-of-work system only allows new transactions to be verified every 10 minutes. The Bitcoin developers acknowledge this problem and encourage the users to accept zero-confirmation payments[4] as long as the transaction is broadcasted to the network.

All Bitcoin transactions happen through a network of autonomous nodes, or participants. This means no intermediation is needed, as the participants share their own hardware resources to provide the service and content offered by the network (Schollmeier, 2001). Transactions are stored in the blockchain, a public ledger that is held by everyone in the network. As soon as a transaction occurs, it gets bundled in a block with other transactions and is broadcasted to the network to be verified. Each participant of the networks helps by dedicating computer power to verifying transactions and maintaining the public ledger.

[1] This act was taken to prevent a run on the dollar because the US government did not have enough gold reserves to ensure to cover the US dollar in foreign banks.
[2] The Argentinian Peso's inflation rate reached 5.000% in July 1989.
[3] In 2008, even bank notes worth of one hundred trillion Zimbabwean dollars existed.
[4] A payment that was broadcasted to the network but has not yet been added to the blockchain.

This verification process is called mining, and it is designed to take around ten minutes to verify a block of transactions. The more nodes, or participants, a network has to verify transactions, the more secure the network is (Cawrey, D., 2014). When a block gets added to the ever-growing blockchain, it becomes impossible to tamper with unless every block is changed all the way back to the genesis block[5].

Transactions are made using an asymmetric key encryption algorithm. This means that to encrypt and decrypt a transaction, different keys are used. The Bitcoin protocol makes use of a public key and a private key. Anyone can send bitcoins to your public key as long as they know the address. However, coins that are sent to a public key can only be spent by someone who knows the corresponding private key. This key proves ownership of the bitcoins in a certain address and should at all times be kept secret to ensure no-one gets access to the key and the bitcoins associated to it. One way of keeping the private key safe is by storing it in a bitcoin wallet. To maximize security and anonymity, it is recommended to use a new public and private key for every transaction. This however does not mean Bitcoin is anonymous, it is pseudonymous and Reid & Harrigan (2013) have shown that transactions can be traced back to the user.

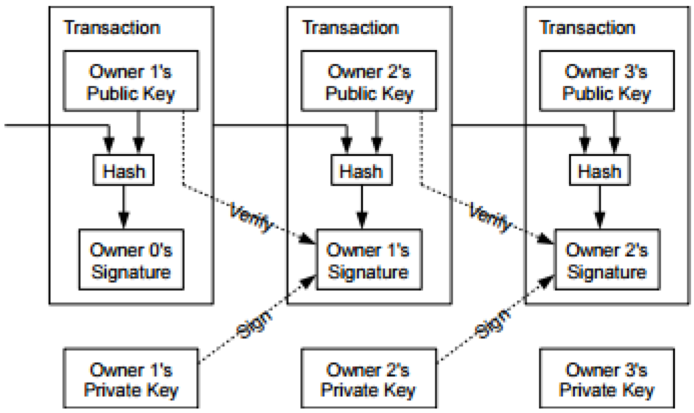


Figure 1: An overview of the Bitcoin transaction process (Nakamoto, 2008).

To reach consensus about transactions, Bitcoin uses the hashcash proof-of-work function. This hashing algorithm uses multiple components to continuously create hash values until a solution is found. The components used to create hash values include a service string[6], a nonce[7] and a counter. If a hash value is incorrect, the nonce increments and a completely new hash value is created. This process is repeated by every miner in the network, until a hash value is found that is lower or equal to a specified target value. Bitcoin's goal is to produce a new block every ten minutes, but with an increasing amount of miners joining the network in search of the solution, it is necessary to frequently adjust the difficulty. This change in

[5] A genesis block is the first block of a blockchain. The Bitcoin genesis block was mined at the easiest difficulty by Satoshi Nakamoto and contained one transaction.
[6] The service string is encoded in the block header data structure, and includes a version field, the hash of the previous block, the root hash of all past transactions in the block, the current time and the difficulty.
[7] The nonce is a 32-bit number that goes up whenever a hash is tried. This allows for a completely new hash value to be created.

difficulty of finding a hash below a certain value happens every 2016 blocks. If Bitcoin can keep up with their ideal of ten minutes per block, this means a new difficulty is implemented every two weeks.

Once the solution has been found, others can quickly verify the answer and know that the miner has put a significant computational effort into finding it, which is the concept of proof-of-work schemes. The first miner to reach a solution is rewarded bitcoins. This serves two purposes, it is both an incentive for miners to maintain the ledger and a steady inflow of coins into the system. Rewarding miners with Bitcoins allows for a controlled supply of money. This will go on until 2140, when a total of 21 million Bitcoins will be in circulation. From then on, Bitcoin will be forced to implement transaction fees to reward miners and keep the incentive alive because without miners, the system will be less secure and more vulnerable to attacks (Kaskaloglu, 2014). Mining for bitcoin is based on luck, as the system is completely random and memoryless (Rosenfeld, 2011). With Bitcoin's popularity comes an increase in mining difficulty, which makes it harder for individuals to find a solution unless they apply more resources. Miners have therefore decided to combine their efforts and create mining pools to decrease the variance of their income (Eyal & Sirer, 2014). These pools reward miners based on their contribution, and make it easier for individual miners to get a share of the profits. The downside to these mining pools is that their size could be disruptive. Dowd & Hutchinson (2015) have shown that Bitcoin is a natural monopoly. Miners that combine forces have an advantage over those that do not, and this process repeats itself until one mining pool remains. As soon as a mining pool reaches the majority of nodes, the currency is no longer considered decentralized (Eyal & Sirer, 2014) and Bitcoin relies on trust again. According to Gervais, Karame, Capkun and Capkun (2014), entities like these are a threat to Bitcoin's decentralized character even without reaching a majority. Mining pool owners can be included in the decision making on Bitcoin's future and help decide the fate of the cryptocurrency.

All mining activities serve one purpose: maintaining the blockchain. This revolutionary piece of technology is turning out to be more important than the cryptocurrencies themselves. Some of the world's largest financial institutions, governments and other industries are investigating the potential of a distributed ledger when applied to their systems. Sir Mark Walport (2016) states that the disruptive potential comes from their real-time processing capability, near tamper-proof system and low cost. Distributed ledgers are available in two forms, permissionless and permissioned. Bitcoin's blockchain is an example of a permissionless distributed ledger, where anyone in the network can add transactions. The other kind, permissioned, only allows whitelisted users to add to the ledger. This is more compatible to the current banking system, Swanson (2015) concludes.

1.2. Currency or commodity?

The classification of Bitcoin has led to a tremendous amount of discussion. Interpreting Bitcoin as money has to be done cautiously. First of all, money has to have three functions: medium of exchange, unit of account and store of value. Yermack (2013) criticizes Bitcoin to perform poorly on these functions. He argues that Bitcoin accomplishes only the first criterion, however at a tiny scale. Worldwide use of Bitcoin is rising, but is not significant as of today. Secondly, considering the volatility of Bitcoin in its limited history, merchants are not likely to call it a solid unit of account. At last, being a store of value and encountering hacking attacks do not go well together. This opinion is shared with Surda (2014), who claims Bitcoin is not yet money, but may be in the future. Financial authorities have mixed views on the digital currency. Both the Internal Revenue Service (IRS) and the Financial Crimes Enforcement Network (FINCEN) state that Bitcoin can be seen as a virtual currency, separating itself of 'real' currencies in absence of a global legal framework (FinCEN, 2013) (IRS, 2014). However, when it comes to tax payments, virtual currencies are commonly seen as commodities.

Consensus on this matter clearly lacks significance. Assuming Bitcoin is indeed money, then what kind of money is it? Selgin (2015) provides a trustworthy view on this matter. At first, money can be separated into two main categories: commodity money and fiat money. Commodity money functions as a medium of exchange and is scarce. On the opposite, fiat money is backed by a central agency and is not scarce, in a sense that the value of the fiat currency far exceeds its marginal cost of production. The US dollar categorizes as the latter type of money. Both have advantages and disadvantages. Commodity money is very sensitive to shocks in supply and it is quite costly. Fiat currencies are a lot less expensive to make. But Selgin (2015) argues that "The disadvantage of fiat money, relative to commodity money, rests precisely in the fact that its scarcity, being thus contrived, is also contingent" (p.93). Inaccuracy in monetary policy has conspicuous drawbacks on the economy. As Bitcoin has elements of both categories, a distinction has to be made. Through the scheme presented underneath, Selgin classifies Bitcoin as synthetic commodity money.

		Nonmonetary use?	
		Yes	**No**
Scarcity	**Absolute**	Commodity	Synthetic commodity
	Contingent	Coase durable[8]	Fiat

Figure 2: Base money types (Selgin, 2015).

[8] These durable goods were named after R.H. Coase who stated that when consumers refuse to pay more than the cost of production of a durable good, by anticipating the possible profit a monopolist could make, the monopolist loses all market power. This results in contingent money supply, even with nonmonetary value (1972).

Synthetic commodity money has no nonmonetary value but its scarcity is absolute. Such money is characterized by a predetermined money supply. This type of money can again be divided into two classes, elastic and inelastic synthetic commodity money. Bitcoin is a bit of both. Its money supply is currently growing at a predetermined rate. But by 2140, the absolute limit of 21 million bitcoins will be reached, forming an inelastic money supply. Selgin's conclusion is that Bitcoin is semi-elastic synthetic commodity money.

A lot of criticism has been created around the digital currency. Aside from thefts and other security problems, the most prominent argument against Bitcoin is its money supply limit. When the money supply reaches its absolute limit in 2140, the digital currency will hardly be able to avoid a deflationary spiral (Barber, Boyen, Shi, & Uzun, 2012). To be able to follow economic growth, an appreciation of the Bitcoin exchange rate would be an absolute necessity from that moment on.

Decentralized money, stipulating no involvement of any central authority brings up promising thoughts. But as Grinberg (2011) indicates, Bitcoin is somehow centralized through a development team containing five members. This team has given itself the task of securing the development of the software behind Bitcoin. Although they can not explicitly induce people to accept the new software they make, if they convince Bitcoin users that the new software outperforms the old software, very few will hesitate to switch. Using that influencing power, some believe they could well change the outcome of the predetermined money supply.

A crystal clear conclusion on the currency vs. commodity discussion cannot be drawn. The main issue lays in the fact that Bitcoin is still too often seen as a speculative asset instead of a currency (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014). Today, Bitcoin customers can generally be divided into two groups (Yermack, 2013). A technology group on the one hand, which focuses on the argument of low transaction fees, and a libertarian group that has had enough of money in the hands of governments. Once Bitcoin becomes mainstream in day-to-day transactions, it will tend to behave as a more mature currency.

1.3. The current state of Bitcoin

Bitcoin has had an interesting lifecycle up to now, and each year denotes something unique that happened to Bitcoin. For most investors and enthusiasts, 2013 will be known as the year of Bitcoin itself. The cryptocurrency grew a staggering 10.250% to its peak of 1.242 USD and entered the spotlight (Christensen, N., 2013). Of course, it would not be Bitcoin if the following year was not full of surprises. With the end of 2014 coming closer, Bitcoin was declared the worst investment of 2014, the complete opposite of previous year (Phillips, M., 2014). After these ups and downs, 2015 was the year in which major financial institutions started paying attention to Bitcoin and the distributed ledger technology (Skinner, C., 2015). Bitcoin was also the best performing currency in 2015, ending the year with a +37% appreciation. Furthermore, 2016 has already been tipped as Bitcoin's best year to date, with record prices incoming due to the reward halving (Kelly, J., 2015). Halfway 2016, the Bitcoin mining reward will halve from 25 to 12,5. The steady inflow will lower and miners will have less influence on the market.

There are currently 15,4 million Bitcoins in circulation, almost three quarters of the total expected supply.[9] It is worth noting that a small share of those 15,4 million coins has been lost forever due to forgotten accounts or by being burned[10], so the amount in circulation will never reach the projected 21 million. The bitcoins that are in circulation however are used in around 200 million unique transactions a day.[11] The majority of those transactions happen in Chinese Yuan and on the Chinese market.[12] Special Bitcoin ATMs have been created to facilitate access to the cryptocurrency. In October 2013, the first Bitcoin ATM was opened in Vancouver, Canada. Since then, hundreds of ATMs have been placed in major cities around the world, putting the total number of Bitcoin ATMs to date at 618. Over 60% are located in North America, with New York City having the most. Belgium currently has three ATMs available, two of which are in Antwerp and one in Ghent.[13]

One way of measuring interest in Bitcoin and the blockchain technology is by taking a look at the investments made in startups. Fueled by the growing interest in distributed ledger technology, 474 million USD venture capital was used to back Bitcoin and blockchain startups in 2015 alone (KPMG, 2016). This surge in investments caused the 1 billion USD total venture capital mark to be reached in the fourth quarter of 2015 (Pagliery, J., 2015). 21 Inc. tops the chart of venture capital raised with 116 million USD, followed closely by Coinbase with 106 million USD (Wong, J. I., 2015). Even with enormous amounts of

[9] https://blockchain.info/charts/total-bitcoins
[10] Proof-of-burn is a method for distributed consensus in which miners destroy coins by sending them to an unspendable address. This is expensive for the miner (just like proof-of-work) but requires no resources except for the asset being burned.
[11] https://blockchain.info/charts/n-transactions
[12] http://bitcoincharts.com/charts/volumepie/
[13] http://coinatmradar.com/

venture capital being raised, not all startups manage to survive. Funding and security issues are the main reason for startups to fail in the early stages of development (Hileman, G., 2016).

Bitcoin has been the biggest and most popular cryptocurrency up to now, but developers have been working on alternatives that could dethrone the original cryptocurrency. Bornholdt & Sneppen (2014) concluded that while Bitcoin is the current 'king of the hill', it has no special advantages over other cryptocurrencies and has a good chance of being replaced. Many of these alternatives are building on the strong foundation that Bitcoin has laid and improving where needed. While all cryptocurrencies use cryptography for security measures, their individual aspects can vary to cater to different needs. Based on market capitalization[14] we can say that Bitcoin's biggest competitors are Ethereum, Ripple and Litecoin.

- Ethereum is a decentralized platform based on the blockchain technology that is used to build and execute smart contracts or distributed applications[15]. It uses the cryptocurrency 'Ether', which is mined in a similar way as bitcoin, to keep the platform alive. One major difference is that Ether has no intention of becoming a method of payment. It can be traded on cryptocurrency exchanges but its main purpose is to be used in the Ethereum network. There is also no limit to the amount of Ethers in circulation. The developers removed the cap to combat speculative behavior and eventually reach an inflation rate of 0 (Buterin, V, 2014).
- Ripple was created to facilitate transactions and exchanges on a global scale by connecting payment systems. The possibility to send currencies around the world with transaction confirmation happening within seconds is something the current financial institutions cannot offer. By implementing the Ripple protocol, some of the world's largest banks are trying to cut costs while improving transaction speed. The protocol has been around since 2012 and uses a similarly named cryptocurrency. The 100 billion Ripples that were created in the beginning are the only ones to be distributed, and more than 50 billion will remain in hands of the Ripple Company. This means that Ripple has a decreasing amount of monetary units available, with losses or destruction of coins being inevitable. One of the main functionalities of the cryptocurrency is to be used as bridge between two currencies when there is no exchange possibility. Ripple sees itself as complementary to Bitcoin, instead of a competitor.
- Litecoin has strong connections to Bitcoin and was created using the same open source data. The main differences are the block generation time and the algorithm used to secure the network. Litecoin will also distribute four times the total amount of Bitcoins, resulting in 84 million Litecoins

[14] http://coinmarketcap.com/
[15] Distributed applications are applications or software that runs on multiple computers within a network at the same time.

in circulation. It was created to offer a solution for Bitcoin’s shortcomings and is the “silver” to Bitcoin’s ‘gold’.

Other digital currencies, or ‘altcoins’, have seen a decline in the last few years, but the top alternatives have been consistent in their growth and popularity, which shows that Bitcoin is not the only attractive cryptocurrency. Other competitors of Bitcoin include more mature payment services such as PayPal and Western Union, who are also unwilling to let new technology invade their territory. Perhaps these competitors could prove to be more challenging for Bitcoin than altcoins. Dowd & Hutchinson (2015) state that in the long run, Bitcoin will not stand a chance against efficient closed-wall systems such as PayPal. As soon as the network stops relying on Bitcoin emissions to stimulate miners, it will have to implement higher fees, which is exactly what Bitcoin is fighting today. In the short run, Bitcoin’s competitive advantage can be found in the micropayments sector where traditional companies cannot compete with the low-cost transaction processing of Bitcoin (Grinberg, 2011).

The real possibilities for Bitcoin and cryptocurrencies alike could be located in the developing countries where high levels of corruption have caused the governments and financial systems to lose all credibility. Areas that have underdeveloped payment systems have already shown great interest in transferring money through digital alternatives. Their power lies in the numbers: over 2,5 billion third world citizens do not have access to a bank account, a target audience that is desperately in need of financial services. M-Pesa, a mobile payment system that mainly operates in Kenya, is one of these digital alternatives that allows mobile phone users to send and receive money without needing a bank account. Mbiti & Weil (2011) have found that M-Pesa is most used for transactions, but it can also provide a means to store wealth for anyone in possession of a mobile phone. However, M-Pesa does not offer a solution for international transfers made by expatriates. In 2015, 441 billion USD was sent to developing countries by international migrants supporting their family from abroad (KNOMAD, 2016). According to a database held by the World Bank, the average global cost of sending remittances was over 7,5% in June 2015. For this reason, Bitcoin is often seen as the solution through the so-called ‘rebittances’. By making use of the Bitcoin network, migrant workers can transfer money in a fast and reliable manner while avoiding the high fees imposed by the remittance industry. This solution however is very dependent on the mainstream acceptance of Bitcoin.

If Bitcoin aims to become the new payment standard, it will need more than a solid framework. For thousands of years, currencies have been used in exchange for goods or services. But if nobody is willing to accept said currency, does it still serve a purpose? Bitcoin is mostly used in exchange with other currencies to speculate on any price changes that might occur. This phenomenon fuels Bitcoin’s volatile price trend, and many believe the only way for Bitcoin to achieve stability is by increasing its use in real transactions. Before entering the spotlight, Bitcoin was exchanged for goods and services on a large scale throughout the world. The products included drugs, weaponry and fake driver's licenses, even assassinations had a price tag. Buyer and seller met through the infamous online black market called 'Silk Road', which used Bitcoin for its pseudonymous character. This made Bitcoin a direct threat to any government because using Bitcoin gives criminals an extra layer of protection (Twomey, 2013). Silk Road was shut down late 2013 following its owner Ross Ulbricht's arrest but the damage to Bitcoin's reputation had been done. With the demise of Silk Road came a Bitcoin price drop from 140 USD to 110 USD, even though Silk Road only accounted for around 4% of the overall Bitcoin trade. The fact that Bitcoin has survived events such as the collapse of Mt.Gox[16] and Silk Road shows its capability to recover.

Despite being associated with illegal goods, over 7.500 venues currently accept Bitcoin payments. Overstock.com was one of the first large companies to accept Bitcoin, with CEO Patrick Byrne being a strong believer in cryptocurrencies. Other brands that accept Bitcoin payments include Microsoft, Dell, DISH Network, Subway and the Sacramento Kings[17]. They provide this service to their customers by partnering with an exchange such as CoinBase, who processes the Bitcoin payment and exchanges it for its dollar equivalent. By cashing out immediately, the market risk is reduced significantly. While companies are starting to accept Bitcoin, they hardly ever hold the currency themselves which shows that the volatility issue is still a reason for skepticism.

[16] Mt.Gox was one of the most prominent Bitcoin exchange markets. It was based in Tokyo, Japan.
[17] The Sacramento Kings are a professional basketball team competing in the NBA.

2. What drives the price of Bitcoin?

To tackle the issue of volatility, research on the compelling factors that influence the Bitcoin price can be of thriving importance. Once that volatility is understood from a historic perspective, uncertainty could take a tumble. Even with information about the Bitcoin price movements, forecasts will be very difficult to make and usually involve large confidence intervals (Chu, Nadarajah, & Chan, 2015). Overall, research on this matter is scarce and has mostly focused on wrong beliefs. Buchholz, Delaney and Warren (2012) argued that all price fluctuations are linked to changes in demand, given the predictable outcome of the money supply. They find that the volatility has had a strong effect on the price of Bitcoin. Speculators saw this volatility as a positive sign to make high returns, as the price was expected to go rapidly upwards. The period of investigation was however very short, leading us to no broader, reliable conclusions. Van Wijk (2013) focused on the impact of movements in stock market and oil indices on the Bitcoin exchange rate. Not only does he find poor results, he assumes that most of the fluctuations are only explainable by human behaviour which is, as he stated, impossible to measure.

Kristoufek (2013) came with first proof of interest-driven impact. He found that both Google Trends and Wikipedia search queries have had a positive impact on the price. This impact worked both ways, as the price also influenced the amount of search queries. A combined research of all three previous studies was done by Ciaian (2013). This was actually the first paper that implemented multiple groups of possible drivers. His results support the findings of previous papers, excluding Van Wijk's research. When all variables are considered, macro-economic factors seemed to have no significant impact on the price.

To counter previous hypotheses made on possible drivers, Kristoufek (2015) expanded his research. Aside from the interest in Bitcoin through search queries, he investigated economic, transaction and technical drivers. On top of that, he answered the possibility of Bitcoin being a safe haven and discussed the influence of China. Economic drivers include the use in real transactions, the price level and the money supply. Trade volume and trade transactions are the possible transaction drivers. The hash rate[18] and the difficulty of mining represent the technical influence. To test the assumption of Bitcoin functioning as a safe haven, the impact of both financial uncertainty and the gold price were analyzed. At last, China's influence is measured through the prices and volumes of BTCC[19], the most representative Chinese Bitcoin exchange market. The main focus lays on Bitcoin specifics, as the digital currency does not behave as common currencies.

Because Kristoufek applied the most accurate hypotheses to date, this study follows most of his insights. Different pathways are taken though. At first, a total of five main hypotheses will be laid out. These

[18] The hash rate is the speed at which a computer is completing an operation in the Bitcoin code.
[19] Formerly BTC China

hypotheses are mainly based on previous work, with a different, longer and more recent period of investigation. Unlike Kristoufek, who used a wavelet coherence analysis[20], we will be using a multivariate regression analysis, combining all possible drivers. This approach allows for a broader view on the leading powers behind the fluctuations.

Additionally, this paper does not apply all of the above variables, for various reasons. The general price level is not specifically tested through a hypothesis, but our model controls for this through the use of the most important exchange rates. Given the fact that the price is solely driven by demand-side factors, the money supply is only incorporated as a control variable (Buchholz et al., 2012). As the hash rate and the difficulty of mining are influenced by the same factors, only the difficulty of mining is included.

Once these hypotheses are explained and tested, an event study will be assessed, focusing on the event-driven aspect in Bitcoin's short history. A broad selection of events will be tested, filtering out only the significant events. Those events will be implemented in our multivariate regression to control for these unusual periods of time. This allows us to see whether the same significant drivers hold importance. At last our analysis will be divided into different years, to detect an evolution in drivers.

Hypothesis 1: the more Bitcoin is used in day-to-day transactions, the higher the price.
As Bitcoin's utility raises in normal life, more people tend to use it and hence the price will move upwards (Kristoufek, 2015). These real transactions are measured through the trade-exchange ratio. This ratio divides the volume of transactions on exchange markets through the volume of trades made for real life, such as buying a pizza. Because a lower ratio indicates more real transactions, expectations are that the influence on the price is negative.

Hypothesis 2: an increase in online Bitcoin interest, results in an increase of the Bitcoin price.
When interest in Bitcoin rises, the use of the digital currency might get a positive boost, presumably resulting in a higher price. Ex ante, the impact is thus assumed to be positive. This interest is best represented by internet search queries, provided by Wikipedia (Kristoufek, 2013).

Hypothesis 3: higher financial uncertainty drives the price of Bitcoin up.
Following previous discussion, times of economic distress tend to move people towards alternatives such as Bitcoin. Therefore, more ambiguity in financial markets can be a price stimulant, as the alternative currency can be seen as a safe haven (Kristoufek, 2015). In fact, this hypothesis incorporates in a sense the entire financial skepticism, which grants the absence of stock market indices. Higher financial uncertainty, or declining stock market indices, should move the price up.

[20] This kind of analysis measures correlation through time

Hypothesis 4: the price of Bitcoin correlates with movements in gold and oil prices.

Referring to the unsolved discussion of Bitcoin being either a currency or a commodity, correlation between the most prominent commodity prices and the Bitcoin price can occur. If Bitcoin can indeed be seen as a safe haven (ut supra), it should follow the same road as the gold price. Reboredo (2013) confirmed gold being a safe haven for the US dollar, while Bredin, Conlon and Potì (2015) found proof that gold has acted as a hedge for stock markets. Aside from gold, correlation with the price of crude oil is also tested. Crude oil not only has a major macro-economic influence, Atems, Kapper and Lam (2015) showed that shocks in the crude oil price provoke asymmetric movement in exchange rates. Additionally, Palombizio and Morris (2012) argue that the oil price is an early indicator of inflation rate movement. This could lead to a change in the price level and eventually a depreciation of the Bitcoin price. We expect a positive relationship with the price of gold and a negative one with the price of crude oil.

Hypothesis 5: the price of Bitcoin is highly influenced by its trading volume in China.

Bitcoin's short history has mainly been a tantalizing Chinese story. "With more than 1 billion citizens living in an economy that was still only partially opened to the free market and whose government imposed strict controls over how much money they could send overseas, bitcoin might provide a work-around" (Casey & Vigna, 2015, p.112). It is no secret that the Chinese government has restricted the exchange of foreign currencies in the past. An alternative to flee from this outdated financial system, is Bitcoin. Chinese interest in the digital currency has soared through time. The huge peak in December 2013, as the value of one Bitcoin climbed above 1.100 USD, is believed to be mainly due to Chinese speculation (Southurst, J., 2013). When comparing the trading volume in currency usage, the Chinese Yuan clearly outperforms other currencies. Because China is currently seen as Bitcoin's central market, our model tests the impact of the Chinese trading volume on the price of the cryptocurrency. Since the investigated trading volume is expressed in Chinese Yuan, the USD/CNY should be considered aside from this trading volume. Either an increased Chinese trading volume or a depreciation of the US Dollar against the Chinese Yuan, should have a positive impact on the Bitcoin price.

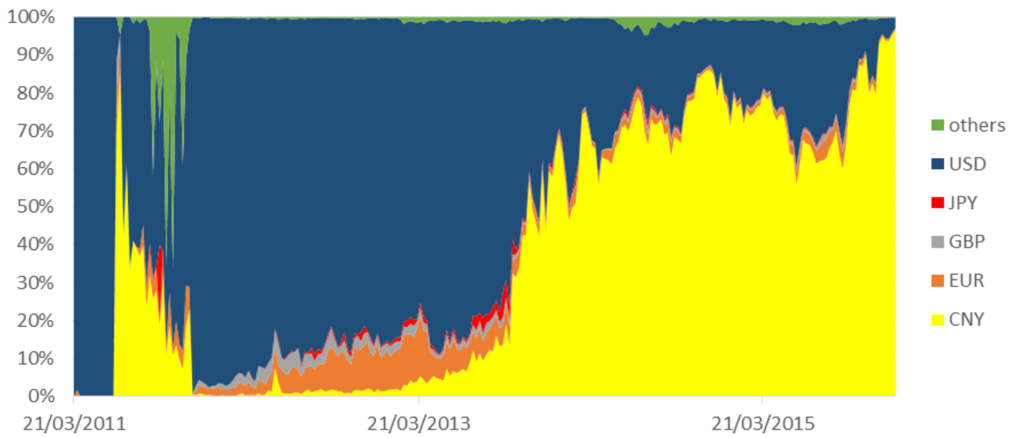


Figure 3: Currency comparison of Bitcoin trading volume from March 2011 till December 2015 (Source: Bitcoinity.org).

3. Data

The Bitcoin price is represented by the Bitcoin Price Index (*BPI*), provided by Coindesk[21]. In terms of price stability, liquidity is of utter importance. By taking this price index, our model avoids illiquid exchange markets. Our investigation period starts at the first of July, 2011. This date is based on two main reasons. First, Kristoufek (2013) showed that the exchange market Mt.Gox[22] only reached the threshold of a benchmark, 8-hour liquid market as of May 2011. We only start our data a month later because data on BTCC is only available as of the end of May 2011. The ending date is 31 December 2015, forming a time span of 4.5 years.

Data of the trade-exchange ratio (*Trade_Exchange*) was retrieved from the official blockchain site[23]. For the hypothesis on the interest-driven impact, either Google Trends data or Wikipedia data should be obtained. Google Trends data is only available on a weekly basis, forcing us to implement the daily Wikipedia data. To be sure this does not affect our hypothesis that much, we test correlation between the two search engines on Bitcoin search queries. Both variables generally follow the same pattern and show significant correlation with each other (Annex 2).

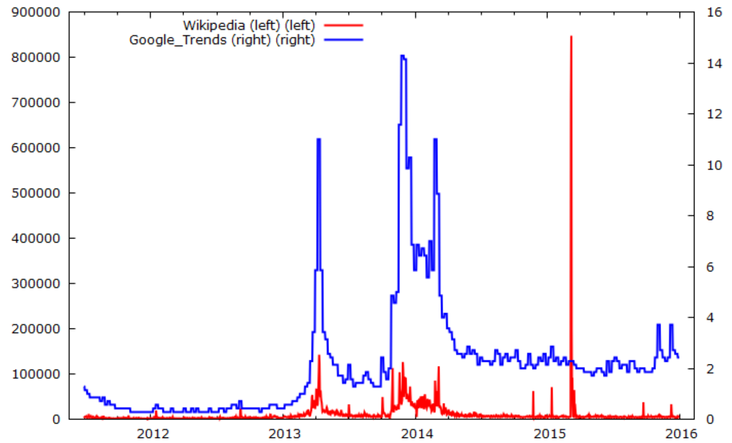


Figure 4: Time series plot of Wikipedia and Google Trends search queries for the term 'Bitcoin'.

This leads us to take the Wikipedia search queries (*Wikipedia*) for the term 'Bitcoin' as representative variable for the online interest in Bitcoin[24]. Financial uncertainty can be indicated by multiple indices. The VIX-index, which mirrors the volatility of the S&P 500-index, is commonly seen as the best indicator of financial uncertainty. A lot of criticism has risen on the index though, as it is believed to underestimate the real volatility (Chow, Jiang, & Li, 2014). The Cleveland Financial Stress Index[25] (*CFSI*) is a better

[21] Coindesk is the most prominent news website of all Bitcoin activity. Its Bitcoin Price Index was launched on September 11th, 2013. Before that date, the Bitcoin price on Mt.Gox is taken. In the price index, only the most liquid markets are included. Several exchange markets were added and revoked through time, based on specific criteria.

[22] Mt.Gox was launched on the 18th of July, 2010.

[23] http://blockhain.info/charts

[24] Data was retrieved from http://stats.grok.se

[25] The Federal Reserve Bank of Cleveland provides online data for this variable.

measure. Aside from equity markets, it also accounts for interbank, foreign exchange and credit markets (Manamperi, 2015). The index balances around 0, with negative values indicating periods of lower financial uncertainty and positive values periods of higher financial stress. For the gold variable[26] (*Gold*), the price per troy ounce was taken. The crude oil price[27] (*Crude_oil*) is represented by the London Brent crude oil price, with data retrieved from Datastream.

Data on Chinese Bitcoin markets should be cautiously considered. Figure 5 shows the trading volume of the most important Bitcoin exchange markets in China.

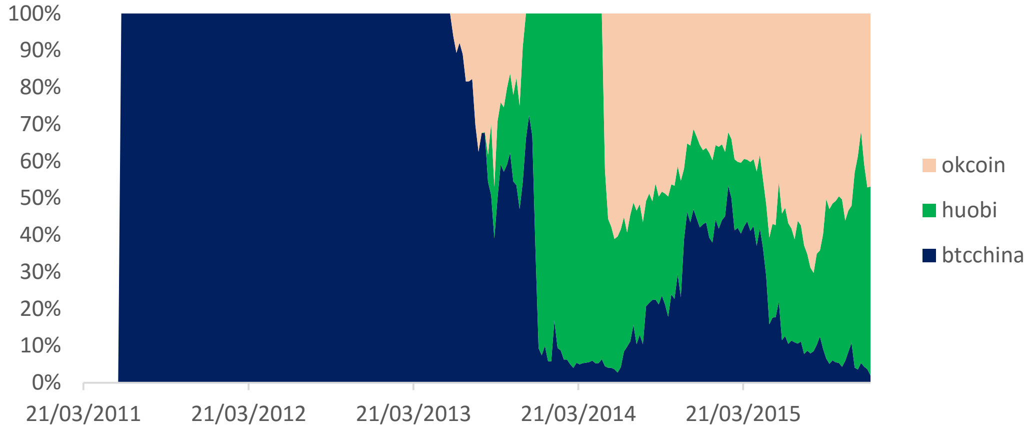


Figure 5: Distribution of the most important Bitcoin exchange markets in China by trading volume (Source: Bitcoinity.org).

Apparently, Huobi and OKCoin outperform BTCC the last two years. This leads us to doubt the accuracy of BTCC representing the Chinese trading volume. But criticism on Huobi and OKCoin has emerged. Both exchange markets are accused of manipulating trading volumes through bots (Southurst, J., 2014). This allows them to represent a far higher trading volume than in reality was achieved. Bobby Lee, CEO of BTCC, claimed in an interview that both Huobi and OKCoin were the only ones responsible for this behaviour (Allison, I., 2015). Although BTCC data cannot be trusted to the fullest extent, we follow Kristoufek (2015) in appointing BTCC (*BTCChina*) as the most representative Bitcoin exchange market in China[28].

As figure 5 indicated, Bitcoin is mainly traded with the US Dollar and the Chinese Yuan. This is taken into account through the USD/CNY exchange rate (*USD_CNY*). To be complete, we also include the Euro through the USD/EUR exchange rate (*USD_EUR*). Data on these exchange rates is retrieved from Datastream. The official blockchain site provides the most reliable data on the difficulty of mining (*Difficulty*) and the total amount of Bitcoins in circulation (*Total_Bitcoins*). For the event study, BPI/USD

[26] Data was retrieved from http://gold.org/research
[27] Datastream provides daily data of the London Blended Crude Oil Price
[28] http://bitcoincharts.com provides data of this market

returns are tested against the market return, for which we chose the MSCI World Index[29] (*MSCI_World_Index*).

3.1. Data transformation

Our time series data consists of 1.645 observations. Since our dataset contains daily data of seven days a week, interpolation was necessary for the MSCI World Index, the gold price and the Brent crude oil price. This allowed data points in the weekends, with an unchanged pattern. In light of this study, interpolation was a better option than omitting data, since Bitcoin price fluctuations are substantially short-term and important price fluctuations would go missing. The Wikipedia data contained nine missing values, for which we also used interpolation.

In order to test the stationarity of our variables, an Augmented Dickey-Fuller test was conducted. Non-stationary variables are characterized by a long-term trend, being either deterministic or stochastic. The presence of a stochastic trend is proof of a unit root in the variable. Granger & Engle (1987) argue that the non-stationarity of economic variables can be solved by taking the first differences of the variables. As most of our variables contained a unit root, first differences were taken of each variable.

One step further is to take the log difference of each variable. Several reasons can be given to motivate this transformation. First of all, the first difference of log transformed variables lets us interpret the results as returns or elasticities. Also, logs are commonly used to narrow the data scale in order to reduce non-linearity. This results in more reliable conclusions in a linear estimation model. At last, some variables show signs of positive skewness and high kurtosis. Consequently, normal distribution of such variables is absent. As a result, the log differences of all variables, excluding *CFSI* due to its negative values, was taken. As *CFSI* fluctuates around 0, with a minimum value of -2,22 and a maximum value of 2,17 in our dataset, a log transformation is not necessary. Nazlioglu, Soytas and Gupta (2015) also found a unit root for the Cleveland Financial Stress Index and solved this by only taking the first differences of *CFSI*, while taking the log differences of the oil prices. To illustrate the accuracy of these transformations, figure 6 shows its effect on the Bitcoin price.

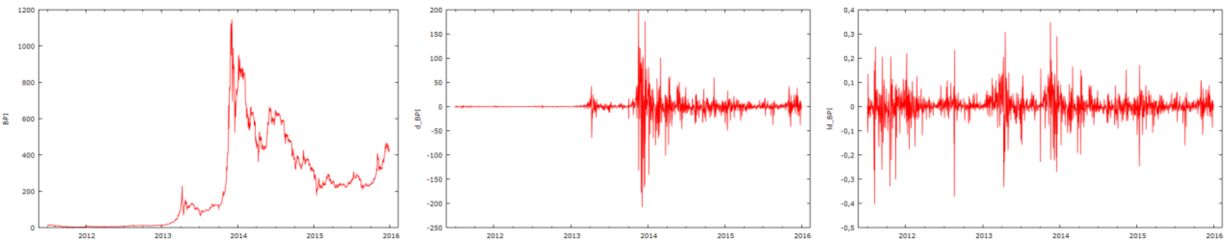


Figure 6: Time series plot of the Bitcoin Price Index, its first differences and its log differences.

[29] Data was retrieved from www.msci.com

4. Methodology

The linear relationship between the dependent variable (*BPI*) and its ten independent variables can be observed through an OLS estimation model. This allows us to find a best fitting line that makes the residuals as small as possible (Koop, 2006). In choosing the appropriate estimation model, awareness of several pitfalls is absolutely necessary. Proper solutions should address these issues.

At first, the problem of omitted variable bias can occur by including an insufficient amount of explanatory variables. As our model contains seven explanatory and three control variables, based on economic theory and previous work, this problem is certainly dealt with.

When two or more independent variables are highly correlated over time, conclusions on empirical results lose major credibility (Blalock, 1963). This problem is better known as the multicollinearity problem and can be tested through a VIF-test. Variance Inflation Factors higher than 10 indicate the presence of multicollinearity. In a normal OLS estimation model, the original variables *Crude_oil*, *Difficulty*, *Total_Bitcoins* showed signs of such behaviour (Annex 3). Additionally, a time series plot indicates that both *Difficulty* and *Total_Bitcoins* show a similar, ever-growing pattern with huge ending values (Annex 4). Although no multicollinearity was detected in the estimation model with the transformed variables, each variable was omitted once in order to verify the robustness of our model.

If the residuals in an estimation model lack a constant variance, heteroscedasticity becomes an issue. This leads to inefficient coefficient estimates and the strong possibility of inappropriate standard errors. The White's general test detected heteroscedasticity in our model (Annex 5). As a solution, the heteroscedasticity-consistent standard errors were used.

Additionally, when two non-stationary variables are regressed against each other, the problem of spurious regression can occur. However, non-stationary variables are absent in our model due to appropriate data transformation. Subsequently, spurious regression poses no threat to our results.

Finally, residual autocorrelation is present in case of correlated error terms over time. This pitfall results in unbiased, but inefficient coefficient estimates, inappropriate standard errors and an R^2 that is likely to be inflated. This issue was solved by using the heteroscedasticity and autocorrelation (HAC) standard errors. Another solution is to take the lags of both the explanatory and the dependent variables, which leads to a distributed lag model. Although the Durbin-Watson test denies the presence of residual autocorrelation, a distributed lag model is preferred in this paper (ut infra).

4.1. Autoregressive Distributed Lag model

Adding lags of both the explanatory variables and the dependent variable can be motivated by three reasons. First of all, inertia of the effect of the explanatory variables on the dependent variable can be present. For example, searching the means of Bitcoin on Wikipedia might trigger its usage. However, actually buying Bitcoins might happen the day after, regarding some consolation on the thought. Secondly, financial markets have a tendency to overreact to good or bad news. These overreactions can be corrected in the next period. Finally, the price level of Bitcoin the day before is an important factor for its current price. Including a lag of the dependent variable allows our model to account for periods of either high levels or low levels. Only one lag of all variables was included based on the Schwarz Bayesian Criterion (BIC) and the Hannan-Quinn Criterion (HQC) (Annex 6). The incorporation of one lag also results in the loss of only one observation. This gives us an ADL-model with the following formula:

$$\begin{aligned} \Delta BPI_t = {} & \alpha + \phi_1 \Delta BPI_{t-1} + \beta_{0,1} \Delta Trade\_Exchange_{t,t-1} + \gamma_{0,1} \Delta Wikipedia_{t,t-1} + \delta_{0,1} \Delta CFSI_{t,t-1} \\ & + \theta_{0,1} \Delta Gold_{t,t-1} + \vartheta_{0,1} \Delta Crude\_oil_{t,t-1} + \mu_{0,1} \Delta BTCChina_{t,t-1} + \rho_{0,1} \Delta USD\_CNY_{t,t-1} \\ & + \varphi_{0,1} \Delta USD\_EUR_{t,t-1} + \omega_{0,1} \Delta Difficulty_{t,t-1} + \partial_{0,1} \Delta Total\_Bitcoins_{t,t-1} + e_t \end{aligned}$$

Every variable represents its logarithmic value, with 'ΔBPI_t' the log difference of the Bitcoin Price Index. 'α' represents the constant term and 'e_t' the error term. The trade-exchange ratio and its lag is included in '$\beta_{0,1}\Delta Trade\_Exchange_{t,t-1}$', which should be read as '$\beta_0 \Delta Trade\_Exchange_t$' + '$\beta_1 \Delta Trade\_Exchange_{t-1}$'. Wikipedia search queries for the term 'Bitcoin' are represented by '$\gamma_{0,1}\Delta Wikipedia_{t,t-1}$' and '$\delta_{0,1}\Delta CFSI_{t,t-1}$' is the representation of the Cleveland Financial Stress Index. The gold price per troy ounce and the Brent crude oil price are represented by respectively '$\theta_{0,1}\Delta Gold_{t,t-1}$' and '$\vartheta_{0,1}\Delta Crude\_oil_{t,t-1}$'. The trading volume of the Bitcoin exchange market BTCC is incorporated through '$\mu_{0,1}\Delta BTCChina_{t,t-1}$'. The two exchange rates in our model are represented by '$\rho_{0,1}\Delta USD\_CNY_{t-,t-1}$' and '$\varphi_{0,1}\Delta USD\_EUR_{t,t-1}$'. Finally, the difficulty of mining and the total amount of Bitcoins in circulation are represented by '$\omega_{0,1}\Delta Difficulty_{t,t-1}$' and '$\partial_{0,1}\Delta Total\_Bitcoins_{t,t-1}$'.

Cointegration tests gave inconclusive results, making it useless to implement an error correction model (ECM). Additionally, Granger causality was tested for several variables, as the dependent variable (*BPI*) might also have an effect on the independent variable. Kristoufek (2013) found such two-way relationship with both Wikipedia and Google Trends search queries. However, this extended dataset denies the presence of such behaviour. Furthermore, from an economic point of view, Bitcoin is not mature enough to trigger other economic variables in our model.

With the absence of any form of two-sided Granger causality, the implementation of a VAR-model was not useful. Finally, it should be mentioned that taking first differences has the consequence of losing the ability to test for long-term effects. As Bitcoin reacts very short-term in its premature state, this loss is believed to be of small importance. In the following section, we will describe our empirical results.

5. Empirical results

5.1. Ordinary Least Squares model

Table 1: OLS regression results using log differences, except for CFSI

Variable	Coefficient	p-value	Std. errors
const	0,0043	0,1183	0,0028
ld_Trade_Exchange	0,0034	0,2596	0,0030
ld_Wikipedia	0,0004	0,9219	0,0038
d_CFSI	−0,0014	0,9667	0,0339
ld_Gold	0,2273	0,2349	0,1913
ld_Crude_oil	−0,1794	0,1044	0,1104
ld_BTCChina	−0,0011	0,6356	0,0022
ld_USD_EUR	−0,2095	0,1899	0,1598
ld_USD_CNY	**−0,1033****	0,0241	0,0457
ld_Difficulty	**0,0617***	0,0636	0,0332
ld_Total_Bitcoins	−5,5458	0,2826	5,5159
R^2	0,0082		

**** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level.*

Table 1 shows the results of an OLS regression using the log differences (excluding CFSI, for which we take the first differences). The USD/CNY exchange rate (*ld_USD_CNY*) shows signs of significance at the 5% level. Using a linear model, it is the only explanatory variable that has a significant effect on the Bitcoin Price Index. The significance of this variable can be explained by the overwhelming dominance of the Chinese market in Bitcoin transactions. In our fifth hypothesis we have discussed the importance of the Chinese Yuan as the most traded currency against Bitcoin. The significant negative coefficient implies that an appreciation of the USD against the CNY triggers a Bitcoin price drop. This confirms our hypothesis that a depreciation of the USD against the CNY has a positive impact on the bitcoin price. The lack of significant variables in this model is a motivation to extend our research by adding lags of each variable and constructing an ADL model.

5.2. Autoregressive Distributed Lag model

Table 2: ADL models tested from the 1st of July 2011 till the 31st of December 2015.

	Coefficients per equation							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	0,0035	0,0012	0,0048	0,0036	0,0020	0,0020	0,0036	0,0021
ld_Trade_Exchange	0,0029	0,0029	0,0030	0,0029	0,0030	0,0030	0,0030	0,0031
ld_Trade_Exchange_1	−0,0007	−0,0007	−0,0004	−0,0007	−0,0004	−0,0004	−0,0007	−0,0004
ld_Wikipedia	−0,0009	−0,0009	−0,0009	−0,0008	−0,0009	−0,0009	−0,0008	−0,0009
ld_Wikipedia_1	−0,0063	−0,0063	−0,0064	−0,0062	−0,0065	−0,0064	−0,0066	−0,0068
d_CFSI	0,0119	0,0117	0,0100	0,0111	0,0094	0,0092	0,0136	0,0111
d_CFSI_1	−0,0190	−0,0194	−0,0168	−0,0179	−0,0171	−0,0168	−0,0200	−0,0181
ld_Gold	0,2386	0,2291	0,2356	0,2376	0,2193	0,2190	0,2259	0,2066
ld_Gold_1	0,1024	0,1012	0,0991	0,1023	0,1013	0,1015	0,0750	0,0742
ld_Crude_oil	**−0,2353****	**−0,2391****	**−0,2290****	**−0,2307****	**−0,2335****	**−0,2316****	-	-
ld_Crude_oil_1	0,1780	0,1750	0,1766	0,1779	0,1732	0,1731	-	-
ld_BTCChina	−0,0022	−0,0022	−0,0023	−0,0022	−0,0023	−0,0023	−0,0023	−0,0023
ld_BTCChina_1	−0,0029	−0,0029	−0,0028	−0,0028	−0,0028	−0,0028	−0,0027	−0,0027
ld_USD_EUR	−0,1805	−0,1823	−0,1846	−0,1848	−0,1873	−0,1889	−0,1867	−0,1933
ld_USD_EUR_1	0,0806	0,0776	0,0762	0,0715	0,0708	0,0673	0,0711	0,0615
ld_USD_CNY	**−0,1145****	**−0,1172****	−0,0419	-	−0,0424	-	**−0,1171****	−0,0449
ld_USD_CNY_1	**−0,1163****	**−0,1199****	**−0,0561*****	-	**−0,0554*****	-	**−0,1028****	**−0,0444****
ld_Difficulty	**0,0640***	**0,0666****	-	**0,0569***	-	-	**0,0641***	-
ld_Difficulty_1	0,0542	0,05791	-	0,0468	-	-	0,0520	-
ld_Total_Bitcoins	−8,3671	-	−15,5295	−9,4891	-	-	−8,9670	-
ld_Total_Bitcoins_1	3,7125	-	9,9506	4,7589	-	-	4,2328	-
ld_BPI_1	0,0348	0,0356	0,0363	0,0349	0,0375	0,0375	0,0342	0,0369
R^2	0,0157	0,0151	0,0126	0,0150	0,0116	0,0115	0,0133	0,0093

**** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level. "-" indicates the absence of a variable in the respective model.*

Table 2 shows the results of an ADL model using one lag of each variable. There were a total of eight regressions conducted, the first including all variables and seven variants with different variables omitted from the model. By performing multiple regressions we control for variables that could absorb most of the explanatory power or that show signs of multicollinearity. The variables omitted in the different regressions are *ld_Total_Bitcoins*, *ld_Difficulty*, *ld_Crude_oil*, *ld_USD_CNY* and combinations. The reasoning behind the first three is the multicollinearity issue that occurred in our original regression. The USD/CNY exchange rate was omitted twice because of its strong significance in each regression. By doing so, we make sure that this variable does not negate the other results. Using log differences allows us to interpret the coefficients as the percentage change in the Bitcoin price when the independent variable experiences a 1% increase.

The London Brent crude oil price (*ld_Crude_oil*) is significant in each regression. The coefficients are stable throughout the different regressions at around -0,23. This means that a 1% increase of the London Brent crude oil price per barrel results in a 0,23% decrease of the bitcoin price. Our results match the findings of Van Wijk (2013) who found a similar negative coefficient in his study. As stated before, the oil price has a major macro-economic influence and an increase means both consumers and industries relying on oil take a hit. This can lower the demand for bitcoins causing the price to drop. A negative coefficient confirms our fourth hypothesis in which we predicted a negative relationship between the oil price and the bitcoin price.

The USD/CNY exchange rate (*ld_USD_CNY*) shows significance in half of the regressions it was included, with the lagged variable showing significance in all of them so the effect is more present after a small delay. The coefficients vary between -0,05 and -0,12. A 1% increase in the USD/CNY exchange rate results in an appreciation of the USD against the CNY and a small decrease of 0,05% to 0,12% in the bitcoin price. The original OLS model with log differences also showed significance of the USD/CNY exchange rate. The consistency throughout both models where we found an inverse relationship is a strong confirmation of our fifth hypothesis in which we expected a depreciation of the USD against the CNY to have a positive influence on the bitcoin price. Furthermore, we ran two regressions without the exchange rate but there were no results worth mentioning.

The difficulty of mining (*ld_Difficulty*) is weakly significant at the 10% level except for one regression where the 5% significance level is reached. This is the case in the regression omitting *ld_Total_Bitcoins*, which can be explained by the high correlation between both variables. A 1% increase in mining difficulty results in a small increase (0,07%) of the bitcoin price. By implementing a higher difficulty, the computational effort required to verify a block of transactions increases and more resources have to be used. To compensate for that, miners will want a higher price for their bitcoins to avoid mining with a loss. The findings are logical but were not predicted in a hypothesis because *ld_Difficulty* was included as a control variable rather than an explanatory variable. When omitting *ld_Difficulty*, there is no change in significance for *ld_Total_Bitcoins*.

The trade-exchange ratio (*ld_Trade_Exchange*) was expected to have a negative effect on the bitcoin price, supported by the research done by Kristoufek (2015). He found a negative correlation to the ratio over the long term. We found no such relationship and argue that the insignificance for *ld_Trade_Exchange* could be due to the fact that Bitcoin has not yet been accepted as a mainstream payment option. Yermack (2013) criticized Bitcoin for its negligible use as a medium of exchange and Glaser et al. (2014) concluded that new users adopt Bitcoin with speculative investment intentions rather than using it as a method of payment. Both studies support our theory that Bitcoin requires more mainstream usage before the amount of real transactions can influence the price level compared to other, more mature variables.

The amount of Wikipedia search queries (*ld_Wikipedia*) does not show signs of significance, contrary to what was found by Kristoufek (2013). He discovered a bidirectional relationship between the price level and Wikipedia views and argues that the absence of underlying fundamentals plays an important role in this. These findings were confirmed in his later research in which he found a long-term relationship and discovered the role of investors' interest in the creation of bubbles (Kristoufek, 2015). The variable could have lost its significance because the search queries increase with both good and bad news. While good news could result in a higher demand for bitcoins, bad news negates this effect with a decrease in demand. These differences cancel each other out and result in high Wikipedia search queries with no significant influence on the bitcoin price.

The trading volume on BTCC (*ld_BTCChina*) was expected to have a positive effect on the bitcoin price but appears to have no significance in our ADL model. Kristoufek (2015) found a connection between the Chinese volume and the bitcoin price in USD. However, when controlling for the American Bitcoin trading volume this relationship disappeared due to the strong correlation between both market volumes. Our results show no relationship even without controlling for the American volume.

The CFSI (*d_CFSI*) is the only variable without a log transformation due to its low range of possible values, ruling out any issues regarding the order of magnitude. It is also the only variable in the model that can reach negative values, making it impossible to perform a log transformation. Because we are using the first differences and not the log differences, the interpretation varies from other variables in the model. When the stress index increases with one unit, our dependent variable (*ld_BPI*) changes with 100 times the found coefficient. While this increase would have little to no effect on most variables, it is actually a drastic change for the CFSI considering its two most extreme values in its existence have been -2,11 and +3,15. An increase in financial uncertainty was expected to provide a positive stimulation for the bitcoin price but no significant result can be found. Kristoufek (2015) was unable to find a strong and lasting relationship between the stress index and the bitcoin price either. An important observation made in his research is that the CFSI and the bitcoin price have one significant interconnection during the Cypriot crisis. The effect of this event could have been lost when adding other variables. This result could prove useful in both our event study and the evolution of price drivers throughout the years.

Gold (*ld_Gold*) has been confirmed to be a safe haven for the US Dollar by Reboredo (2013) before. If Bitcoin is the safe haven that many claim it is, there should be a positive relationship between both price trends. *ld_Gold* shows no such connection, from which we can conclude that Bitcoin is not necessarily a safe haven. Kristoufek (2015) found the same results and concluded that Bitcoin has no connection to the dynamics of gold.

We acknowledge the strongly changing Bitcoin environment and the impossibility of capturing the bitcoin price drivers in one model. While this ADL model shows promising results and confirms some of our predictions, it is important that we do not neglect the impact of events on developing cryptocurrencies. In the next section we will perform an event study to select the events that have had a significant impact on the bitcoin price movement and control for them in the following models.

6. Event Study

6.1. Methodology

To properly measure the event-driven impact on the Bitcoin price, a separate event study is an absolute necessity. Event studies in the past have focused on stock price movements, hence Bitcoin is interpreted as a security in this section of our paper. MacKinlay (1997) argues that the abnormal return of a security around a specific event, can be interpreted as the event's impact on the stock price. The normal return is the calculated expected return based on historical returns. An actual return that differs significantly from that normal return, is proof of an event-driven impact. MacKinlay uses the following formula, with *i* representing the firm and *t* representing the event date:

$$AR_{it} = R_{it} - E(R_{it} \mid X_t)$$

With AR_{it} the abnormal return, R_{it} the actual return and $E(R_{it} \mid X_t)$ the normal return for time *t*. X_t is the conditioning information for normal performance. This theory can be divided into two applications: the constant mean return model and the market model. The latter is chosen because it removes the portion of the return related to the market behaviour, resulting in more accurate event effects. The market model bases its normal return on a market index:

$$E[R_{it} \mid X_i] = \alpha_i + \beta_i R_{mt}$$

With X_t the market return R_{mt}. The return of the MSCI World Index represents the market return. This leaves us to decide the length of the estimation window and the event window. The estimation window represents the historical period of time in which the normal, expected return is calculated. Based on previous studies, our estimation window contains 120 days. The event window is the period of time in which the abnormal returns, in comparison with the normal returns, are calculated. The event itself is in the middle of the event window. Previous research on stock price abnormality due to events, mostly took an event window of 31 trading days, with 15 days before and after the event. As Bitcoin reacts very short-term to specific events, we take an event window of only five days, with two days before and after the event. Leaving out data of the Bitcoin price over the weekend was avoided by interpolating the MSCI World Index, which only has data of five days a week.

According to MacKinlay the specific impact of an event can only be correctly measured if the event window does not contain any other related events. Even with the narrow event window, a lot of important events had to be left out for this reason[30]. Finally, a total of 26 bitcoin-related events were investigated.

[30] To give an example: on the 30th of October 2014, BTCC announced it will start accepting direct deposits from bank accounts. This means that all customers who have Chinese bank accounts will be able to make direct deposits through ATM transfers or online banking. News that was highly important for Bitcoin in China (Davis, O., Brown, M, 2015). However, a day later Bitcoin was featured on the front page of The Economist. The article especially praised the Blockhain technology (The Economist, 2015).

These events were chosen based on price movement significance. Every event was not only the single important event that took place in the event window, we also see a price shock of at least 5% during that 5-day period. This leaves out important events that did not cause any notable price movement. The investigated bitcoin-related events can be divided into four different groups:

- 6 technical events: issues with exchange markets due to hacks or other technical problems.
- 4 news events: media coverage on bitcoin that got notable attention.
- 6 company events: launch of new bitcoin companies or bitcoin acceptance by huge firms.
- 10 jurisdictional events: important regulatory announcements and court decisions.

Aside from these events, the impact of both the Cypriot and the Greek crisis was measured. These macro-economic events are closely related to Bitcoin, as the citizens had to look for alternatives to their home currency. For this separate event study, an event window of 21 days was taken. This is motivated through the fact that the impact is not as short-term, as Bitcoin was not the only alternative and hence was not considered at first. In the event window of 21 days, no other bitcoin-related event took place.

The purpose of this event study is to not only measure the significant impact of these events, but to also incorporate those significant events into our multivariate regression through dummy variables. This allows us to control for these unusual situations and leads to more accurate estimations regarding the general impact of the discussed variables.

For an event to have a significant impact, the t-value of its abnormal return during the event window has to be greater than 1.96, considering a 95% confidentiality. The market model measures this abnormal return through the following formula:

$$AR_{it} = R_{it} - \alpha_i - \beta_i R_{it}$$

With AR_{it} representing the residual of the normal, expected return. Conclusions on this abnormal return unfortunately only apply to one event on one specific point of time. In order to measure the overall significance across events and time, these abnormal returns must be aggregated. Aggregation over time leads to conclusions on one specific event, while aggregation across events and time leads to general indications on the event-driven impact. Accumulation of the abnormal returns gives us the total impact of the event on the Bitcoin price. In order to test the significance of the price movement, the t-value is calculated as follow:

$$t = \frac{CAR_i(t_1, t_2)}{\sqrt{(t_2 - t_1 + 1)\sigma_{\varepsilon_i}^2}}$$

6.2. Empirical results

The historical variance of the estimation window is multiplied by the number of days in the event window minus one. If an event has a t-value greater than 1,96, we are 95% confident that the event had a significant impact on the fluctuating Bitcoin price. Annexes 9, 10 and 11 present the t-values of each event separately. A total of eight events showed significance through this test:

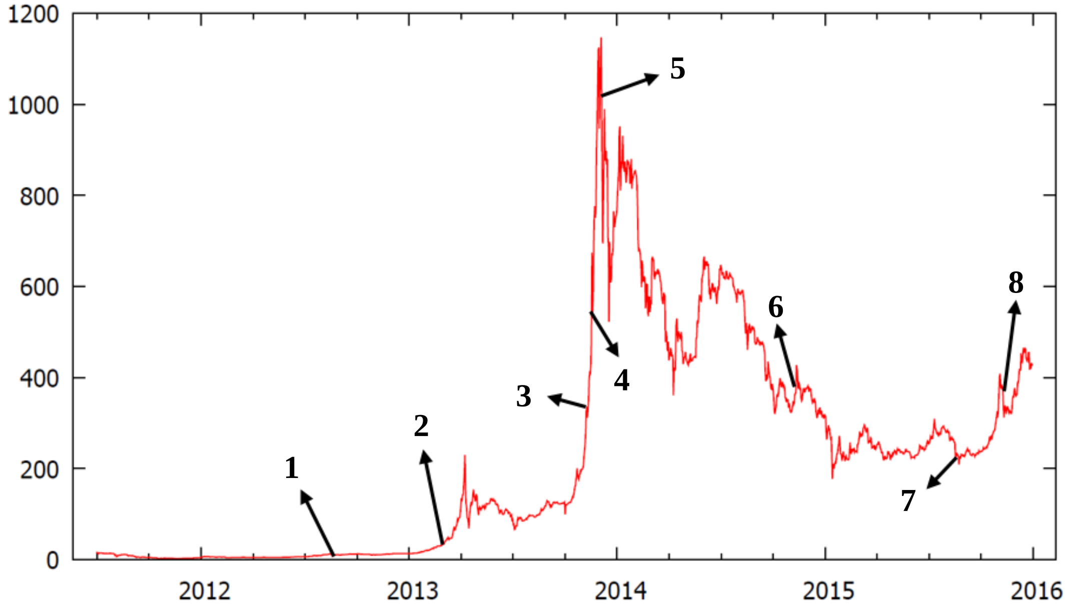


Figure 7: Events with a significant impact on the Bitcoin price.

Event 1: 17th of August 2012. Trendon T. Shavers shut down the Bitcoin Savings & Trust. It was a fund, in which bitcoins were invested, that promised high returns to its investors. On the day of the shutdown, the investment trust contained little more than 5,6 million USD, representing approximately 500.000 bitcoins at the time. Later, the SEC charged Shavers for running a Bitcoin ponzi scheme (Jeffries, A., 2012). The Bitcoin price tumbled with 14,22% at the day of the announcement.

Event 2: 16th of March 2013. The Cypriot crisis started to erupt. In June of 2012, Cyprus asked for financial help in the Eurozone. From that moment on, numerous discussions were held to look for a solution. On the 16th of March, Eurozone finance ministers and the IMF agreed on a 10 billion EUR bailout deal for Cyprus, the fifth Eurozone member to be saved from bankruptcy. As deposits of traditional banks no longer seemed safe in times of crisis, digital currencies were believed to be a safe haven. That believe rose significantly, causing the bitcoin price to move upwards as more people embraced the digital currency (Farrell, M., 2013). Ten days later, the hike of the Bitcoin price reached 67,02%.

Event 3: 10th of November 2013. Subway started accepting Bitcoin. Speculation began on the 8th of November on the social platform Reddit. On the 10th, proof was added. This was the first announcement of a major food company that started accepting Bitcoin (Shubber, K., 2013). Two days after the announcement, the price had already risen by 12%.

Event 4: 20th of November 2013. The People's Bank of China (PBOC), China's central bank, approved Bitcoin. Director Mr. Yi said that it is impossible for the Central Bank not to recognize Bitcoin. An important day for Bitcoin in China (Century, A., 2013). A day after this press release, the price of the digital currency increased with 21,51%.

Event 5: 5th of December 2013. Financial Institutions are forbidden to use Bitcoin by the Chinese government. After the announcement on the 20th of November, Bitcoin trading volumes boomed in China. With this act, the Chinese government wanted to protect the home currency, the Chinese Yuan, as it wanted financial stability. This caused the bitcoin price to plummet (Riley, C., Dayu, Z., 2013). One day later, bitcoin's price fell by almost 20%.

Event 6: 11th of November 2014. Microsoft announced that it will start accepting Bitcoin (Smith, A., 2014). As Microsoft is one of the world's largest companies, this message was of utter importance for Bitcoin awareness in the USA and worldwide. The bitcoin price reaches a short peak of 14,10%.

Event 7: 18th of August 2015. Bitfinex suffered a 'flash crash'. Bitfinex, one of the most prominent Bitcoin exchange markets, offers margin trading, which allows traders to ramp up their leverage. Now, in a traditional setting, those trades have position limits. Should the position in question fall below the bottom limit, it will generate a sell order, and traders will get one of the most distressing things: the margin call. In Bitcoin trading, the margin call is executed automatically (Caffyn, G., 2015). This caused the bitcoin price to fall by 16,93%.

Event 8: 10th of November 2015. An article in The Financial Times stated that the recent bubble of the bitcoin price was mainly caused by a Russian ponzi scheme. In the article, writer Dan McCrum had lots of arguments against the digital currency and even called Bitcoin a pyramid scheme, comparing it to the tulip bubble in 17th century (2015). The negative article got a lot of attention, leading the bitcoin price to fall by more than 17% a day later.

These eight events will be incorporated as a dummy variable in our multivariate regression. A further investigation of the specific impact of the events can be useful, given the absence of event studies on the bitcoin price. Dividing the 26 Bitcoin-related events into good news events and bad news events gives us an indication of possible differences in behaviour[31].

Aggregating these specific types of events can be done by simply using the average abnormal returns over the selected events. Table 3 shows our results for the investigated event:

[31] Nine good news events and 17 bad news events

Market Model						
Event day	**Good news (9)**			**Bad news (17)**		
	AR	t-statistic	CAR	AR	t-statistic	CAR
-2	7,72%	5,046	7,72%	-0,90%	-0,555	-0,90%
-1	-1,28%	-0,836	6,44%	0,61%	0,376	-0,29%
0	2,06%	1,349	8,50%	-7,24%	-4,462	-7,53%
1	8,21%	5,371	16,71%	-8,72%	-5,374	-16,25%
2	0,01%	0,008	16,73%	-1,97%	-1,211	-18,22%

Table 3: Statistical results of the average abnormal results of good and bad bitcoin-related events

At the announcement day, bad news seems to have a more direct impact than good news on the price of bitcoin. This is in line with the findings of Bouoiyour and Selmi (2015), whose research proved higher downward volatility of the bitcoin price. Confirmation of the sceptical behaviour of Bitcoin users clearly leads to an immediate selling attitude, with an overall value loss of 7,4%. That scepticism can also be seen in the effect of good news on the price of the digital currency. The announcement does not lead to direct buying behaviour, probably because investors are still waiting for more sources to lift their trust on the news. We say investors, as the group of true believers are in it for the long run and do not overreact on a single news fact. However, a jump of 8,21% is noted the day after the announcement, which implicates signs of short-term belief in the cryptocurrency.

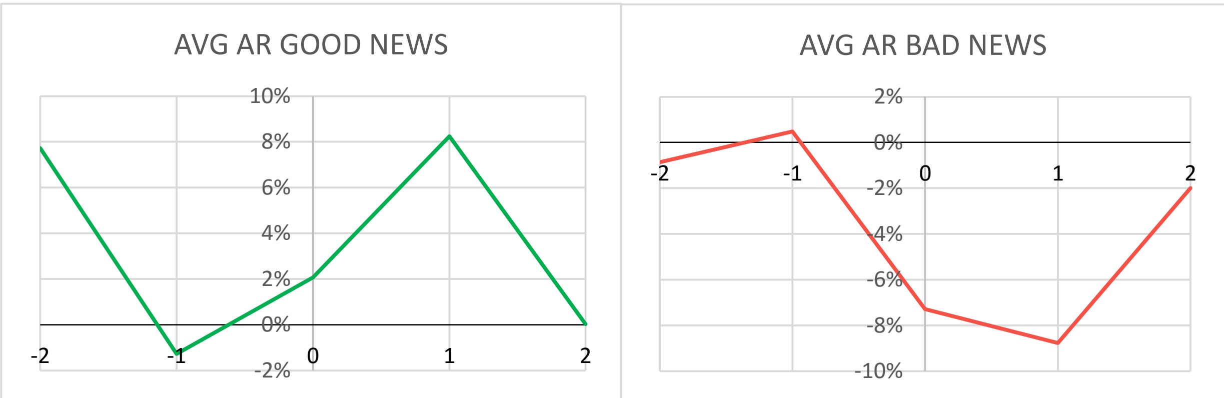


Figure 8: Average abnormal returns of the Bitcoin price around both good news and bad news.

The patterns shown in figure 8 confirm our statement on short-term reactions, which was the main motivation for choosing narrow event windows. It should be mentioned that these returns are abnormal returns compared to the market returns. Even with fluctuating financial market returns, bitcoin price behaviour clearly outperforms the market around these events. News about Bitcoin is mostly sudden and leads to an immediate reaction by its owners, especially in case of bad news.

Two days before good news is made public, an average abnormal return of almost 8% is noted. This can either indicate rumour behaviour or influence from a previous event. Because this weakens our results, some events will be dropped out. At first, we exclude all the selected events in November and December of 2013, when the major peak took place. This is motivated by the fact that the sequence of events was very short term and was characterized by huge price changes. Two events of both good and bad nature were dropped out, leaving us with 22 bitcoin-related events.

Market Model						
Event day	**Good news (7)**			**Bad news (15)**		
	AR	t-statistic	CAR	AR	t-statistic	CAR
-2	2,24%	1,465	2,24%	-1,01%	-0,623	-1,01%
-1	1,07%	0,701	3,31%	1,76%	1,087	0,75%
0	3,31%	2,164	6,62%	-7,00%	-4,313	-6,25%
1	6,86%	4,485	13,48%	-6,80%	-4,192	-13,05%
2	-1,42%	-0,928	12,06%	-3,09%	-1,905	-16,14%

Table 4: Statistical results of the impact of 22 bitcoin-related events on its price.

The results clearly indicate an immediate reaction to these important bitcoin-related events, with significant abnormal returns on the announcement day and the day after that. Additionally, there is not any significant influence of a previous event. We can say that the events within the price peak at the end of 2013, are too closely related for an event study like this.

When an event window of 21 days is taken, which is also used for the two macro-economic events, only nine events remain. This is another indication that Bitcoin events occur on a short-term basis, leaving no patience for its price behaviour.

Due to the small amount of events, no broad conclusions can be made on the general event-driven impact. We see that the main price movement concentrates itself within the five day event window. This can be an indication that an event window of five days indeed captures most of the impact of an event on the bitcoin price. Good news events may be influenced by rumour behaviour, but with only events investigated, that statement is not reliable. When looking at the significance of events itself, only one bad news event shows a t-value higher than 1,96. Causing a rapid, short-term price fluctuation, the bitcoin price seems to stabilize after two days.

Market Model						
Event day	**Good news (2)**			**Bad news (7)**		
	AR	t-statistic	CAR	AR	t-statistic	CAR
-10	-1,74%	-1,1390	-1,74%	0,39%	0,237	0,39%
-9	1,86%	1,2167	0,12%	0,22%	0,137	0,61%
-8	4,12%	2,6949	4,24%	-1,29%	-0,786	-0,67%
-7	-0,40%	-0,2634	3,84%	1,96%	1,201	1,29%
-6	4,41%	2,8821	8,25%	0,53%	0,325	1,82%
-5	1,47%	0,9605	9,72%	-1,49%	-0,913	0,33%
-4	0,25%	0,1601	9,97%	1,09%	0,664	1,41%
-3	0,99%	0,6440	10,95%	-2,76%	-1,689	-1,35%
-2	3,62%	2,3633	14,57%	-0,37%	-0,227	-1,72%
-1	0,93%	0,6085	15,50%	4,15%	2,541	2,43%
0	6,21%	4,0603	21,71%	-7,19%	-4,398	-4,76%
1	13,88%	9,0673	35,59%	-7,63%	-4,668	-12,39%
2	-1,30%	-0,8475	34,29%	-6,52%	-3,988	-18,91%
3	-1,92%	-1,2560	32,37%	-1,63%	-0,998	-20,54%
4	-1,85%	-1,2079	30,52%	0,64%	0,394	-19,90%
5	2,26%	1,4796	32,78%	0,79%	0,481	-19,11%
6	3,81%	2,4892	36,59%	-3,20%	-1,957	-22,31%
7	-3,20%	-2,0928	33,39%	-4,13%	-2,527	-26,44%
8	1,80%	1,1745	35,19%	6,46%	3,952	-19,98%
9	-0,14%	-0,0930	35,05%	4,03%	2,463	-15,96%
10	-0,71%	-0,4637	34,34%	1,49%	0,911	-14,47%

Table 5: Statistical results of the impact of 9 bitcoin-related events on its price.

Obviously, it seems difficult to capture the specific event-driven impact on the bitcoin price. This is mainly due to overlapping events and very short-term price reactions. The latter is the only clear conclusion that can be made on the impact of Bitcoin-related events on its price. A different, intraday approach seems more reasonable to investigate that short-term behaviour.

Looking at the two macro-economic events leads to different conclusions. The crises of both Cyprus in 2013 and Greece in 2015 were in fact good news for the cryptocurrency. The financial system showed signs of incapability as citizens sought alternatives to get their money out of the country. Rising speculation on the exit of both countries out of the European Union due to massive indebtedness drove people to this panic reaction.

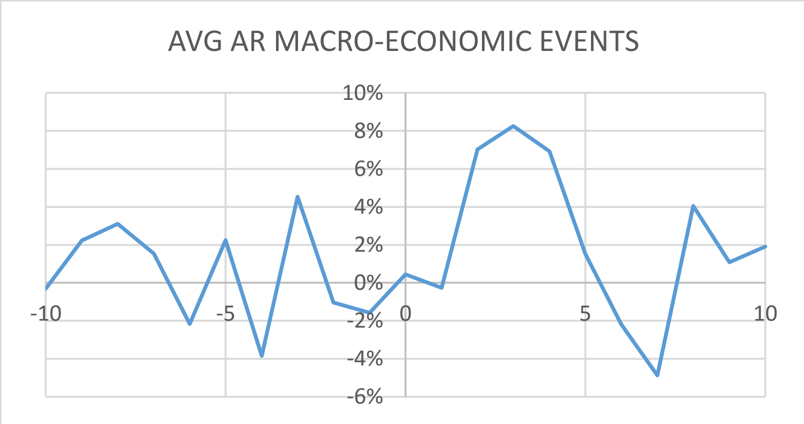


Figure 9: Pattern of average abnormal returns around a macro-economic event.

Figure 9 shows that the announcement did not affect Bitcoin usage at first but only after two days. The period of rapid price rise only lasts three days, which can indicate short-term speculation, with investors opting out with the earned returns. No conclusion can be drawn for the days before the announcement. This pattern confirms our thoughts on a lagged impact, as people hesitated to use Bitcoin as an alternative to the Euro.

Market Model						
Event day	**Cypriot crisis**			**Greek crisis**		
	AR	t-statistic	CAR	AR	t-statistic	CAR
-10	0,52%	0,204	0,52%	-1,15%	-0,499	-1,15%
-9	1,16%	0,458	1,68%	3,30%	1,430	2,15%
-8	3,90%	1,535	5,59%	2,30%	0,999	4,45%
-7	4,85%	1,908	10,44%	-1,79%	-0,775	2,66%
-6	-3,01%	-1,183	7,43%	-1,30%	-0,566	1,36%
-5	4,03%	1,583	11,45%	0,45%	0,197	1,81%
-4	-9,49%	-3,735	1,96%	1,81%	0,784	3,62%
-3	5,04%	1,981	7,00%	4,05%	1,756	7,67%
-2	-1,10%	-0,434	5,89%	-0,98%	-0,427	6,68%
-1	-1,78%	-0,699	4,12%	-1,36%	-0,591	5,32%
0	-0,74%	-0,291	3,38%	1,64%	0,711	6,96%
1	0,00%	0,002	3,38%	-0,53%	-0,228	6,43%
2	8,01%	3,153	11,40%	6,02%	2,612	12,45%
3	13,75%	5,410	25,15%	2,76%	1,198	15,22%
4	7,56%	2,973	32,71%	6,28%	2,725	21,50%
5	9,18%	3,613	41,89%	-6,15%	-2,669	15,35%
6	-2,78%	-1,095	39,11%	-1,57%	-0,681	13,78%
7	-8,87%	-3,490	30,23%	-0,86%	-0,371	12,92%
8	10,13%	3,983	40,36%	-2,05%	-0,889	10,87%
9	1,95%	0,768	42,31%	0,21%	0,091	11,08%
10	5,26%	2,068	47,57%	-1,45%	-0,631	9,63%

Table 6: Statistical results of abnormal results of the crisis in Cyprus (2013) and Greece (2015).

When the results of these two events are separated, the effect of the Cypriot crisis is clearly bigger than the effect of the Greek crisis. The latter only has a short-term upwards reaction, with a total hike of 9,63% at the end of the event window, just over 3% compared to the announcement day. The difference with the Cypriot crisis is huge. Apart from the short-term peak, the bitcoin price keeps rising at the end of the event window. Compared to the announcement day, the price increased with 44,19%. This supports the findings of Kristoufek (2015), who found a significant correlation between the bitcoin price and the Cleveland Financial Stress Index during the Cypriot crisis. The difference in change of Bitcoin usage between these two periods can be explained by the lower awareness of the digital currency in 2013. Due to the proposed alternatives, many people became aware of the existence of Bitcoin. By the time the Greek crisis emerged, Bitcoin knowledge was already widespread. Either way, both events confirm our presumption of the upwards price reaction of bitcoin.

7. Evolution of price drivers

During its years of existence, Bitcoin awareness grew at a rather slow pace. By the time the great peak took place in 2013, the digital currency had already circulated for more than three years. Subsequently, a general view on the price drivers of bitcoin may not lead to the most accurate results. An interesting approach can be to divide the investigated time period in a year-to-year dataset. The influencing factors at the end of 2011 might have lost that importance by 2015 for example. To conclude our research, we separate our ADL-model in five periods, each representing a certain year. Since our dataset only starts as from the first of July 2011, the first period only contains six months.

7.1. 2011

Table 7: ADL models tested from the 1st of July 2011 till the 31st of December 2011

	Coefficients per equation			
Variable	(1)	(2)	(3)	(4)
const	0,0249	−0,0031	0,0308	0,0259
ld_Trade_Exchange	0,0094	0,0093	0,0095	0,0092
ld_Trade_Exchange_1	−0,0115	−0,0115	−0,0113	−0,0116
ld_Wikipedia	−0,0144	−0,0140	−0,0147	−0,0138
ld_Wikipedia_1	0,0086	0,0077	0,0094	0,0079
d_CFSI	0,1154	0,1198	0,1052	0,1151
d_CFSI_1	−0,3809	−0,3969	−0,3598	−0,3490
ld_Gold	**0,8799***	0,7904	**0,8786***	0,8537
ld_Gold_1	**0,8277****	**0,8167****	**0,8673****	**0,7946****
ld_Crude_oil	−0,6649	−0,6519	−0,6870	-
ld_Crude_oil_1	0,5958	0,5955	0,6241	-
ld_BTCChina	**−0,0172****	**−0,0179****	**−0,0165****	**−0,0176****
ld_BTCChina_1	**−0,0320*****	**−0,0326*****	**−0,0314*****	**−0,0311*****
ld_USD_EUR	−1,2860	−1,3372	−1,2711	−1,5459
ld_USD_EUR_1	−0,6011	−0,6978	−0,5303	−0,5636
ld_USD_CNY	−0,4381	−0,0175	−0,5789	0,7559
ld_USD_CNY_1	4,1274	4,0003	3,9869	4,1790
ld_Difficulty	−0,1046	−0,1176	-	−0,0835
ld_Difficulty_1	−0,1629	−0,1767	-	−0,2046
ld_Total_Bitcoins	−35,8179	-	−36,4596	−31,9434
ld_Total_Bitcoins_1	6,2079	-	0,6895	1,4155
ld_BPI_1	0,0225	0,0261	0,0186	0,0243

**** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level. "-" indicates the absence of a variable in the respective model*

First, the gold price (*ld_Gold*) and its lag (*ld_Gold_1*) seem to have had a significant correlation with the Bitcoin price in the second half of 2011. This actually confirms the findings of Kristoufek (2015). His results indicate a minor correlation in general, except for some short periods of time. One of those periods was around September 2011, when the gold price increased rapidly in a short time span. Since this model investigates the last 6 months of 2011, it is therefore no coincidence that the gold price shows significance. The relationship is positive, which confirms our fourth hypothesis. A 1% increase of the gold price the day before results in a 0,83% increase of the Bitcoin price. The effect of a similar movement of the gold price on the bitcoin price the same day is 0,88%.

Aside from the gold price, trading volumes on the Bitcoin exchange market BTCC also show significant correlation with the price of the digital currency. Figure 3 already showed a short peak in CNY exchange volumes in 2011, which could indicate temporary high activity in BTCC. However, the impact seems to be negative, with a 0,03% price decreases due to a 1% increase in trading volume the day before and a 0,02% price decrease due to a 1% increase in trading volume the same day.

The event dummy was not included because of the absence of significant events in that year. Accompanied with the fact that these results only reflect effects on six months of data, no further conclusions can be drawn.

7.2. 2012

Table 8: ADL models tested from the 1st of January 2012 till the 31st of December 2012

	Coefficients per equation				
Variable	(1)	(2)	(3)	(4)	(5)
const	0,0007	0,0030	0,0005	0,0007	0,0003
ld_Trade_Exchange	−0,0029	−0,0028	−0,0029	−0,0029	−0,0038
ld_Trade_Exchange_1	0,0041	0,0041	0,0041	0,0040	0,0026
ld_Wikipedia	0,0116	0,0118	0,0115	0,0116	0,0103
ld_Wikipedia_1	−0,0032	−0,0031	−0,0032	−0,0031	−0,0040
d_CFSI	−0,0433	−0,0430	−0,0448	−0,0439	−0,0641
d_CFSI_1	0,0918	0,0918	0,0917	0,0921	0,0801
ld_Gold	−0,0165	−0,0161	−0,0160	−0,0210	0,0331
ld_Gold_1	−0,3161	−0,3215	−0,3069	−0,3037	−0,2244
ld_Crude_oil	0,0323	0,0363	0,0303	-	0,0545
ld_Crude_oil_1	−0,0111	−0,0106	−0,0085	-	0,0585
ld_BTCChina	0,0012	0,0011	0,0011	0,0012	0,0016
ld_BTCChina_1	0,0019	0,0019	0,0019	0,0019	0,0019
ld_USD_EUR	−0,2021	−0,2050	−0,2112	−0,2060	−0,1420
ld_USD_EUR_1	−0,2647	−0,2589	−0,2508	−0,2641	−0,1685
ld_USD_CNY	**3,2358***	**3,2318***	**3,2257***	**3,2360***	**3,2155***
ld_USD_CNY_1	−1,1244	−1,1274	−1,1132	−1,0893	−1,1338
ld_Difficulty	−0,0003	0,0029	-	−0,0002	−0,0205
ld_Difficulty_1	0,0327	0,0343	-	0,0322	0,0128
ld_Total_Bitcoins	3,8193	-	3,3444	4,0612	4,6875
ld_Total_Bitcoins_1	−0,7558	-	0,0937	−0,9511	0,3927
ld_BPI_1	−0,0918	−0,0918	−0,0920	−0,0919	−0,0980
Event_Dummy	-	-	-	-	−0,0883

**** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level. "-" indicates the absence of a variable in the respective model.*

The year 2012 can be characterized as the year where the least explainable movement was found. Only the USD/CNY exchange rate (*ld_USD_CNY*) shows significance, however only at the 10% level. Coefficients stay positive, fluctuating around an upwards reaction of 3,23% of the Bitcoin price due to a 1% increase of the exchange rate. Kristoufek (2015) already pointed out that trading volumes were quite low that year, especially on the CNY market. Figure 3 confirms this statement, showing a leading role for the USD in Bitcoin exchange traffic. The price evolution of that year indicates a steady upward movement, from 5,27 USD on the 1st of January to 13,51 USD by the end of the year, with no big price shocks. The only shock that draws attention was included in the event dummy. The fact that the bitcoin price quickly recovered from its immediate plummet, explains the insignificant outcome of the event dummy in general.

7.3. 2013

Table 9: ADL models tested from the 1st of January 2013 till the 31st of December 2013

	Coefficients per equation					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
const	0,0231	**0,0080****	0,0161	0,0193	0,0278	0,0234
ld_Trade_Exchange	−0,0004	−0,0006	−0,0003	0,0002	−0,0001	-0,0005
ld_Trade_Exchange_1	0,0020	0,0016	0,0023	0,0013	0,0021	0,0019
ld_Wikipedia	0,0027	0,0028	0,0028	0,0031	0,0022	0,0022
ld_Wikipedia_1	0,0006	0,0007	0,0005	−0,0004	0,0000	-0,0002
d_CFSI	0,1752	0,1734	0,1722	0,1867	0,1716	0,1754
d_CFSI_1	−0,1423	−0,1444	−0,1337	−0,1506	−0,1391	-0,1396
ld_Gold	**0,5282***	**0,5336***	0,4852	0,440	**0,5360***	**0,5343***
ld_Gold_1	0,0609	0,0516	0,0463	−0,150	0,0830	0,0713
ld_Crude_oil	**−1,3815*****	**−1,3623*****	**−1,2783*****	-	**−1,3810*****	**-1,3931*****
ld_Crude_oil_1	0,1669	0,1640	0,1343	-	0,1775	0,1653
ld_BTCChina	−0,0020	−0,0022	−0,0025	−0,0022	−0,0014	-0,0018
ld_BTCChina_1	0,0019	0,0015	0,0015	0,0025	0,0021	0,0020
ld_USD_EUR	−0,0246	−0,0299	−0,0699	0,0200	−0,1089	-0,0354
ld_USD_EUR_1	**3,4418*****	**3,4347*****	**3,4233*****	**3,4930*****	**3,3636*****	**3,3830*****
ld_USD_CNY	−2,5653	−2,4690	−2,8853	−2,5671	0,0000	-2,5326
ld_USD_CNY_1	−4,7200	−4,7040	−4,8110	−5,1838	0,0000	-4,5962
ld_Difficulty	**0,0964***	**0,0854***	-	**0,0869***	−2,4964	0,0982
ld_Difficulty_1	0,0854	0,0781	-	0,0703	−4,7347	**0,0854***
ld_Total_Bitcoins	10,7931	-	−38,0017	5,9233	0,0929	7,2851
ld_Total_Bitcoins_1	−51,0857	-	23,5769	−36,1394	0,0784	-51,4706
ld_BPI_1	0,0958	0,0966	0,0978	0,0992	0,0899	0,0892
Event_dummy	-	-	-	-	**0,0177***	**-**
Event_dummy_2	-	-	-	-	**-**	0,0127

**** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level. "-" indicates the absence of a variable in the respective model.*

In 2013, more significant price effects occur. To begin with, hypothesis four is confirmed by a positive correlation with the gold price (*ld_Gold*) and a negative correlation with the London Brent crude oil price (*ld_Crude_oil*). However, when omitting the crude oil variable, gold loses its significance. This might indicate a general commodity influence, which can be added to the motivation for running a regression without the crude oil variable. The latter shows strong significance at all times, consistently pointing towards a negative relationship. As indicated earlier, Van Wijk (2013) found similar results. If all those variables are included, a 1% increase in the Brent crude oil price, results in a -1,38% decrease of the bitcoin price. The effect does not change much when explanatory variables are left out of the regression. The lag shows no significance in any of the above regressions.

Another variable that shows consistent significance is the lag of the USD/EUR exchange rate (*ld_USD_EUR_1*). 2013 was characterized by a notable depreciation of the Euro, mainly in the aftermath of the Cypriot crisis. The conducted event study already proved its short-term impact on the bitcoin price. In a sense, this means higher financial uncertainty and should be reflected in the Cleveland Financial Stress Index (*ld_CFSI*). However, given the fact that this index bases itself on the financial markets as a whole, specific impact of the Euro crisis might get lost. Given the fact that the USD appreciated against the Euro, a positive effect on the bitcoin price is not a surprise. Additionally, figure 3 still indicates a leading role for the USD in Bitcoin trading volume for most of 2013. If all explanatory variables are included, a 1% increase in the USD/EUR exchange rate drives the bitcoin price up by 3,44%.

Figure 3 also indicates a spectacular hike of Bitcoin trading volume in Chinese Yuan. This trend seems to follow the same pattern of the Bitcoin price peak at the end of 2013. Many argue that China was the main reason behind this tremendous upward movement (Southurst, J., 2013). However, there appears to be no significance in either the BTCC trading volume or the USD/CNY exchange rate. The explanation can lie in the fact that many of the other rising variables, such as the Wikipedia search queries for example, had a similar movement and may have absorbed that Chinese significance. On top of that, the hike did not last long, as the price already dropped with around 400 USD at the very end of 2013. Keep in mind that the motivation for the incorporation of the event dummy was to control for unusual periods of time in order to measure general price drivers.

The event dummy was separated into two variants. *Event_dummy* omitted the last three significant events in 2013 as part of the huge peak, which we indicated in our event study (ut supra). Small significance is found because the dummy only contains the 21-day long event window of the Cypriot crisis. *Event_dummy_2* contains all four significant events in 2013 but lacks any form of significance in this model. This can be explained by the fact that the last event was of bad nature, with a spectacular price drop as a consequence. This negative effect might have ruled out positive significance. As the event dummy only serves the purpose of control variable, this contrary effect holds no importance.

7.4. 2014

Table 10: ADL models tested from the 1st of January 2014 till the 31st of December 2014

Variable	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
Const	0,0003	−0,0026	0,0015	−0,0056	−0,0075
ld_Trade_Exchange	0,0032	0,0030	0,0026	0,0027	0,0039
ld_Trade_Exchange_1	**0,0079***	**0,0080***	**0,0082***	**0,0081***	**0,0083***
ld_Wikipedia	−0,0050	−0,0048	−0,0052	−0,0051	−0,0052
ld_Wikipedia_1	−0,0077	−0,0078	−0,0076	−0,0073	−0,0075
d_CFSI	−0,0620	−0,0628	−0,0634	−0,0660	−0,0656
d_CFSI_1	**0,0955***	0,0963	**0,0971***	**0,1009***	**0,1021***
ld_Gold	−0,4181	−0,4296	−0,3872	−0,3696	−0,4202
ld_Gold_1	0,0433	0,0427	0,0281	0,07880	0,0153
ld_Crude_oil	**0,7201****	**0,7124****	**0,7253****	-	**0,7013****
ld_Crude_oil_1	0,1235	0,1197	0,1065	-	0,1160
ld_BTCChina	−0,0005	−0,0005	−0,0007	−0,0003	−0,0014
ld_BTCChina_1	0,0066	0,0067	0,0067	0,0074	0,0058
ld_USD_EUR	0,3812	0,3941	0,3677	0,2590	0,4542
ld_USD_EUR_1	−0,2418	−0,2515	−0,1891	−0,2569	−0,2023
ld_USD_CNY	−1,0355	−1,0751	−1,1305	−1,0381	−1,0657
ld_USD_CNY_1	1,8055	1,8426	2,1247	1,9637	1,7465
ld_Difficulty	−0,0238	−0,0230	-	−0,0299	−0,0263
ld_Difficulty_1	0,0543	0,0574	-	0,0515	0,0578
ld_Total_Bitcoins	−23,3517	-	−32,7714	−12,6620	−10,2754
ld_Total_Bitcoins_1	14,0168	-	20,2868	20,1845	23,6193
ld_BPI_1	−0,0393	−0,0383	−0,0390	−0,0415	−0,0618
Event_dummy	-	-	-	-	**0,0494*****

**** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level. "-" indicates the absence of a variable in the respective model.*

In 2014, the lag of the trade-exchange ratio (*ld_Trade_Exchange_1*) shows minor significance. However, the effect is positive, which contradicts the assumption made in the first hypothesis. A 1% increase of the ratio, which indicates a decrease in real day-to-day Bitcoin transactions, results in an upward price movement of 0,01%.

Secondly, more financial uncertainty (*ld_CFSI_1*) has had a small but positive effect on the bitcoin price. A 1% augmentation of the CFSI, drove the price up by 0,10% a day later, all variables considered.

The most prominent price driver in 2014 was the change of the London Brent crude oil price. If the price per barrel went up with 1%, a 0,72% rise of the bitcoin price followed. This relationship is positive, denying our hypothesis. It should be mentioned that the spectacular dive of the crude oil price began in the second half of 2014, ending at 40 USD lower than the beginning of the year. On the other hand, bitcoin's price suffered a serious fall continuing the trend of late 2013. The price started at 770,44 USD and ended at 319,70 USD. Hence, both prices following the same negative pattern might have led to this positive significance, regardless of a tight connection. Finally, the one event included in the event dummy was highly significant.

7.5. 2015

Table 11: ADL models tested from the 1st of January 2015 till the 31st of December 2015

Variable	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
const	−0,0514	0,0010	−0,0528	−0,0515	−0,0477
ld_Trade_Exchange	0,0054	0,0051	0,0054	0,0051	0,0052
ld_Trade_Exchange_1	−0,0013	−0,0014	−0,0012	−0,0011	−0,0012
ld_Wikipedia	0,0018	0,0022	0,0015	0,0018	0,0021
ld_Wikipedia_1	−0,0132	−0,0128	−0,0132	−0,0136	−0,0130
d_CFSI	0,0076	0,0136	0,0059	0,0103	0,0130
d_CFSI_1	−0,0782	−0,0678	−0,0752	−0,0815	**−0,0848***
ld_Gold	−0,0282	−0,0675	−0,0495	−0,0936	−0,0007
ld_Gold_1	−0,2948	−0,2664	−0,3212	−0,2731	−0,2537
ld_Crude_oil	**−0,2235****	**−0,2245****	**−0,2240****	-	**−0,2257****
ld_Crude_oil_1	0,1277	0,1353	0,1346	-	0,1306
ld_BTCChina	0,0030	0,0021	0,0027	0,0030	0,0038
ld_BTCChina_1	−0,0067	−0,0069	−0,0067	−0,0062	−0,0056
ld_USD_EUR	−0,2460	−0,2416	−0,2470	−0,2330	−0,2499
ld_USD_EUR_1	−0,0611	−0,0684	−0,0603	−0,0615	−0,0668
ld_USD_CNY	−0,0787	−0,0914	−0,0457	−0,1033	−0,0843
ld_USD_CNY_1	0,0744	0,0861	**−0,0736****	0,0844	0,0706
ld_Difficulty	0,0297	0,0362	-	0,0501	0,0381
ld_Difficulty_1	−0,1295	−0,1297	-	−0,1279	−0,1252
ld_Total_Bitcoins	63,1212	-	70,9143	59,9703	54,1782
ld_Total_Bitcoins_1	139,7280	-	136,2610	143,4090	136,8430
ld_BPI_1	0,0333	0,0340	0,0324	0,0313	0,0154
Event_dummy	-	-	-	-	**−0,0235****

**** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level. "-" indicates the absence of a variable in the respective model.*

In 2015, the effect of the crude oil price on the bitcoin price stays significant, however in a negative way. Now, our hypothesis that both prices move in opposite ways, is confirmed. But given the fact that the effect has changed over time, the credibility of the variable having a viable impact drops. A 1% increase of the crude oil price has a 0,22% price decrease of Bitcoin as overall consequence in 2015. Again, the findings of Van Wijk (2013) are confirmed.

The lag of the CFSI (*d_CFSI*) only has significance when the dummy variable controls for the significant event in 2015. As Kristoufek (2015) found, this variable has almost no influence in general but only for short periods of time (ut supra). Additionally, the lag of the USD/CNY exchange rate (*ld_USD_CNY_1*) was only significant when the difficulty of mining and its lag were omitted.

At last, the event dummy, regardless of accounting for only one significant event, has a negative impact confirming the bad nature of the event.

8. Conclusion

Bitcoin's price volatility is an important issue that hinders the currency's potential growth by intimidating new users. The uncertainty and scepticism surrounding Bitcoin have a negative impact on its development and further evolution. In this research, we attempted to document the main drivers of the price movement in search of an explanation for the volatile trend. Furthermore, we analyzed the impact of events on the bitcoin price through an in-depth event study. These two components were then combined to analyze the year-to-year evolution of Bitcoin price drivers to find an answer to our research question whether the currency is moving towards stability or not. We decided to look further than financial factors and included variables of multiple domains because we believe that Bitcoin's unique structure can be influenced by a wide variety of factors. Based on previous research and our own predictions we established five hypotheses that were tested throughout this study.

In our main model, which tested all five hypotheses, we found significance for three variables. The London Brent crude oil price, USD/CNY exchange rate and the mining difficulty appear to have an effect on the bitcoin price level. The observed coefficients are in line with our expectations expressed in the hypotheses concerning the oil price and the Chinese market. Difficulty was not discussed in a hypothesis because it was included as a control variable, but shows weak signs of significance. The results highlight the classification problem of Bitcoin. Both an exchange rate and a commodity price influencing the bitcoin price confirms Selgin's (2015) classification of Bitcoin as synthetic commodity money. The USD/CNY significance also reflects the impact of China on bitcoin's price level.

Up to now, existing literature paid little to no attention to the impact of events on the price of the digital currency. Uncertainty makes Bitcoin very susceptible to both good and bad news events. Our event study shows significant abnormal returns on both the announcement day and the following day. These short-term price reactions are observed in a positive and negative sense which means investors react heavily to both good and bad news. Abnormal returns for bad news events have slightly higher values, indicating a bigger influence on the bitcoin price level than good news events. This can be explained by investors' general tendency to be more loss-averse. Furthermore we analysed the impact of two macro-economic events on the bitcoin price. Both the Cypriot and the Greek crisis triggered a bitcoin price increase as demand rose due to financial uncertainty.

To find an answer to our research question whether the evolution is heading towards stability, we tested the price drivers on a year-to-year basis while controlling for the significant events found in our event study. Five different time periods were analysed from which we can conclude that the bitcoin price is influenced by multiple different factors per year. This inconsistency is understandable from an economic point of view because Bitcoin is still relatively young. We expect stability to come when Bitcoin reaches maturity and becomes widely accepted as method of payment rather than speculative investment.

Although not all hypotheses were confirmed, most of our results are in line with the earlier findings of Ladislav Kristoufek (2013) (2015), who inspired us to research the bitcoin price drivers. Our main contribution to the existing literature is the proven impact of both Bitcoin-specific and macro-economic events on the bitcoin price. Improvements to this research are possible on multiple levels. While we believe the variables used reflect relevant domains, it is still possible to expand the amount of variables used. Furthermore, hypotheses such as the Bitcoin interest could show different results if more data would be available. Both Google Trends and Bing data were unable to be used which limited our research capability. Twitter hashtag data could also be useful to measure this online interest in Bitcoin. For our year-to-year analysis we applied the ADL model found earlier. A more in-depth analysis could consist of different models per year depending on the pitfalls found. To further expand our event study, we suggest analysing the impact of events using intraday data to filter out events that have had no significant impact on the price level. By using intraday data, it is possible to pinpoint the exact moment an event happened and the immediate reaction. Finally, a longer time period would be beneficial when investigating price drivers since more observations means more accurate results.

References

Allison, I. (2015, October 27). *BTCC chief Bobby Lee: Bitcoin is not anti-bank, it's pro-innovation*. Retrieved from International Business Times: http://www.ibtimes.co.uk/btcc-chief-bobby-lee-bitcoin-not-anti-bank-its-pro-innovation-1525964

Atems, B., Kapper, D., & Lam, E. (2015). Do exchange rates respond asymmetrically to shocks in the crude oil market? *Journal of Energy Economics (49)*, 227-238.

Barber, S., Boyen, X., Shi, E., & Uzun, E. (2012). Bitter to Better: How to make Bitcoin a better currency. In *Financial Cryptography and Data Security (7397)*, 399-414.

Blalock, H. M. (1963). Correlated independent variables: The problem of multicollinearity. *Social Forces*, *42*(2), 233-237.

Bornholdt, S., & Sneppen, K. (2014). Do Bitcoins make the world go round? On the dynamics of competing crypto-currencies. *arXiv preprint arXiv:1403.6378*.

Bouoiyour, J., & Selmi, R. (2015, July 13). *Bitcoin Price: Is it really that New Round of Valatility can be on way?* Retrieved from MPRA Wokring papers: http://mpra.ub.uni-muenchen.de/65580/

Bredin, D., Conlon, T., & Poti, V. (2015). Does gold glitter in the long-run? Gold as a hedge and safe haven across time and investment horizon. *International Review of Financial Analysis (41)*, 320-328.

Buchholz, M., Delaney, J., Warren, J., & Parker, J. (2012). Bits and Bets: Information, Price Volatility, and Demand for Bitcoin. *Economics, 312.*

Buterin, V. (2014, January 24). *Ethereum: A Next-Generation Cryptocurrency and Decentralized Application Platform*. Retrieved from Bitcoin Magazine: https://bitcoinmagazine.com/articles/ethereum-next-generation-cryptocurrency-decentralized-application-platform-1390528211

Caffyn, G. (2015, August 19). *Bitcoin Price Falls 14% Following Bitfinex 'Flash Crash'*. Retrieved from Coindesk: http://www.coindesk.com/bitcoin-price-falls-14-following-bitfinex-flash-crash/

Casey, M. J., & Vigna, P. (2015). *The Age of Cryptocurrency: How Bitcoin and Digital Money are Challenging the Global Economic Order.*

Cawrey, D. (2014, May 9). *What Are Bitcoin Nodes and Why Do We Need Them?* Retrieved from Coindesk.com: http://www.coindesk.com/bitcoin-nodes-need/

Century, A. (2013, November 22). *Bitcoin Gets a Cautious Nod From China's Central Bank*. Retrieved from The New York Times: http://sinosphere.blogs.nytimes.com/2013/11/22/bitcoin-gets-a-cautious-nod-from-chinas-central-bank/?_r=1&

Chow, V. K., Jiang, W., & Li, J. (2014, August 30). Does VIX Truly Measure Return Volatility? Available at SSRN 2489345.

Christensen, N. (2013, December 10). *2013: Year Of The Bitcoin*. Retrieved from Forbes: http://www.forbes.com/sites/kitconews/2013/12/10/2013-year-of-the-bitcoin/#10bb267e2295

Chu, J., Nadarajah, S., & Chan, S. (2015). Statistical Analysis of the Exchange Rate of Bitcoin. *PLoS ONE 10 (7)*.

Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2013). The economics of BitCoin price formation. *Applied Economics*, 1-17.

Coase, R. (1972). Durable goods monopolists. *Journal of Law and economics (15)*, 143-150.

Davis, O., Brown, M. (2015, November 4). *Bitcoin Rally: Digital Currency's Surge Driven By China, Speculators, The Blockchain (And Ponzi Schemers?)*. Retrieved from International Business

Times: http://www.ibtimes.com/bitcoin-rally-digital-currencys-surge-driven-china-speculators-blockchain-ponzi-2169480

Dowd, K., & Hutchinson, M. (2015). Bitcoin will bite the dust. *Cato Journal (35)*, 357-382.

Eyal, I., & Sirer, E. G. (2014). Majority is not enough: Bitcoin mining is vulnerable. *Financial Cryptograhy and Data Security*, 436-454.

Farrell, M. (2013, March 16). *Bitcoin prices surge post-Cyprus bailout*. Retrieved from CNN Money: http://money.cnn.com/2013/03/28/investing/bitcoin-cyprus/

FinCEN. (2013, March 18). Application of FinCEN's Regulations to Persons Administering, Exchanging, or Using Virtual Currencies.

Friedman, M., 1962. Should there be an independent monetary authority? In: Leland, B.Y. (Ed.), In Search of a Monetary Constitution. Harvard University Press, Cambridge, MA, pp. 219–243.

Gervais, A., Karame, G. O., Capkun, V., & Capkun, S. (2014). Is Bitcoin a Decentralized Currency? *IEEE Security & Privacy, Vol. 12 (3)*, 54-60.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M. (2014, April 15). Bitcoin - Asset or Currency? Revealing Users' Hidden Intentions.

Granger, C., & Engle, R. F. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. Econometrica vol. 55 No.2., 251-276.

Grinberg, R. (2011, December 9). Bitcoin: An Innovative Alternative Digital Currency.

Hileman, G. (2016, January 28). *State of Bitcoin and Blockchain 2016: Blockchain Hits Critical Mass*. Retrieved from Coindesk: http://www.coindesk.com/state-of-bitcoin-blockchain-2016/

IRS. (2014). General tax principles to transactions using virtual currency.

Jeffries, A. (2012, August 27). *Suspected multi-million dollar Bitcoin pyramid scheme shuts down, investors revolt*. Retrieved from van The Verge: http://www.theverge.com/2012/8/27/3271637/bitcoin-savings-trust-pyramid-scheme-shuts-down

Karame, G. O., Androulaki, E., & Capkun, S. (2012). Double-spending fast payments in bitcoin. *Proceedings of the 2012 ACM conference on Computer and communications security*, 906-917.

Kaskaloglu, K. (2014). Near zero Bitcoin transaction fees Cannot last forever.

Kelly, J. (2015, December 23). *Record highs predicted for bitcoin in 2016 as new money supply halves*. Retrieved from Reuters: http://www.reuters.com/article/us-global-markets-bitcoin-analysis-idUSKBN0U60GM20151223

KNOMAD. (2016). *Migration and Remittances Factbook 2016.* World Bank Group.

KPMG. (2016, March 9). The Pulse of Fintech, 2015 in Review. Retrieved from https://www.kpmg.com/CN/en/IssuesAndInsights/ArticlesPublications/Documents/pulse-of-fintech-2015-in-review.pdf

Kristoufek, L. (2013, December 4). Bitcoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific reports, 3.*

Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PloS one, 10*(4), e0123923.

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature, Vol. 35, No. 1*, 13-39.

Manamperi, N. (2015). A Comparative Analysis on US Financial Stress Indicators. *International Journal of Economics and Financial Issues Vol. 5 (2)*, 613-623.

Mbiti, I., & Weil, D. N. (2011). *Mobile banking: The impact of M-Pesa in Kenya* (No. w17129). National Bureau of Economic Research.

McCrum, D. (2015, November 10). *Bitcoin's place in the long history of pyramid schemes*. Retrieved from The Financial Times: http://www.ft.com/intl/cms/s/0/1877c388-8797-11e5-90de-f44762bf9896.html#axzz3zfsrncN7

Nakamoto, S. (2008, November 7). Bitcoin: A Peer-to-Peer Electronic Cash System.

Nazlioglu, S., Soytas, U., & Gupta, R. (2015). Oil prices and financial stress: A volatility spillover analysis. *Journal of Energy Policy (82)*, 278-288.

Pagliery, J. (2015, November 3). *Record $1 billion invested in Bitcoin firms so far*. Retrieved from CNN Money: http://money.cnn.com/2015/11/02/technology/bitcoin-1-billion-invested/

Palombizio, E., & Morris, L. (2012). Forecasting exchange rates using leading economic indicators. *Open Acces Scientific Reports, 1(8)*, 1-6.

Phillips, M. (2014, December 15). *Bitcoin is the worst investment of 2014*. Retrieved from Quartz: http://qz.com/312598/bitcoin-is-the-worst-investment-of-2014/

Reboredo, J. C. (2013). Is gold a safe haven or a hedge for the US dollar? implications for risk manegement. *Journal of Banking & Finance (37)*, 2665-2676.

Reid, F., & Harrigan, M. (2013). *An analysis of anonymity in the bitcoin system.* Springer New York.

Riley, C., Dayu, Z. (2013, December 5). *China cracks down on Bitcoin*. Retrieved from CNN Money: http://money.cnn.com/2013/12/05/investing/china-bitcoin/

Rosenfeld, M. (2011, November 17). *Analysis of Bitcoin Pooled Mining Reward Systems.* Retrieved from https://bitcoil.co.il/pool_analysis.pdf

Schollmeier, R. (2001, August). [16] A Definition of Peer-to-Peer Networking for the Classification of Peer-to-Peer Architectures and Applications. In *p2p* (p. 0101). IEEE.

Selgin, G. (2015). Synthetic commodity money. *Journal of Financial Stability (17)*, 92-99.

Shubber, K. (2013, November 12). *Bitcoin-accepting Subway sandwich shop discovered in the US*. Retrieved from Coindesk: http://www.coindesk.com/bitcoin-accepting-subway-sandwich-shop-discovered-us/

Skinner, C. (2015, December 22). *2015 Was the Year of the Blockchain*. Retrieved from Coindesk: http://www.coindesk.com/2015-year-of-blockchain/

Smith, A. (2014, December 11). *Microsoft begins accepting Bitcoin*. Retrieved from CNN Money: http://money.cnn.com/2014/12/11/technology/microsoft-bitcoin/

Southurst, J. (2013, November 18). *Why China is Leading the Global rise of Bitcoin*. Retrieved from Coindesk: http://www.coindesk.com/china-leading-global-rise-bitcoin/

Southurst, J. (2014, January 28). *The Reality of Chinese Bitcoin Trading Volumes*. Retrieved from Coindesk: http://www.coindesk.com/reality-chinese-trading-volumes/

Surda, P. (2014, May 14). The origin, classification and utility of Bitcoin.

Swanson, T. (2015, April 6). *Consensus-as-a-service: a brief report on the emergence of permissioned, distributed ledger systems.* Retrieved from Working paper: http://www.ofnumbers. com/wp-content/uploads/2015/04/Permissioned-distributedledgers. pdf

The Economist. (2015, November 31). *The trust machine. The technology behind bitcoin could transform how the economy works*. Retrieved from The Economist: http://www.economist.com/news/leaders/21677198-technology-behind-bitcoin-could-transform-how-economy-works-trust-machine

Twomey, P. (2013). Halting a Shift in the Paradigm: The Need for Bitcoin Regulation. *Trinity CL Rev. (16),* 67.

Van Wijk, D. (2013, July 18). What can be expected from the Bitcoin? *Erasmus Universiteit Rotterdam.*

Walport, M. (2016). *Distributed Ledger Technology: beyond block chain.* United Kingdom: Government Office for Science.

Wong, J. I. (2015, March 10). *Bitcoin Startup 21 Announces $116 Million All-Star Backing*. Retrieved from Coindesk: http://www.coindesk.com/21-record-116-million-funding-all-star-investors/

Yermack, D. (2013, December). Is Bitcoin a Real Currency? An Economic Appraisal.

Appendix

Annex 1: Descriptive statistics of daily variables

	Description	Mean	Std. Dev.
Dependent variable			
BPI	The Bitcoin Price Index, expressed in US Dollars	221,85	236,54
Independent variables			
Hypothesis 1			
Trade_Exchange	Ratio between the volume of Bitcoin transactions on exchange markets divided by the volume of Bitcoin trades made for real life	11,63	11,25
Hypothesis 2			
Wikipedia	Wikipedia search queries for the term 'Bitcoin'	11.094	30.784
Hypothesis 3			
CFSI	The Cleveland Financial Stress Index	0,10	1,05
Hypothesis 4			
Gold	The price of gold per troy ounce, expressed in US Dollars	1424,6	219,04
Crude oil	The London Brent crude oil price per barrel, expressed in US Dollars	97,33	22,68
Hypothesis 5			
BTCChina	Trading volumes on the Chinese Bitcoin exchange market BTCC, expressed in Chinese Yuan	30.067	58.456
USD_CNY	The USD/CNY exchange rate	6,25	0,12
Control variables			
USD_EUR	The USD/EUR exchange rate	0,79	0,07
Difficulty	The difficulty of finding a new block in Bitcoin's blockchain system compared to the easiest it can ever be	1,62e10	2,33e10
Total_Bitcoins	The total amount of Bitcoins in circulation	1,15e07	2,34e07

Annex 2: Correlation between Wikipedia and Google Trends search queries for the term 'Bitcoin'

Correlation coefficients, using the observations 2011-07-01 - 2015-12-31
5% critical value (two-tailed) = 0,0483 for n = 1645

Wikipedia	Google Trends	
1,0000	0,3818	Wikipedia
	1,0000	Google Trends

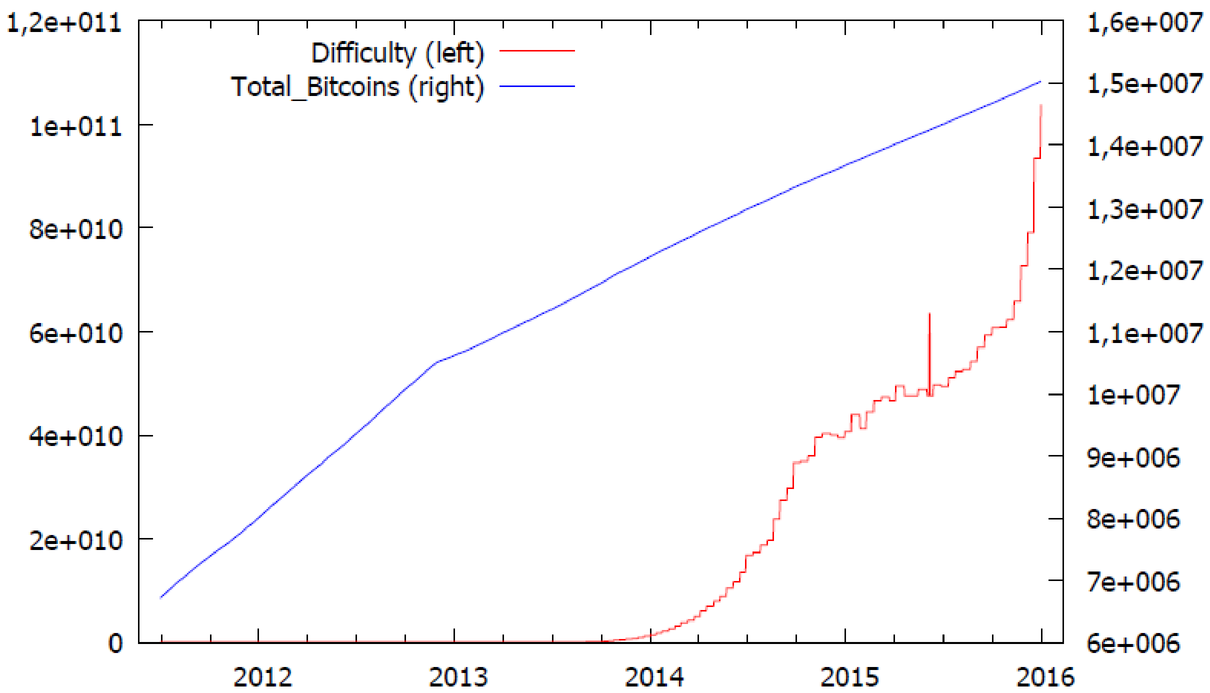
Annex 3: Collinearity test on original variables

Variance Inflation Factors
Minimum possible value = 1.0
Values > 10.0 may indicate a collinearity problem

Trade_Exchange	1,595
Wikipedia	1,108
CFSI	5,891
Gold	7,249
Crude_oil	13,537
BTCChina	1,698
USD_EUR	8,635
USD_CNY	2,469
Difficulty	12,642
Total_Bitcoins	14,622

VIF(j) = 1/(1 - R(j)^2), where R(j) is the multiple correlation coefficient between variable j and the other independent variables

Annex 4: Time series plot of *Difficulty* and *Total_Bitcoins*



Annex 5: White's test for heteroscedasticity on OLS estimation model

White's test for heteroscedasticity
OLS, using observations 2011-07-02:2015-12-31 (T = 1644)
Dependent variable: uhat^2

Test statistic: TR^2 = 237,253795,
with p-value = P(Chi-square(65) > 237,253795) = 0,000000

Annex 6: VAR lag selection

VAR system, maximum lag order 7

The asterisks below indicate the best (that is, minimized) values of the respective information criteria, AIC = Akaike criterion, BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

lags	loglik	p(LR)	AIC	BIC	HQC
1	2459,84674		-2,989428	**-2,946540***	**-2,973520***
2	2461,16914	0,10389	-2,989822	-2,943634	-2,972691
3	2461,18545	0,85664	-2,988620	-2,939134	-2,970265
4	2461,86971	0,24207	-2,988234	-2,935449	-2,968656
5	2463,62736	0,06080	-2,989160	-2,933075	-2,968358
6	2466,29096	0,02100	-2,991192	-2,931809	-2,969167
7	2467,64046	0,10041	**-2,991619***	-2,928937	-2,968370

Annex 7: T-values of general ADL-model per equation

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
const	1,3175	0,8986	1,7441	1,3659	1,5183	1,5191	1,3603	1,5394
ld_Trade_Exchange	0,9414	0,9333	0,9902	0,9299	0,9777	0,9712	0,9787	1,0163
ld_Trade_Exchange_1	−0,2134	−0,2194	−0,1312	−0,2115	−0,1283	−0,1328	−0,2012	−0,1175
ld_Wikipedia	−0,2395	−0,2482	−0,2500	−0,2130	−0,2631	−0,2519	−0,2094	−0,2353
ld_Wikipedia_1	−1,0681	−1,0754	−1,0883	−1,0605	−1,1039	−1,0992	−1,1220	−1,1569
d_CFSI	0,2744	0,2690	0,2314	0,2558	0,2182	0,2126	0,3128	0,2570
d_CFSI_1	−0,4492	−0,4567	−0,3971	−0,4251	−0,4020	−0,3952	−0,4761	−0,4275
ld_Gold	1,2354	1,1955	1,2261	1,2313	1,1497	1,1478	1,1756	1,0880
ld_Gold_1	0,5646	0,5557	0,5446	0,5638	0,5538	0,5548	0,4161	0,4087
ld_Crude_oil	−2,0427	−2,0815	−1,9842	−2,0069	−2,0258	−2,0127	-	-
ld_Crude_oil_1	1,4538	1,4330	1,4448	1,4543	1,4206	1,4214	-	-
ld_BTCChina	−0,8183	−0,8207	−0,8478	−0,8187	−0,8478	−0,8469	−0,8395	−0,8669
ld_BTCChina_1	−0,8342	−0,8393	−0,8094	−0,8157	−0,8165	−0,8101	−0,7855	−0,7682
ld_USD_EUR	−0,9229	−0,9292	−0,9439	−0,9450	−0,9527	−0,9612	−0,9437	−0,9728
ld_USD_EUR_1	0,4134	0,3962	0,3937	0,3704	0,3642	0,3476	0,3621	0,3137
ld_USD_CNY	−2,2968	−2,3367	−1,3809	-	−1,3577	-	−2,3281	−1,4499
ld_USD_CNY_1	−2,2765	−2,3541	−2,6015	-	−2,6185	-	−2,0509	−2,1443
ld_Difficulty	1,9040	1,9897	-	1,7725	-	-	1,8945	-
ld_Difficulty_1	1,4043	1,4982	-	1,2876	-	-	1,3531	-
ld_Total_Bitcoins	−0,4605	-	−0,8604	−0,5232	-	-	−0,4927	-
ld_Total_Bitcoins_1	0,2104	-	0,5692	0,2703	-	-	0,2392	-
ld_BPI_1	0,7161	0,7334	0,7435	0,7187	0,7687	0,7683	0,7079	0,7605

Annex 8: List of events investigated in the event study

Date	Event	Price evolution
05/08/11	MyBitcoin, the Bitcoin transaction processor lost over 150.000 bitcoins, worth over 2 million USD at the time. Source: http://observer.com/2011/08/mybitcoin-disappeared-with-bitcoins/	BPI: $9,80 1 day later: $6,55 (-33,16%)
19/12/11	"The Good Wife" announces it will air a “Bitcoin for Dummies" TV-episode. “The Good Wife” is a famous TV-series in the USA. About 9,45 million viewers tuned in to watch "Bitcoin for Dummies" on January 15, 2012. The story involved a government manhunt for the creator of Bitcoin, who is charged with creating a currency in competition with the US Dollar. Despite the massive exposure, prices remained stagnant following the show's airing. Source: http://www.imdb.com/title/tt2148561/	BPI: $3,52 1 day later: $3,89 (+10,51%)
11/02/12	Paxum and Tradehill drop Bitcoin. Paxum, an online payment service and popular means for exchanging bitcoin announced it will cease all dealings related to the currency due to concerns of its legality. Two days later, the popular Bitcoin exchange and services firm TradeHill was forced to terminate its business and immediately begin selling its Bitcoin assets to refund their customers and creditors. Source: http://blog.bitcointitan.com/post/17660291959/cause-of-the-btcusd-crash-on-february-13th-2012	BPI: $5,60 2 days later: $4,46 (-19,06%)
17/08/12	Trendon T. Shavers shuts down the Bitcoin Savings & Trust. It was a fund that promised high returns to its investors (up to 7% a week). On the day of the shutdown, the investment trust contained little more than 5,6 million USD, representing approximately 500.000 bitcoins. Source: http://www.theverge.com/2012/8/27/3271637/bitcoin-savings-trust-pyramid-scheme-shuts-down	1 day before: $13,50 BPI 17/08: $11,58 (-14,22%) 2 days later: $8,00 (-40,74%)
16/03/13	The Cypriot crisis starts to erupt. On this date, Eurozone finance ministers and the IMF agree on a 10 billion EUR bailout deal for Cyprus, the fifth Eurozone member to be saved from bankruptcy. As deposits of traditional banks no longer seemed safe in times of crisis, digital currencies were believed to be a safe haven, causing the bitcoin price to move up. Source: http://money.cnn.com/2013/03/28/investing/bitcoin-cyprus/	BPI 16/03: $47,00 10 days later: $78,50 (+67,02%)
09/04/13	Increased trading volume broke Mt. Gox. With Bitcoin rising to the attention of the public due to the Cypriot crisis, trading volume hikes on Mt. Gox. The exchange market could not hold the trend and trades started to fail as the system seemed insufficient. Investors started to panic and a wave of selling orders started. Source: https://bitcoinmagazine.com/articles/the-bitcoin-crash-an-examination-1365911041	BPI 09/04: $230,00 1 day later: $165,00 (-28,26%) 2 days later: $124,90 (-45,70%)
In between this event and the next significant event-related jump/downfall, a lot of events took place that did not effect the BPI significantly. On the 1st of May, Coindesk was launched by a business angel. The next day, the first ATM, located in San Diego (California) is presented. In July, the Winklevoss twins asked the SEC for approval to release their Bitcoin-based ETF. On the 6th of August, a judge of the Eastern-District of Texas ruled Bitcoin as a		

currency in a case. Three days later, Bloomberg added the Bitcoin-ticker to its website. 12/08/13 was the date 22 Bitcoin companies were subpoenaed by the NYSDFS. At the end of August, TradeHill was shut down.		
02/10/13	Silk Road was shut down by the FBI. The digital currency was quite often related to this criminal website. The bitcoin price tumbled, but quickly recovered. Source: http://www.wired.com/2013/10/bitcoin-market-drops-600-million-on-silk-road-bust/	1 day earlier: $125,49 BPI 02/10: $99,81 (-20,46%) 1 day later: $116,82 (-6,91%)
14/10/13	Baidu, China's largest search engine started accepting bitcoin. Source: https://www.rt.com/news/china-baidu-accept-bitcoin-276/	2 days earlier: $126,52 BPI 14/10: $133,04 (+5,15%) 1 day later: $138,64 (+9,58%)
10/11/13	Subway started accepting bitcoin. Speculation began on the 8th of November on the popular site Reddit. On the 10th, proof was added. Source: http://www.coindesk.com/bitcoin-accepting-subway-sandwich-shop-discovered-us/	BPI 10/11: $311,90 1 day later: $322,63 (+3,64%) 2 days later: $349,34 (+12,00%)
20/11/13	People's Bank of China approved Bitcoin. Director Mr. Yi said it was impossible for the central bank not to recognize Bitcoin. Sources: http://sinosphere.blogs.nytimes.com/2013/11/22/bitcoin-gets-a-cautious-nod-from-chinas-central-bank/?_r=1& http://www.coindesk.com/people-free-use-bitcoin-exchanges-says-chinese-central-bank-official/	BPI 20/11: $572,67 1 day later: $695,87 (+21,51%) 2 days later: $747,48 (+30,52%)
05/12/13	Financial Institutions were forbidden to use Bitcoin by the Chinese government. With this act, they wanted to protect the home currency, the Chinese Yuan, as the government wanted financial stability. This caused the price to plummet. A day later, Baidu also stopped accepting bitcoin. Sources: http://money.cnn.com/2013/12/05/investing/china-bitcoin/ http://www.nytimes.com/2013/12/06/business/international/china-bars-banks-from-using-bitcoin.html	BPI 05/12: $1042,03 1 day later: $843,03 (-19,96%) 2 days later: $694,47 (-33,35%)
17/12/13	China further banned Bitcoin. Companies that were offering clearing services had to end their services by the Chinese new year, a weeklong holiday that begins on the 31st of January. Source: http://www.bloomberg.com/news/articles/2013-12-17/china-bans-payment-companies-from-clearing-bitcoin-news-says	BPI: $683,84 1 day later: $522,23 (-23,63%) 2 days later: $698,45 (+2,14%)
26/01/14	Charlie Shrem, BitInstant's CEO was accused of money laundering. BitInstant functioned as a middleman between customers and Bitcoin exchange markets, making transactions easier for customers. Two days later, Shrem resigned from the Bitcoin Foundation. Later that year, he was sentenced to two years in prison. Source: http://time.com/1892/bitinstant-ceo-charlie-shrem-arrested-for-alleged-money-laundering/	BPI 26/01: $880,15 1 day later: $814,53 (-7,46%)
07/02/14	Mt. Gox, Bitstamp and BTC-e all suffer DDoS attacks. DDoS stands for distributed denial of service, a type of hacking attack. Mt. Gox' issues already started a day earlier, forcing the stop of withdrawals. This proved that the technicality of these exchange markets was still vulnerable. The bitcoin price almost went straight down after the news.	1 day earlier: $783,62 BPI 07/02: $703,57 (-10,21%)

	Source: http://www.forbes.com/sites/leoking/2014/02/12/bitcoin-hit-by-massive-ddos-attack-as-tensions-rise/#504f90bc6023	
24/02/14	Mt. Gox closes. Since the DDoS attacks, withdrawals had been suspended. After two weeks, the largest Bitcoin exchange market was declared insolvent. As a reaction, other major exchange markets combined forces and planned to work together in the future to prevent these issues. The Bitcoin community reacted positively to this news, as prices went upwards. Sources: http://www.forbes.com/sites/cameronkeng/2014/02/25/bitcoins-mt-gox-shuts-down-loses-409200000-dollars-recovery-steps-and-taking-your-tax-losses/#2bbd65aa7ed6	1 day earlier: $604,58 BPI 24/02: $545,32 (-9,80%) 1 day later: $534,71 (-11,56%)
06/03/14	A journalist of Newsweek claimed Dorian Nakamoto was Bitcoin's inventor. Leah McGrath wrote the article 'The Face behind Bitcoin'. Dorian Nakamoto denied every involvement. Satoshi's real account on a blog posted: "I am not Dorian Nakamoto". Source: http://www.forbes.com/sites/kashmirhill/2014/03/06/bitcoin-creator-returns-to-internet-to-say-i-am-not-dorian-nakamoto/#25a96cbe7f43	BPI 06/03: $658,72 1 day later: $625,83 (-4,99%) 2 days later: $615,24 (-6,60%)
26/03/14	IRS declared Bitcoin as a property. The consequence was that profits were taxed as capital gains. As Bitcoin was claimed to be tax-free, a negative reaction was seen in the market. Source: http://www.bloomberg.com/news/articles/2014-03-25/bitcoin-is-property-not-currency-in-tax-system-irs-says	BPI 26/03: $579,07 1 day later: $478,16 (-17,43%)
10/04/14	Chinese exchanges' bank accounts were closed due to restrictions of the People's Bank of China. Source: http://www.coindesk.com/bitcoin-price-crashes-chinese-exchanges-stop-bank-deposits/	1 day earlier: $440,20 BPI 10/04: $360,84 (-18,03%) 1 day later: $420,06 (-4,57%)
19/05/14	An article was published in The Guardian, where the Winklevoss twins praised Bitcoin and indicated it will be bigger than Facebook. Source: http://www.theguardian.com/technology/2014/may/19/winklevoss-twins-bitcoin-bigger-than-facebook-investors	BPI 19/05: $444,31 1 day later: $485,43 (+9,25%)
29/05/14	US satellite service provider DISH Network announced that it would start accepting bitcoin payments later that year. The Colorado-based company was one of the biggest content providers in America, with more than 14 million paying subscribers. Source: http://www.coindesk.com/dish-becomes-worlds-largest-company-accept-bitcoin/	BPI 29/05: $565,51 1 day later: $616,47 (-8,27%)
11/08/14	Consumer Financial Protection Bureau (CFPB) issued a consumer advisory, warning consumers about the risks of virtual currencies as Bitcoin. The CFPB advised consumers to be aware of potential issues with virtual currencies such as unclear costs, volatile exchange rates, the threat of hacking and scams, and that companies may not offer to help or refund for lost or stolen money. Source: http://time.com/3103495/bitcoin-government-warning/	BPI 11/08: $573,31 1 day later: $568,21 (-0,88%) 2 days later: $544,57 (-5,01%)
11/11/14	Microsoft announced it will start accepting bitcoin. The bitcoin price makes a short peak. Source:	BPI 11/11: $366,99 1 day later: $427,24 (+14,10%)

	http://money.cnn.com/2014/12/11/technology/microsoft-bitcoin/	
09/01/15	The Bitstamp market was hacked earlier in January. The market was suspended from the BPI for four days, returning on January 9th, this exact date. As the hacker raided 19.000 BTC, the theft created a lot of negative reactions. This caused many deposit holders on Bitstamp to withdraw their money as soon as the market restarted operations. Source: http://www.coindesk.com/bitstamp-back-online-bitcoin-traders-return/	1 day earlier: \$283,25 BPI 09/01: \$288,84 (+1,97%) 1 day later: \$274,07 (-3,24%) 2 days later: \$265,37 (-6,31%)
26/01/15	Coinbase launched the first US licensed Bitcoin exchange market. The bitcoin price was positively stimulated by this news. The news was announced on the 25th and the exchange market was launched the day after. Source: http://www.coindesk.com/coinbase-secures-approval-launch-regulated-us-bitcoin-exchange/	2 days earlier: \$247,99 BPI 26/01: \$271,95 (+8,81%)
08/07/15	Greek's cash crisis fuels Bitcoin activity. Withdrawing problems in Greece forced many Greeks to start looking for alternatives. A lot of them started buying bitcoins. The uncertainty of the Greek crisis around Europe makes Bitcoin more attractive. Sources: http://www.bloomberg.com/news/articles/2015-07-08/greece-s-cash-crisis-is-bitcoin-s-boost-ibuhh68	5 days earlier: \$255,6 BPI 08/07: \$269,65 (+5,50%) 5 days later: \$290,88 (+13,80%)
18/08/15	Bitfinex suffers a 'flash crash'. Bitfinex offers margin trading, which allowed traders to ramp up their leverage. On Bitfinex, the margin call was executed automatically. So when a number of positions on the exchange hit their limits amid the general sell-off, orders were generated to sell and raise enough money to cover the positions. Source: http://www.coindesk.com/bitcoin-price-falls-14-following-bitfinex-flash-crash/	1 day earlier: \$256,08 BPI 18/08: \$219,00 (-16,93%)
22/10/15	The European Court of Justice declared no value-added tax on Bitcoin. This ruling was in contrast to the United States' classification of Bitcoin as both a currency (according to FINCEN) and commodity (according to CFTC/IRS). Source: http://www.coindesk.com/bitcoin-is-exempt-from-vat-says-european-court-of-justice/	1 day earlier: \$267,33 BPI 22/10: \$274,41 (+2,65%) 2 days later: \$282,66 (+5,73%)
10/11/15	An article in The Financial Times said the recent bubble of the bitcoin price was mainly caused by a Russian ponzi scheme. In the article, the writer had many arguments against the virtual currency and even called Bitcoin a pyramid scheme, comparing it to the tulip bubble in the 17th century. The negative article got a lot of attention, causing the bitcoin price to fall down in a short period of time. Sources: http://www.ft.com/intl/cms/s/0/1877c388-8797-11e5-90de-f44762bf9896.html#axzz3zfsrncN7 https://www.cryptocoinsnews.com/financial-times-writer-calls-bitcoin-pyramid-scheme/	1 day earlier: \$380,04 BPI 10/11: \$337,93 (-11,08%) 1 day later: \$312,58 (-17,75%)

Annex 9: Statistical results of the total amount of 'good news' events in the event study

Aggregate CAR over time per 'good news' event									
	N1	**C2**	**C3**	**J3**	**N3**	**C4**	**C5**	**C6**	**J10**
CAR	0,2291	0,0798	0,1753	0,4859	0,1199	0,0881	0,2331	0,0319	0,0622
t-stat	1,3767	0,8443	2,0705	5,1748	1,0921	0,7798	3,7462	0,3163	1,1006

Aggregate CAR across 'good news' events											
VAR	0,0189										
SE	0,0153										
Days Relative to Event	**AVG AR**	**T-stat AVG AR**	**AR N1**	**AR C2**	**AR C3**	**AR J3**	**AR N3**	**AR C4**	**AR C5**	**AR C6**	**AR J10**
-2	7,72%	5,0458	0,0101	0,0056	0,1374	0,4002	0,0073	-0,0170	0,0618	0,0680	0,0210
-1	-1,28%	-0,8358	0,0070	0,0283	0,0277	-0,2178	0,0008	0,0095	0,0112	0,0299	-0,0116
0	2,06%	1,3494	0,1136	0,0176	-0,0826	0,0367	0,0032	-0,0103	0,0103	0,0721	0,0252
1	8,21%	5,3713	0,1066	0,0396	0,0560	0,2032	0,0953	0,0928	0,1682	-0,0324	0,0099
2	0,01%	0,0079	-0,0082	-0,0113	0,0367	0,0637	0,0133	0,0131	-0,0184	-0,1057	0,0177

Aggregate across 'good news' events and over time	
Avg CAR	0,1673
SE	0,0342
t-stat AVG CAR	4,8918

Annex 10: Statistical results of the total amount of ‘bad news’ events in the event study

Aggregate CAR over time per 'bad news' event																	
	T1	**C1**	**J1**	**T2**	**J2**	**J4**	**J5**	**J6**	**T3**	**T4**	**N2**	**J7**	**J8**	**J9**	**T5**	**T6**	**N5**
CAR	-0,38	-0,08	-0,38	-0,11	0,00	-0,47	-0,21	-0,17	-0,28	-0,04	-0,11	-0,07	-0,04	-0,09	-0,04	-0,11	-0,13
t-stat	-1,50	-0,49	-6,72	-1,16	0,05	-3,16	-1,23	-0,83	-1,47	-0,20	-0,54	-0,45	-0,25	-1,22	-0,57	-2,39	-2,01

Aggregate CAR across 'bad news' events																			
VAR	0,0761																		
SE	0,0162																		
Days Relative to Event	**AVG AR**	**T-stat AVG AR**	**AR T1**	**AR C1**	**AR J1**	**AR T2**	**AR J2**	**AR J4**	**AR J5**	**AR J6**	**AR T3**	**AR T4**	**AR N2**	**AR J7**	**AR J8**	**AR J9**	**AR T5**	**AR T6**	**AR N5**
-2	-0,90%	-0,55	-0,26	0,03	0,08	0,12	-0,02	0,00	-0,01	-0,09	-0,04	0,05	0,02	0,04	0,02	-0,01	-0,05	-0,01	-0,03
-1	0,61%	0,38	0,16	0,02	0,01	0,13	0,02	0,05	-0,21	0,02	-0,06	-0,01	-0,02	0,01	-0,01	0,00	-0,03	0,00	0,01
0	-7,24%	-4,46	-0,11	-0,06	-0,15	0,21	-0,21	-0,12	-0,06	0,00	-0,11	-0,11	-0,01	-0,01	-0,20	-0,03	0,01	-0,15	-0,11
1	-8,72%	-5,37	-0,35	-0,02	-0,01	-0,30	0,17	-0,22	-0,25	-0,10	-0,06	-0,03	-0,07	-0,18	0,15	-0,02	-0,15	0,02	-0,08
2	-1,97%	-1,21	0,19	-0,05	-0,32	-0,26	0,04	-0,19	0,32	0,01	-0,01	0,06	-0,03	0,06	0,01	-0,04	-0,22	0,03	0,08

Aggregate across 'bad news' events and over time	
Avg CAR	-0,1822
SE	0,0363
t-stat AVG CAR	-5,0203

Annex 11: Statistical results of the macro-economic events in the event study

Aggregate CAR over time per macro-economic event		
	M1	M2
CAR	0,4757	0,0963
t-stat	4,0836	0,9117

Aggregate CAR across macro-economic events				
VAR	0,0012			
SE	0,0172			
Days Relative to Event	AVG AR	T-stat AVG AR	AR M1	AR M2
-10	-0,3154%	-0,1839	0,0052	-0,0115
-9	2,2305%	1,3001	0,0116	0,0330
-8	3,1024%	1,8083	0,0390	0,0230
-7	1,5321%	0,8930	0,0485	-0,0179
-6	-2,1557%	-1,2565	-0,0301	-0,0130
-5	2,2397%	1,3055	0,0403	0,0045
-4	-3,8431%	-2,2400	-0,0949	0,0181
-3	4,5420%	2,6474	0,0504	0,0405
-2	-1,0434%	-0,6082	-0,0110	-0,0098
-1	-1,5694%	-0,9148	-0,0178	-0,0136
0	0,4492%	0,2619	-0,0074	0,0164
1	-0,2609%	-0,1521	0,0000	-0,0053
2	7,0174%	4,0903	0,0801	0,0602
3	8,2568%	4,8127	0,1375	0,0276
4	6,9191%	4,0330	0,0756	0,0628
5	1,5168%	0,8841	0,0918	-0,0615
6	-2,1760%	-1,2684	-0,0278	-0,0157
7	-4,8642%	-2,8352	-0,0887	-0,0086
8	4,0387%	2,3541	0,1013	-0,0205
9	1,0816%	0,6304	0,0195	0,0021
10	1,9019%	1,1086	0,0526	-0,0145

Aggregate across macro-economic events and over time	
Avg CAR	0,2860
SE	0,0786
t-stat AVG CAR	3,6378

Annex 12: T-values of ADL-models of each separate year per equation

2011

Variable	(1)	(2)	(3)	(4)
const	0,5985	−0,6060	0,7546	0,6167
ld_Trade_Exchange	1,2771	1,2510	1,2877	1,2392
ld_Trade_Exchange_1	−1,5600	−1,5507	−1,5377	−1,5426
ld_Wikipedia	−1,0961	−1,0777	−1,1161	−0,9802
ld_Wikipedia_1	0,6996	0,6208	0,7937	0,6290
d_CFSI	0,6741	0,6997	0,6387	0,6653
d_CFSI_1	−1,3627	−1,4279	−1,3311	−1,3324
ld_Gold	1,6865	1,5796	1,6888	1,5605
ld_Gold_1	2,1902	2,2015	2,3043	2,1204
ld_Crude_oil	−1,1556	−1,1368	−1,2394	-
ld_Crude_oil_1	0,9315	0,9311	0,9741	-
ld_BTCChina	−2,0993	−2,2954	−2,0394	−2,1232
ld_BTCChina_1	−3,0217	−3,1163	−2,9764	−2,8987
ld_USD_EUR	−1,2411	−1,3050	−1,2362	−1,4432
ld_USD_EUR_1	−0,8370	−0,9374	−0,7334	−0,7468
ld_USD_CNY	−0,0849	−0,0035	−0,1115	0,1484
ld_USD_CNY_1	1,0619	1,0427	1,0753	1,0707
ld_Difficulty	−0,9953	−1,2827	-	−0,7813
ld_Difficulty_1	−1,0141	−1,0603	-	−1,2457
ld_Total_Bitcoins	−0,6822	-	−0,6964	−0,6010
ld_Total_Bitcoins_1	0,1335	-	0,0151	0,0295
ld_BPI_1	0,2505	0,3027	0,2082	0,2754

2012

Variable	(1)	(2)	(3)	(4)	(5)
const	0,1104	1,5973	0,0818	0,1050	0,0514
ld_Trade_Exchange	−0,6402	−0,6409	−0,6524	−0,6502	−0,8122
ld_Trade_Exchange_1	0,7787	0,7838	0,7913	0,7752	0,5758
ld_Wikipedia	1,5741	1,5717	1,5682	1,5810	1,5232
ld_Wikipedia_1	−0,1753	−0,1722	−0,1797	−0,1729	−0,2257
d_CFSI	−0,4977	−0,5016	−0,5247	−0,5008	−0,7241
d_CFSI_1	1,5459	1,5439	1,5409	1,5294	1,3742
ld_Gold	−0,0492	−0,0474	−0,0479	−0,0629	0,0998
ld_Gold_1	−1,4764	−1,5011	−1,5075	−1,4072	−0,9373
ld_Crude_oil	0,1587	0,1825	0,1486	-	0,2669
ld_Crude_oil_1	−0,0655	−0,0635	−0,0500	-	0,3390
ld_BTCChina	0,4094	0,3994	0,3916	0,4152	0,5957
ld_BTCChina_1	0,6690	0,6754	0,6858	0,6701	0,6763
ld_USD_EUR	−0,2454	−0,2478	−0,2618	−0,2525	−0,1742
ld_USD_EUR_1	−0,7577	−0,7312	−0,7161	−0,7588	−0,4700
ld_USD_CNY	1,7801	1,7942	1,7821	1,7678	1,8324
ld_USD_CNY_1	−0,6195	−0,6116	−0,6164	−0,6207	−0,6244
ld_Difficulty	−0,0028	0,0254	-	−0,0019	−0,1697
ld_Difficulty_1	0,3893	0,4187	-	0,3821	0,1470
ld_Total_Bitcoins	0,2150	-	0,1898	0,2346	0,2628
ld_Total_Bitcoins_1	−0,0380	-	0,0049	−0,0487	0,0198
ld_BPI_1	−0,7317	−0,7293	−0,7351	−0,7334	-0,7318
Event_Dummy	-	-	-	-	-1,5504

2013

Variable	(1)	(2)	(3)	(4)	(5)	(6)
const	0,9531	2,0158	0,6806	0,7731	1,1231	0,9783
ld_Trade_Exchange	−0,0546	−0,0786	−0,0346	0,0239	−0,0178	-0,0615
ld_Trade_Exchange_1	0,2455	0,2017	0,2872	0,1597	0,2711	0,2406
ld_Wikipedia	0,2401	0,2473	0,2469	0,2668	0,2012	0,1994
ld_Wikipedia_1	0,0323	0,0470	0,0320	−0,0250	−0,0022	-0,0144
d_CFSI	1,4502	1,4378	1,4261	1,5331	1,4367	1,470
d_CFSI_1	−1,3426	−1,3647	−1,2644	−1,3954	−1,2722	-1,307
ld_Gold	1,6624	1,7012	1,5569	1,5029	1,6630	1,693
ld_Gold_1	0,1972	0,1675	0,1490	−0,5318	0,2724	0,2350
ld_Crude_oil	−2,8668	−2,8611	−2,6855	-	−2,7513	-2,9130
ld_Crude_oil_1	0,3068	0,2995	0,2517	-	0,3224	0,3037
ld_BTCChina	−0,2548	−0,2867	−0,3214	−0,2923	−0,1876	-0,2322
ld_BTCChina_1	0,2731	0,2164	0,2112	0,3636	0,3068	0,2827
ld_USD_EUR	−0,0246	−0,0298	−0,0690	0,0202	−0,1113	-0,0356
ld_USD_EUR_1	3,1250	3,1503	3,1389	3,1944	3,0777	3,0660
ld_USD_CNY	−0,5397	−0,5205	−0,5981	−0,5288	0,1365	-0,5344
ld_USD_CNY_1	−1,2119	−1,2124	−1,2386	−1,3323	0,0794	-1,1970
ld_Difficulty	1,8407	1,7759	-	1,7145	−0,4957	1,8970
ld_Difficulty_1	1,3233	1,2612	-	1,1203	−1,2147	1,3340
ld_Total_Bitcoins	0,1190	-	−0,4210	0,0635	1,3403	0,0813
ld_Total_Bitcoins_1	−0,5854	-	0,3042	−0,4206	1,1633	-0,5802
ld_BPI_1	0,9707	0,9751	0,9841	1,0648	0,9133	0,8747
Event_dummy	-	-	-	-	1,7670	-
Event_dummy_2	-	-	-	-	-	0,7832

2014

Variable	(1)	(2)	(3)	(4)	(5)
Const	0,0162	−1,3975	0,0833	−0,3068	−0,3943
ld_Trade_Exchange	0,7892	0,7835	0,6598	0,6736	0,9673
ld_Trade_Exchange_1	1,8204	1,8169	1,9647	1,8909	1,9025
ld_Wikipedia	−0,7287	−0,6875	−0,7533	−0,7286	−0,7489
ld_Wikipedia_1	−0,9511	−0,9702	−0,9409	−0,8737	−0,9170
d_CFSI	−1,4724	−1,4750	−1,5119	−1,5510	−1,5708
d_CFSI_1	1,6509	1,6363	1,7075	1,7588	1,7631
ld_Gold	−1,0040	−1,0271	−0,9298	−0,8913	−1,0201
ld_Gold_1	0,1037	0,0992	0,0667	0,1828	0,0373
ld_Crude_oil	2,0155	2,0480	2,0264	-	1,9733
ld_Crude_oil_1	0,3927	0,3932	0,3391	-	0,3681
ld_BTCChina	−0,0799	−0,0928	−0,1258	−0,0537	−0,2307
ld_BTCChina_1	1,4009	1,4348	1,4425	1,5221	1,2225
ld_USD_EUR	0,5657	0,5897	0,5498	0,3829	0,6623
ld_USD_EUR_1	−0,3879	−0,4187	−0,3056	−0,4048	−0,3290
ld_USD_CNY	−0,4132	−0,4357	−0,4672	−0,4060	−0,4270
ld_USD_CNY_1	0,8069	0,8107	0,9562	0,8954	0,7893
ld_Difficulty	−0,4479	−0,4799	-	−0,5822	−0,4929
ld_Difficulty_1	1,2128	1,4064	-	1,1415	1,2696
ld_Total_Bitcoins	−0,4238	-	−0,6143	−0,2262	−0,1946
ld_Total_Bitcoins_1	0,1927	-	0,3175	0,2781	0,3228
ld_BPI_1	−0,7194	−0,7084	−0,7179	−0,7425	−1,0737
Event_dummy	-	-	-	-	4,4964

2015

Variable	(1)	(2)	(3)	(4)	(5)
const	−1,5333	0,6190	−1,5268	−1,5381	−1,4004
ld_Trade_Exchange	0,8967	0,8493	0,9005	0,8689	0,8420
ld_Trade_Exchange_1	−0,2732	−0,2946	−0,2452	−0,2373	−0,2556
ld_Wikipedia	0,5101	0,5876	0,4119	0,4838	0,5842
ld_Wikipedia_1	−1,1850	−1,1459	−1,1781	−1,2091	−1,1627
d_CFSI	0,1868	0,3120	0,1450	0,2497	0,3008
d_CFSI_1	−1,5812	−1,4524	−1,5641	−1,6428	−1,7258
ld_Gold	−0,1190	−0,2790	−0,2145	−0,4033	−0,0031
ld_Gold_1	−1,0234	−0,9155	−1,0817	−0,9576	−0,8454
ld_Crude_oil	−1,9845	−2,0393	−2,0262	-	−2,0704
ld_Crude_oil_1	1,2382	1,3006	1,2743	-	1,2770
ld_BTCChina	0,3564	0,2432	0,3176	0,3468	0,4480
ld_BTCChina_1	−0,7370	−0,7526	−0,7406	−0,6823	−0,6090
ld_USD_EUR	−0,9780	−0,9486	−0,9752	−0,9203	−1,0043
ld_USD_EUR_1	−0,2917	−0,3158	−0,2863	−0,2939	−0,3208
ld_USD_CNY	−0,6842	−0,7924	−1,3493	−0,9052	−0,7543
ld_USD_CNY_1	0,3698	0,4205	−2,5667	0,4199	0,3396
ld_Difficulty	0,3050	0,3717	-	0,5138	0,4059
ld_Difficulty_1	−0,6972	−0,6899	-	−0,6870	−0,6527
ld_Total_Bitcoins	0,6998	-	0,7351	0,6731	0,5972
ld_Total_Bitcoins_1	1,6024	-	1,5975	1,6389	1,5557
ld_BPI_1	0,4943	0,5137	0,4850	0,4745	0,2206
Event_dummy	-	-	-	-	−2,0421