

Effect of Bitcoin spot and derivative trading volumes on price volatility

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## **Abstract**

This study argues that the value of Bitcoin is dependent on the likelihood of its price volatility reducing in the future. This study attempted to shed light on whether increased speculation, in both spot and derivative market volumes, will eventually lead to a reduction in Bitcoin price volatility. The study investigates several factors that influence Bitcoin volatility and tests empirically whether trading volumes in the spot market and trading volumes in the new derivative markets have had an effect on the price volatility. The study used, among other tests, an ARCH(1) and Granger-causality test and found that spot trading volumes had a significant positive effect on price volatility in the study period. The study also found that, in the year of introduction of Bitmex derivative contracts, derivative trading volumes had a significant negative effect on Bitcoin price volatility. In the years thereafter though, the relationship was not sustained and therefore it is not definitive whether derivative contracts trading volume increases has led to reduced volatility in the Bitcoin price.

## **Keywords**

Bitcoin, volatility, derivatives, cryptocurrencies

*I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.*

Joseph Johannes Badenhorst

Date

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# 1 Problem definition and purpose

## 1.1 Introduction

Digital currencies, specifically cryptocurrencies, are a global, spreading phenomenon that has caught the attention of the government, media and financial institutions, as well as the retail investor. The largest cryptocurrency by market capitalisation is Bitcoin with a market dominance of 51% at the time of this writing (Coinmarketcap, 2018). Search volumes on Google for keywords associated with Bitcoin have increased by up to 1000% during 2017 and the price of a single Bitcoin reached an all-time high close to \$20 000 in December 2017 before correcting to \$6 400 at the time of this writing. This highlights the increased interest and awareness in the subject (Haig, 2018).

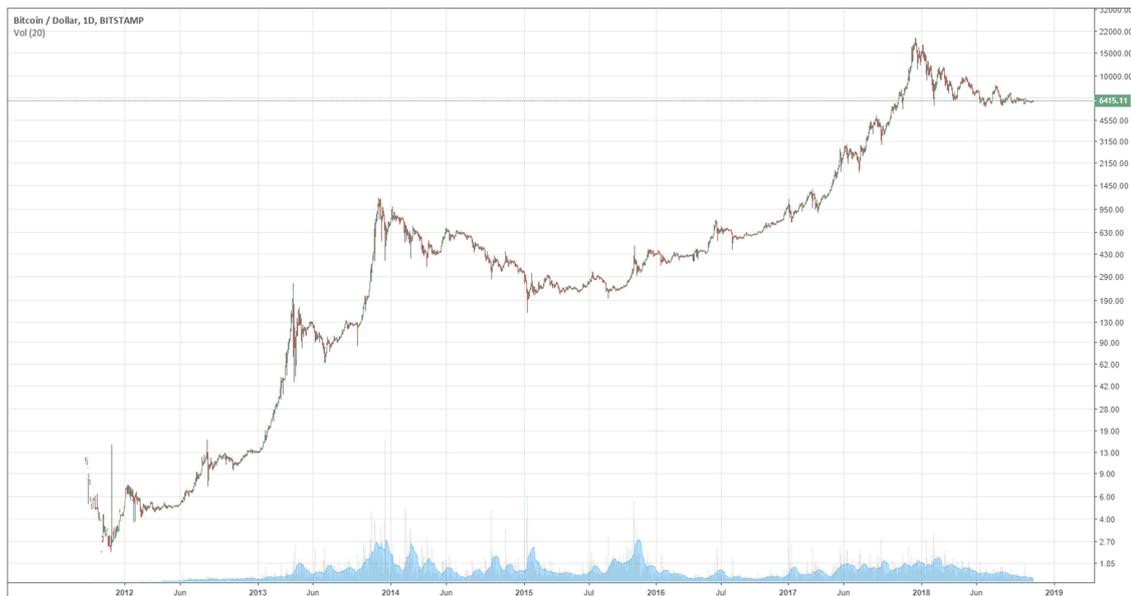
Despite this exponential increase in price and attention it is not certain that Bitcoin will actually be adopted as a currency, which is its original purpose (see literature review section 2.2). This paper will argue that one of the important factors standing in the way of Bitcoin adoption as a widespread currency is its price volatility (Dwyer, 2015). Bitcoin's volatility is determined by various factors, discussed further in this study, such as market and informational efficiency (Urquhart, 2016), actual transactional usage, sophistication of speculators, attention in the media (Urquhart, 2018) and speculation volumes (Corbet, Lucey, Peat & Vigne, 2018). There therefore exists a need to research whether these factors can, in the future, cause a reduction in Bitcoin price volatility, which could lead to widespread adoption as a currency and subsequently also a higher Bitcoin price.

This study will focus on the effect that speculation volumes have on the price volatility of Bitcoin. Speculation is the buying or selling of an asset or instrument with the hopes of making a profit. In the Bitcoin ecosystem speculation is done in mainly two ways. The first way is in the spot market, where actual Bitcoin is bought and held on an exchange or in a private wallet. The second way is through derivative instruments such as futures contracts and swaps where the actual Bitcoin is never held, but exposure is gained to the Bitcoin price. This study will test the effect of the volumes of each of these methods of speculation on the Bitcoin price volatility to ascertain if an increase in volumes of these methods of speculation is likely to decrease Bitcoin price volatility in the future. This study aims to contribute to the literature and business knowledge in this regard.

## 1.2 The purpose and function of Bitcoin

Despite the recent decline in the Bitcoin price the rapid price escalation has awarded early investors with impressive returns in the last year alone and significantly more going back to its creation in 2008, as seen in Figure 1 (Coinmarketcap, 2018).

**Figure 1 - Logarithmic BTCUSD Price Bitstamp 2011-2018 (Tradingview, 2018)**



The initial intention of Bitcoin's creator, Satoshi Nakamoto, however was not for it to award speculative investors as an exotic investment vehicle, but to be used as a decentralised networked payment system, in other words, a currency (Nakamoto, 2008).

Bitcoin can accomplish this value transfer using a network of nodes and miners that cryptographically secure the transactions processed on the network and update a distributed ledger of transactions called the blockchain. These miners and nodes can establish an emergent consensus of the state of all transactions and balances by means of a proof of work algorithm. This allowed for the first time a decentralised application of currency that can inherently solve the double spend problem and give an electronic currency a finite predetermined supply and monetary policy. Bitcoin was not the first virtual currency to exist, but it was the first widely adopted one to solve the double spend problem and remain decentralised (Peng, Albuquerque, de Sá, Padula & Montenegro, 2018).

The decentralisation of Bitcoin contributed to its popularity among libertarians and the lower transaction fees relative to credit cards and international transactions have made Bitcoin competitive as a payment method (Böhme et al., 2015; Angel & McCabe,

2015). The pseudonymous nature of transactions has also allowed transactions without oversight or censorship.

Cryptocurrencies can also be an important development for the billions of unbanked as it allows secure transactions between them. The high transaction costs of remittances (which can be up to 10%) can also be avoided using cryptocurrencies (Cermak, 2017).

### **1.3 Bitcoin opportunities and challenges**

Transaction fees on cryptocurrencies can be at least an order of magnitude lower than that of normal credit cards for merchants, especially for large amounts. At the time of writing the transaction fee for a Bitcoin blockchain transaction was \$0.13 fixed on any amount (Bitcoin Transaction Fees, 2018). Credit card transaction fees are typically in the range of 2%-4% and even more when payments are made across borders with currency conversions. For businesses with small margins this difference can also be very significant (Böhme et al., 2015). Bitcoin transaction fees for remittances are estimated to be approximately 1%, while the traditional bank wire transfers typically cost 7.7% on average. This is a dramatic reduction in fees (Cermak, 2017).

The number of merchants who accept Bitcoin has increased over the last few years. In 2015 over 150 000 merchants accepted Bitcoins as payment, and in 2017 large companies like Overstock.com, Microsoft and Dell have accepted Bitcoin payments, but only through partners (such as BitPay or Coinbase) who convert the Bitcoin directly and immediately to fiat currency. By converting the Bitcoin directly to fiat currency when accepted it does however introduce some transaction costs that could have been avoided if Bitcoin was directly accepted (Cermak, 2017).

If Bitcoin eventually does become more stable and is adopted as a medium of exchange, it will likely be worth significantly more than it is now. This is because of the value it can capture from existing payment systems like credit cards, where annual fees in the USA alone are in excess of \$90 Billion (Fin24, 2018).

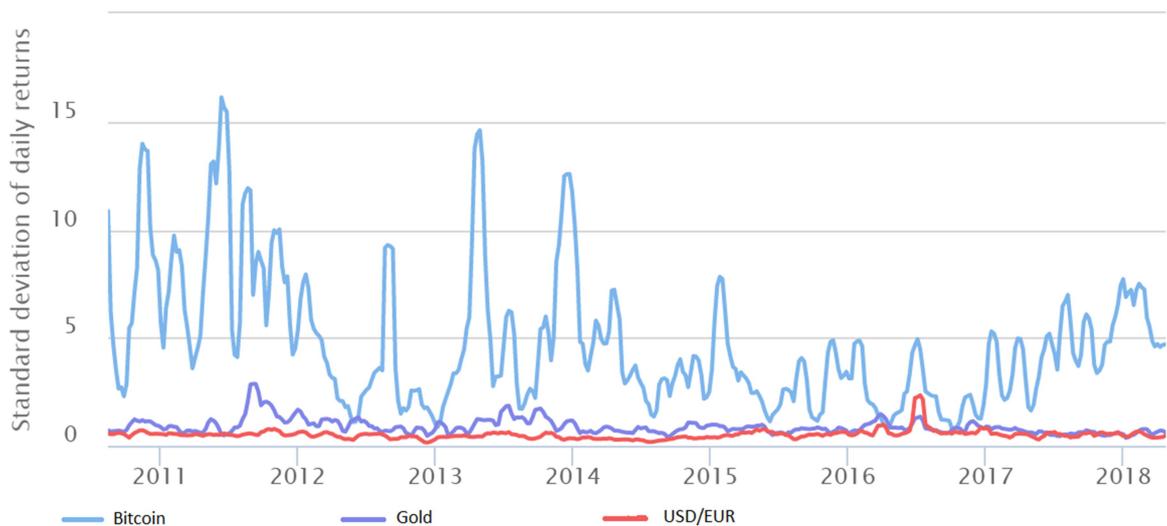
With general demand increasing rapidly the Bitcoin network has run into some scaling issues over peak times. During these times the transaction fees for Bitcoin can escalate. The fees essentially operate on an auction system and therefore fluctuate. Currently a Bitcoin transaction can also take between 30 minutes and a few hours to clear, depending on the network load. These teething problems are addressed by new second layer technologies currently being built on top of Bitcoin, such as the Lightning Network (Cuen, 2018).

The Lightning Network would allow Bitcoin transaction fees to be fractions of a cent as well as allow millions of transactions per second to clear immediately. It will also add more anonymity and fungibility. This is accomplished without compromising on its decentralisation. This study argues that with these improvements the Bitcoin payment system could be extremely competitive to existing payment systems.

#### 1.4 Bitcoin as a currency

Some regulators, financial analysts and researchers argue that Bitcoin acts less like money or a currency and more like a speculative asset (Yermack, 2014). Most experts and economists agree that money must serve three purposes, namely that it must be a “medium of exchange, a unit of account and a store of value” (Peng et al., 2018, p. 180). It is said that the high volatility of the Bitcoin spot price therefore disqualifies it from being money as it does not constitute a stable store of value like gold for instance, as can be seen in the volatility comparison in Figure 2.

**Figure 2 - BTC/USD 30-Day Volatility Comparison (Buy Bitcoin Worldwide, 2018)**



It is also proposed that Bitcoin is a bad unit of account as the volatility prevents Bitcoin from being a measurement standard of the value for goods and services (if goods were to ever be priced in Bitcoin the price would have to change too often). Bjerg (2016) categorises money into three theories: fiat theory, commodity theory and credit theory. He argues that cryptocurrencies can be commodity money, fiat money and credit money with some fundamental differences.

This study argues that, while Bitcoin excels at other properties of currencies like scarcity, divisibility, fungibility, durability and transferability, it is still too volatile to be classified as a currency. This study also argues that if the volatility decreases it will be

a disruptive innovation in the payments industry because of its low transaction costs, security and portability.

**Figure 3 - US Dollar / Gold price, not adjusted for inflation (macrotrends, 2018)**



The US\$ gold price is important to compare to Bitcoin because of gold being the original currency and the US\$ being the dominant currency in the world for the last 70 years. As can be seen in the figure above the US\$/Gold price volatility has also significantly increased since countries discarded the gold standard, most notably the USA in 1971. This can also bring into question whether gold's volatility has increased because its utility has decreased. It can be argued that in the 1970s when the USA discarded the gold standard they essentially created a new non-collateralised currency. It is also clear that the introduction of the new dollar was volatile in the beginning until price discovery concluded. It could indicate that Bitcoin is similarly simply still in price discovery mode and will eventually become less volatile. The Bitcoin/US\$ price actually bear striking similarities to the Gold/US\$ price after 1971, only on a shorter time-frame.

The question then arises of what needs to change for the Bitcoin price to become less volatile and more useful as a currency and medium of exchange. The rest of this paper will discuss methods and mechanisms (such as monetary policy and increases in speculation volume) to stabilise the price of Bitcoin. It will then test if some of those mechanisms have worked empirically up to date.

## **1.5 Ways of stabilising Bitcoin**

### **1.5.1 Monetary policy**

One way of stabilising a currency's value is through its monetary policy. More currency can be created to debase the value of the existing currency in circulation and vice versa (Friedman, 1969). The creators of Bitcoin have decided however to design Bitcoin with a fixed deterministic inelastic monetary policy (limiting total supply to 21 million) (Nakamoto, 2008). This makes it almost impossible to change the rate of issuance of new Bitcoin currency. At the time of writing 12.5 new Bitcoins are issued to miners approximately every 10 minutes (Coinmarketcap, 2018). Early users of Bitcoin see this policy as one of Bitcoin's strongest value propositions as it makes it immune to hyperinflation. It does however limit the use of monetary policy in stabilising the Bitcoin price. The opportunity exists for a different cryptocurrency to implement alternative monetary policy and mechanisms to stabilise its price. This paper will focus on Bitcoin, but will also discuss some of the mechanisms currently being implemented or investigated to create other stable cryptocurrency coins.

### **1.5.2 Stable coins**

"Stable coins" are defined as a cryptocurrency that is pegged to another stable asset like the US dollar or gold (Forbes, 2018). Stable coins are being investigated by multiple businesses and cryptocurrency projects. It is considered a possible solution to the cryptocurrency volatility problem (Forbes, 2018). Stable coins can be utilised by exchanges who wish to provide cryptocurrency trading pairs in USD without the need for a USD bank account. The stable coin then functions similar to a cryptocurrency but is backed up by some reserve or algorithm to keep the peg stable. Stable coins are also used in extremely volatile times by traders to decrease their risk, by selling Bitcoin for Tether for instance (Wei, 2018).

The largest stable coin at the time of writing is Tether with a market capitalisation of \$2.4 billion (Coinmarketcap, 2018). The Tether company claims to have the full amount of market capitalisation in reserve in bank accounts, but Tether is freely issued by a centralised organisation and shrouded in controversy. Some even claim that the Tether company issued tokens to manipulate the Bitcoin price during its bear market in 2018 (Wei, 2018; Zuckerman, 2018).

Wei (2018) tested the relationship between the transparent issuing of Tether tokens and the subsequent Bitcoin trading volumes. He concluded that the issuing of Tether tokens have a positive relationship with trading volumes thereafter. He concluded

though that Tether issuance does not influence Bitcoin returns that day, which, if it did, would have resulted in a successful trading strategy. It is also argued that the issuance of new or retraction of Tether tokens act as monetary policy to stabilise the entire cryptocurrency market.

Another popular stable coin is TrueUSD (TrueUSD, 2018). TrueUSD is similar to Tether, but with one important difference, the USD reserves are kept in escrow instead of unknown bank accounts like Tether. By keeping the USD in escrow it is easily auditable, but also vulnerable to government intervention.

Some stablecoins are also attempting to reduce volatility, while simultaneously remaining decentralised, by backing the coin on other cryptocurrency assets. MakerDAO is a decentralised organisation which created the DAI stablecoin. DAI is not backed by USD, but backed by Ethereum. It is the largest crypto-collateralised stablecoin by market capitalisation. ReserveCoin also attempt to create a stable peg to the USD dollar by using a reserve of different cryptocurrencies and then issuing/retracting tokens on only a part of the reserve. This allows it to control the token price. It does mean however that the reserve has to be bigger than the issued amount of Reservecoin tokens and has to be very dynamic to adapt to changes in the USD value of the reserve currencies.

A dozen other stablecoins are also in the market or in development currently. A possible future solution for Bitcoin might also be to develop a stablecoin as a second layer protocol similar to the Lightning Network on Bitcoin itself. Stable coins can combine the functional advantages (lower fees, speed, and decentralisation) of cryptocurrencies with the stability of existing fiat currencies.

Because of existing network effects it would be quicker for adoption of cryptocurrencies though if Bitcoin itself could be less volatile, and therefore this paper will focus on achievable solutions for the Bitcoin volatility problem specifically.

### **1.5.3 Speculation**

Another possible way for a cryptocurrency to stabilise over time is through increased speculation. Researchers have for some time studied the effects of speculation on the volatility of mature currency and commodity markets (see literature review section 2.8). Most studies suggest that under conditions speculation does not destabilise a market spot price (Mayhew, 2000). Blau (2017) concluded that normal speculation up until 2014 also did not destabilise the Bitcoin market. Some studies have concluded that increased speculation has stabilised specific commodity and currency markets (see

literature review section 2.8). It is therefore not clear whether increased speculation volume has affected the Bitcoin price volatility in recent years. This research aims to shed some light on that question.

The effect of speculation on these markets using derivative instruments specifically has also been studied (Mayhew, 2000). Derivative instruments like future contracts convey information to the spot price markets of commodities that can dampen the volatility. This is especially applicable and relevant today since the CBOE (Chicago Board Options Exchange) and the highest volume futures exchange in the world, the CME (Chicago Mercantile Exchange), launched Bitcoin futures contracts in December 2017.

These exchanges are not the first to launch Bitcoin derivative products, but they are thought to bring in more institutional investors and mature speculators into the Cryptocurrency markets. One of the reasons for optimism in the Bitcoin community at the end of 2017 was that these new mature entrants would stabilise the price. Some opponents to the futures listing argued though that the futures market would allow the price of Bitcoin to be shorted lower and collapse the price, which would increase volatility (Alam, 2017).

The derivative with the biggest daily volume for Bitcoin globally is a perpetual swap traded on the Bitmex exchange. On 17 August 2018 for instance the Bitmex perpetual swap traded \$4 Billion of notional value in contracts in 24 hours (Bitmex, 2018). The biggest cryptocurrency options exchange is LedgerX which only started trading in October 2017. Daily notional value trading volume on LedgerX is around \$1m, which is less than 0.01% of spot and other derivative market trading volumes. (De, 2018)

This study therefore argues that if the increased volumes of derivative instrument trading did indeed contribute to Bitcoin price stability, and derivative instrument trading increases even more with the new introduction of markets, price volatility should eventually go down to levels where Bitcoin can be a functional exchange medium and currency.

Shi (2018) studied the relationship between futures trading volume and the spot price volatility of Bitcoin. Shi (2018) did find a dampening effect in the Bitcoin spot price in the first 2 weeks after the CBOE futures launch. This paper will however attempt to test the relationship over a longer time frame and using data from derivative contract exchanges with more significant volumes than the CBOE had in its first 2 weeks of trading.

The research problem addressed in this report is to establish the effect Bitcoin spot trading volume has on Bitcoin price volatility and then to establish the effect Bitcoin derivative instruments trading volume specifically has on the volatility of the Bitcoin spot price.

## **1.6 Contribution to business**

This study increases the business understanding of the effects of speculation and especially Bitcoin derivative volumes on the fluctuations of the underlying spot Bitcoin price. If Bitcoin does eventually stabilise because of increased speculation and becomes a global medium of exchange it is likely significantly undervalued and can be a promising investment opportunity.

This paper is also relevant today as regulators around the world are imposing regulations on the cryptocurrency markets and the result of this study can inform them on the best course of action if the intention is to stabilise the market.

Volatility is also used as a measure of risk and has real implications for fund managers managing risk in these new markets, especially in establishing an options market. An understanding of the effect of the increased speculation in Bitcoin derivatives will therefore improve understanding of the risks associated with investing in Bitcoin markets and pricing of options contracts in the future.

Recently cryptocurrency companies have also been attempting to get a Bitcoin ETF (Exchange Traded Fund) approved. A more stable Bitcoin would also improve the chances of an ETF getting approved.

## **1.7 Contribution to literature**

A substantial amount of research has been conducted studying the effect of trading volumes on volatility of traditional markets of currencies and commodities (see literature review section 2.8). As far as can be ascertained only two published peer-reviewed studies have been done to evaluate the effect of Bitcoin trading volume on Bitcoin price volatility. One study was done very recently for spot trading volumes by Corbet et al. (2018) and one study was done by Balcilar, Bouri, Gupta and Roubaud (2017) for derivative trading volumes. This research added to this small theoretical base on the effects of derivative speculation on price volatility, specifically in the Bitcoin markets. The study distinguished itself from Corbet et al. (2018) and Balcilar et al. (2017) by using a longer timeframe and richer data sets from exchanges with more trading volume. The study also distinguished itself from Balcilar et al. (2017) by

including data from the recent volatility spike around December 2017, which is crucial in understanding modern Bitcoin volatility.

### **1.8 The scope of the study**

The scope of this paper was to focus on Bitcoin, but the results will be valuable to other and future cryptocurrencies, in that it can guide their monetary policy and mechanisms to increase their stability. The study could also provide some insight into the volatility behaviour of currencies in general.

The study focused on Bitcoin primarily because Bitcoin has the highest trading volumes and liquidity in the cryptocurrency space. Bitcoin also has the richest and longest datasets in the derivative markets at the time of the study. This study focused on Bitcoin futures and swaps and not Bitcoin Options, Contracts for Difference (CFDs) or other derivatives. This is because currently the vast majority of derivative trading volume in Bitcoin is in futures and swaps.

### **1.9 The purpose of this paper**

The purpose of this research was then to ascertain if there is an effect between Bitcoin volatility and spot and derivative trading volumes to determine the likelihood of Bitcoin volatility reducing in the future. If the introduction of derivative markets for Bitcoin has indeed reduced volatility of the spot market price it can be argued that Bitcoin has the potential of becoming more like a medium of exchange in the future and is probably undervalued at the moment. This study also aims to contribute to the scarce existing literature on the effect of trading volumes on volatility in the cryptocurrency context.

The rest of the paper is laid out as follows: Chapter 2 is a literature review on the economics and finance of Bitcoin markets. Chapter 3 discusses the methodology that was used. This is followed by the results in chapter 4 and the discussion of the results in chapter 5. Finally the conclusion is presented.

## **2 Literature Review**

### **2.1 Introduction**

Literature in the cryptocurrency field has increased significantly in the last 5 years, and especially in the last year as can be seen from the number of recent articles discussed below, but the field is still new and research is spread thin over various subtopics. One of the questions that still remain unconfirmed is that of the effect of spot and derivative trading volumes on the Bitcoin price volatility, as discussed in this chapter. Some seminal work is also discussed in volatility studies and techniques of traditional financial markets. With the increases in price and markets for cryptocurrencies, the Finance, Economics, Econometrics and Econophysics literature for cryptocurrencies have developed in recent years, as will be discussed for the remainder of this chapter. A multitude of unpublished working papers and popular articles are also adding to the literature on digital currencies.

This chapter will review the literature of what has been done up to date and focus on the economic and financial literature available. Literature on technical, legal or ethical aspects will only be discussed when it is deemed important to the economics of Bitcoin prices and markets.

### **2.2 What is Bitcoin**

Bitcoin was not the first digital currency to be created. Virtual currencies like eCash and e-Gold were created before Bitcoin as mentioned by Peng et al. (2018), as well as countless loyalty rewards currencies and systems. E-Gold allowed anonymous transfers of ownership of precious metals between accounts. At its peak e-Gold reached US\$2 billion of transfers a year and over a million users. But the system attracted cyber-criminals and other kinds of criminal behaviour and was shut down in 2008 because of it. Other early digital currencies had similar ends (Peng et al., 2018).

A cryptocurrency is defined as “a digital asset designed to work as a medium of exchange, using cryptography to secure the transactions and to control the creation of additional units of the currency” (Chu, Chan, Nadarajah & Osterrieder, 2017, p. 1). The first cryptocurrency was Bitcoin.

The seminal whitepaper of Nakamoto (2008) proposed Bitcoin with a peer-to-peer network architecture similar to the BitTorrent network used to exchange files online. This among other advancements allowed the Bitcoin network to become decentralised and almost indestructible as long as a single node exists, overcoming the main reasons

for failure of e-Gold (Antonopoulos, 2014). Nakamoto (2008) intended for Bitcoin to be an easy, fast, cheap way of sending value over the internet that is independent from a banking or state institution. It used cryptography for various functions including security, limiting the total supply of Bitcoin to 21 million units and limiting the rate of issue of Bitcoin, in order to curb hyperinflation. Cryptography was also used in Bitcoin technological breakthroughs to solve problems like third party trust and double-spending (Dwyer, 2015).

Most cryptocurrencies and tokens use a blockchain to store transactions. A blockchain is essentially a distributed ledger of past transfers/transactions validated by the network. The blockchain is a “chain” of blocks linked by cryptography, each block containing the transactions validated in the last 10 minutes (in the case of Bitcoin). Using these blocks, each node on the network can reconstruct every transaction that has happened since the currency’s first block (the genesis block) and calculate current ownership of the coins in circulation (Antonopoulos, 2014). To make a new transaction a user uses his private key to sign the transfer and then sends it over the peer-to-peer network. The network nodes and miners then validate the transaction and the miners incorporate it into the next block. This, along with other advancements, allows for a decentralised emergent consensus on the ownership of every coin without the need for an intermediary (Antonopoulos, 2014). Some parties however argue that Bitcoin is not as decentralised as it is made out to be. Gervais, Karame, Capkun and Capkun (2014) for instance claimed that Bitcoin decision-making and mining are controlled by a limited set of entities.

According to Brandvold, Molnár, Vagstad and Valstad (2015) the perceived failure of banks and government during the 2008 financial crisis caused Bitcoin to gain traction, especially among libertarians. Combined with cheaper and faster payments, it offered a compelling value proposition for its users according to Angel and McCabe (2015). Bitcoin also attracted users requiring anonymity, even though Bitcoin itself is not really anonymous but instead pseudonymous. Bitcoin transactions are actually completely transparent and every transaction in history can be traced between wallet addresses. It is not immediately transparent who owns the wallets though, until the Bitcoin is sent to an exchange where KYC (“know your client”) controls are in place. Overall though, it can be argued that Bitcoin is less anonymous than existing cash such as paper notes (Antonopoulos, 2014).

### **2.3 Bitcoin's value as a currency**

Currently, some academic debate is on the appropriate classification of Bitcoin, as either an asset or a currency (Cheah & Fry, 2015). Gold and paper notes have perceived value since they can be used to buy goods and services. Klein, Thu and Walther (2018) however argue that, although Bitcoin is sometimes called the “new gold”, it has very different conditional variance properties and structures. It in fact behaves exactly the opposite way as it positively correlates with downward markets and is not a hedge against markets like gold is. They do however suggest revisiting the study when markets are more mature and have a larger sample size. Dyhrberg (2016a) in contrast found that Bitcoin does indeed show similarities to the dollar and gold and can similarly be used as a tool to hedge against stocks and market specific risk. In fact Bitcoin's mining procedures was designed to simulate the costs of production and supply introduction normally associated with commodities like gold (Antonopoulos, 2014). Selmi, Mensi, Hammoudeh and Bouoiyour (2018) however argued that compared to gold or traditional currencies Bitcoin is more difficult to understand and explain, is less known, younger, volatile and more speculative. They argue that Bitcoin is not backed by a government like fiat currencies and that the price formation is more complex. They also comment that Bitcoin wallets are less secure and that scandals and fraud are widespread in the cryptocurrency ecosystem. Selmi et al. (2018) however also highlights advantages of Bitcoin over gold or traditional currencies by stating that Bitcoin has more utility and portability. Selmi et al. (2018) also agrees though that Bitcoin is similar to Gold in that it is a hedge during times of uncertainty.

It is generally argued by some that gold has “intrinsic value”, whereas cryptocurrencies does not have intrinsic or fundamental value and cannot therefore function as a currency like gold (Cheah & Fry, 2015). Hayes (2017) however attempted to model value formation using the cost of production model and concluded that the different costs in production of different cryptocurrencies are one of the primary factors influencing their intrinsic value/price. Polasik, Piotrowska, Wisniewski, Kotkowski and Lightfoot (2015) concluded that the value of Bitcoin depends on the transactional needs of its users and the customer's knowledge of it. They also found that its value tends to depend on its popularity in the media/press.

The conventional definition of “money” states that it must have the potential as a “medium of exchange, a store of value and a unit of account” (Peng et al., 2018, p. 180). Literature differs on whether Bitcoin can meet these requirements and be

classified as money, which is further discussed below. Cermak (2017) examined whether Bitcoin can replace fiat currencies. He concluded that Bitcoin cannot currently comply with the three properties of money as listed above because of its biggest impediment, namely its volatility. He did however find that Bitcoin has similar characteristics than traditional currencies in China, the U.S.A. and the European Union. This conclusion did not hold for Japan though. He mentions the volatility of Bitcoin and concludes that it has been decreasing steadily over the last six years and, if the trend continues, might function as an alternative currency by 2020. Cheung, Roca and Su (2015), Cheah and Fry (2015) and Weber (2014) argue that Bitcoin does not constitute a good value store because of its historical tendency of relying solely on market sentiments, causing boom-and-bust episodes and high volatility. Authors like Böhme, Christin, Edelman and Moore (2015) however found evidence of both currency and commodity characteristics in different time windows and different Bitcoin markets. Dyhrberg (2016a, p. 1) also states that Bitcoin classifies somewhere between a “store of value” and a “medium of exchange”. He states that while Bitcoin is not like traditional currencies, it combines advantages of both the US dollar and gold. She adds that Bitcoin has an important part to play in financial markets and portfolio risk management. While, in the United States of America, the Internal Revenue Service classifies Bitcoin as property, the German Finance Ministry treats Bitcoin as a unit of account for trading and tax implications (Van Alstyne, 2014).

Bjerg (2016) categorises money into three theories, namely fiat theory, commodity theory and credit theory. He argues that cryptocurrencies can be commodity money, fiat money and credit money with some fundamental differences. Selgin (2015) agrees that Bitcoin involves attributes of fiat money and commodity money, but states that Bitcoin does not fit the original definition of these classifications and therefore refers to it as “synthetic commodity moneys” (Selgin, 2015, p. 2). Corbet et al. (2018) on the other hand found strong indications that the majority of users/investors of Bitcoin are uninformed and that they are primarily using Bitcoin to participate in speculation instead of an alternative transaction system.

Böhme et al. (2015) state that Bitcoin transactions function optimally, with very competitive transaction fees, if both parties are willing to store and transact in it, and not just use it as an intermediate payment channel. The reason why people are not willing to store the Bitcoin is because of its volatility, especially if they have no appetite for that risk.

## **2.4 Bitcoin as a hedge and safe haven**

Dyhrberg (2016b) indicates that, similar to gold, Bitcoin could be used for hedging against negative shocks in global markets. Selmi et al. (2018) concurred and found that Bitcoin is a hedge (like gold), specifically against oil price movements. They did however limit the observation to specific Bitcoin, gold and oil market conditions. The study reinforced that Bitcoin acts as a safe haven in times of political and economic uncertainty. Bouri, Shahzad and Roubaud (2018) also examined the relationship between Bitcoin volatility and price returns and agreed that Bitcoin acts as a safe-haven. A robustness analyses showed that the VIX (USA index for volatility) and Bitcoin volatility are negatively correlated, reinforcing this point. Symitsi and Chalvatzis (2018) concurs that Bitcoin has low correlations with stock indices and therefore offers hedging benefits.

Despite these advantages it is clear that, despite the original intention of Nakamoto (2008) to create Bitcoin as currency; in the literature it is undecided whether Bitcoin classifies as an alternative currency or a speculative investment vehicle/hedge. It is also clear that one of the major reasons given for Bitcoin's inadequacy as a currency is its high price volatility. This paper will further discuss Bitcoin's volatility and the methods used in the past to reduce currency volatility and its applicability on Bitcoin to ascertain if they would be effective in helping Bitcoin achieve its original purpose.

## **2.5 Bitcoin volatility**

Dwyer (2015) found that Bitcoin's volatility is excessively higher than other US Dollar currency pairs. Pichl and Kaizoji (2017) agree and conclude that the Bitcoin price time series data is substantially more volatile than Euro/USD rates. Kurihara and Fukushima (2018) however studied Bitcoin volatility empirically and concluded that the short-run Bitcoin volatility is different from its long-run volatility. They added that people should not just look at the short-term volatility, but also take long-term developments into account.

A variety of factors have been introduced in literature to address Bitcoin price volatility, such as its reaction to news/events, speculative trading, bubbles, its link to global economic factors and other assets, market sentiment, information efficiency and market efficiency. These factors are addressed below.

Dyhrberg (2016a) discusses Bitcoin's volatility compared to gold and the US Dollar, which is traditionally regarded as safe-haven assets and stores of value. The paper stated that Bitcoin compares to other markets in its volatility effect after news events

and ability to be used for hedging. Takaishi (2018) studied the statistical properties of Bitcoin and found no evidence of volatility asymmetry (a property of an asset that has higher volatility when the broader market is performing poorly). Cheah and Fry (2015) suggest that Bitcoin faces scrutiny of being purely speculative and susceptible to bubbles. Dowd (2014) agrees that Bitcoin has a large speculative property. Dale, Johnson and Tang (2005) have in the past also linked a big speculative component to bubble behaviour and therefore high volatility. Su, Li, Tao and Si (2018) used a generalised Augmented Dickey-Fuller test method and concluded that Bitcoin has indeed experienced four bubbles in its history. They suggest that administrative authorities' intervention have typically caused the bubbles to correct. Weber (2014) agrees that because of the dominating speculative aspects of the Bitcoin market the prices seem to be mostly driven by sentiments and that this has led to unpredictable volatility. Urquhart (2016) suggests attempting to separate the fundamental and speculative components of the Bitcoin price to ascertain their separate effects on Bitcoin volatility. Conrad, Custovic and Ghysels (2018) in contrast used a GARCH-MIDAS model and found that Bitcoin price volatility is linked closely with actual activity in the global economy and therefore not just speculation. They found that high S&P volatility typically corresponds to low Bitcoin volatility and vice versa. This is an unusual finding for volatility relationships. They also found a significantly positive effect from the S&P 500 volatility risk premium to Bitcoin volatility. They even found a positive relationship between Bitcoin volatility and the Baltic dry index. In contrast they did not find any correlation between Bitcoin volatility and crime statistics, a topic recently brought to the fore in popular press. They did admit to having only a short sampling period. Symitsi and Chalvatzis (2018) also found spill-overs to Bitcoin prices and short-term volatility from energy and technology companies. They found long-run volatility effects transmitted from Bitcoin to energy stocks, specifically clean energy and fossil fuel stocks, primarily explained by the Bitcoin mining energy consumption. Symitsi and Chalvatzis (2018) also suggested that Bitcoin and stock indices are linked when presented with shock events.

Urquhart (2016) argues that the volatility is in part only because the market is still presenting informational inefficiency in its infancy, even though it is trending towards being more efficient. He argues that separating the volatility analysis between time horizons may provide a better understanding of Bitcoin volatility. Market price volatility is typically associated with market efficiency and market informational efficiency (Foldvari & van Leeuwen, 2011). By 2018, Tiwari, Jana, Das and Roubaud (2018) revisited the issue of informational efficiency and concluded that the Bitcoin market has

indeed reached informational efficiency. Vidal-Tomás and Ibañez (2018) also confirmed that Bitcoin is less inefficient as it used to be when studying its reaction to events. Bariviera (2017) agrees that after 2014 Bitcoin price behaviour is more informationally efficient. Brandvold et al. (2015) also studied the informational efficiency between exchanges and found that some exchanges are more efficient than others. They found that price discovery happens disproportionately on different exchanges, leading to some exchanges lagging others. This lagging effect is then taken advantage of by arbitrageurs to equalise prices across exchanges. Pieters and Vivanco (2017) add that Bitcoin volatility varies greatly between exchanges, depending on their liquidity and whether they employ KYC (“know your client”) legal measures. This implies caution when selecting which exchange data to use, or advises combining data from different exchanges. Only a few studies however included the recent Bitcoin volatility spike in December 2017 and therefore these conclusions could be invalidated by it.

Dyhrberg, Foley and Svec (2018) examined Bitcoin’s investability, specifically concerning trading dynamics and the microstructure of the market. They found that most trading volume and volatility happens during US market trading hours. This resulted in them concluding that most trading is done by retail investors and not algorithmic traders. They also concluded that Bitcoin is highly investable for retail size investments especially because of the low trading fees, high liquidity and small spreads of the markets at that investment size.

Koutmos (2018) investigated the impact that Bitcoin transaction activity has on the Bitcoin price to attempt to ascertain if there are any links between the volume of currency transactions on the Bitcoin blockchain and its price. It found that instead of the transaction volume on the blockchain influencing the price, the price instead influenced the transaction volume. This could possibly be explained by increased transaction volumes by arbitrageurs between exchanges during highly volatile periods. It is therefore not clear whether an increased usage of Bitcoin as a currency will lead to an increase in the price of Bitcoin.

Brauneis and Mestel (2018) studied the volatility and risk/return of combining various cryptocurrencies in a portfolio and found it less risky and therefore less volatile when investing in various cryptocurrencies instead of just one. Ciaian and Rajcaniova (2018) on the other hand studied the relationships between Bitcoin and 16 alternative cryptocurrencies and stated that there is a significant positive relationship between the Bitcoin and “altcoin” (alternative cryptocurrencies) prices and volatility. This correlation

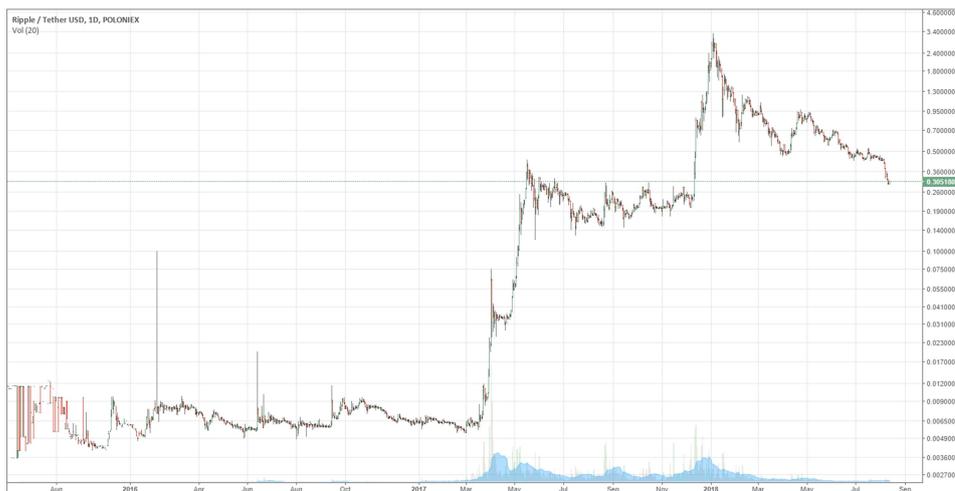
is weaker in the long term than in the short term, but should indicate that combining Bitcoin with other “altcoins” will not reduce volatility.

From the above it is therefore known that Bitcoin is significantly more volatile than traditional currencies to date, although some argue that volatility is decreasing. Volatility sometimes also goes hand-in-hand with bubble behaviour, which is discussed below.

## **2.6 Bitcoin bubbles**

Ardia, Bluteau and Ruede (2018) found strong evidence of regime changes using a Markov-switching GARCH (General Autoregressive Conditional Heteroskedasticity) model, such as bull markets, bear markets and bubbles. An asset bubble is defined as “part of the market price which exceeds or undershoots an asset’s fundamental value” (Cheung et al., 2015, p. 4). Tarlie, Sakoulis and Henriksson (2018, p. 1) also define bubbles and anti-bubbles as “periods in which the dynamics of valuation is temporarily explosive.” Cheung et al. (2015) detected several huge bubbles in Bitcoin price action over the period from 2010-2014. Fry and Cheah (2016) used econophysics modelling and also detected anti-bubbles in the Bitcoin and Ripple markets. A recent article by Fry (2018) addressed high volatility bubbles in the Bitcoin markets. It found bubble behaviour in Bitcoin and Ethereum because of heavy-tails caused by liquidity risks, but did not find any bubble behaviour in the Ripple price market, after heavy tails and liquidity risks are accounted for. Fry (2018) argues that Ripple might not have bubbles because of its centralised control, technological advantages and monetary policy. It cautioned that even without bubbles there might be booms and busts leading to a complete collapse of the price of Bitcoin. It is however surprising how Fry (2018) could claim that Ripple does not have bubbles as an inspection of the Ripple price graph appears to actually have extreme bubble behaviour (Figure 4).

**Figure 4 - Ripple (XRP) Dollar price (Tradingview, 2018)**



Bouri et al. (2018) also explored the co-explosivity behaviour between different cryptocurrencies (in other words, that different cryptocurrencies bubble together), specifically to determine if explosive behaviour in Bitcoin for instance can cause explosive behaviour in smaller cryptocurrencies. They found evidence of co-explosivity in both directions (up and down) between cryptocurrencies, however not from Bitcoin to smaller currencies specifically.

Urquhart (2018) investigated the cause of attention that Bitcoin gets by using Google Trends datasets. He found that the volatility and trading action of a specific day greatly influences the following days' attention. He did not find any method to use this realisation to predict the next day's volatility or returns though. This highlights the autocorrelation effect on the price of Bitcoin during bubble regimes.

## **2.7 Volatility and monetary policy**

Traditional currencies have the ability to stabilise its own volatility by using monetary policy to control supply of said currency. This is in part done by controlling interest rates and thereby limiting inflation and deflation as described by some seminal work by Friedman (1969). This approach is, however, not viable for Bitcoin because of the algorithmic limitation on new Bitcoin issuance. The current state of Bitcoin's monetary policy allows for only a maximum of 21 million Bitcoin in existence (Peng et al., 2018). At the time of this writing, 12.5 new Bitcoins are minted through the mining process every 10 minutes, which will halve every 4 years (Antonopoulos, 2014). Vidal-Tomás and Ibañez (2018) studied central banks' policies' effect on the Bitcoin price and confirmed that Bitcoin is unaffected by policies of fiat currency central banks.

This inelasticity of supply can be an advantage as it limits hyperinflation, but can also be a disadvantage because of the limitations it puts on its ability to adapt. This

inelastic supply was proposed by Friedman (1969) as the optimal supply of money on condition that the demand for money is stable and the loss of money is negligible. This study argues that this limited ability to change monetary supply to adapt to volatility and demand does however prevent Bitcoin from using this means to reduce volatility. It is also evident that the demand for Bitcoin is still fluctuating wildly, which means it does not fit the conditions imposed by Friedman (1969).

Ametrano (2014) proposes a solution for the volatility in cryptocurrencies. He proposes that stability can be attained by continuously rebasing the amount of money outstanding, which could be seen as being similar to the effect interest rates have on fiat money supply. He also makes suggestions on how to ease the effect of contractionary/deflationary monetary policy. He claims that this can be done without centralisation. This method would be extremely difficult for Bitcoin to adopt at this time as it would require substantial support from the ecosystem to make such drastic changes to the protocol, which is unlikely to happen (most proponents of Bitcoin find its limited stable supply one of Bitcoin's most appealing advantages). This technique would therefore only be useful for a different or new cryptocurrency.

## **2.8 Spot market trading volume and volatility**

Another possible solution to the Bitcoin stability problem is increased spot market speculation that can possibly reduce volatility in the Bitcoin spot market prices in the long term.

The early seminal literature discusses speculators' ability to reduce commodity prices' seasonal volatility. Smith (1776) saw that speculators aid in preventing volatile price movements by preventing extreme shortages. Mill (1871) expanded on Smith and concluded that speculators are useful for price stability because they buy at low prices and sell at high prices. This behaviour improved the inter-temporal allocation of resources and stabilises supply and prices from seasonal fluctuations. He also added that price volatility is reduced locally when speculators redistribute goods geographically. These authors argued that speculation cannot destabilise a market unless it is unprofitable. Friedman (1969) agreed later that speculation generally can only be destabilising if speculators in total lose money. Authors over the years have disagreed, including Kaldor (1939), saying it is feasible to think that speculators in total does actually lose money, and that it is simply the seasoned speculators who profit from the entering novices. Baumol (1957) constructed a model under which speculation is destabilising by suggesting that, without speculators, prices have a predictable seasonal fluctuation, but when speculators start trading they increase

volatility by exacerbating up and down moves. On the other hand, Knittel and Pindyck (2016) found recently that speculation had a slight stabilising effect on the oil price movements after 2000. This result agrees with the study by Brunetti, Büyükşahin and Harris (2016), but not with the study by Chevallier and Sévi (2012) who found a largely significant positive relationship between spot trading volumes and volatility using high frequency data of oil and gas markets.

Even though literature is mixed on the issue, in recent times, the majority of authors agree that speculation is more likely to stabilise prices in mature markets, especially with the introduction of derivative instrument speculation. This is confirmed by a meta-study by Mayhew (2000). This study will attempt to support this literature, in the Bitcoin context, that increased speculation (measured in terms of trading volumes) has led to a less volatile Bitcoin spot market price.

For Bitcoin specifically Blau (2017) tested whether the price volatility is a result of speculative spot trading during 2013 and found that it is not. He also concluded that speculation has not directly caused Bitcoin's volatility in general. The market is significantly larger now than it was in 2013 and this result accordingly requires revisiting. Urquhart (2017) found a significant positive correlation between the Bitcoin price and speculative trading volumes. He also found significant price clustering at whole numbers. But he did not investigate the effect of volume on volatility of the price.

The only research found that attempted to find an effect between spot trading volume and volatility for the Bitcoin market specifically is by Balcilar et al. (2017). They used a novel quantiles-based approach to determine if trading volume could predict Bitcoin returns and volatility. They failed to use trading volume to predict Bitcoin volatility over the entire period. Their study also ended in April 2016, which is before the recent volatility spike and drastic increases in trading volumes.

Because no peer reviewed research was found that successfully predicted Bitcoin volatility using spot trading volumes over the entire time series, this paper will look at this relatively unanswered question.

Hypothesis 1: Bitcoin spot trading volume has a negative effect on Bitcoin price volatility.

## **2.9 Derivative trading and its effect on volatility**

A derivative instrument or “derivative” is a contract between multiple parties of which the value is determined by the underlying value of an asset or security. Typical

underlying assets or securities include bonds, commodities (such as Bitcoin), currencies, stocks or indices. While a derivative's price depends on the underlying asset, the owner of the derivative does not own the underlying or rights thereto. Some examples of derivatives are futures contracts, options, swaps and warrants. These instruments are typically useful for speculation or hedging of risk. A futures contract is a derivative instrument where two parties agree to exchange an underlying asset at a prearranged price at a predetermined time in the future. They can also be cash settled where the actual asset does not need to be delivered at settlement on the specified date, but only the associated cash position transferred between parties. This allows speculation or hedging without ever touching the underlying asset. A swap is a derivative contract where parties agree to buy or sell financial instruments or assets based on a certain predetermined rule set. An options contract on the other hand is a derivative instrument where parties agree to execute a trade on the underlying asset at the predetermined rate, called the strike price, before the expiration date. One of the differences between a futures contract and an options contract is that the entity purchasing the option has the option of executing the contract, where a futures contract buyer or seller is obliged to deliver on the contract. (Eales & Choudhry, 2003).

A variety of approaches have been used to study the effect that speculative derivative trading specifically might have on the stability and liquidity of asset markets, as well as how it conveys information to the spot market. For currency futures specifically, Singh and Tripathi (2015) finds that the commencement of futures has aided in stabilising the Indian foreign exchange market. This result agrees with the study by Brunetti et al. (2016) who found that hedge funds, which trade derivative instruments, increase price discovery and therefore aid in lowering volatility. Todorova and Clements (2018) studied the relationship between volatility and trading volume in the derivative markets for metals and also found that they are related. Bohl, Diesteldorf and Siklos (2015) agrees and studied the effect that the introduction of derivatives in the Chinese futures market had on the Chinese, Singapore and Hong Kong stock markets' spot volatility. They used GARCH models to confirm that the introduction of the derivatives, specifically futures contracts in this case, had reduced the volatility in the underlying stocks' prices of all three markets. They stated that the Chinese stock market is younger than other markets and mostly used by retail investors, which is similar to Bitcoin. Bohl, Salm and Wilfling (2011) also investigated whether the introduction of futures derivative trading had an effect on the Polish stock market. They even used a Markov-switching-GARCH approach to determine volatility regimes, and found that the new derivative trading did not destabilise the spot markets. They did not test

specifically whether it stabilises the market though. They did however mention that the derivative market can increase volatility in the spot market if derivative speculators are uninformed and therefore introduce noise in the process of price discovery.

In general it was difficult to find any recent literature that showed a destabilising effect of derivative trading on spot volatility. More studies concluded that the derivative market reduced volatility of the spot price of the underlying asset or instrument than studies who concluded the opposite, but under some conditions it might go either way or does not influence at all. This is according to Mayhew (2000) who did a meta-analysis on the effect of derivative trading on markets (commodities, currencies etc.) and found that out of 94 studies, 38 found that the introduction of derivatives lowered volatility, 47 found no effect and 9 found higher volatility. It is also worth noting that he suggests that it is possible to manipulate the spot market if it is not completely competitive by using the derivative markets.

## **2.10 Derivatives' effect on Bitcoin price stability**

It is clear from the previous sections that a significant amount of research has been done on the effect of speculation on volatility and that this effect is generally known, resulting in little research being done on it in recent years (since 2000). What is not known is how this effect is witnessed in the new cryptocurrency markets empirically.

Research that studied the effects of derivative markets on the volatility of the Bitcoin price specifically was conducted by Shi (2018). He did find a dampening effect in the Bitcoin underlying price with the commencement of the CBOE futures launch in December 2017. Although he used high frequency data it was for only two weeks and the CBOE exchange had very small volumes compared to the global trade of Bitcoin at that time. The study by Shi (2018) is not peer reviewed and is only included here because this topic of research is very scarce. The only peer-reviewed article found is a very recent article by Corbet et al. (2018), published in November 2018, investigating the effect that the introduction of Bitcoin derivatives has had on the price volatility. They however concluded, contrary to other markets, that the volatility has in fact been exacerbated by the introduction of CBOE and CME derivative contracts in December 2017, and that the futures have not acted as a hedge. They also concluded that price discovery is mainly determined by inexperienced speculators in the spot market, even after introduction of futures trading. The study also concluded that Bitcoin is still driven by speculation and is therefore not suitable to be a currency. Corbet et al. (2018) however only used data up to 22 February, after which volatility died down

substantially. They also did not use data from Bitmex, which in fact has the largest derivative contracts volume (Table 1).

Because literature is scarce on this topic of how derivative trading volumes specifically influences Bitcoin spot market volatility, it is prudent to test the effect of derivatives volume traded on the spot price volatility of Bitcoin over a longer timeframe to establish if the introduction of derivative contracts could aid Bitcoin in reducing its volatility going into the future.

Hypothesis 2: Trading volume of Bitcoin derivative instruments negatively affects the volatility of the Bitcoin spot price.

## **2.11 Hedging strategies**

A final possible solution to the Bitcoin volatility problem could be to combine a holding of Bitcoin itself with a holding in Bitcoin derivative short contracts. This combined portfolio would cancel out movements in the Bitcoin spot price with the short contracts, while simultaneously providing the increased utility of a cryptocurrency. This has only ever been tested by the most recent study by Corbet et al. (2018), which concluded that the hedging strategy increased volatility. Because of their timeframe and data, as mentioned before, this idea might need to be retested though, but because of the time limitations of this paper however this was left to future research.

## **2.12 Conclusion**

This chapter analysed the current literature available in the Finance, Economics and Econometrics field in relation to Bitcoin and other cryptocurrencies. It found that the literature base is growing quickly in recent years, but that some specific questions still remain unanswered. Specific questions that remained unanswered and need clarification are concerning the effect that speculation volume has on the Bitcoin price volatility, both spot trading volumes and specifically derivative trading volumes. This paper therefore proceeded to test the two hypotheses presented in this chapter using the methodology as described in the next chapter.

### **3 Research Methodology and Design**

#### **3.1 Introduction**

The research methodology that was followed in order to test the effect between Bitcoin spot and derivative trading volumes and Bitcoin price volatility will now be discussed in detail and validated by appropriate literature on each section. It will start by an explanation of the research design, followed by the unit of analysis, population, sample size, sampling method, analysis methods and research techniques that was used. The data gathering process used will also be discussed. This chapter will conclude by discussing the limitations of the research that was done.

#### **3.2 Research methodology and design**

The design of this research study was a mono-method quantitative causal study using longitudinal secondary data (Saunders & Lewis, 2012). The literature suggests a possible effect that speculation volume has on the price volatility of a market. Prior literature on volatility studies almost exclusively use quantitative research methods (Katsiampa, 2017). This research was an empirical finance/econometrics study. Because of these reasons this research therefore was quantitative by nature. The constructs in the study like volatility and trading volume were deduced from literature and was not induced during the study, making the deductive approach appropriate. The assumptions underlying volatility and its definition were assumed to be valid for this study's purpose. This study applied the existing theoretical constructs in a new context of Bitcoin data. Raw time series data was converted into standardised data. The data is available online from free sources.

This study followed a Positivism philosophy to examine the effect of speculative trading to predict the likelihood of volatility changes in the future (Saunders & Lewis, 2012). This study aimed to understand the cause and effect of speculative trading volume on volatility. The positivism philosophy was selected in order to maintain objectivity in this endeavour and to aim for the highest possible reliability of the results, especially since views on Bitcoin in general are polarised.

The study was explanatory as it went beyond being simply descriptive and rather built on literature available to explain the market phenomena and relationships between trading volumes and volatility (Saunders & Lewis, 2012). Attempts have been made to eliminate other possible causes for the results found.

The techniques and procedures used will be discussed in more detail in the following sections.

### **3.3 Population**

The population for this research entailed all the available datasets of longitudinal Bitcoin trading data from all the exchanges currently in operation. Bitcoin started trading on open exchanges in 2010 and there is currently in excess of 200 exchanges.

### **3.4 Unit of analysis**

The unit of analysis was Bitcoin's volatility over a time period, from 2014 to 2018.

### **3.5 Sampling method and sample size**

This study used non-probability purposive sampling based on certain premises and reasons for selecting data that would be the most reliable and valid.

The validity and reliability of the dataset affected the credibility of the research findings. Some effects that could have impacted the reliability and validity of the data for this study specifically were:

- Missing data points for specific times because of exchange Application Programmable Interface (API) overloads (Brandvold et al., 2015).
- Big spreads between bid and ask offers of the Bitcoin market on the exchanges used.
- Insufficient trading volumes and liquidity on exchanges used.
- Big differences between prices on different exchanges for the same currency pairs at the same time. This can result from technical issues on an exchange inhibiting arbitrage (Brandvold et al., 2015).

The research and sampling was carried out in such a way to eliminate these abovementioned causes of validity and reliability issues as far as possible.

Additionally, Bitcoin futures contracts use specific exchanges as the underlying price to base the future contract settlement price on. It was preferable to include the price data from the same exchanges used as the futures' underlying settlement price.

The sampling was selected in order to minimise the causes as mentioned above, and accordingly the following datasets were used.

For the first hypothesis:

- Daily Bitcoin price data from Coinmarketcap (Coinmarketcap, 2018)

- Daily global Bitcoin trading volume from Coinmarketcap

For the second hypothesis:

- Daily Bitcoin price data from Coinmarketcap (Coinmarketcap, 2018)
- Daily data on all Bitmex historical derivative contracts' trading volume (both futures contracts and swap contracts) (Bitmex, 2018)

Bitmex was used as it has the longest history of derivative trading data as well as the highest volumes and highest liquidity. Even though the CME futures and CBOE futures are more widely used among institutional investors, the table below shows how Bitmex has substantially more volumes traded for recent derivative contracts.

**Table 1 - Bitcoin derivative contracts volume comparison**

<b>Instrument</b>	<b>24 Hour Volume (recorded 28 April 2018)</b>
Cboe XBT/K8 (Expiry 16 May 2018)	3 711 Bitcoins
Cboe XBT/M8 (Expiry 13 June 2018)	1 027 Bitcoins
Cboe XBT/N8 (Expiry 18 July 2018)	360 Bitcoins
<b>Total CBOE Derivative Contracts</b>	<b>5 098 Bitcoins</b>
CME Group May 2018	24 620 Bitcoins (each contract is for 5 Bitcoins)
CME Group June 2018	2 630 Bitcoins (each contract is for 5 Bitcoins)
<b>Total CME Derivative Contracts</b>	<b>27 250 Bitcoins</b>
Bitmex Jun 29 2018	10 994 Bitcoins
Bitmex Sept 28 2018	2 567 Bitcoins
Bitmex Perpetual Swap	347 098 Bitcoins
<b>Total Bitmex Derivative Contracts</b>	<b>360 659 Bitcoins</b>
<b>Total Bitcoin traded volume (spot market)</b>	<b>849 345 Bitcoins</b>

The timeframe used for the first hypothesis was from January 2014 to 1 July 2018. This excluded the Bitcoin price data from when the prices were still illiquid and when

there were extreme price differences between exchanges. This was done to increase reliability and validity of the data.

Bitmex started listing derivative contracts at the end of September 2015. The timeframe used for the second hypothesis was therefore from 25 September 2015 to 1 July 2018.

Bitmex and other cryptocurrency exchanges operate 365 days a year, 24 hours a day. This means the time-series data had 1696 daily observations for the first hypothesis and 1035 observations for the second hypothesis. This sample size is deemed sufficient as it is similar to other studies into Bitcoin volatility (Chu et al., 2017; Fry, 2018).

### **3.6 Measurement instruments and data collection tool**

Volatility is measured in various ways. It can be measured using standard deviations of time series data or it can be analysed and visualised using a histogram method. Realised volatility is another way of calculating volatility and will be discussed. Finally the ARCH (Autoregressive Conditional Heteroskedasticity) models will be discussed as a way to model and analyse volatility.

#### **3.6.1 Standard deviation**

The standard deviation of a time-series is a basic statistic to measure volatility over an entire period. The standard deviation is shown by the formula below (Wegner, 2016).

$$\text{Standard Deviation} = \sqrt{\frac{\sum |x - \bar{x}|^2}{n}}$$

Where:

$\bar{x}$  = Mean of the series

$n$  = Number of observations

While the standard deviation is relatively easy to calculate, it has complex assumptions which in turn raise concerns around its accuracy and validity as a measure of risk and volatility. For the standard deviation to be used to test and measure volatility it has to be assumed that the data is normally distributed (Wegner, 2016). There are at least three reasons why time series data may not be normally distributed.

The first reason is that time series data like investments and Bitcoin specifically are typically skewed. Investment returns are typically asymmetrical because there are time periods of superior or poor performance (Chu et al., 2017).

The second reason is that time series data for Bitcoin typically show leptokurtosis, which means that the tails of the return distribution are typically fat. This indicates that there are a significant number of outliers in the returns of the investment (Selmi et al., 2018).

Lastly heteroskedasticity is a cause for concern. Heteroskedasticity is defined as a property of a time series where the variance of the sample data varies over time. It's also referred to as volatility clustering which typically happens during highly volatile times like bubbles, for which Bitcoin is known (Chu et al., 2017).

These three reasons result in the data not being normally distributed and therefore standard deviation alone is not a reliable and valid measure of volatility.

### **3.6.2 Histogram using the historical returns performance**

An easier and more accurate method of measuring and visualising risk is by graphing a histogram with the proportion of return observations that fell within a specific range. This allows the reader to determine the percentage of times when the investment had returns within a specific range.

Using the histogram method instead of the standard deviation method has the following advantages:

- The historical histogram method doesn't require the returns data to be normally distributed.
- The impact of skewness and kurtosis is captured in the histogram.

These advantages provide observers with the required information to inspect the volatility.

Disadvantages of the historical histogram method, however, is that it does not account for the data's heteroskedasticity and does not allow statistical hypotheses testing.

### **3.6.3 Historical realised volatility method**

The historical (realised) volatility is calculated as below (RealVol, 2018)

$$Volatility = 100 \times \sqrt{\frac{252}{n} \sum_{t=1}^n R_t^2}$$

252 is a conventional constant for trading days in a year. Even though Bitcoin trades 365 days a year, we use the standard 252 days used in finance literature, which enables comparisons with traditional currencies.  $t$  is the trading day counter and  $n$  is the total days in the time period.  $R_t$  is the continuous daily compounded return.

$R_t$  is calculated as below (RealVol, 2018)

$$R_t = \ln \frac{P_t}{P_{t-1}}$$

$\ln$  is the Natural logarithm and  $P_t$  is the underlying Bitcoin closing price at day  $t$ .  $P_{t-1}$  is the underlying Bitcoin closing price the previous day.

Returns are logged and differenced to account for the auto-correlation typically associated with non-stationary time-series data. Although the realised historical volatility method above also accounts for skewness and kurtosis it does not account for heteroskedasticity as mentioned.

#### **3.6.4 ARCH methods**

As all the previous methods do not account for volatility clustering (heteroskedasticity) in time-series data, ARCH (Autoregressive Conditional Heteroskedasticity) models have been widely adopted to model volatility in recent decades (Peng et al., 2018).

The GARCH models have been a valuable tool since it was introduced by the seminal work of Engle (1982). The GARCH models are based on the ARCH models for which Engle received the Nobel Memorial Prize in Economic Sciences in 2003. ARCH models use high order lagged disturbance to properly model the behaviour of conditional variance. Marcucci (2005) agrees that the GARCH model is a parsimonious model specifically equipped to handle time series data on volatility. Takaishi (2018) confirms that Bitcoin shows similar time series properties than other time series assets, like fat-tailed return distributions, serial correlation in returns and volatility clustering, where GARCH models are appropriate.

Various GARCH-type models exist (300+), for example the linear GARCH, the Threshold GARCH (TGARCH) by Dyhrberg (2016b), the Exponential GARCH (EGARCH) by Dyhrberg (2016a), and the Component with Multiple Threshold-GARCH (CMTGARCH) (Bouoiyour & Selmi, 2016).

Katsiampa (2017) found the optimal fitting model for analysing Bitcoin data specifically to be the AR-CGARCH model. However Charles and Darné (2018) replicated his study and found partially different results.

Meanwhile Chu et al. (2017) found that the IGARCH and GJRGARCH models are the optimal fit for modelling returns in the majority of large cryptocurrencies. Mensi, Al-Yahyaee and Kang (2018) on the other hand found that the FIGARCH model with structural break variables provides relatively increased forecasting accuracy.

There is accordingly no consensus in current literature on the best ARCH model to use for Bitcoin volatility modelling, especially since Bitcoin is prone to structural breaks and literature tests have been done during different time periods. This research therefore attempted to fit the best available model to the data in the time available and found that the ARCH model with a lag of 1 year was appropriate, shown by the formula below.

$$ARCH(1) = \sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$$

$\epsilon$  denotes the error terms and  $\sigma_t^2$  is the variance.

Long memory and structural breaks in the time series data are also two important elements in modelling. If a market exhibits long memory, yesterday's news events still influence today's volatility and prices. Structural breaks are defined as unexpected shifts in a time series that invalidates existing models and can lead to forecasting errors (Preuss, Puchstein & Dette, 2015).

Another phenomenon that can sometimes be observed in time-series data are the leverage effect defined as the tendency of rising asset prices to be accompanied by declining volatility (Bouchaud, Matacz & Potters, 2001).

Although GARCH models are currently the most widely used model for Bitcoin volatility modelling, as established above, its limitation is that it does not model correctly for asymmetry and nonlinearity in the volatility data.

### **3.6.5 Other volatility measurements**

Some other less popular methods are the Parkinson volatility method which uses the high and low values in a particular period and the Rogers and Satchell method which uses first, high, low and end of period prices. The Support Vector Regression (SVR) model, have been used by Gavrishchaka and Ganguli (2003). Other studies employ neural networks, machine learning or technical analysis (Pichl & Kaizoji, 2017).

## **3.7 Data gathering process and collection method**

Data was gathered and collected in the following way:

- The daily historical Bitcoin price and volume raw data was downloaded from Coinmarketcap.com (Coinmarketcap, 2018).

- The historical daily Bitmex derivative contracts' volume (futures contracts and swap contracts) was downloaded through the Bitmex API and added together (Bitmex, 2018).

The data was then gathered in Excel and the necessary calculations were done to calculate daily returns and volatility. The data was then standardised where necessary. Lastly the data was imported into STATA version 14 for statistical tests and analysis.

### **3.8 Data analysis approach**

The data was analysed in STATA version 14, at a 95% confidence interval. STATA was used as it has the best support for ARCH analysis from the available options. Both hypotheses separately used the same method as described below.

Firstly, after the raw data was collected it was processed to ensure the data meets the required formats and to determine if there are any faulty data point outliers or missing data points.

A descriptive analysis was done to determine the following characteristics of the data (Katsiampa, 2017):

- Maximum value in the dataset
- Minimum value in the dataset
- Standard deviation of the dataset
- Skewness of the data
- Kurtosis of the distributions of the dataset

The descriptive statistics was done for the price dataset, the volume datasets and finally the logged differences of the daily returns, which is the proxy for the volatility of the prices. A historical volatility histogram was graphed to give some visual insight into the return distribution.

The data showed signs of extreme non-normality as is expected from time-series data and was then standardised. In cases where time series data is not normally distributed, the data was transformed to be more normal in order to make the statistical conclusions more valid. Using log transformations are considered one of the most popular transformations available to transform severely skewed data to be more normally distributed. In this case data was transformed using the natural log (10) due to the huge standard deviations and to correct for the skewed data. For daily returns negative values, double exponential smoothing was done to correct for the negatives

(Changyong, Hongyue, Naiji, Tian, Hua & Ying, 2014; Dyhrberg A. H., 2016a; Chu et al., 2017). A yearly mean analysis was done to see the effects over time and possibly the effects of price regime changes and structural breaks.

The normality of the data was inspected and scatterplots were presented to visually attempt to see relationships between variables. A trends analysis was also done to determine trends in the underlying data and inspect the relationships of the variables over time.

To test for the validity of the analysis, a Ljung-Box-Pierce portmanteau test was done to test if the standardised residuals/returns are free from serial autocorrelation. The test tested the white noise process to ensure that the variable does not have autocorrelation. Because of the detected white noise presence, further tests were done to check for stationarity or unit roots in the data series. Data has to have a trend for the models to fit well, meaning it has to be stationary (Balcilar et al., 2017).

A stationarity test was run. The existence of a unit-root in a dataset indicates that more than one trend exists in the data. By testing for unit-roots the study also tests if the data is stationary. The Dickey-Fuller test was used to test for stationarity (Dickey and Fuller, 1979). Stationarity is established when the mean and variance of the data stays the same over time. A time-series with a persistently changing mean over time are non-stationary. For time series analysis it is preferable to have a stationary process (MacKinnon, 1994). In a Dickey-Fuller test, the null hypothesis is that a unit root exists in the dataset. The t-statistic critical values are then used to decide on whether to accept or reject this null hypothesis (MacKinnon, 1994). If the test results in a failure to reject the null hypothesis it can be concluded that data has a unit root and is therefore only useful for poor forecasts. This will affect the validity of the results and conclusions. The Phillips-Perron Test for unit roots was also employed to test for unit roots (Phillips and Perron, 1988).

To test for the ARCH effect we tested if there is serial correlation of the heteroskedasticity. Therefore a Johansen co-integration test was done. Co-integration indicates that different time series share a stochastic trend. Co-integration between variables can therefore indicate that there is unidirectional causality between variables and therefore that one has an effect on the other (Gujarati, 1999: 623). The test also determined the optimal lag to use for the next ARCH model analysis.

The appropriate ARCH model was then fitted and examined to determine the results of the hypotheses. Since the data was not normally distributed, the ARCH model applied

a t-distribution as was also previously done by Klein et al. (2018). The ARCH model was also run yearly to attempt to gain insight into the relationships at different price regimes and times.

Finally a Granger test analysis was done to confirm Granger-causation between two time-series and to establish the direction of the effect if there is in fact an effect between the two (Granger, 1981). The Granger test suggests that when the coefficients are significantly different from zero at a specific significance level, the one variable can Granger-cause the other. The test ran an ordinary least square model to determine if unidirectional causality exists between the time-series datasets.

### **3.9 Strategies to ensure quality of data**

As mentioned the quality of the dataset could have been impacted by missing data points, big spreads between bids and ask offers, liquidity on exchanges and big differences between different exchanges for the BTC/USD pair at the same time. The research and sampling was carried out in such a way to eliminate these abovementioned causes of validity and reliability issues as far as possible by using an index of prices, combining the largest exchanges, published by Coinmarketcap. Because of using this Coinmarketcap index there were no missing data. Concerns regarding spreads and liquidity are also avoided because of combining multiple exchanges. Coinmarketcap is also extensively used by existing studies (Chu et al., 2017; Klein et al., 2018; Fry, 2018).

The study period used for the first hypothesis was from January 2014 to 1 July 2018. This study period was selected because the data is of better quality during that period; since the markets were already more liquid and spreads were smaller.

Additionally, Bitcoin futures contracts use specific exchanges as the underlying price to base the future contract settlement price on. The Bitmex futures contracts use the Bitstamp and GDAX prices as the underlying. These two exchanges are included in the Coinmarketcap index and it is therefore optimal.

### **3.10 Research ethics**

This research was not harmful in any way. In fact, if it can shed some light on Bitcoin volatility behaviour it can reduce risk for speculators and investors alike by aiding in informational and market efficiency.

### **3.11 Research limitations**

Although every measure was taken to minimise possible research limitations, some restrictions will apply.

Daily data is considered low frequency data in the analysis of Bitcoin prices. Using higher frequency data could possibly get more significant results, but getting historic intraday data for derivative exchanges proved difficult. All intraday market movements and information contained therein will therefore not reflect in the results.

One characteristic of the Cryptocurrency markets is that the prices between exchanges differ. By using only selected exchanges the data might not represent the entire Bitcoin market. This study was however not able to obtain data from all 200 exchanges within the limited time available. Using data from Coinmarketcap though ensured that the most widely used exchanges were indexed into the data used. Coinmarketcap is also used extensively by other studies (Chu et al., 2017; Fry, 2018).

Using a relatively short time frame of three years of data is not long compared to other financial studies, not surrounding Bitcoin. Bitcoin is however still young and reliable data is not available for longer time frames. In excess of 1000 observations per hypothesis are considered sufficient though in this context of Bitcoin (Chu et al., 2017; Fry, 2018).

Any missing data from datasets might skew the analysis. All measures were taken to process the data in a sufficient manner to limit effects of missing data. No data points were missing from the Coinmarketcap or Bitmex data, but some might be missing inside the Coinmarketcap index.

This study relied on various models for volatility. No perfect model exists for volatility and therefore poses a validity concern for the study. Realised volatility or ARCH models are also not an error-free measure of volatility.

## 4 Results

The purpose of this research is to ascertain if Bitcoin trading volumes (both spot and derivative) have an effect on Bitcoin volatility and therefore to determine the likelihood of Bitcoin volatility reducing in the future if trading volumes increase.

The chapter starts with descriptive statistics, followed by time series tests (Portmanteau white noise, Dick Fuller tests for stationarity and unit roots tests). This is followed by ARCH models to determine the results of the hypotheses. Lastly Granger causality models are done to confirm if there are long run relationships. The tests are the same for both hypotheses, but are described separately for clarity and because the time periods are different.

### 4.1 Hypothesis 1

Firstly, the impact of spot trading volume on volatility is examined.

#### 4.1.1 Descriptive statistics

This section provides descriptive statistics for the original raw dataset. Figure 5 shows the Bitcoin price from 2015-2018 and Figure 6 shows the Bitcoin spot trading volume graph.

Figure 5 - Bitcoin price (2015- 2018)

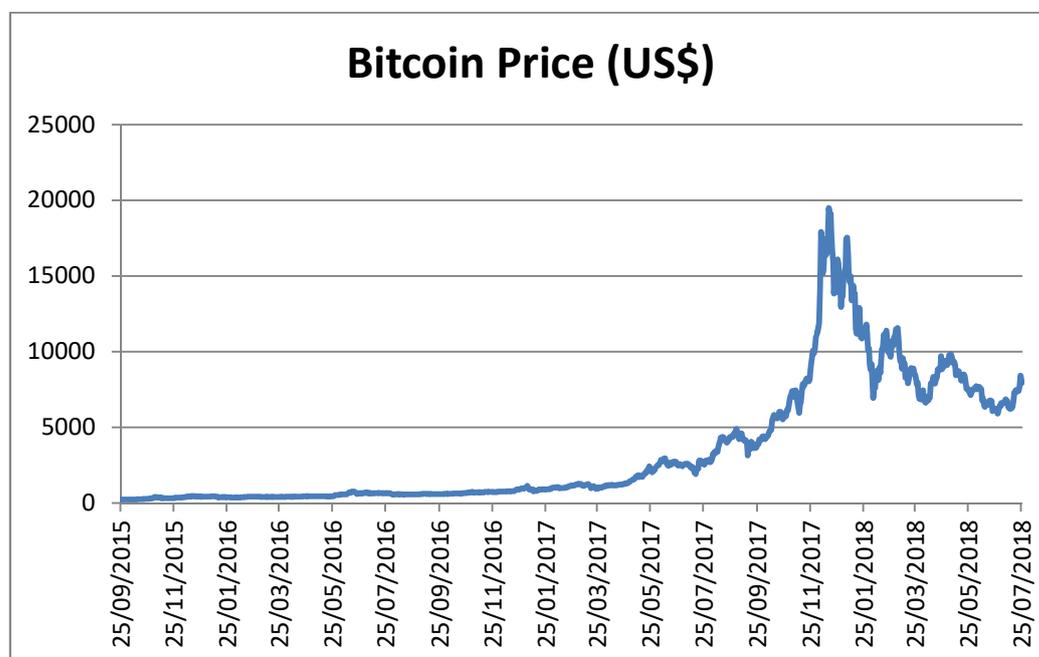


Figure 6 - Bitcoin spot trading volume

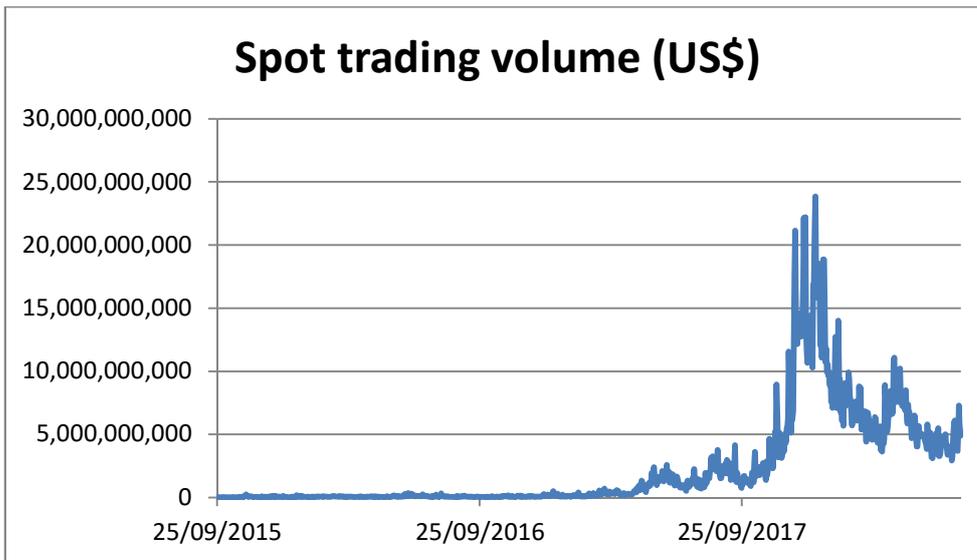


Figure 7 shows the daily price returns for Bitcoin while Figure 8 shows the 30-day realised price returns volatility.

Figure 7 - Bitcoin daily price returns

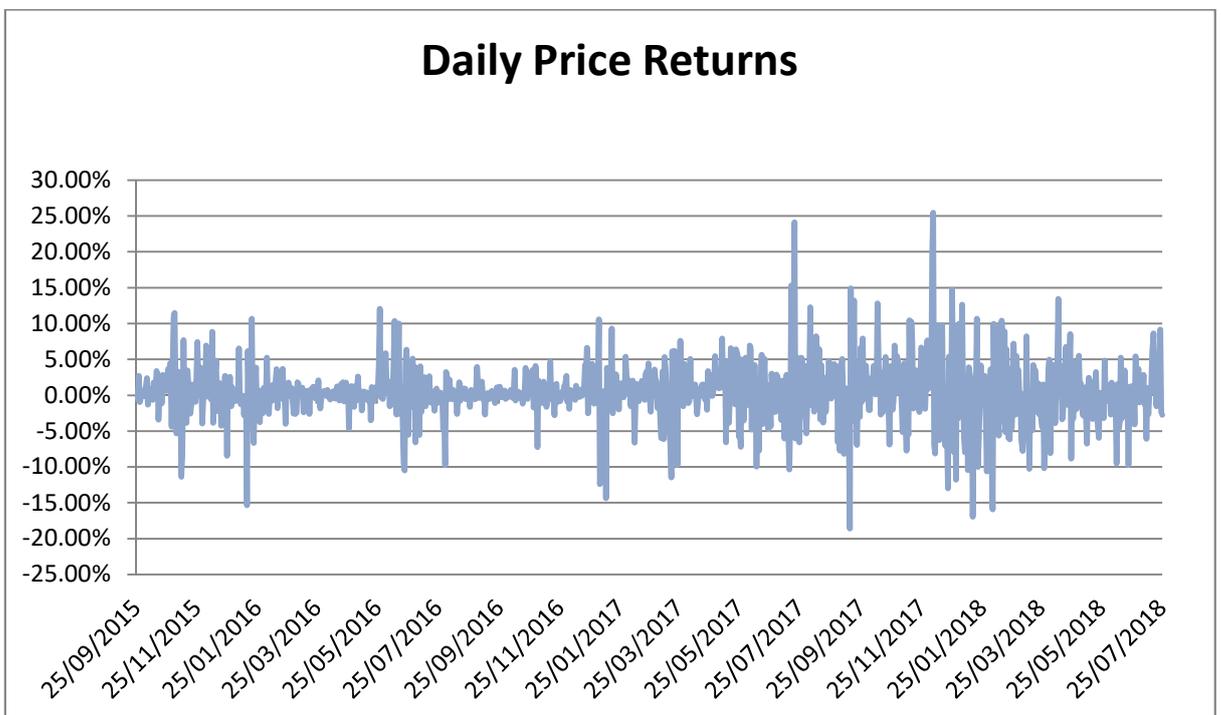
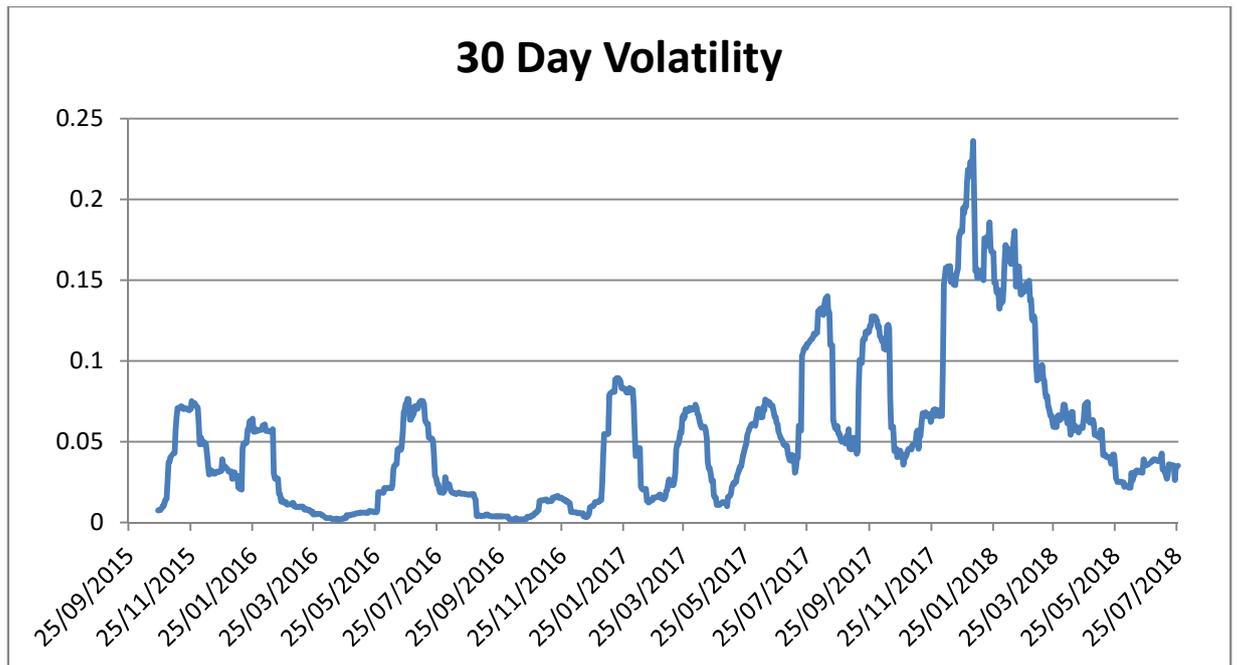


Figure 8 - 30-day price volatility



Notably, spot trading volume (\$) was the most volatile, followed by Price, and then by the Daily Returns. Table 2 shows the descriptive statistics results.

Table 2 - Hypothesis 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Kurtosis	Skew.
Price (\$)	1,697	\$2340.65	3,554	178	19497	4.02	2.08
Spot trading Volume	1,697	\$1.48B	\$3,2B	\$2.8M	\$23.8B	11.38	3.11
Daily Return (Absolute)	1,696	3.40271	254.62	-2329	3608	47.32	1.44
Return (Volatility)	1,696	0.001285	0.040	-.2375	.2251	5.64	-0.4161

Note that the daily returns and volatility datasets have 1 less observation as they are a calculation taking into account the difference between two days of prices.

Because the data is not normally distributed, with extreme standard deviations, there is a need to transform all the data.

#### 4.1.2 Transforming non-normal distribution of primary data

In this case data was transformed using the natural log (10) due to the huge standard deviations and to correct for the skewed data. For daily returns negative values, double exponential smoothing was done to take care of negatives. In this case, the skewness of the data was removed or reduced by the data standardisation.

**Table 3 - Hypothesis 1: Standardised data descriptive statistics (2014-2018)**

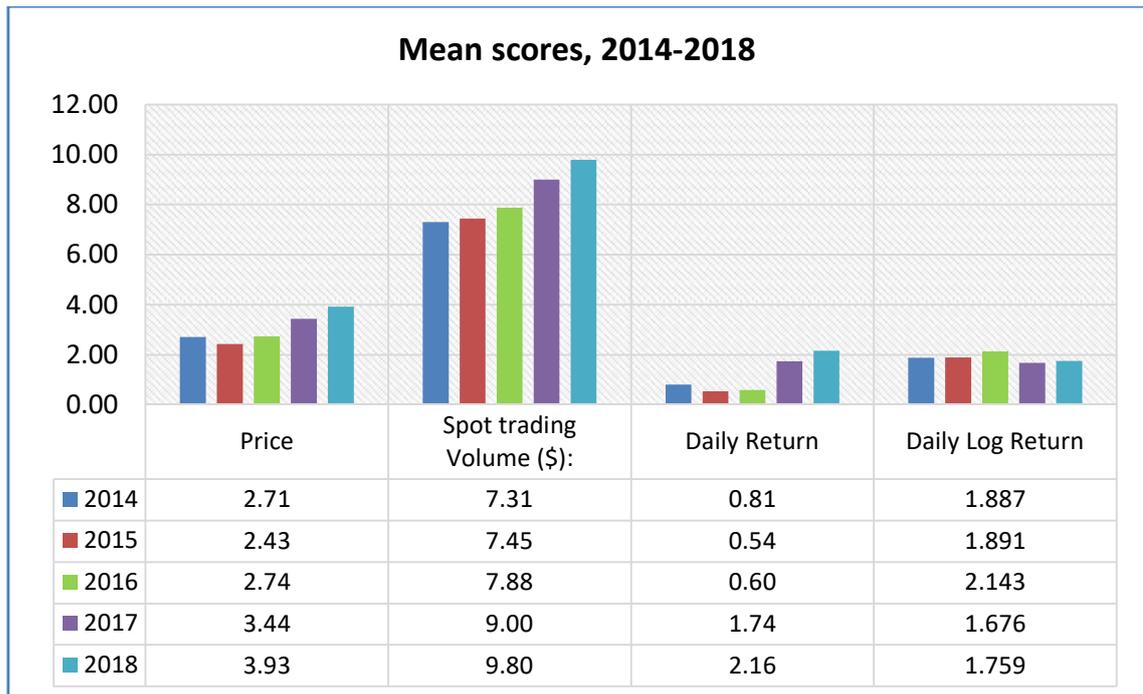
<b>Variable</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>	<b>Kurtosis</b>	<b>Skewness</b>
<b>l_price</b>	2.98	0.55	2.25	4.29	-0.65	0.84
<b>l_volume</b>	8.17	0.96	6.46	10.38	-0.85	0.72
<b>l_daily_returns</b>	1.11	0.87	-2.00	3.56	-0.072	0.13
<b>l_volatility</b>	-1.88	0.57	-4.66	-0.65	1.07	-0.76

As can be seen in Table 3, between 2014 and 2018, the Mean (2.98) for the Price variable was not far from the maximum (4.29) and the minimum (2.25) with a standard deviation less than 1, suggesting the transformed data series for the Price variable is closer to normality.

The mean for the transformed Spot Trading Volume was 8.17, also with a minimal standard deviation, showing the values are closer to normality after transformation. The transformed Daily Return mean (1.1) was positive while that for the transformed volatility of the Bitcoin spot price was negative (-1.88).

A yearly analysis was done to see the effects over time and possibly the effects of price regime changes.

**Table 4 - Hypothesis 1: Yearly mean scores**



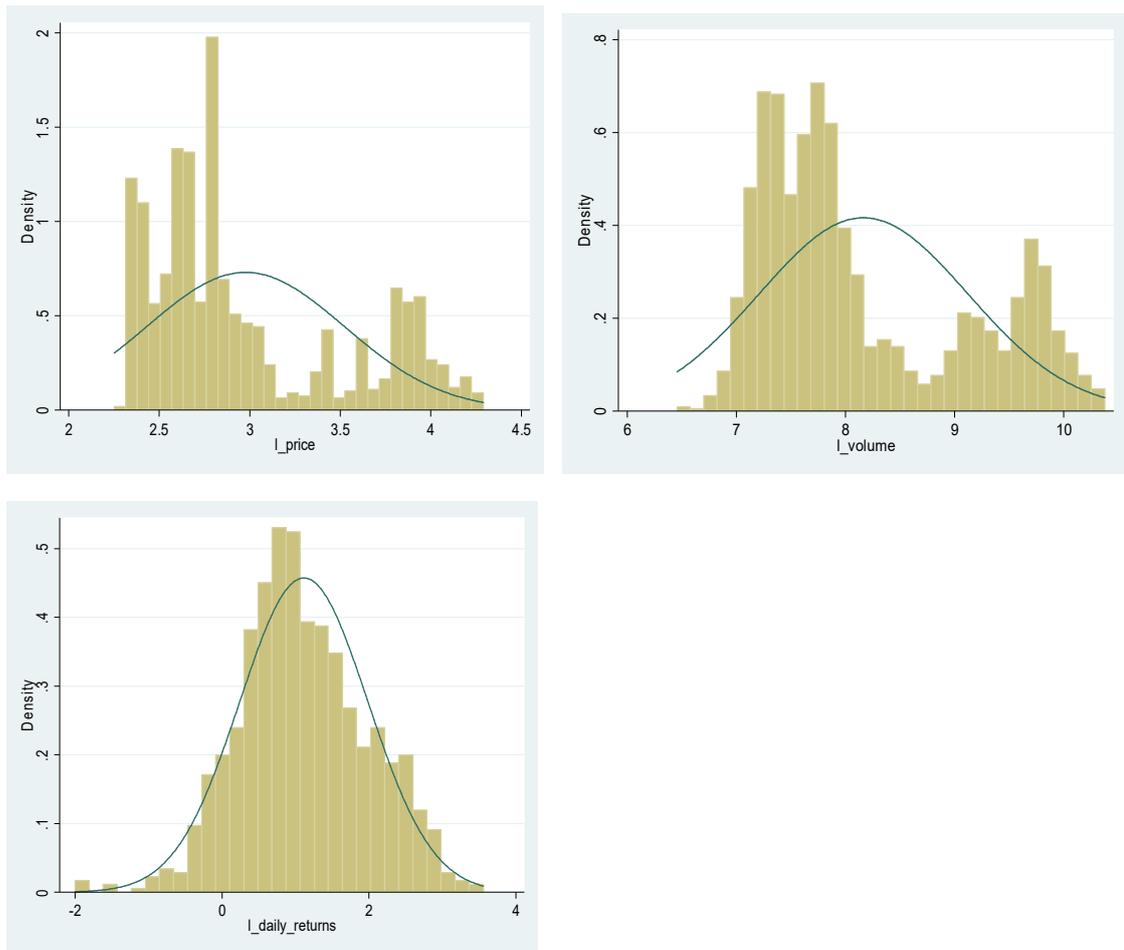
The mean logarithmic transformed price over the years has been increasing steadily, from 2.7 in 2014, to 3.44 in 2017. The highest transformed price value was 3.93 in 2018. Transformed spot trading volume has increased from 7.3 in 2014, to 9.8 in 2018.

Mean values for the transformed daily absolute returns (“Daily Returns”) started with a decrease, from 0.81 in 2014, to 0.54 (2015), and 0.6 in 2016. This increased to 1.74 in 2017 and to 2.16 in 2018.

#### **4.1.3 Distribution Normality**

Figure 9 illustrates the distribution histograms for the variables to be discussed in the next chapter.

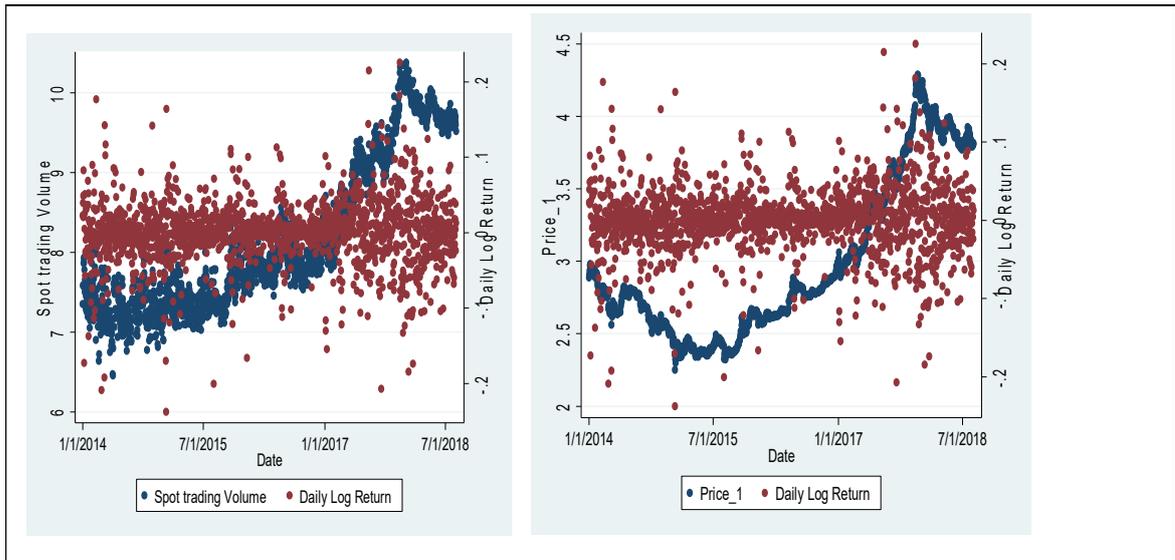
**Figure 9 - Hypothesis 1: Transformed data distributions**



#### **4.1.4 Scatter plots**

Figure 10 shows the scatter plots to be discussed in the next chapter.

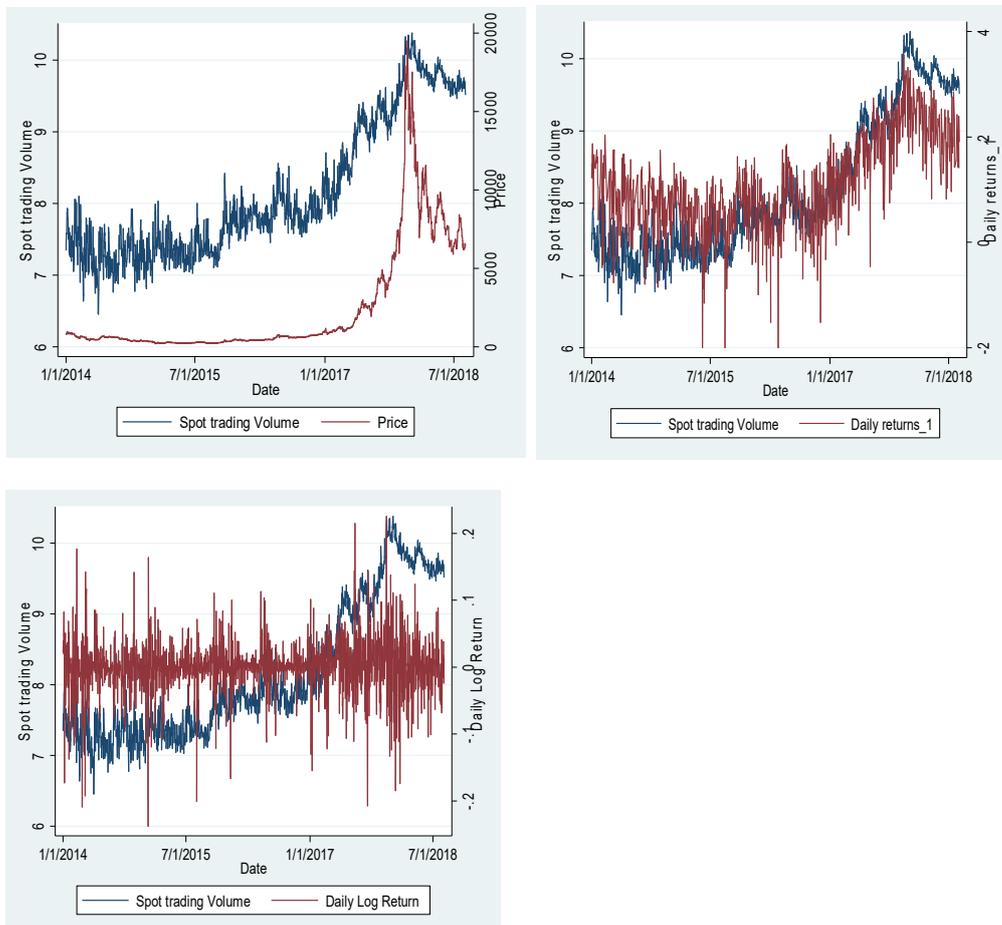
**Figure 10 - Hypothesis 1: Scatter plots**



#### 4.1.5 Trends Analysis

A trend analysis (Figure 11) was done to gain some insights into the time series data trends.

**Figure 11 - Hypothesis 1: Trend analysis**



#### 4.1.6 Autocorrelation and stationarity tests

The Ljung-Box-Pierce portmanteau test was done to test the autocorrelation between variables (white noise) in the data which affects the future validity of the results.

**Table 5 - Hypothesis 1: Portmanteau test for white noise**

<b>Portmanteau test for white noise</b>		
<b>Price</b>	Portmanteau (Q) statistic	65158.14
	Prob > chi2(40)	P<0.05
<b>Spot trading volume</b>	Portmanteau (Q) statistic	60383.98
	Prob > chi2(40)	P<0.05
<b>Daily returns</b>	Portmanteau (Q) statistic	4333.426
	Prob > chi2(40)	P<0.05
<b>Volatility (Daily log returns)</b>	Portmanteau (Q) statistic	54.582
	Prob > chi2(40)	P<0.05

According to Table 5, the p-value for all variables is lower than 0.05. The Portmanteau test's null hypothesis, that there is no serial correlation, is rejected. This means that the four data series have serial correlations between different periods and trends could possibly repeat themselves. This presence of white noise warranted further tests for stationarity and unit roots.

#### 4.1.7 Unit Roots Test: Dickey-Fuller (DF)

The DF test was done to further check for unit roots and the validity of the future results of the study.

**Table 6 - Hypothesis 1: Unit roots test**

		<b>Test Statistic</b>	<b>Critical Value 1%</b>	<b>Critical Value 5%</b>	<b>Critical Value 10%</b>	<b>MacKinnon approximate p-value for Z(t)</b>
<b>Price</b>	Z(t)	-2.037	-3.96	-3.41	-3.12	0.581
<b>Spot trading volume</b>	Z(t)	-8.701	-3.96	-3.41	-3.12	0.000
<b>Daily returns (Absolute)</b>	Z(t)	-12.719	-3.98	-3.421	-3.13	0.000
<b>Volatility (Returns)</b>	Z(t)	-16.55	-3.98	-3.421	-3.13	0.000

Table 6 shows the test statistic for Price is above the critical value of 0.05. Therefore we conclude that although the data shows autocorrelations, the price has no unit roots, in other words it is consistent or has a trend.

The other three data series are non-stationary shown by the p-values which are less than 0.05. The test statistics are much lower than the critical values for these three variables. Hence there is a need to interpret the results in the final models with caution.

#### 4.1.8 Johansen tests for co-integration

The co-integration test below (Table 7) investigates correlations among several time series variables in the long run. At lag 1, the critical value at 5% is greater than the trace statistics (2.81); hence a conclusion can be made that at most there is one cointegrating equation in the bivariate model.

**Table 7 - Hypothesis 1: Johansen test for cointegration**

<b>Maximum rank</b>					
	<b>params</b>	<b>LL</b>	<b>eigenvalue</b>	<b>Trace statistic</b>	<b>Critical value 5%</b>
<b>0</b>	6	26737.1	.	56.90	15.41
<b>1</b>	9	26764.14	0.0315	2.81*	3.76
<b>2</b>	10	26765.55	0.00166		
Sample: 1/3/2014 - 8/19/2018					
Lags = 2					

The above tests for stationarity and unit roots therefore indicate that the ARCH model is appropriate. The Johansen test also indicated that a lag of 1 year is appropriate for the ARCH model to fit best.

#### 4.1.9 Autoregressive Conditional Heteroskedasticity (ARCH) method

Since the data is not normally distributed, the ARCH model applies a t-distribution. The regression is run with a 1-year lag as directed by the cointegration tests above.

**Table 8 - Hypothesis 1: ARCH test results**

Volatility	Coef.	Std. Err.	z	P>z	95% Conf. Interval	
<b>Bitcoin trading volume</b>	0.56	0.06	10.15	0	0.453	0.669
<b>Price</b>	-0.69	0.10	3.22	0.001	-0.889	-0.499
<b>_cons</b>	-4.38	0.20	-21.79	0	-4.771	-3.983
<b>L1.</b>	0.09	0.07	1.4	0.162	-0.038	0.225
<b>_cons</b>	0.25	0.02	11.9	0	0.212	0.296
<b>/Indfm2</b>	1.71	0.26	6.68	0	1.207	2.209
<b>df</b>	7.52	1.41			5.342	11.108
<b>Sample: 1/1/2014 - 8/19/2018</b>						
<b>Distribution: t-distribution</b>						
<b>Wald chi2(2) = 120.66</b>						
<b>Lags 1 Prob &gt; chi2 = 0</b>						

The null hypothesis is that Bitcoin speculative trading volume does have a negative effect on Bitcoin price volatility. The results from Table 8 show that Bitcoin speculative trading volume has as much as 56% **positive** effect on Bitcoin price volatility (Daily returns), results significant at 5% level ( $\beta=0.563$ ;  $p<0.05$ ). Absolute Price on the other hand has negative effects on Bitcoin price volatility, as much as 69% effect strength.

The ARCH model will be run yearly to attempt to gain more insight into the changes in the effect and possible effect of regime changes and structural breaks in the price. Table 9 confirmed the previous results for every year individually.

**Table 9 - Hypothesis 1: Yearly ARCH test results**

	2014		2015		2016		2017		2018	
Volatility	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
<b>I_volume</b>	<b>1.195</b>	0	<b>1.532</b>	0	<b>2.121</b>	0	<b>0.938</b>	0	<b>1.629</b>	0.001
<b>I_price</b>	<b>-0.15</b>	0.657	<b>-1.73</b>	0.007	<b>-1.19</b>	0.003	<b>-1.05</b>	0	<b>-1.35</b>	0.082
<b>_cons</b>	-10.2	0	-9.11	0	-15.6	0	-6.49	0	-12.4	0
<b>/SIGMA2</b>	0.212	0	0.215	0	0.23	0	0.196	0	0.209	0

#### 4.1.10 Granger Causality test

Finally this study also conducted a Granger Causality test to confirm long-run relationship in time series data.

Table 10 - Hypothesis 1: Granger causality test

Equation	Excluded	chi2	df	P-value
<b>I_volatility</b>	I_volume	1.9354	2	0.38
	I_price	0.50833	2	0.776
	ALL	2.6468	4	0.619
<b>I_volume</b>	I_volatility	9.0867	2	0.011
	I_price	0.70836	2	0.702
	ALL	16.907	4	0.002
<b>I_price</b>	I_volatility	1.3798	2	0.502
	I_volume	1.4906	2	0.475
	ALL	2.6471	4	0.619

Table 10 shows the existence of a long-run positive relationship between Spot Trading Volume and Volatility (on daily returns). There is only one long-run relationship, between Volatility (on daily returns) and Bitcoin Trading Volume, results are statistically significant ( $p < 0.05$ ).

## 4.2 Hypothesis 2

Tests have found that **spot** trading volume of Bitcoin has a significant positive effect on Bitcoin volatility. Now the effect of **derivative** trading volumes on volatility will be investigated.

### 4.2.1 Descriptive statistics

Figure 12 shows the Bitcoin derivative trading volumes. The graphs for the other variables are similar to the ones for hypothesis 1 and will therefore not be included again here.

Figure 12 - Bitmex Bitcoin derivative trading volumes

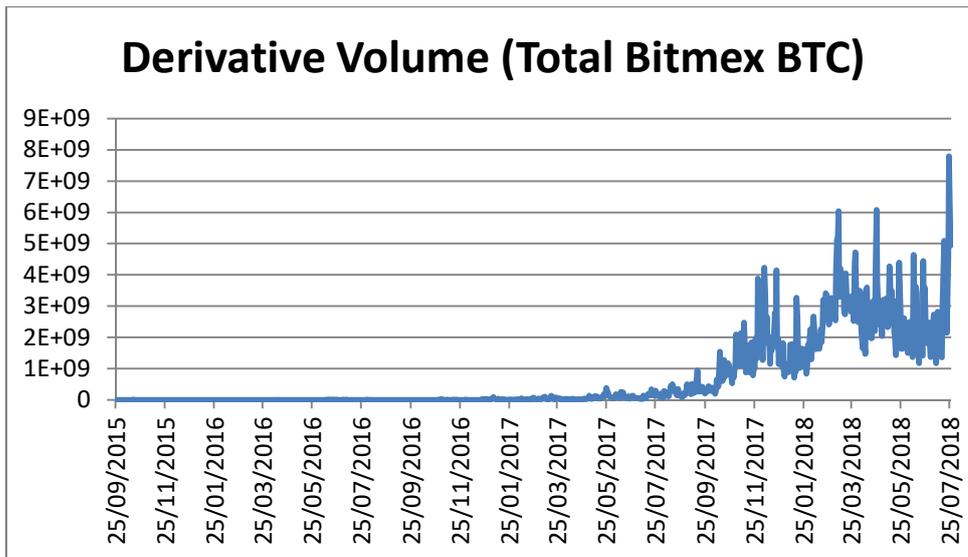


Table 11 below shows the descriptive statistics for the datasets. Because of the introduction of derivatives only in 2015, this dataset only starts in 2015. Note that the daily returns and volatility datasets have 1 less observation as they are a calculation taking into account the difference between two days of prices.

Table 11 - Hypothesis 2: Descriptive statistics (unstandardised data)

Unstandardised descriptive statistics							
Variable	Obs	Mean	Std. Dev.	Min	Max	Kurtosis	Skewness
Price	1,036	3,419.34	4,088.88	232.76	19497.4	1.53	1.47
Bitmex Derivative Volume	1,036	\$0.668B	\$1,16B	112112	\$7.79B	3.89	1.98
Daily Returns	1,035	7.46	324.13	-2329	3608	28.4	1.12
Daily Volatility	1,035	0.003	0.04	-0.207	0.2251	4.41	-0.16

#### 4.2.2 Transforming non-normal distribution of primary data

Because most of the data is not normally distributed, with extreme standard deviations, there is a need to transform all the data to its natural logarithm. In this section the log transformation method is applied to reduce skewness of data in order for it to conform more to normality.

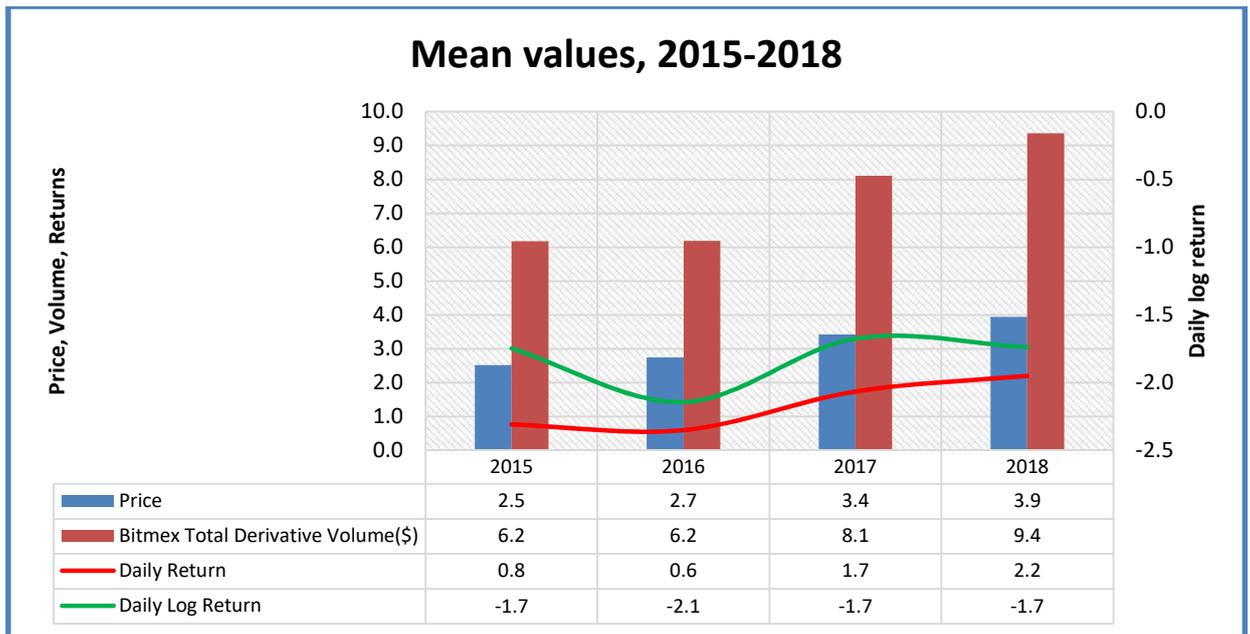
Two of the observations were dropped from the daily returns and volatility samples as there were no changes in price between those days, resulting in a log (0) mathematical undefined number.

**Table 12 - Hypothesis 2: Standardised data for the variables**

<b>Standardised values (log(10))</b>							
<b>Variable</b>	<b>Obs</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>	<b>Skew</b>	<b>Kurtosis</b>
<b>Price</b>	1,036	3.20	0.55	2.37	4.29	.3429	1.641
<b>Bitmex Total Derivative Volumes (\$)</b>	1,036	7.50	1.38	5.05	9.89	.11776	1.614
<b>Daily Returns</b>	1,033	1.30	0.75	0.01	2.66	-.1209	2.742
<b>Daily returns Volatility</b>	1,033	-1.86	0.24	-2.31	-1.47	-.8708	4.624

Table 12 shows the transformed price mean (3.2) and median (3.02) were almost equal, with a standard deviation less than 1, suggesting the transformed data series for the Price variable did not part from normality in that sense. The mean for Bitmex Total Derivative Volume (7.5) was almost equal to the median (7.33), with a standard deviation that is minimal, showing the values did not part much from normality. The transformed daily returns' mean (1.3) and median (1.33), and the standard deviation below 1 indicate the data series did not part much from normality. Negative skewness (-0.12) is due to the fact that the mean was slightly lower than the median. Daily Log Return's (the proxy for volatility) mean (-1.86) was slightly lower than the median (-1.813), causing negative skewness (-0.87). The means for each year is shown in Table 13 to illustrate the changes over time.

Table 13 - Hypothesis 2: Yearly mean values



The transformed Daily Log Return (the proxy for volatility) reached an all-time low in 2016 and an all-time high in 2017. In 2015, 2017 and 2018 the mean volatility reached was a negative -1.7, while it was more negative in 2016. The transformed absolute daily return values exponentially increased from 2015 (0.8) to 2018 (2.2), with episodes of lows in 2016 (mean=0.6) which picked up in 2017 (mean=1.7) before reaching a record high in 2018 (mean=2.2).

Bitmex Total Derivative trading Volume increased exponentially from 2015/16 period (mean=6.2) to 8.1 in 2017 and went higher by a 1.3 percentage point in 2018 (mean=9.4). The mean price of Bitcoin also rose incrementally between 2015/16 (mean=2.5) and 2017 (mean=3.4) and to 3.9 in 2018.

Notably, the mean volatility of the Bitcoin spot price (proxied by the daily log returns) had been almost constant throughout the study period, having its lowest in 2016, while Trading volume of Bitcoin derivative instruments incrementally rose from 2016 to 2018.

### 4.2.3 Distribution Normality

Figure 13 - Hypothesis 2: Price and volumes distribution histogram

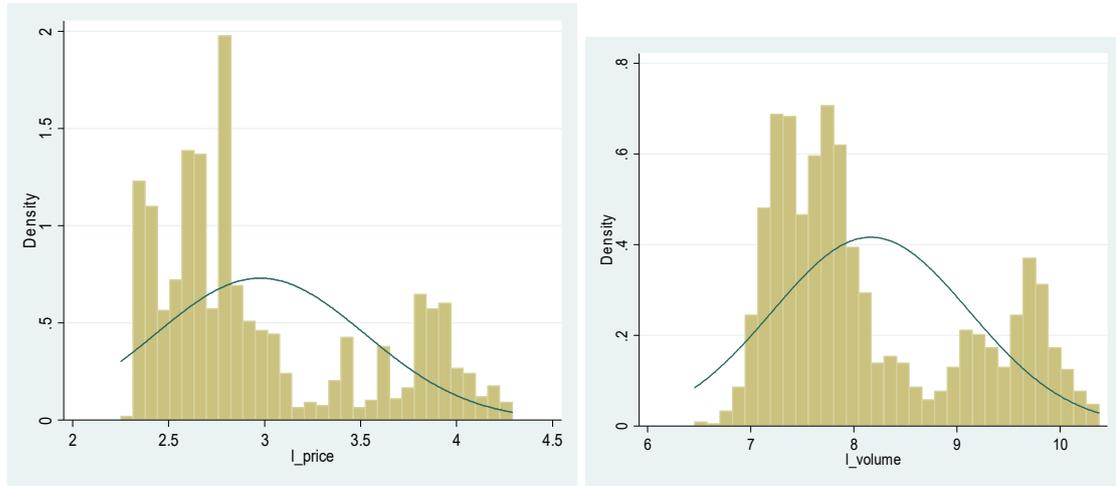


Figure 13 illustrates the distribution histograms for the variables. This indicates that the data series for price and Bitmex Total Derivative Volume parts from normality as depicted by Kurtosis and skewness. Values were not constant over time but over time deviated from the mean. For Price, values were clustered between 2.5 and 3, with a peak around 3, while for Bitmex Total Derivative Volume the values were clustered around 7 and 8. The non-normal distribution of the data could be an indication of non-stationarity in the data series.

Figure 14 - Hypothesis 2: Returns and volatility of returns histograms

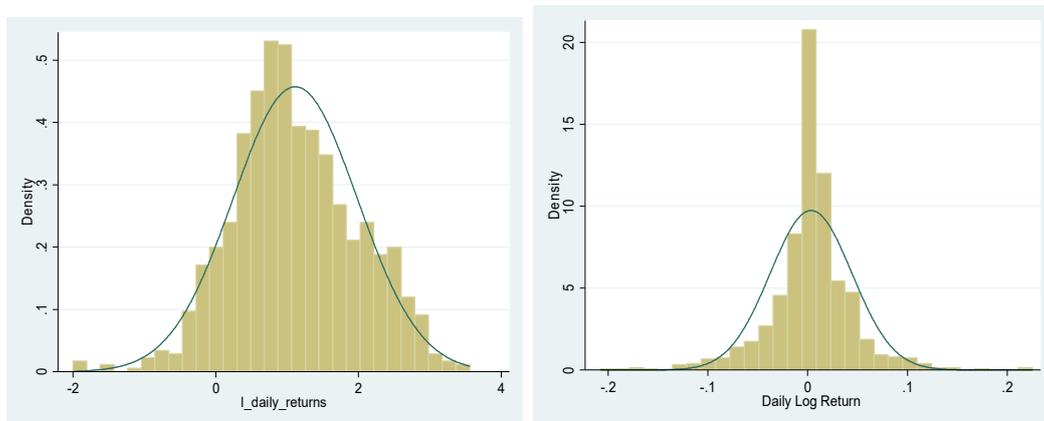


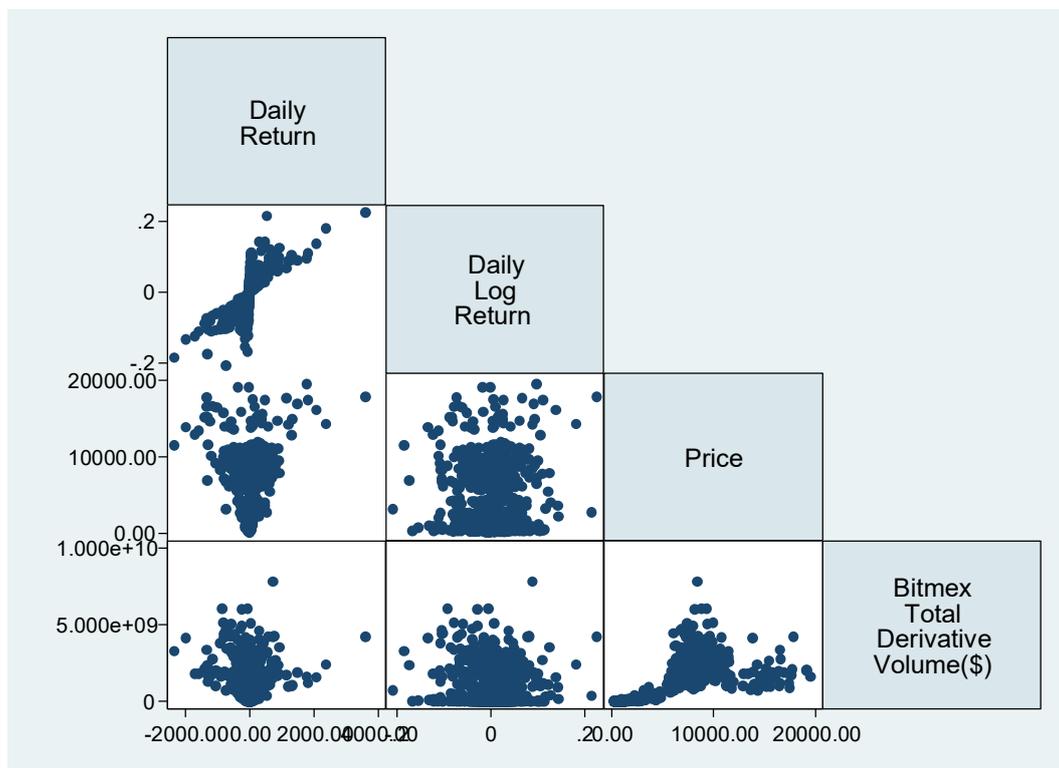
Figure 14 above indicates that the data series for Daily Returns and its associated volatility (“Daily Log Returns”) do not part from normality as depicted by the almost perfect symmetric bell shapes. The values were almost constant over time; they did not

deviate much from the mean. The normal distribution tendency of the data is an indication of non-stationarity in the data series; it might not have a trend/less variation and therefore more tests need to be done to ascertain if there is a trend or relationships.

#### 4.2.4 Scatter plot

The following figure is a scatterplot for each independent variable with the dependent variable to see if the relationships are linear.

**Figure 15 - Hypothesis 2: Variables scatter plots**



The scatterplot above (Figure 15) shows how spread the data points are. These scatter plots are discussed in the next chapter.

#### 4.2.5 Trends Analysis

A trend analysis is done to gain some insights into the time series data.

**Figure 16 - Hypothesis 2: Price and returns trend analysis**

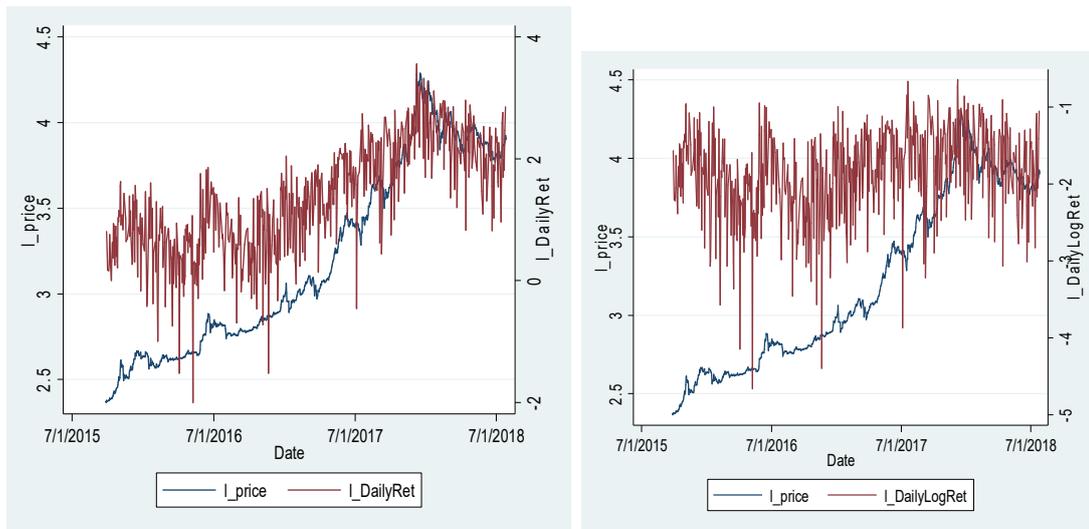


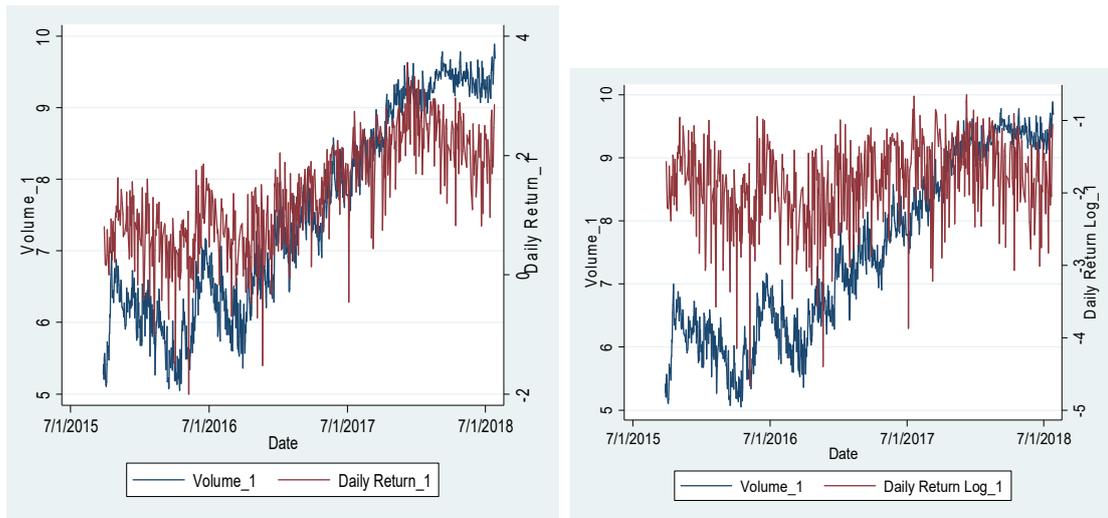
Figure 16 indicates that there was an increasing trend for both Price and Daily Returns over time (2015-2018). Price values rose steadily between 2015 and 2016, with two periods of highs within that year. The prices dropped mid-year and rose again in the last quarter. There was a significant upward slope for Price values between 2016 and 2017, which further became steeper towards 2018 when the values reached the highest point.

Notably, daily return values were volatile (spiky) throughout the study period, with periodic record lows and highs. The same pattern occurs between Prices and Daily Log Returns; as Prices increase so does volatility (shown by the daily log returns). The rate of increase for the volatility is not noticeable (slow) while Prices had a steep positive slope over the years.

Volatility is characterised by the spiky pattern. There were record low values for volatility in the last quarter of 2015, mid 2016 and at the start of 2017.

Figure 17 shows the trends comparison for the daily returns, volume and volatility, discussed in Chapter 5.

**Figure 17 - Hypothesis 2: Volume and volatility trend analysis**



**4.2.6 Autocorrelation and stationarity tests**

The Ljung-Box-Pierce portmanteau test was done to test the autocorrelation between variables (white noise) in the data which affects the future validity of the results.

Table 14 shows the p-values for all variables are under 0.05. The Portmanteau null hypothesis is therefore rejected, indicating the four data series have autocorrelations during different periods.

**Table 14 - Hypothesis 2: Portmanteau test**

Portmanteau test for white noise		
Price	Portmanteau (Q) statistic	38296.18
	Prob > chi2(40)	P<0.05
Vol	Portmanteau (Q) statistic	35577.54
	Prob > chi2(40)	P<0.05
Daily Returns	Portmanteau (Q) statistic	3379.021
	Prob > chi2(40)	P<0.05
Daily Log Returns	Portmanteau (Q) statistic	303.63
	Prob > chi2(40)	P<0.05

**4.2.7 Unit Roots Test: Dickey-Fuller (DF)**

The following section tests for unit roots in each of the datasets.

**Table 15 - Hypothesis 2: Dickey-Fuller test for unit roots**

		Dickey-Fuller test for unit root				
		Test Statistic	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)	MacKinnon approximate p-value for Z(t)
<b>Price</b>	Z(t)	-1.532	-3.96	-3.41	-3.12	0.8179
<b>Derivative trading volumes</b>	Z(t)	-7.923	-3.96	-3.41	-3.12	0
<b>Absolute returns</b>	Z(t)	-10.72	-3.986	-3.426	-3.13	0
<b>Volatility</b>	Z(t)	-12.831	-3.986	-3.426	-3.13	0

Figure 15 showed that the test statistics for Price is higher than the critical value; p-value above 0.05. Therefore we can conclude that the data series has no unit roots and therefore has a trend. The Dickey-Fuller test indicates that the other three datasets are non-stationary. These variables have a data series that does not show to vary much over time (the test statistics are much lower than the critical value).

**Table 16 - Hypothesis 2: Phillips-Perron test for unit roots**

		Phillips-Perron test for unit root				
		Test Statistic	Critical Value	Critical Value	Critical Value	MacKinnon approximate p-value for Z(t)
<b>Price</b>	Z(t)	-0.857	-3.43	-2.86	-2.57	<b>0.8019</b>
<b>Derivative trading volumes</b>	Z(t)	-1.617	-3.43	-2.86	-2.57	<b>0.4744</b>
<b>Absolute returns</b>	Z(t)	-7.66	-3.453	-2.876	-2.57	0
<b>Volatility</b>	Z(t)	-12.917	-3.453	-2.876	-2.57	0

Table 16 shows the Phillips-Perron test above provides the same results of stationarity on the Price data series, and non-stationarity (no trend) on returns and volatility. It however differs with the Dickey-Fuller test in that it shows the volume data series also has a trend (it has strict white noise).

#### 4.2.8 Johansen tests for co-integration

The co-integration test below (Table 17) investigates correlations among several time series variables in the long run by year. At lag 1, the critical value at 5% is greater than the trace statistics (13.9); hence evidence that at most there is one co-integrating equation in the model.

Table 17 - Hypothesis 2: Johansen tests for cointegration

Maximum rank (lag)	params	LL	eigenvalue	Trace statistic	Critical value 5%
0	12	16477.15	.	580.51	29.68
1	17	16760.41	0.42276	13.98*	15.41
2	20	16766.98	0.01265	0.8588	3.76
3	21	16767.4	0.00083		

The above tests for stationarity and unit roots therefore indicate that the ARCH model is also appropriate for the second hypothesis. The Johansen test also indicated that a single lag is appropriate for the ARCH model to fit best.

#### 4.2.9 Autoregressive Conditional Heteroskedasticity (ARCH) method

Since the data is not normally distributed, the ARCH model applies a t-distribution. The regression is run with 1 lag as directed by the cointegration tests above.

Table 18 - Hypothesis 2: ARCH test results

Volatility	Coef.	Std. Err.	z	P>z	95% Conf. Interval	
I_Price	0.368486	0.04147	8.89	0	0.287206	0.449767
I_Volume	<b>-0.01736</b>	0.015102	-1.15	0.25	-0.04696	0.012235
_cons	-2.90765	0.038305	-75.91	0	-2.98272	-2.83257
/SIGMA2	0.025444	0.001419	17.93	0	0.022662	0.028226
Sample: 9/28/2015 - 7/26/2018			Number of obs = 1,033			
Wald chi2(2) = 685.39						
Log likelihood = 430.447			Prob > chi2 = 0.000			

The table above (Table 18) indicates that overall Trading volume of Bitcoin derivative instruments has a negative effect on the volatility of the Bitcoin spot price ( $\beta=-0.01736$ ). The results are not significant, the null hypothesis that Bitcoin derivative trading volume lowers price volatility is rejected and the alternative hypothesis is accepted.

**Table 19 - Hypothesis 2: Yearly ARCH test results**

	2015		2016		2017		2018	
Volatility	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
I_Price	1.91485	0	-0.9055	0	0.433935	0	1.037255	0
I_Volume	-0.0961	0.001	0.04253	0.081	-0.0276	0.119	0.095391	0.024
_cons	-6.1874	0	0.16459	0.631	-3.0246	0	-6.61246	0
/SIGMA2	0.00476	0	0.02753	0	0.008574	0	0.010133	0
	<i>Sample:</i> 9/28/2015 - 12/30/2015		<i>Sample:</i> 12/31/2015 - 12/31/2016		<i>Sample:</i> 1/1/2017 - 12/27/2017		<i>Sample:</i> 12/28/2017 - 7/26/2018	

This section explores the same relationships over the years (within months). Table 19 shows that trading volume of Bitcoin derivative instruments had negative effects on the volatility of the Bitcoin spot price in 2015 ( $\beta=-0.096$ ), results are significant. No effect is noticed in 2017 ( $\beta=-0.0276$ , not significant). Trading volume of Bitcoin derivative instruments had positive effects on the volatility of the Bitcoin spot price in 2016 ( $\beta=0.0425$ ) and in 2018 ( $\beta=0.095$ ). These results are significant at 10% and 5% respectively.

#### 4.2.10 Granger causality test

Finally the Granger causality test was concluded to test whether the one time-series (Derivative volume traded) is useful in forecasting the other (volatility) by finding predictive causality.

**Table 20 - Hypothesis 2: Granger causality test**

Equation	Excluded	chi2	df	p-value
<b>PRICE</b>	I_Volume	3.8986	2	0.142
	I_Daily Returns	4.1982	2	0.123
	I_Volatility	3.036	2	0.219
	ALL	9.1474	6	0.165
<b>Trading volume of Bitcoin derivative instruments</b>	I_Price	30.195	2	0
	I_Daily Returns	9.5954	2	0.008
	I_Volatility	11.11	2	0.004
	ALL	73.374	6	0

<b>Daily Returns</b>	I_Price	0.16277	2	0.922
	I_Volume	18.773	2	0
	L_Volatility	3.7395	2	0.154
	ALL	42.987	6	0
<b>Volatility (Daily Log Returns)</b>	I_Price	4.2276	2	0.121
	I_Volume	19.489	2	0
	L_Daily Returns	7.1113	2	0.029
	ALL	34.21	6	0

**Price:** Bitcoin speculative trading volume, Daily returns, Daily Log Returns (volatility) all have p-values greater than 0.05. The Granger test null hypothesis (that they do not Granger-cause Price fluctuations) is not rejected. A conclusion is made that these endogenous factors have no long-run relationship with the absolute prices.

**Trading volume of Bitcoin derivative instruments:** Prices, Daily returns, Daily Log Returns (volatility) all have p-values less than 5%. The Granger test null hypothesis (that they do not Granger-cause Price fluctuations) is rejected. A conclusion is made that these endogenous factors had a long-run relationship with trading volume of Bitcoin derivative instruments in this study.

**Daily Returns:** Trading volume of Bitcoin derivative instruments has p-values less than 5%; hence the Granger test null hypothesis is rejected. A conclusion is made that trading volume of Bitcoin derivative instruments had a long-run relationship with Daily Returns. Price did not have any long run relationship with returns (p-value>0.05).

**Daily Log Returns (Volatility):** Trading volume of Bitcoin derivative instruments and Daily Returns had p-values less than 5%; hence the Granger test null hypothesis is rejected. A conclusion is made that trading volume of Bitcoin derivative instruments and Daily returns had a long-run relationship with Daily Log Returns (volatility). Price did not have any long run relationship with volatility (p-value>0.05).

### 4.3 Results on reliability and validity of the data

The datasets were complete throughout the study period and therefore there were no missing data points.

Coinmarketcap has a global rank of 341 on Alexa.com. Alexa.com ranks websites by popularity and page views. This is by far the highest ranked cryptocurrency website on the internet and therefore it was chosen to ensure reliability and validity of the data (Alexa, 2018).

Coinmarketcap creates an index for the Bitcoin price by combining the prices on various exchanges. By doing this it is a more accurate representation of the Bitcoin price at any time, compared to only taking a single exchange where liquidity issues could be present.

Bitmex is the largest exchange for Bitcoin derivative trading as shown in Table 1. It is therefore considered the most reliable and valid source of data for derivative trading volume.

The Dickey-Fuller tests indicated that three datasets are non-stationary. These variables have a data series that does not show to vary much over time (the test statistics are much lower than the critical values). Hence there is a need to interpret the results and the validity in the final models with caution.

The Ljung-Box-Pierce portmanteau tests were done to test the autocorrelation between variables (white noise) in the data. The presence of white noise was detected and the results should therefore be interpreted with caution.

## **5 Discussion of results**

This chapter will discuss the results of the statistical tests conducted in chapter 4 and the possible implications thereof. It will start by discussing the time series trends and descriptive analytics. It will then discuss the results of the hypothesis tests used to ascertain if there are relationships between spot and derivative trading volumes and Bitcoin price volatility.

### **5.1 Bitcoin Price**

The highest price was \$19 497 and the lowest price was \$178 in the study period (2014 - 2018). The mean price was \$2 340, deviating much from the maximum and minimum, leading to skewness. The standard deviation is extreme, which is an indication that the raw price data is not normally distributed.

Figure 11 indicates that there was an increasing trend for both Price and Volatility (Daily Log Returns) over time. Price values were almost steady and constant from 2014 to January 2017. The prices then drastically increased between 2017 and 2018, reaching a record high in December 2018, before steeply declining again until July 2018.

Despite the recent decline in the Bitcoin price, this paper argues that the uptrend seems to still be intact and the bear market of the last 7 months of the study period seems to merely be a return to the mean, as can be seen on the logarithmic chart of Figure 1 specifically and also Figure 6.

### **5.2 Absolute Bitcoin Price Daily Returns**

The maximum (\$3 608) and minimum (-\$2 329) values were extremely far apart and both deviated extremely from the Mean ( $M = 254$ ), leading to a huge standard deviation ( $>2$ ), indicating a non-normal distribution of data.

From Figure 7 it is clear that the percentage daily return of the Bitcoin price is extremely volatile as well, with some daily returns in excess of 10% and even 20%.

It is also immediately apparent from Figure 7 that there is some volatility clustering (heteroskedasticity) in the data, specifically around January 2016, July 2016, February 2017, May 2017 and the entire period from September 2017 to March 2018. This fact reinforces the need for an ARCH analysis (Katsiampa, 2017; Dyrberg, 2016b; Chu et al., 2017).

The trend analysis (Figure 11) showed that Daily return values were volatile throughout the study period, with periodic record lows and highs. These do not seem to display any upward or downward trend.

### **5.3 Bitcoin Spot trading volume**

Spot trading volumes increased from a minimum of \$2.8 million daily at the start of the hypothesis 1 study period to \$23.5 billion daily at the peak. The spot trading volume came down from the peak and was hovering around \$5 billion at the end of the study period (Figure 6). This shows extreme variation between the highest and lowest values for Spot trading Volume leading to an extreme standard deviation ( $>2$ ), an indication of extreme non-normality of the spot trading volumes data series.

The trend analysis (Figure 11) showed that the Spot Trading volume had an overall exponentially increasing tendency/pattern up to 2017, before steeply rising towards the end of 2018, and dropping afterwards to July 2018. Despite the fact that Bitcoin spot trading volume is down significantly from the highs of December 2017, the current volumes are still orders of magnitude higher than that of only a few years ago, signalling a sustained growth in spot trading interest over the long term.

### **5.4 Bitcoin Derivative trading volume**

Bitmex derivative trading volumes increased from a minimum of \$100 000 daily at the start of the study period (when they were introduced) to \$7.79 billion daily at the peak.

There was extreme variation between the highest and lowest values for Bitmex Total Derivative Volume (expected), leading to an extreme standard deviation ( $>2$ ), an indication of extreme non-normality of the data series. The mean and median values vary extremely, indicating positive skewness of the data, which confirms that the data is not normally distributed (expected).

Figure 17 indicates that as absolute daily returns increased so did derivative trading volumes. Notably, both variables had spiky and clustering patterns showing highly volatile times at the start of the series to mid-2016. Derivative volumes started with an upward surge in 2015 after its introduction, followed by a drastic spiky drop towards 2016 before drastically increasing and decreasing again in 2016. These short episodes of drastic increase and decrease are characteristic of volatility clustering.

Volatility reached its record high at the end of 2017 and stabilised towards the middle of 2018, a period where Daily returns had a downward trend (decreased). Notably, daily returns had highs and lows at the same time derivative volumes did, except from

mid-2017 towards 2018, when derivative volumes went up and daily returns went down (short term negative association).

Bitmex derivative trading volumes of Bitcoin futures and swaps are reaching new highs in 2018 despite the bear market (Figure 12). This is important as it is showing a shift in speculation volume from the spot market to the derivative market.

## **5.5 Bitcoin volatility**

Figure 2, Figure 8 and Figure 7 show clearly that the Bitcoin volatility is significantly higher than that of gold and fiat currencies during the study period. This agrees with conclusions by Dwyer (2015) and Pichl and Kaizoji (2017). The data suggests that the Bitcoin price is still mostly speculative and sentiment driven as suggested by Weber (2014). This study did not find any link between Bitcoin price volatility and other global economic activity as suggested by Conrad et al. (2018), as this was not within the scope of this study.

In fact, despite the 2700% total increase in price over the study period (4.5 years), if the investor were out of the market for the best 20 days (in terms of daily returns), the returns would only have been 167%. This emphasises the fat tails in the returns distribution also mentioned by other studies such as Balcilar et al. (2017) and Charles and Darné (2018).

From Figure 2 it is clear that the overall volatility has decreased over the entire lifetime of Bitcoin as suggested by Bouoiyour and Selmi (2016), but the recent spike in volatility at the end of 2017 is the highest volatility experienced in the last 3 years. This shows that price regimes like bubbles are still causing excessive volatility. This supports the study by Fry (2018).

There are significant outliers in the data. There were three fundamental events that led to the outlying returns for four of the days. Dropping the four days of outliers from the dataset actually reduces the kurtosis of the price data enough ( $< 2$ ) to consider the return distribution normally distributed, but these days were not ignored as they are crucial to the validity of the study.

These events are important as they show how the volatility reacts to news events, both positive and negative. These reactions then also shed light on the informational efficiency and market efficiency of the modern Bitcoin market as previously studied by Urquhart (2016), Foldvari and van Leeuwen (2011), Tiwari et al. (2018), Vidal-Tomás and Ibañez (2018) and Bariviera (2017).

The fundamental events associated with each of the outliers are as follows:

On 20 July 2017 consensus was reached between the major factions within the Bitcoin community on the technical implementation of the protocol changes, which eventually increased Bitcoin scalability significantly. This ended a deadlock between the factions around the correct way of increasing scalability. This resulted in a 24% increase in price on that day (CNBC, 2017a).

On 6 December 2017 the CBOE and CME announced the date for the launch of Bitcoin futures contracts. This resulted in speculation that institutional investors would push up the Bitcoin price significantly in the future. The Bitcoin price gained 19.8% on the 6th of December and continued the rally the next day by gaining 25% on the 7th of December (CNBC, 2017b).

The largest daily drop in price in the study period was on 14 September 2017. This was the result of a complete ban of cryptocurrencies trading in China. On the day the price of Bitcoin fell 18.5% (Business Insider, 2017).

The study shows that the Bitcoin price has gone through a volatile bubble and anti-bubble period from mid-2017 to the beginning of 2018 as defined by Cheung et al. (2015) and Tarlie et al. (2018). This supports the comments by Cheah and Fry (2015), Fry (2018) and Dale et al. (2005). Although the study period from Su et al. (2018) ended before the latest mentioned bubble, this also supports their views.

Because of the methodology used in this study, the concerns by Pieters and Vivanco (2017) around volatility differing between exchanges have been avoided, since the Coinmarketcap index was used.

During the bubble at the end of 2017, Bitcoin received the highest attention to date (Haig, 2018). This supports Urquhart's (2018) theory that attention on Bitcoin can cause a feedback loop into the price and cause bubble volatility behaviour.

## **5.6 Means over time**

Table 4 showed the changing of the means of the different standardised data series over the years and highlights that all the data series gained momentum over time and continued to do so every year to date.

## **5.7 Data normality**

Since the raw data was almost all non-normally distributed the data was transformed to remove the skewness and standardise the data to be more normally distributed. Table

3 showed that the transformed data conformed more to normality in terms of the standard deviations and kurtosis.

Despite the transformations, Figure 9 indicates that the data series for Price and Spot Trading Volume still part from normality as depicted by the skewness. Values were not constant over time and deviated from the mean. The non-normal distribution of the data is an indication of non-stationarity in the data series meaning it does not have a strong trend. It could still have a weak trend, which is a requirement for time series analysis. It is only the percentage Daily returns (the difference between two days' prices) that show a stronger symmetric bell shape, near normality. This indicated that non-parametric statistical tests had to be done which was expected as literature in the study of Bitcoin volatility almost exclusively uses non-parametric tests (Katsiampa, 2017; Peng et al., 2018; Dyrberg, 2016a; Dyrberg, 2016b; Bouoiyour & Selmi, 2016).

## **5.8 Hypothesis 1**

This hypothesis tested for a negative effect of spot trading volumes on Bitcoin price volatility.

### **5.8.1 Scatter Plots**

As can be seen from the scatter plots in Figure 10, there is stronger linear clustering between Daily Log Returns (Volatility) and two independent variables; Price and Spot Total Volume (variable of interest). Note the numerous outliers on the volatility data though, suggesting daily values deviate extremely on a daily and annual basis. These outliers could have affected the inferential statistics and models.

### **5.8.2 Tests for white noise and unit roots**

The Portmanteau test indicated that there might be serial correlation in the data series and that trends could possibly repeat themselves in the data series. The presence of white noise also warranted further tests and a DF test was done.

The DF test showed that all the time series, except the price itself, has unit roots. This affects the validity of the results going forward and therefore results should be interpreted with caution.

### **5.8.3 Tests for co-integration**

A Johansen test for co-integration was done to investigate correlations among several time series variables in the long run. At lag 1, the critical value at 5% is greater than the trace statistics (2.81); hence a conclusion was made that at most there is one cointegrating equation in the bivariate model. The coefficients of lag 1 of these rates

suggest that the changes at a particular earlier time in Bitcoin spot trading volume affected values of Bitcoin price volatility in the next time periods (1-year lag), and vice versa.

The above tests for stationarity and unit roots therefore indicated that the ARCH model is appropriate. The Johansen test also indicated that a lag of 1 year is appropriate for the ARCH model to fit best.

#### **5.8.4 ARCH Analysis**

Since the data was not normally distributed, the ARCH model applied a t-distribution as was also previously done by Klein et al. (2018).

Hypothesis 1 tested for a negative effect of spot trading volume on Bitcoin price volatility. The null hypothesis that Bitcoin spot trading volume has a negative effect on the price volatility of Bitcoin was rejected by the ARCH analysis. In fact, the opposite seems true. Spot trading volume has a significant **positive** effect on volatility, as much as a 56% **positive** effect. Results were significant at a 95% confidence interval ( $\beta=0.563$ ;  $p<0.05$ ). In this case the null hypothesis was rejected and it was concluded that Bitcoin spot trading volume does **not** have a negative effect on Bitcoin price volatility.

Price by itself on the other hand had negative effects on Bitcoin price volatility, as much as 69% effect strength, possibly explained by the leverage effect. This was not confirmed by the Granger-causality test though. A unit increase in price is likely to result in a reduction in volatility while a unit increase in Bitcoin spot trading volume is likely to result in a unit increase in Bitcoin price volatility (Bouchaud et al., 2001).

The ARCH model was also run yearly to attempt to gain more insight into the structural breaks and regime changes on the relationships. Table 9 showed Bitcoin speculative trading volume had positive effects on Bitcoin price volatility every year between 2014 and 2018. The effect size was 1.2 times in 2014, increased to 1.5 times in 2015, to 2.1 in 2016 before dropping to 0.9 times in 2017. In 2018 there has been the strongest effect, 1.6 times. In all these years, the effect is small, between 1-2 times. Price had negative effects in all the years, lowest effect being in 2015 and relatively highest effect in 2017. These wide ranges of statistics provide a conclusive rejection of the hypothesis that the Bitcoin speculative trading volume does have a negative effect on Bitcoin price volatility. Other unexplored factors might also play a role in affecting

volatility that was not tested for here, as discussed in the literature review, such as speculator sophistication and market and informational efficiencies.

#### **5.8.5 Granger-causality test**

The Granger-causality test confirmed, in Table 10, the existence of a positive long-run relationship between Spot Trading Volume and Volatility (on daily returns). There is only one long-run relationship, that between Volatility (on daily returns) and Bitcoin Trading Volume with statistically significant results ( $p < 0.05$ ), among the variables tested. The results confirm the previous results, that there could be unidirectional relationship between the two variables in the long term. Although the Granger test did not confirm that there is a long-run relationship between Volatility (on daily returns) and the absolute Price ( $p > 0.05$ ), short run relationships (temporal) could still exist.

#### **5.8.6 Further Discussion**

The null hypothesis that Bitcoin spot trading volume has a negative effect on the price volatility of Bitcoin was rejected by this study. In fact, the opposite seems true. Spot trading volume has a significant **positive** effect on volatility, as much as a 56% **positive** effect. One possible reason for this result is that the market is still in its infancy and that it is still in a price discovery period. This study therefore supports the studies by Urquhart (2016) and Bouoiyour and Selmi (2016), who suggests that the market is still far from mature. Tiwari et al. (2018) and Vidal-Tomás and Ibañez (2018) on the other hand concluded that the Bitcoin market has reached informational efficiency in 2018, but these studies failed to include the recent bubble period at the end of 2017 in their data and therefore should be ignored as including this period might alter their results.

Another possible reason is that the speculators in the spot market are less sophisticated retail investors and is on average losing money as proposed by the seminal work of Kaldor (1939) and Friedman (1969). This supports the theory by Bouoiyour and Selmi (2016), which suggests that volatility increases when uninformed/inexperienced speculators lose money. This is especially valid as Bitcoin may suffer from information asymmetry as it is complex to understand. Florian, Kai, Martin, Moritz and Siering (2014) also theorised that the majority of users/investors of Bitcoin are uninformed and this study can therefore support that view. This seems likely as the attention that Bitcoin got during the bubble period of December 2017 attracted a significant amount of uninformed and novice speculators to the market, of which most probably lost money on average (Kaldor, 1939; Friedman, 1969).

A third possible reason proposed by Bouri et al. (2017), Balcilar et al. (2017) and Ardia et al. (2018) is that the volatility relationships depend on the current price regime. In other words, that the volatility increases drastically during bull or bear markets or bubbles and settles in between. This is somewhat shown to be unlikely by the fact that the effect persisted every year during the study period as seen in Table 9. It might be prudent though to attempt to break up the study period further into different regime periods and test the relationships per period in a future study.

This study therefore does not support the findings by Balcilar et al. (2017), who failed to find a relationship between volumes and volatility. The difference in this study and that of Balcilar et al. (2017) is that different methodologies were used and that this study used data ending in July 2018, while Balcilar et al. (2017) used data ending April 2016. This is a significant difference as volumes picked up considerably over the period not covered by Balcilar et al. (2017).

The ARCH analysis did find a significant negative relationship between the Price itself and the volatility, indicating that as the price is increasing the volatility is decreasing. This could possibly be explained by the leverage effect as described by Bouchaud et al. (2001), but this result was not confirmed by the Granger causality test and is beyond the scope of this study.

## **5.9 Hypothesis 2**

Now the results of hypothesis 2 will be discussed. Hypothesis 2 tested for the effect that **derivative** trading volume specifically had on Bitcoin price volatility.

### **5.9.1 Scatter plots**

The scatterplot of these hypothesis variables (Figure 15) showed how spread the data points were. Notably, there were linear clustering between Daily Log Return (volatility) and Daily Returns (expected). There were also some linear clustering between Derivative trading volume and Price. There was some clustering between Price and Daily Log Returns (volatility), with many outliers. There was also clustering between Derivative Volumes and Daily Log Returns (proxy for volatility). These results suggested that there were associations between Daily Log Returns (volatility) and the two independent variables, but marred with outliers, which could affect the inferential statistics and models.

### **5.9.2 Tests for white noise and unit roots**

The Portmanteau null hypothesis was rejected, indicating the four data series have autocorrelations during different periods. This could have an effect on the inferential

models since there seems to be co-movement of the minor trends over time (trend repeats itself). This presence of white noise warranted further tests for stationarity and unit roots as it affects the study's validity.

As with hypothesis 1 the DF test confirmed that all the time series, except the price itself, have unit roots. This affects the validity of the results going forward and therefore results should be interpreted with caution.

### 5.9.3 Tests for co-integration

A Johansen test for co-integration was done to investigate correlations among several time series variables in the long run for hypothesis 2 specifically. At lag 1, the critical value at 5% is greater than the trace statistics (13.9); hence a conclusion was made that at most there is one cointegrating equation in the bivariate model. The coefficients of lag 1 of these rates suggested that the changes at a particular earlier time in Bitcoin spot trading volume affected values of Bitcoin price volatility in the next time periods (1-year lag), and vice versa.

The above tests for stationarity and unit roots therefore indicated that the ARCH model is appropriate. The Johansen test also indicated that a lag of 1 year is appropriate for the ARCH model to fit best.

### 5.9.4 ARCH Analysis

Hypothesis 2 tested for a negative effect between Bitcoin derivative trading volume specifically and the price volatility. From the ARCH analysis in Table 18 it is concluded that in this study trading volume of Bitcoin derivative instruments had **no significant effect** on the volatility of the Bitcoin spot price. A negligible effect is demonstrated by the fact that trading volume of Bitcoin derivative instruments had a 2% negative effect in the volatility of the Bitcoin spot price, but this result was not significant.

Although the ARCH analysis indicated a 2% negative effect (Table 18), the result was not significant over the entire study period and the null hypothesis was rejected. It does indicate though that speculation on the futures market is less prone to increase volatility than speculation on the spot market where the effect of spot trading volume was significantly positive.

The ARCH model was also run yearly (Table 19) to attempt to gain more insight into the structural breaks and regime changes on the relationships. Price had inverse relationships over time, positive effects when Trading volume of Bitcoin derivative

instruments showed negative effects (2015 and 2017), and negative effects when Trading volume of Bitcoin derivative instruments showed positive effects (2016).

#### **5.9.5 Granger-causality test**

The Granger test confirmed that trading volume of Bitcoin derivative instruments and Daily returns had a long run relationship with Daily Log Returns (volatility). Price itself did not have any long run relationship with volatility ( $p\text{-value} > 0.05$ ) according to the Granger test.

#### **5.9.6 Further Discussion**

One possible reason why the derivative market volume leads to less volatility than the spot market speculation might be that the instruments are more advanced and tends to be used more by advanced speculators. These speculators are more likely to be profitable and therefore conform to the requirements proposed by Kaldor (1939) and Friedman (1969) for speculation to reduce volatility.

Although the results were not significant over the entire study period it was significant in 2015, the year of the introduction of the Bitmex derivatives. In 2015 the derivative trading volume did have a significant 10% negative effect on volatility (Table 19). This supports the view by Singh and Tripathi (2015) and Brunetti et al. (2016) that the introduction of derivative contracts completed the market and improved informational efficiency and reduced volatility.

The effect however was positive by 10% in 2018 and this suggests that the price regimes and bubble behaviour at the start of 2018 still has a bigger effect on short term volatility than trading volumes. This supports the views of Adrangi and Chatruth (1998) that big spikes in derivative trading volumes can destabilise the spot market in the short term.

The fact that during different years the derivative trading volumes had significant effects (either positive or negative) indicates again that the effects might depend on the price regime as also suggested by Bouri et al. (2017), Balcilar et al. (2017) and Ardia et al. (2018)..

Despite the inconsistent effect of derivative trading volumes on volatility it is clear that it is more stabilising for the volatility of Bitcoin if speculators trade on the derivative markets instead of the spot market. With the trading volumes shifting more and more from the spot market to the derivative market, as seen in the ratio of derivative volumes to spot volumes increasing (Figure 6 compared to Figure 12), it is conceivable that the

volatility might come down eventually as more and more derivative instruments are introduced. The trading of options contracts might also have a stabilising effect as proposed by Mukherjee (2017), but this can only be tested when the options markets mature.

## **6 Conclusion**

The conclusion of the study is set out below. This study attempted to find support for the hypotheses that increased speculation (in both spot and derivative market volumes) will eventually lead to a reduction in Bitcoin price volatility.

### **6.1 Principal theoretical findings**

This study supports the findings by Dwyer (2015) and Pichl and Kaizoji (2017) that Bitcoin volatility is still significantly higher than that of gold and fiat currencies.

This study found that there is a significant positive relationship between spot trading volumes and price volatility in the Bitcoin market. This is in contradiction with what the study set out to do. This means that increased speculation in the spot market alone will not lead to lower Bitcoin price volatility and eventual adoption as a more stable currency. This study therefore does not support the findings by Balcilar et al. (2017), who failed to find a relationship between spot trading volumes and volatility. This study therefore contributed to the literature by introducing a different methodology and superior dataset to this question. It also contributed to this relatively unresearched field and topic of study by applying traditional finance and econometrics knowledge to the Bitcoin context.

This study also found that derivative trading volumes have a small negative effect on price volatility in the Bitcoin market, although this result was not significant over the entire study period. The negative relationship was significant though in the first year of introduction of Bitmex derivative trading instruments, indicating that the introduction of Bitmex derivative trading coincided with decreased volatility. This finding contributes to the small literature base on this subject and does not support the finding by Corbet et al. (2018) that the introduction of Bitcoin derivatives increased Bitcoin price volatility. This contribution could be attributed to the fact that this study used the Bitmex exchange data, a richer and longer dataset for derivative trading volumes. This study therefore contributed to the literature on this question, where only one, very recent peer-reviewed study, has been done before (Corbet et al., 2018).

### **6.2 Implications for management**

Bitcoin has clear potential as a technology because of its reduced transaction fees and speed of transfer, especially for large, cross-border payments. If the introduction of the Lightning Network is successful, Bitcoin can also be useful for faster, small, local payments (Antonopoulos, 2014; Cermak, 2017; Angel and McCabe, 2015).

As an investment though, this study agrees with Cheah and Fry (2015) and Dowd (2014) that Bitcoin is still extremely volatile and speculative. It is also impossible to value one Bitcoin as the value formation is generally unknown, as argued by Hayes (2017), Cheah and Fry (2015) and Polasik et al. (2015).

The volatility is unlikely to reduce just because of increased spot trading volumes and attention, and in fact will increase as shown by this study. The introduction of derivative trading contracts shows some signs of reducing volatility in this study; however the results are not significant. Comparing Figure 6 with Figure 12 does show that speculation is gradually moving from the spot market to the derivative market as the speculators are becoming more sophisticated and knowledgeable. With speculation moving to the derivative market, and the derivative market showing a small negative (albeit not significant) effect on volatility, it is conceivable that volatility will go down in the future as derivative trading increases. This is especially relevant as institutional investors are getting involved in the new CME and CBOE Bitcoin futures and are generally more informed and therefore assists in price discovery.

If Bitcoin eventually does become more stable and is adopted as a medium of exchange, it will likely be worth significantly more than it is now. This is because of the value it can capture from existing payment systems like credit cards, where annual fees in the USA alone are in excess of \$90 Billion (Fin24, 2018). This paper however argues that if the Bitcoin price does not stabilise it is unlikely to become adopted in the long run as a medium of exchange by the masses and will mostly be used for speculation and as a short term intermediate channel for cross-border payments.

This author however suggests that, because of the advantages of cryptocurrencies, it is likely that, if Bitcoin does not get adopted, a 'stable coin' will become the currency of the future. It is not clear whether this stable coin will be government regulated or algorithmically controlled.

### **6.3 Limitations of the research**

Although every measure was taken to minimise possible research limitations, some restrictions do apply.

Even with 1000+ daily observations the Bitcoin market is still immature. It would be prudent to reproduce the study when the market is more mature and more data is available.

This study relied on various models for volatility. No perfect model exists for volatility and therefore poses a validity concern for the study. Realised volatility or ARCH models are also not an error-free measure of volatility as can be seen by the number of conflicting results from studies attempting to find the best fit for Bitcoin volatility modelling (Katsiampa, 2017; Charles & Darné, 2018; Chu et al., 2017). Some of the datasets showed signs of non-stationarity and the results should therefore be interpreted with caution. Significant outliers were also detected in the data that could affect the results.

This study focused on one factor that influences price volatility, trading volumes. Other unexplored factors might also play a role in affecting volatility that was not tested for here, as discussed in the literature review, such as speculator sophistication and market informational efficiencies.

Results for this study was obtained and tested on historical data only. Findings should not be applied recklessly on future strategies.

#### **6.4 Suggestions for future research**

This study assumed that all Bitcoin transactions on the blockchain are transactional and all trading on exchanges were speculative. For a future study it might be more useful to analyse the Bitcoin blockchain and attempt to determine which transactions are speculative and which are commercial (Urquhart, 2016). This might prove difficult though because of the pseudonymity of the blockchain, but could possibly be done by investigating the time that Bitcoin is held in a wallet before it is moved.

From the results of this study it is clear that the current Bitcoin price regime plays a large role in the short term volatility. Future studies can benefit from dividing the Bitcoin history into periods of bull markets, bear market, bubbles and anti-bubbles in order to ascertain volatility relationships within these regimes and structural breaks in the dataset. This might enable more insight into factors that influence volatility relationships during a specific regime as also suggested by Bouri et al. (2017), Balcilar et al. (2017) and Ardia et al. (2018).

The Bitcoin market is still young compared to other commodity and currency markets and is still changing drastically every year. This results in structural breaks and behaviour changes. It is therefore necessary to keep confirming the results of this study in later periods and as more data becomes available.

Although Corbet et al. (2018) tested some hedging strategies to determine if a combination of derivatives and Bitcoin held could result in a less volatile combined investment, more research should be done in this regard. If such a combination can be found to be less volatile it can be used to hedge away any volatility risk while still allowing for the utility and advantages of using Bitcoin.

As mentioned other factors might also play a role in the volatility dynamics of Bitcoin, such as speculator sophistication, reaction to news events and shocks and market informational efficiencies. Future research, with more time available, can also look into these factors to build a more complete model for Bitcoin volatility.

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## Appendix A: Journals References rankings

Journal	Number of articles referenced	ABS Ranking
Journal of Business Finance & Accounting	1	3
Journal of Business Ethics	1	3
The Review of Economics and Statistics	1	4
Theory, Culture & Society	1	3
Research in International Business and Finance	1	2
Journal of Economic Perspectives	1	4
Economics Bulletin	1	N/A
Journal of International Financial Markets, Institutions & Money	1	3
Journal of Financial and Quantitative Analysis	1	4
Economics Letters	13	3
Applied Economics	1	2
Journal of Futures Markets	1	3
Economic History Review	1	4
Journal of Financial Stability	1	3
Finance Research Letters	7	2
Econometrica	1	4*
International Review of Financial Analysis	1	3
Neurocomputing	1	N/A
The Review of Economic Studies	1	4*
American Economic Journal: Macroeconomics	1	3
Studies in Nonlinear Dynamics & Econometrics	1	2
Expert Systems With Applications	1	3
Journal of Financial Stability	1	3
Global Journal of Multidisciplinary Studies	1	N/A
Cambridge Journal of Economics	1	3
<i>Economic Modelling</i>	1	2
<i>Physical review letters</i>	1	N/A
<i>Shanghai archives of psychiatry</i>	1	N/A
<i>International Economics</i>	1	4
<i>Journal of econometrics</i>	1	4
<i>Journal of Risk and Financial Management</i>	2	N/A

<i>Journal of the American statistical association</i>	1	4
<i>Clometrica</i>	1	2
<i>IEEE security &amp; privacy</i>	1	N/A
<i>Telematics and Informatics</i>	1	N/A
<i>International Review of Financial Analysis</i>	1	3
<i>International Research in Economics and Finance</i>	1	N/A
<i>Journal of applied econometrics</i>	1	3
<i>Biometrika</i>	1	4
<i>Quantitative Finance and Economics</i>	1	N/A
<i>Information Economics and Policy</i>	1	2
<i>Journal of the American Statistical Association</i>	1	4
<i>Energy Economics</i>	2	3
<i>Japan and the World Economy</i>	1	1
<i>Physica A</i>	1	2
<i>International Review of Financial Analysis</i>	1	3
<i>Communications of the ACM</i>	1	2
<i>Handbook of digital currency</i>	1	N/A
<i>China Economic Review</i>	1	2
<i>International Journal of Electronic Commerce</i>	1	3
<i>Resources Policy</i>	1	2
<b>Total articles used with 3+ rankings</b>	<b>41</b>	

# Gordon Institute of Business Science

University  
of Pretoria

08 August 2018

Badenhorst Joseph

Dear Joseph

*Please be advised that your application for Ethical Clearance has been approved.*

*You are therefore allowed to continue collecting your data.*

*Please note that approval is granted based on the methodology and research instruments provided in the application. If there is any deviation change or addition to the research method or tools, a supplementary application for approval must be obtained*

*We wish you everything of the best for the rest of the project.*

*Kind Regards*

GIBS MBA Research Ethical Clearance Committee

21. APPENDIX 5 CERTIFICATION OF ADDITIONAL SUPPORT

(Additional support retained or not - to be completed by all students)

**Please note that failure to comply and report on this honestly will result in disciplinary action**

I hereby certify that (please indicate which statement applies):

~~• I DID NOT RECEIVE any additional/outside assistance (i.e. statistical, transcriptional, thematic, coding, and/or editorial services) on my research report: .....~~

• I RECEIVED additional/outside assistance (i.e. statistical, transcriptional, thematic, coding, and/or editorial services) on my research report

Statistical .....

If any additional services were retained— please indicate below which:

Statistician

Coding (quantitative and qualitative)

Transcriber

Editor

Please provide the name(s) and contact details of all retained:

NAME: Chris Manyamba (PhD) .....

EMAIL ADDRESS: chrismanyamba@gmail.com .....

CONTACT NUMBER: 073 2177216 .....

TYPE OF SERVICE: Statistician .....

NAME: .....

EMAIL ADDRESS: .....

CONTACT NUMBER: .....

TYPE OF SERVICE: .....

NAME: .....

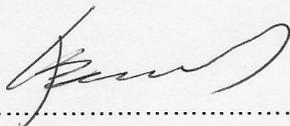
EMAIL ADDRESS: .....

CONTACT NUMBER: .....

TYPE OF SERVICE: .....

**I hereby declare that all interpretations (statistical and/or thematic) arising from the analysis; and write-up of the results for my study was completed by myself without outside assistance**

NAME OF STUDENT: JJ Badenhurst .....

SIGNATURE:  .....

STUDENT NUMBER: 23016893 .....

STUDENT EMAIL ADDRESS: badenhurst.johan@gmail.com .....

### 19.1 COPYRIGHT DECLARATION FORM

Student details			
Surname:	BADENHORST	Initials:	JJ
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Course details			
Degree:	MBA	Year completed:	2018
Department:	GIBS		
Supervisor:	Craig Penfold		
Supervisor email:	craig@blox.co.za		
Confidentiality / Embargo			
Do you need to have your report embargoed? If so, attach a motivation letter. Without a letter this will not be granted.			
Yes		No	X
If yes, please indicate period requested			
Two years		**Permanent	
<b>**If permanent, please attach a copy of the letter of permission from the Vice-Principal: Research and Postgraduate Studies. Without a letter this will not be granted.</b>			
Access			
A copy of your research report will be uploaded to UPSpace Can the Information Centre add your email address to the UPSpace web site?			
Yes	X	No	
If no, please motivate (ignore if report is to be embargoed)			
Copyright declaration			
I hereby certify that, where appropriate, I have obtained and attached hereto a written permission statement from the owner(s) of each third-party copyrighted matter to be included in my research report ("the work"), allowing distribution as specified below. I certify that the version of the work I submitted is the same as that, which was approved by my examiners and that all the changes to the document, as requested by the examiners, have been included.			
I understand that all rights with regard to intellectual property in the work vest in the University who has the right to reproduce, distribute and/or publish the work in any manner it may deem fit.			
I agree that, a hardcopy of the abovementioned work be placed in the Gordon Institute of Business Science Information Centre and worldwide electronic access be given to the softcopy on UPSpace.			
Signature:			Date: 29/10/2018