VIRTUAL CURRENCY: A COINTEGRATION ANALYSIS BETWEEN BITCOIN PRICES AND ECONOMIC AND FINANCIAL DATA

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Resumo

A criação e crescimento de moedas virtuais pelo mundo têm sido alvo de vários estudos e notícias divulgadas pelos *media*, especulando-se quanto à sua continuidade, aplicabilidade e segurança. Dessas moedas, destaca-se a Bitcoin, a moeda virtual que apresentou até hoje o maior valor de mercado e que se tem mantido em circulação há mais de 5 anos.

O presente estudo tem como objetivo investigar a existência de uma relação dinâmica entre os preços da Bitcoin e indicadores económico-financeiros cuja relação com as moedas físicas é conhecida ou foi demonstrada em estudos anteriores. Esses indicadores são os preços do petróleo e do ouro, as taxas de juro a 6 meses e a 1 ano das obrigações do Tesouro americanas e os valores de fecho do índice S&P 500.

Os resultados deste estudo demonstram que apenas as taxas de juro a 6 meses de obrigações do Tesouro americanas apresentam uma relação de longo prazo com as cotações da Bitcoin.

Palavras-chave: bitcoin, não estacionariedade, cointegração, modelo vetorial de correção de erros.

Classificação JEL:

C32 – Modelos Cronológicos; Regressões por Quantis Dinâmicas; Modelos de Tratamento Dinâmico

E47 – Previsão e Simulação

Abstract

The cryptocurrencies development around the world has been studied and published by the media, speculating on its continuity, applicability and security. The Bitcoin stands out as the virtual currency that has achieved the highest market value to date and for being in circulation for more than 5 years.

This study intends to investigate the existence of a dynamic relationship between Bitcoin prices and economic and financial data whose relationship with physical currencies is known or it has been showed in previous studies. This data includes the Crude and Gold prices, the 6-month and 1-year U.S. Treasury Yields and the S&P 500 Index prices.

The results of the study suggests that only the 6-month U.S. Treasury Yields presents a long-term relationship with the Bitcoin prices.

Keywords: bitcoin, nonstationarity, cointegration, vector error correction model.

JEL Classification:

C32 – Time-Series Models; Dynamic Quantile Regressions; Dynamic Treatment Effect Models

E47 – Forecasting and Simulation

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List of Abbreviations

ADF – Augmented Dickey-Fuller

AIC – Akaike Criterion

Amazon – Amazon.com, Inc.

ARCH – Autoregressive Conditional Heteroskedasticity

ARIMA – Autoregressive Integrated Moving Average

ARMA – Autoregressive Moving Average

ATM – Automated Teller Machine

BBC – British Broadcasting Corporation

BDS – Brock, Dechert and Scheinkman

BMPI – Bitcoin Market Potential Index

CE – Cointegration Equation

CL1:COM – Price per barrel of West Texas Intermediate (WTI) crude oil

CNN – Cable News Network, Inc.

CNY – Chinese Yuan

Coinbase – Coinbase, Inc.

CPU – Central Processing Unit

Dell – Dell Inc.

DFS – New York State Department of Financial Services

DISH Network - DISH Network Corporation

EBA – European Banking Authority

EMH – Efficient Market Hypothesis

EMI – Electronic Money Institutions

ES – Expected Shortfall

ETF – Exchange Traded Fund

EU – European Union

EUR – Euro

Expedia – Expedia, Inc.

FATF – Financial Action Task Force

FBI – Federal Bureau of Investigation

FinCEN – United States Financial Crimes Enforcement Network

GC1:COM – Gold price

HBO – Home Box Office, Inc.

HMRC – Her Majesty's Revenue and Customs

HQC – Hannan-Quinn Criterion

ICANN – Internet Corporation for Assigned Names and Numbers, Inc.

IMF – International Monetary Fund

LL – Log Likelihood

LR – Likelihood-Ratio

MGARCH – Multivariate Generalized Autoregressive Conditional Heteroskedasticity

OECD – Organization for Economic Cooperation and Development

Overstock – Overstock.com, Inc.

PayPal – PayPal Holdings, Inc.

Pecunix – Pecunix Inc.

PoW – Proof-of-Work

Prob. – Probability

S&P 500 Index – Standard & Poor’s 500 Index

SC – Schwarz Criterion

SHA – Secure Hash Algorithm

SPX:IND - S&P 500 Index

Thash – Trillion hashes

U.K. – United Kingdom

U.S. – United States of America

U.S.A. – United States of America

ULC – Uniform Law Commission

USD – U.S. Dollar

USGG10YR – 10-year U.S. Treasury Yield

USGG6M – 6-month U.S. Treasury Yield

VaR – Value at Risk

VAR – Vector Autoregressive

VEC – Vector Error Correction

VECM – Vector Error Correction Model

WebMoney – WebMoney Transfer Ltd.

Western Union – Western Union Company

Windows – Microsoft Windows

WTI – West Texas Intermediate

XBT – Bitcoin

XBTUSD – XBT/USD exchange rate

Sumário Executivo

O presente estudo visa analisar a existência de relação entre os preços da Bitcoin e indicadores económico-financeiros, definindo-a através da estimativa de um modelo. Adicionalmente, esta dissertação identifica um conjunto de caraterísticas que poderão impulsionar a procura desta moeda ou, pelo contrário, afastar os seus investidores.

Atualmente, a introdução e desenvolvimento de moedas virtuais têm sido temas em foco dos investidores, das instituições financeiras e dos seus reguladores. O facto de a Bitcoin permanecer em circulação desde 2009, com maior destaque desde 2013, e ter vindo a apresentar valores de mercado históricos chama cada vez mais a atenção de estudiosos e investidores.

Na realidade, vários estudos e notícias têm vindo a identificar vantagens e desvantagens à sua utilização, os quais poderão atrair os investidores mais conservadores e acautelar os mais entusiastas, respetivamente. Parte das vantagens apresentadas são a transparência, a segurança, os reduzidos custos de transação, o anonimato, a possibilidade de troca por bens ou serviços reais e a descentralização. Por outro lado, as desvantagens englobam, por exemplo, o uso indevido da autoridade discricionária, a associação da moeda a atividades ilegais, a instabilidade dos preços e falhas no anonimato e segurança das carteiras ou transações de Bitcoin.

Inerente a estas caraterísticas está a permanência da Bitcoin ainda numa zona cinzenta da legislação e política monetária, na grande maioria dos países. Isto associado à atividade criminal em que a moeda tem sido envolvida, alertou as autoridades de segurança e as entidades reguladoras dos mercados monetários, nomeadamente a *Financial Action Task Force* e a *Financial Crimes Enforcement Network*, deixando mais relutantes as entidades competentes quanto ao avanço para a sua regulamentação.

Ainda assim, as cotações da Bitcoin têm apresentado uma tendência de crescimento, sendo o seu valor a 28 de agosto de 2017 de 4.332 USD, onde o valor máximo de 4.346 USD foi registado no dia 17 de agosto de 2017.

Certamente que seria aliciante identificar quais os fatores que têm vindo a impulsionar o aumento de valor desta moeda virtual e, ainda mais atrativo, é a identificação de dados que possam ser utilizados na sua estimativa e previsão. De notar que as cotações da Bitcoin têm sido estudados por vários autores, sob diferentes perspetivas, nomeadamente na tentativa de identificar bolhas nos preços, identificar qual a distribuição que melhor representa o comportamento da taxa de câmbio da Bitcoin, examinar as dinâmicas dos preços e prever a sua evolução futura.

Neste sentido, foi também através de estudos efetuados que demonstraram a existência de relação entre o valor de moedas físicas, como, por exemplo o Dólar americano, e determinados indicadores económico-financeiros, que foi feita a seleção das variáveis a utilizar neste estudo. Desta forma, as séries temporais consideradas são, além da taxa de câmbio XBT/USD, os preços do petróleo e do ouro, as taxas de juro a 6 meses e a 1 ano de obrigações do Tesouro americanas e os preços do índice S&P 500. Todos os preços estão expressos em USD e as taxas em percentagem.

Depois de identificados o objetivo e as variáveis em estudo, importa compreender se se verifica relação no longo prazo entre a taxa de câmbio XBT/USD e cada uma das variáveis identificadas. Desta forma, consideram-se as bases metodológicas dos autores Perron (2005), Johansen (1991, 1995) e Granger (1969), compreendendo as respetivas três grandes parcelas: (i) em primeiro lugar, a identificação da presença de não-estacionariedade e integração de primeira ordem nas séries temporárias em análise; (ii) em seguida, o teste de cointegração das combinações entre a taxa de câmbio XBT/USD e cada uma das restantes variáveis em estudo e, caso se verifique, a estimativa dos respetivos modelos vetoriais de correção de erros; e (iii) o teste de exogeneidade que, caso se verifique exogeneidade fraca, implicará a ausência de ajustamentos significativos na relação de longo prazo e, consequentemente, a impossibilidade de utilização do modelo para previsão da taxa de câmbio XBT/USD.

Relativamente ao estudo da não-estacionariedade das séries, optou-se pela execução do *breakpoint unit root test*, uma vez que as representações gráficas parecem indicar a existência de quebras estruturais no comportamento da taxa de câmbio XBT/USD.

Por outro lado, o teste de cointegração de Johansen foi efetuado para cada combinação de duas variáveis, isto é, para cada sistema entre as cotações da Bitcoin e cada uma das restantes variáveis consideradas. Desta forma, simplifica-se a interpretação dos resultados e permite-se concluir se existe relação, assim como, de que forma se relaciona cada uma das variáveis com a taxa de câmbio XBT/USD.

No que respeita ao teste de exogeneidade, foi testada a presença de exogeneidade forte, para as variáveis com exogeneidade fraca, por forma a verificar a existência, ou não, de relação no curto prazo das respetivas variáveis.

Desta forma, os resultados do estudo indicam que, embora se verifique cointegração entre as cotações da Bitcoin e as variáveis em análise, apenas as taxas de juro a 6 meses de obrigações do Tesouro americanas apresentam uma relação de longo prazo com as cotações da Bitcoin. Por outro lado, as cotações da Bitcoin e do ouro apresentam uma relação de curto prazo, visto ter sido apenas identificada exogeneidade fraca.

De salientar que somente o modelo Vetorial de Correção de Erros estimado com as taxas de juro a 6 meses de obrigações do Tesouro americanas poderá ser utilizado para estimar os preços da Bitcoin, visto não apresentar exogeneidade.

Por fim importa reter que, embora este estudo aponte para a possibilidade de utilização das taxas de juro a 6 meses de obrigações do Tesouro americanas para previsão das cotações da Bitcoin no curto prazo, outros inúmeros fatores e limitações da metodologia poderão contrariá-lo, nomeadamente o facto do teste de cointegração de Johansen assumir a inexistência de quebras estruturais.

1. Introduction

Financial Markets cover a huge amount of information, activities and tools used by people in their quotidian actions or/and by organizations from all business areas. These Markets can be divided into three main categories: Money Markets, Exchange Markets and Capital Markets (Custódio *et al*, 2008).

Focusing on the Exchange Markets segment, its basis is the purchase and sale of different national currencies, establishing a relative price – the exchange rate. Anyone who has travelled to countries with a different domestic currency is familiar with this concept. In these cases, as it is exemplified by Hoover (2012), people can buy the foreign currency in banks, kiosks in international airports, train stations or even in most cities on the relevant places. However, the same author refers that most foreign-exchange transactions do not involve tourists, but rather banks and nonfinancial companies engaged in foreign trade. Actually, foreign-exchange markets cover not only the exchange of real goods and services, but also of financial assets (Hoover, 2012), where the purchase and sale of currencies are included. Although these transactions could be done in a short time range and when there is a need, they can be used as an investment.

Since exchange rates suffer appreciations and depreciations over time, there is an investment opportunity that does not come free of risk or of the cost of specialized analysis. The risk factors that are unique to international investments are exchange rate risk and political risk. (Bodie *et al*, 2011).

An investor can take a profit when the foreign currency he holds appreciates relative to his national currency. He can sell the foreign currency and then, the value he will receive, in national currency, will be higher than what he paid to buy it. However, the exchange rate fluctuation can also result in losses, when the appreciated currency is the national one. Therefore, at an organization level, international financial managers are responsible for handling the continued high volatility of the relative values of currencies. Despite efforts to forecast foreign exchange behaviour, a wide range of economic, financial and speculative instabilities create major uncertainties (Copeland *et al*, 2005). In a crisis context, as the one that has affected the financial markets since 2008, these drivers are even more crucial.

Nevertheless, it was during this unstable period that the Bitcoin (XBT) emerged. Undoubtedly, it had a huge impact in exchange markets as we knew them. Bitcoin is a digital, decentralized, partially anonymous currency, not backed by any government or other legal entity, and not redeemable for gold or other commodity (Grinberg, 2011). It was created in 2009 (Bojanova *et al*, 2014) and it follows the white paper [50] of Satoshi Nakamoto (Chan *et al*, 2015), whose true identity no one knows.

In Bloomberg, there are quotations of exchange rates XBT/USD and XBT/EUR since 1st December 2011 and 10th September 2013, respectively. Similarly to the physical currencies, Bitcoin is subject to volatility, although on a higher scale. Observing the historical prices of XBT/USD (see appendix A), it is possible to conclude that the maximum value of Bitcoin was registered at 17th August 2017, when 1 XBT was worth 4.346USD. Looking back, at 29th November 2013, there was also a maximum value of 1.137USD, followed by a huge depreciation. Indeed, since that date, the minimum value was recorded at 14th January 2015, when 1 Bitcoin was worth 185USD.

In Portugal, despite the existence of some machines where is possible to buy Bitcoins, this topic does not deserve so much attention. One possible reason can be that the application of this digital currency is still not very expressive in the country. However, this tends to change with the growing media attention to this currency. It should be noted that several foreign authors have studied the Bitcoin prices under different perspectives, namely in the attempt to identify price bubbles, to identify the distribution that gives the best prices fit, to examine the prices dynamics and to forecast them in the future. With the continuous increase of Bitcoin prices, as well as the increase in the available observations number, the investigation related with it study becomes even more interesting.

In this context, it would be appealing to identify what factors have been driving the Bitcoin prices increase and, even more attractive, to identify what data factors can be used to forecast them. Consequently, it arises the present dissertation “Virtual currency: A cointegration analysis between Bitcoin prices and economic and financial data”. The current study examines the long-run and short-run relationships between the exchange rate XBT/USD and other economic and financial factors. Objectively, this study explores the existence of a cointegration relationship between the variables. Additionally, it is estimated the vector error correction model which could be used (with lack of success, quite sure) to forecast the exchange rate XBT/USD.

In fact, Engle & Granger (1987) defined the cointegration as a formulation of the phenomenon that nonstationary processes can have linear combinations that are stationary. Therefore, it will be considered the methodological approaches of Perron (2015), Johansen (1991, 1995) and Granger (1969), comprising the respective following steps: (i) testing the presence of non-stationarity and first-order integration in each time series considered in this analysis; (ii) testing the cointegration between the exchange rate XBT/USD and each of the remaining variables under study; and (iii) testing the exogeneity, since a weak exonegeity will imply the absence of significant adjustments in the long-run relationship and, consequently, the preclusion of using the model to forecast the Bitcoin prices.

Regarding the first step, it is applied the breakpoint unit root test, since there are signs of structural breaks in the behaviour of the Bitcoin prices.

Next, it is computed the Johansen cointegration test for each combination of two variables, that is, for each system between Bitcoin prices and each of the other variables. In this way, the bivariate test simplifies the results interpretation, allowing to conclude whether there is a long-run relationship and how the variables are related to the exchange rate XBT/USD.

Finally, it is tested the strong exogeneity, when the weak exogeneity is detected, in order to verify the existence, or not, of a short-term relationship between the variables that do not show a long-term equilibrium.

The economic and financial data under analysis are the crude and the gold prices, the 6-month and the 10-year U.S. Treasury Yields and the S&P 500 Index quotes. The reason for choosing these variables is that several studies have already showed their relationship with different physical currencies. Nevertheless, since Bitcoin is a virtual currency and there are many legal blanks with regard to this, it is expected that the impact of economic and financial instabilities should be lower than in physical currencies. Then, the tricky question is to understand if the data related to physical currencies also relate to virtual currencies, in this case the Bitcoin.

Thereby, this thesis aims to present and discuss models to explain the relationship between the Bitcoin prices and the economic and financial data referred before.

Indeed, the results showed that only the 6-month U.S. Treasury Yields present a long-run relationship with the Bitcoin prices, being possible to use their rates to forecast the exchange rate XBT/USD in the short term.

The Chapter 2. begins with an overview of the present status of the Bitcoin information and researches. It is split into eight sub-sections, including a brief description of Bitcoin, its exchange markets and prices, its users, its main advantages, its main disadvantages and risks, a comparison between physical and digital currencies, the current Bitcoin regulation and main studies performed and their conclusions. Chapter 3. presents the data considered in this study, their sources and why they were included.

Chapter 4. outlines the econometric specifications and procedures applied to the data, including the methodology and approaches under non-stationarity, cointegration and VEC Model and exogeneity. Chapter 5. shows the empirical findings and the Chapter 6. presents the conclusions.

2. Literature Review

Bitcoin is a digital and decentralized currency which was created in 2009 (Bojanova *et al*, 2014). However, the Bloomberg platform only provides quotations of XBT/USD and XBT/EUR exchange rates since December 2011 and September 2013, respectively. This can be explained by the residual value of one Bitcoin during the first years of its life.

On the other hand, given its recent creation and short life span, until recently, Bitcoin has not received that much attention. As the notoriety of Bitcoin has increased in the last few years, mainly due to the social media, by consequence the number of electronic documents and academic journals articles on it has follow the same path. Even so, the knowledge on Bitcoin still does not offer a lot of insights (Carrick, 2016).

This chapter presents an overview of a body of research and the present status of the Bitcoin information.

2.1. Bitcoin: A Virtual Currency

According to the white paper of the Bitcoin's creator, known as Satoshi Nakamoto, an electronic coin is defined as a chain of digital signature, where each owner transfers the coin to the next by digitally signing a hash of the previous transaction and the public key of the next owner and adding these to the end of the coin. A payee can verify the signatures to verify the chain of ownership [50].

Beginning by the way it works, Bitcoin is a digital currency system based on peer-to-peer[1] virtual data. The peer-to-peer network used to distribute a master transparent public ledger is also called blockchain (Harrel *et al*, 2017).

On the other hand, Harrel *et al* (2017) described Bitcoin as a Proof-of-Work[2] (PoW) based currency that allows users to generate digital coins by performing computations, in order to limit the replication of Bitcoins and to preserve their value.

Additionally, as referred by Bojanova *et al* (2014), to use Bitcoins, individual must establish a Bitcoin 'wallet' on a computer. Therefore, Bitcoins can be transmitted to other user wallets using a combination of public and private key cryptology. According to

[1] A Peer-to-Peer, or P2P, Economy is a decentralized model whereby two individuals interact to buy or sell goods and services directly with each other, without intermediation by a third-party, or without the use of a company of business [38].

[2] Proof of work describes a system that requires a not-insignificant but feasible amount of effort in order to deter frivolous or malicious uses of computing power, such as sending spam emails or launching denial of service attacks. The concept was adapted to money by Hal Finney in 2004 through the idea of "reusable proof of work." Proof of work forms the basis of most, though not all, other cryptocurrencies as well [39].

Gouriéroux *et al* (2015), there are three types of wallets: the software wallet, the mobile wallet and the web wallet.

In their study, Harrel *et al* (2017) also explained that through the acquisition of a Bitcoin wallet and one or more Bitcoin addresses, they can be accumulated on a computer's hard drive as electronic files or transferred just like an e-mail. By using a blockchain, each Bitcoin transaction is registered for all to see, protecting the Bitcoin network against fraud and ensure that the files are not counterfeited. The blockchain is used to verify that the identical Bitcoins haven't been used in a previous transaction, there for preventing double-spending of the same Bitcoins.

The same authors clarified that the money supply is determined by a specific type of data "mining" activity, which depends on the amount of resources (electricity and CPU time) that "miners" expend to solving specific mathematical problems. In this sense, the Bitcoin mining process involves repeatedly running a computationally intensive mathematical function (called a cryptographic hash function) on a set of randomly seeded inputs until a specific pattern pops up.

Furthermore, Harrel *et al* (2017) mentioned that as of July 2016, the Bitcoin network hash rate (total number of hashes per second made by all players) is estimated to be in the neighbourhood of 1.432.000 trillion hashes per second (1.432.000 Thash/s), contrasted with the 2014 rate of approximately 30.000 trillion hashes per second (30.000 Thash/s), increasing at an astonishing rate due to more efficient specialized mining hardware now available on the market. At this rate, Bitcoin has become one of the largest distributed computational efforts ever.

As noted by Guadamuz *et al* (2015), it is important to note that Bitcoin concept has built-in scarcity because mining for coins becomes more difficult as time goes by and the market grows. The algorithms that produce new Bitcoin coins increase the amount of processing power necessary to create each new block, so producing new coins is more difficult. This difficulty is built into the system to in order to keep the total amount of Bitcoins at a maximum of 21 million. In practice, the first block "mined" was at difficulty 1 and this is known as the genesis block. By June 2011, there were 131.301 blocks, making a total of 6.560.000 Bitcoins and a difficulty of 877.227. In June 2014, there were 303.162 blocks with a total 12.800.000 Bitcoins in existence and a difficulty of over 10 billion. At the time of their article writing, Guadamuz *et al* (2015) identified the existence of 359.657 blocks and just over 14 million Bitcoins had been "mined", with a difficulty of over 47,5 billion, meaning that to make a new block is 47 billion times more difficult than it was for the initial block and four times more difficult than it was exactly one year before.

Given its complexity, this topic has been increasingly studied by computer engineers and programming technicians.

Following the Bitcoins creation, they can be bought and sold on trading websites known as “exchanges”, each of them are independently operated and accessible 24 hours a day, 7 days a week to a global clientele (Pieters *et al*, 2016).

Harrel *et al* (2017) pointed that some centralized virtual currencies take the form of digital precious metals, such as e-Gold and Pecunix, where users exchange digital currency units ostensibly backed by gold bullion or other precious metals. Others exist within popular online games or virtual worlds, such as Farmville, Second Life, or World of Warcraft. Still others are online payment systems such as WebMoney and Liberty Reserve, which are available generally outside of specific online communities and denominate users’ accounts in virtual currency rather than U.S. Dollars, Euros or some other national currency. Decentralized systems such as Bitcoin, which is relatively recent, are growing rapidly. A network of sites and services, including exchangers who buy and sell virtual currencies in exchange for national currencies or other mediums of value, have developed around virtual currency systems, as well.

Moreover, Pieters *et al* (2016) stated that Bitcoin has gained links to the physical goods economy over time as retailers – including Windows, Dell, Overstock, and gift card merchants – began accepting it as a form of payment, though not all use the same method. For example, Dell accepts direct Bitcoin payments, but Amazon instead provides digital gift cards which may be purchased with Bitcoin and then used to purchase goods on their website.

Indeed, the analysis of Baek *et al* (2015) suggested that the Bitcoin returns are internally driven by buyers and sellers and are not influenced by fundamental economic factors.

2.2. Exchange Markets and Bitcoin Prices

In order to accommodate growing demand several exchanges have been created, offering exchanges between Bitcoin and traditional currencies, including the Euro and U.S. Dollar and other digital currencies. According to Grinberg (2011), they include Liberty Reserve, Pecunix, and WebMoney. Several sites provide transaction services, allowing individuals to keep, send, and receive Bitcoins without ever running the Bitcoin client on their own computers. This author also stated that the Mt. Gox[3] seemed to be the most popular exchange with $10.000 in trading volume in March 2011, which had an easy to use website. It allowed sending Bitcoins through email, as Bitcoin Mail. In the other hand, Instawallet provides a website that allows individuals to create Bitcoin addresses, send Bitcoins to any address for free and check balances.

Harrel *et al* (2017) referred that new entrants appear almost daily in the Bitcoin ecosystem and include exchanges, transaction services providers, market information and chart providers, escrow providers, joint mining operations and so on. However, absent from this ecosystem at present are futures markets and entities offering legitimate investment returns, such as fractional reserve banks, although some individuals have announced plans to build these. Their article also gives some examples of these well-funded entrants, as Coinbase which was founded in June 2012 as a Bitcoin wallet and platform where merchants and consumers can transact. Led by venture capital firm Andreessen Horowitz, Coinbase received a validation of concept and an initial $25 million investment. Coinbase lists contributed July 2016 capital of $1,06 million, and other metrics as: 3.200.000 users, 42.000 merchants, U.S. bank integration, 800.000 consumer wallets and 8.000 developer applications.

These exchanges have acquiring special importance, since late adopters and interested individuals cannot hope to mine new coins and, therefore, the Bicoin economy relies on users buying Bitcoins with fiat currencies[4] through exchanges (Guadamuz *et al*, 2015).

Moreover, it was also introduced in the market “Bitcoin ATM machines”. They were available in Canada, London, Seattle, Washington and Austin (Texas) as of early 2014, and this availability had grown to 560 machines worldwide by early 2016, with 239 located in the United States (Harrel *et al*, 2017).

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[3] Mt. Gox was one of the earliest and most public downfalls of the Bitcoin era. In early 2014, Mt. Gox stood atop the field of Bitcoin exchanges as the largest, until it declared bankruptcy following the disappearance of almost $500 million Bitcoins and cash from its coffers. Some 200.000 of those Bitcoins were eventually found, leaving 650.000 still missing. In the time since, many analysts, former Mt. Gox investors, and others have speculated as to where the missing currency is. This is particularly important as Bitcoin's price has soared in recent months: the missing Bitcoins could be worth as much as $2 billion at this point [41].

[4] Fiat money is currency that a government has declared to be legal tender, but it is not backed by a physical commodity [36].

Given the many different Bitcoin exchanges available, each with varying popularity and currencies that Bitcoin is denoted in, Urquhart (2016) resorted to the *www.bitcoinaverage.com,* to collect data to its study. This is the first aggregated Bitcoin price index that aggregates rates from all available Bitcoin exchanges around the world and provides a volume weighted average Bitcoin price, enabling a worldwide perspective on the price and therefore efficiency of Bitcoin. At present Bitcoin adoption can be measured with varying degrees of accuracy across a variety of metrics, such as number of wallets, number of Bitcoin accepting businesses, number of transactions and exchange trading volume (Hileman, 2015).

Several studies had being performed indicating that Bitcoin users must be exposed to exchange rate fluctuations, as exhibited in appendix A. Indeed, fluctuating Bitcoin prices have attracted media attention and have been associated with billions of dollars of trading volume. The exchange rate for Bitcoin to fiat currencies is determined by supply and demand and there is no governmental authority or company making guarantees about its value. (Athey *et al*, 2016).

On a different note, Carrick (2016) emphasized the currencies influence from news sources. It is common knowledge that information disseminated to the public influences the supply and demand of currencies. For most currencies, the value is determined by the markets, which relies on information to determine the price. Various studies have looked at the effect of news announcements on currency prices, most of these studies looked at the volatility that was linked to the news. In spite of no study has looked specifically at Bitcoin or other cryptocurrencies, the Carrick's article mentions that news and information on the internet seems to influence the price of Bitcoin and, overall, the literature shows that the forces influencing fiat currencies apply to Bitcoin.

In fact, there are communication channels spread around the world that report maximum values reached by Bitcoin, such as “O Jornal Económico” [25], “BBC” [7] and “CNN” [56], also more in-depth articles on Bitcoin can be found, for example, in “Forbes” [26].

2.3. Bitcoin Users

According to Grinberg (2011), individuals holding this currency represent a number of interests, including technology early adopters, privacy and cryptography enthusiasts, government-mistrusting “gold bugs”, criminals and speculators.

On the other hand, the article of Guadamuz *et al* (2015) refers that the average Bitcoin user is a 32-year-old libertarian male, motivated by curiosity, profit and politics. Additionally it is mentioned that computer science and illegal activity were some of the most prevalent topics linked with Bitcoin, with less correlation to political discourse and investment. The same authors also affirmed that an important core of the Bitcoin community consists of libertarian types of all stripes, from those who want to see the end of all fiat currencies, to slightly more moderate and pragmatic supporters.

Given the existence of group of Bitcoin enthusiasts and users, a large number of online merchants is currently accepting Bitcoins, catering to individuals with these interests, including web hosts, online casinos, illicit drug marketplaces, auction sites, technology consulting firms, and adult media and sex toy merchants. Farther, a number of non-profit organizations such as Wikileaks accept donations in Bitcoin. And a small handful of retail businesses accept Bitcoins, even if there is little indication that these retail establishments are significant (Grinberg, 2011). Likewise, Harrel *et al* (2017) mentioned in their article that by mid-year 2014, at least 65.000 global companies had announced acceptance of Bitcoins, including DISH Network, online travel site Expedia and Dell, which alone had nearly $57 billion in 2013 sales.

Alternatively, in the first attempt to provide a rigorous answer to the question of where a cryptocurrency like Bitcoin has the most and the least relative potential for adoption, Hileman (2015) introduced a new composite indicator that ranks Bitcoin's potential utility across 178 countries - the Bitcoin Market Potential Index (BMPI). Some of the 40 BMPI variables are likely to have a greater degree of influence over Bitcoin adoption than other variables and these variables were therefore afforded additional weight in the index. A variety of factors were considered in determining variable weightings.

The results showed that the 10 countries with the highest relative potential for Bitcoin adoption according to the Bitcoin Market Potential Index are Argentina, Venezuela, Zimbabwe, Malawi, United States, Belarus, Nigeria, Congo, Iceland and Iran by the standardized method. The index rankings re-scaled data are broadly similar to standardized results.

Given the BMPI's criteria it is not surprising to see Argentina ranked number one. The country suffers from persistently high inflation, has a large informal economy and regularly experiences financial crisis. In addition, Argentina has a relatively high degree of technology penetration and controls on the movement of capital. Argentina also recently defaulted on its sovereign debt for the second time in 13 years.

The same author also mentioned a country that often features in Bitcoin discussions, which is ranked 27th - China. China's BMPI ranking is lowered by its relatively-small black market and fewer recent financial crises. For some time, Bitcoin exchanges have reported Yuan-Bitcoin trading volume well in excess of the second most active currency pair, Dollar-Bitcoin. However, non-Chinese nationals are free to trade Yuan-Bitcoin on exchanges, and there are unconfirmed rumours that self-reported Bitcoin exchange trading volume is significantly inflated for marketing purposes.

Near the bottom of the overall BMPI rankings at number 169 is Ireland. While Ireland scores well in some categories, such as technology and Bitcoin penetration, the country has wrestled with deflationary pressures in recent years and also has a relatively limited set of restrictions on the flow of capital. Following a similar perspective, Portugal is in the 123rd BMPI rank.

Lastly, it should be noted that it is unclear how to score Bitcoin regulation and it has therefore been excluded from the BMPI. Nevertheless, a more aggressive Bitcoin regulation in countries such as Ecuador and Bolivia may ultimately serve as a significant barrier.

2.4. Main Bitcoin Advantages

Based on the various studies on Bitcoin, there are a number of advantages that this cybercurrency presents.

i) Transparency: All transactions are publicly available and verifiable in the electronic ledger called the blockchain, providing an unprecedented level of transparency and peer verification. It is one of the features that transcends currency elements (Guadamuz *et al*, 2015).

ii) Security: Bitcoin uses the 256-bit version of the secure hash algorithm (SHA), an encryption protocol designed by the U.S. National Security Agency. The protocol maintains the integrity of the blockchain, but is also used to sign and secure Bitcoin wallets, providing a mathematical proof that transactions are performed from the owner of the wallet. The signature also prevents the transaction from being altered by anybody once it has been issued (Guadamuz *et al*, 2015).

iii) Lower transaction costs: One of the main advantages of Bitcoin is that its transactions are open to the public and, as there are no intermediates involved, supposed to be without transactions fees. In fact, the system usually has transaction fees that vary from one exchange to the other. Even with these fees, which go to the miner as an incentive, Bitcoin still boasts lower transaction costs when compared to other payment methods. Some merchants estimate that the average is at one percent, as opposed to other intermediary clearinghouses such as PayPal and Western Union, which charge from two to four percent. However, it must be noted that some researchers believe that low transaction costs will not sustainable in the future (Guadamuz *et al*, 2015).

This is especially relevant to improve the quality of life for the world's poorest, enabling migrants to make cheaper remittances of payments to their families in developing countries. Indeed, the World Bank estimates that such remittances totalled $582 billion in 2015, of which $432 billion went to developing countries, involving some 232 million migrants. By 2016, data shows that world remittances have grown to more than $601 billion, with developing countries receiving over $440 billion (Harrel *et al*, 2017).

iv) <u>Anonymity</u>: Bitcoin is theoretically anonymous. A person in possession of Bitcoin in an encrypted wallet can spend it in any service without identification (Guadamuz *et al*, 2015).

v) <u>Resilience</u>: Since Bitcoin is a decentralized currency with no central authority and no issuing body, it is resilient to attacks and in theory it also cannot be brought down (Guadamuz *et al*, 2015).

vi) <u>Engine for innovation</u>: While it is easy to ignore some criticisms made to Bitcoin, it cannot be denied that its creation has given a much needed push towards innovation in the way in which we think about money, financial institutions and centrality (Guadamuz *et al*, 2015).

vii) <u>Real-life payments</u>: In contrary to the most virtual currencies, Bitcoin can be exchanged for real-life goods and services on a limited basis (Pandey *et al*, 2014).

viii) <u>Decentralized markets</u>: Blockchains compete with banks as organizations, enabling banking transactions to shift out of centralized hierarchical organizations and back into decentralized markets. As blockchain technologies work through banking, at the margins of measurement, monitoring and new forms of automated governance, they will enable a deeper process of institutional evolution to begin to unfold (Allen *et al*, 2016). In Baek *et al*'s perspective (2015), Bitcoin is a panacea to replace financial institutions, an alternative to cash and a hedge against economies with rampant inflation.

2.5. Main Bitcoin Disadvantages and Risks

In contrast to the advantages presented above, there is also a set of disadvantages or risks identified by some authors.

i) Improper use of discretionary authority: Bitcoin is believed to have no central institution with discretionary authority to increase the money supply more quickly than the inflation rate built into the software. However, either the developers or a "convincing coalition"[5] could probably exercise discretionary authority to change the inflation rate. Such an exercise of discretion, even if done with good intentions and supported by a majority of Bitcoin users, may nevertheless cause many individuals to lose confidence in Bitcoin and sell off their holdings, starting a panic (Grinberg, 2011).

ii) Government crackdown: Currently the Bitcoin system fails to satisfy the "Misean Regression Theorem," which explains that money becomes accepted not because of a government decree or social convention, but because it has its roots in a commodity expressing a certain purchasing power (Harrel *et al*, 2017). Although Bitcoin may be difficult to shut down because of its decentralized nature, a government crackdown on Bitcoin may nevertheless cause a crisis of confidence, especially if many Bitcoin users do not want to own a currency that is associated with criminality (Grinberg, 2011).

iii) Illegal activity: Illegal transactions were one of the first economic activities where Bitcoin gained use as an alternative currency due to its relative anonymity, efficiencies and other conveniences (Hileman, 2015). According to Harrel *et al* (2017), the evolution of virtual currencies has suffered from a highly visible connection to criminal activities including: attacks on businesses and corporate extortion, child and sexual exploitation, pornography, corporate espionage, illicit drug distribution, commerce in fake identifications and passports, investment fraud, stolen credit cards, terrorism and trafficking in weapons. The U.S. Secret Service believes the reasons of digital currencies preference by criminals are: anonymity for both users and transactions, ability to quickly and confidently move illicit proceeds from one country to another, widespread adoption in the criminal underground and trustworthiness. Actually, on January 16, 2014, the U.S. Attorney for the Southern District of New York announced the forfeiture of 29,655 Bitcoins (worth approximately $28 million) and the forfeiture of the Silk Road hidden website, which was just one of several anonymous networks that

[5] This is, a group that releases a compatible version of Bitcoin with different inflation settings and convinces a majority of users to switch (Grinberg, 2011).

became possible with the advent of relatively easy-to-use browser interfaces (Harrel *et al*, 2017). This bad reputation has a negative and direct impact on the Bitcoin users' confidence.

One of the most recent and widely publicized criminal actions involving Bitcoin was the HBO files theft, including what appear to be scripts from five “Game of Thrones” episodes, by hackers who demanded millions in Bitcoins [57].

iv) Instability: Bitcoin has been tremendously unstable throughout its trading history. Indeed, the currency has crashed several times and the price continues to swing up and down repeatedly. Such instability is one of the reasons why it is very unlikely to be a viable currency. With wild variations in price, it is possible to lose money even before some transaction has been completed. This makes it too unstable and seems to be keeping away investors, making it an unreliable means of payment (Guadamuz *et al*, 2015).

v) Deflationary spiral: Also related with the instability, Bitcoin might undergo a deflationary spiral that causes certain individuals or industries to abandon Bitcoin, possibly causing a panic or just a permanent depression in Bitcoin’s value. Since the upper limit of Bitcoins is fixed at 21 million, Bitcoins will become more valuable over time as the supply of government-backed fiat currencies continue to increase. As prices denominated in Bitcoins fall, producers may respond by lowering production, leading to lower wages, lower demand, and further decreases in prices. The end result of such a spiral is underemployed human capital and other means of production and destruction of wealth. Thus, industries using Bitcoin that fall into such a spiral may decide to abandon Bitcoin. Even the possibility of such a spiral may limit Bitcoin’s reach (Grinberg, 2011).

vi) Anonymity failure: All Bitcoin transactions are public, but are considered anonymous because nothing ties individuals or organizations to the accounts that are identified in the transactions (Grinberg, 2011). Since the currency is encrypted, there is theoretically no method to trace any given transaction to individual users (Guadamuz *et al*, 2015).

However, Guadamuz *et al* (2015) stated that many papers express serious doubts on the much-heralded anonymity present in Bitcoin. If any of this information was publicly available, or accessible by, say, law enforcement agencies, then the identities of users involved in related transactions may also be at risk. The same authors mentioned a case study, where it was considered a highly-publicised theft of 25.000 Bitcoins, with a value at the time of theft of approximately US$ 500.000. On this case, it was possible to follow the involved transactions using network tools and charted these with high level of accuracy. Therefore, it was concluded that using network analysis and network representation it is possible to map many users to their public keys. Grinberg (2011) also underlined that such unexpected and sudden exposure would obviously be deleterious to Bitcoin's value.

vii) Lack of security: As referred by Grinberg (2011), keeping Bitcoins on one's computer can be as dangerous as keeping large sums of cash in one's physical wallet, and each user should take care to backup and secure his Bitcoin wallet. A large-scale theft of Bitcoins from many users could create a confidence crisis, similar to what happened with Mt. Gox in 2014 [41].

viii) Denial of service: Although Bitcoin is decentralized and generally has no single point of failure, it is nevertheless susceptible to a form of denial of service attack. Individuals with a majority of the computational power in the Bitcoin mining network can effectively preclude any transaction from being processed. Such a sustained attack might significantly depress the exchange rate and lead to a collapse of confidence. Actually, several parties might have sufficient interest to do it: governments who want to shut Bitcoin down, individuals with future liabilities in Bitcoins, or hackers who want to blackmail a business that relies on Bitcoins (Grinberg, 2011).

ix) Lack of transparency: A main selling points of Bitcoin is transparency. The addresses do not identify the person, only the possessor of the key that unlocks the address, what makes it both anonymous and transparent at the same time. However, this transparency is in practice limited when one considers the currency's origins. Satoshi Nakamoto, the fabled originator of the scheme, remains anonymous to this day. The fact that some investors have amassed large Bitcoin fortunes is an indication that this could be used to leverage the market. There have been several examples of possible market manipulation, with sudden large volumes in trade used to shift the price up or down. For such a transparent currency from a technical standpoint, this remains a rather difficult area for outsiders (Guadamuz *et al*, 2015).

x) Lack of replicability: Most Bitcoins exist only as files in a computer or mobile device. This creates one of the biggest issues with Bitcoin to date: the ease of losing one. If the wallet file is lost, then the Bitcoins it contains are lost forever. It must be said that missing and lost coins has not been seen as a problem for enthusiasts, as they point out that each Bitcoin is divisible up to eight decimal points. However, this difficulty will only go up, so an individual cannot hope to have the processing power to develop new coins, since this can only be done currently through pool mining CPU resources. While this model is trying to replicate scarcity in the market, it acts as a punishing disadvantage for late adopters, and means that early adopters have market power if they hoarded coins (Guadamuz *et al*, 2015).

xi) Growing centrality: One of the foundational principles of Bitcoin is its decentralized nature. Assuming that thousands of people are mining separately, the system remains decentralized and the prospect of a single entity gaining control of the network was seen as very remote. However, in June 2014 two computer scientists from Cornell University stated that a large mining conglomerate was becoming too powerful, and had actually reached 51 percent of all mining capacity for Bitcoin during a few hours. Essentially the system was no longer decentralized. More pragmatic developers have proposed technical solutions. However, the truth is that until a long-term technical solution is reached, Bitcoin's decentralized nature relies entirely on the good will of miners. If Bitcoin in its present shape reached an important share of the financial market, it would be possible for an entity with substantial computing power to take over the entire system. The prospect of a government or corporation taking over Bitcoin would be a real threat (Guadamuz *et al*, 2015).

xii) Computational inefficiency: A less-explored area of concern with Bitcoin is that, at least as currently implemented, it might be energy inefficient. Bitcoin generates value by requiring those who participate in the network to dedicate computing power to verify transactions. This presents two problems for the scalability of the network, namely the computational power required to mine Bitcoins and the size of the blockchain itself. Indeed, the computational power dedicated to mining has continued to increase over time and there are some authors believing that the cost of Bitcoin mining on commodity hardware now exceeds the value of the rewards (Guadamuz *et al*, 2015).

xiii) Superior competing currency: A superior competing currency could lead to a crisis of confidence causing either a collapse of Bitcoin's value or merely a permanent reduction of Bitcoin's value. As stated by Grinberg (2011), Bitcoin has at least two classes of competitor products, which are products that facilitate internet-based commerce and gold-backed currencies. The first one can be divided into three sub-types: traditional e-commerce, micropayments and the virtual world and game-related commerce. In practice, the same author referred that Bitcoin is unlikely to make significant headway in the traditional ecommerce market because consumers generally do not care about the kind of anonymity that Bitcoin provides, prefer to compare prices of most goods and services in a currency they are familiar with and want fraud protection, which Bitcoin currently lacks.

However, Bitcoin may be specially competitive in the micropayment and virtual world markets, where consumers care less about pricing in a familiar currency. Bitcoin is likely to be attractive to those who like gold-backed currencies because its value depends on the availability of a limited resource rather than discretionary actions by central bankers.

In the article of Harrel *et al* (2017), it was also mentioned that as of July 15, 2016, *Coinmarketcap.com* listed 656 different cybercurrencies, having a total market capitalization of approximately $13.011 billion, where Bitcoin was in the 1st place with $10.501 billion.

Additionally, Guadamuz et al (2015) stated that Amazon has announced that it will be launching its own virtual currency for their Kindle app store, Amazon Coins. These authors also identified some of the most popular implementations, with some improvements relative to Bitcoin, standing out the following ones:

• IxCoin: It is the first Bitcoin clone. It was released in 2011 and it can be mined at the same time as Bitcoin. It also has a limit of 21 million coins, but much shorter mining period (all coins should have been mined in 2015).

• Namecoin: It is one of the most innovative altcoins. It uses Bitcoin to create a decentralized domain name system outside of the existing international system operated by ICANN. The service allows the registration of domain names that cannot be shut down or taken over by law enforcement.

• Litecoin: This is one of the more popular Bitcoin alternatives, it was created specifically to fix perceived shortcomings in Bitcoin, and it boasts faster transaction verification times and improved storage efficiency.

• Bitcoin XT: This is a very recent and controversial fork to the original Bitcoin source code that adds two main changes, the block size is increased and it removes the need to download the entire blockchain.

2.6. Physical versus Digital Currencies

According to Allen *et al* (2016), it is clear that beyond the physical storage of precious metals and other financial assets, a bank is a centralized ledger of transactions, whether of capital or payments, which records balances between many different parties. A bank, in the modern sense, is an internalized market: it is an organization that functions as a platform to match those with excess supply of capital (savers) with those with excess demand for capital (borrowers). In sum, banks exist as third party intermediating organizations, where the presence of opportunism in many transactions makes hierarchies and relational contracting more transaction cost efficient mechanisms of governance.

On the other hand, the same authors also referred that a blockchain is a public decentralized ledger platform and, as a specific technology for digital currencies, it is a technical solution to the double-spending problem. Blockchains are best understood as a new institutional technology that makes possible new types of contracts and organizations. In this sense, blockchains look to have changed the comparative governance efficiencies by eliminating opportunism. Therefore blockchains, as institutional technologies, undermine the strong case for the economic efficiency of hierarchies and relational contracting over markets. If blockchains can eliminate opportunism they will, at least theoretically, outcompete traditional organizational hierarchies and relational contracts.

Furthermore, Bitcoin transactions are irreversible in the same way cash transactions are irreversible (Grinberg, 2011).

In the article of Guadamuz *et al* (2015), it is mentioned that modern fiat currencies have value based on the economic strength of the issuer. In some libertarian and anarchist circles, it is said that fiat money does not have any inherent value, but this fails to recognize that neither does the gold standard. Gold does not have intrinsic value, under the right circumstances gold could be valueless except as an industrial input. In fact, there is no such thing as inherent value, all value is dependent on circumstances. The value in fiat money arises from the law, the currency has the support of the government as sovereign and therefore it is supported by the economy of the territory where it is accepted.

On the contrary, Bitcoin was devised as a non-fiat currency. In other words, its proponents claim that it has 'real' value. The value arises from computing power, that is, the only way to create new coins is by allocating distributed CPU power through computer programs named 'miners'. Another way of looking at the currency is that Bitcoin is simply allocating value arbitrarily to a program that performs the mathematical equations necessary to support the creation of a Bitcoin. It is a self-referential and circular currency, and its only value is that which people give it, just like fiat money, but with faith placed in computer programming, not sovereign states.

Indeed, the vast majority of currencies are backed by governments (or other legal entities), commodities, or both. Unlike the U.S. Dollar, Bitcoin is not backed by the U.S.

Government or any other legal institution. It is a digital rather than paper currency, storable on electronic media and transferable over the internet (Grinberg, 2011).

Even so, a growing ecosystem surrounds Bitcoin, including exchanges, transaction services providers, market information and chart providers, escrow providers, joint mining operations and so on. Additionally, individuals can send Bitcoins for free, but may add optional transaction fees to ensure their transactions are quickly processed. By contrast, credit card charges can be charged back to merchants.

However, absent from this ecosystem at present are futures markets and entities offering legitimate investment returns, such as fractional reserve banks, although some individuals have announced plans to build these (Grinberg, 2011). Harrel *et al* (2017) also identified other Bitcoin issues such as the as the particularly difficult transactional, regulatory and law enforcement challenges caused by their anonymity due to encryption, their ability to transcend national borders in the fraction of a second and their unique jurisdictional issues. Moreover, in contrast to negotiable instruments, a virtual or cybercurrency is intangible and potentially ephemeral.

Furthermore, at present, goods and services priced in Bitcoin units tend to see the number of Bitcoin fluctuate in lock-step with changes in Bitcoin's exchange rate against a national currency, like the U.S. dollar. If Bitcoin was serving as a true, widely-used unit of account we would not expect to see such constant fluctuations in the number of Bitcoin required to complete a purchase. Further, Bitcoin is unlikely to become a widely used unit of account until either its relative volatility decreases and or it becomes more widely used as a medium of exchange (Hileman, 2015).

In these regards, Athey *et al* (2016) added that Bitcoin also shares some features with risky assets where beliefs about the future underlying value of the asset evolve over time as information is revealed.

In this sense, it is important to understand, based on the Bitcoin's characteristics, what "security" does it match (if applicable).

In fact, Grinberg (2011) developed this topic, comparing Bitcoin with Notes, Stocks, Investment Contracts, Commodities and Currencies. This author concluded that Bitcoin is not a "note" because it lacks the promise by the maker to pay a sum of money to another party. Similarly, it is not "stock" since it does not confer the right to receive dividends contingent upon an apportionment of profits neither vote rights.

On the other hand, an investment contract has a broader definition: it is a contract, transaction or scheme whereby a person invests his money in a common enterprise and is led to expect profits solely from the efforts of the promoter or a third party. Given this, the author concluded that, because there is likely no common enterprise, Bitcoin is unlikely to be an investment contract. Indeed, the individuals who choose to promote Bitcoin are independent of one another, and there is no one money-making business that seeks to raise money through investments.

Next, “commodities” enter into the discussion. Grinberg (2011) put the hypothesis that Bitcoins are commodities, which are generally held not to be securities. Indeed, owning a Bitcoin gives one only rights to use the Bitcoin in any way one sees fit and to sell or make contracts involving that Bitcoin. However, decisions explaining why commodities are not securities have also noted that commodities are “tangible” and have “inherent value,” unlike securities. Bitcoins are not “tangible,” and one may argue that by design they have no inherent value because there is no government or commodity backing them. Thus, although Bitcoins share many features with commodities, they also share features with securities and are unlikely to evade categorization as an “investment contract” on this ground. As well, Guadamuz *et al* (2015) also presented this discussion. In fact, these authors mentioned that Bitcoin fulfils all of three security requirements, and therefore can easily be classified as such, at least until the law changes to classify it more adequately. Nevertheless, it would also be easy for Bitcoin to be treated as a commodity under the broad definition present in the Commodity Exchange Act 1936[6].

Finally, only remains the “currency”. According to Harrel *et al* (2017), a functional approach to the definition of money is based on the observation of the three primary functions: (1) a means of exchange in terms of (2) a defined unit of account that is used as (3) a measure and store of value.

The first requirement of a currency is that it can be used for transactions. At this stage, Carrick (2016) mentioned that there are thousands of websites that accept Bitcoin and in December of 2015, there were approximately 200.000 daily Bitcoin transactions per day, but this volume is tiny compared to other currencies. However, there are still many smaller recognized currencies that have far less daily volume. Overall, it is unclear whether Bitcoin meets the transactional requirement of a currency – this depends on the interpretation of this requirement.

The second requirement of a currency is that is can be used as a unit of account. This is also debatable for Bitcoin. It clearly has unit of account characteristics. First, a

[6] An act passed in 1936 by the U.S. Government that provides federal regulation of all futures trading activities. This act replaced the Grain Futures Act of 1922 [35].

Bitcoin can be divided into an infinite number of pieces, and these can be put back together to form a full Bitcoin. Second, Bitcoin is fungible since all Bitcoins are created equally and they can all be interchanged. Third, it is countable and subject to mathematical operations. Although Bitcoin seems to clearly meet the unit of account requirements, there is still debate on this. The debate primarily revolves around Bitcoin's ability to value goods and services, given its volatility. However, many currencies incur extreme volatility and are still considered currencies (Carrick, 2016).

The third requirement of a currency is that it be able to be used as a store value of account. Some authors have argued that Bitcoin's volatility marginalizes its store value. To that point, many investors gauge the credibility of a currency by its stability and ability to be a safe haven when other financial assets are experiencing volatility (Carrick, 2016).

At this stage, Grinberg (2011) referred that the narrow definition would likely exclude Bitcoins until Bitcoins become generally accepted in any geographical or political area. This leads to the need for Bitcoin regulation.

2.7. Bitcoin Regulation

Although Bitcoin may be more resistant to government attack because of its decentralized nature, many Bitcoin users, including both consumers and businesses, are anxious about its legal status. As mentioned before, actually Bitcoin operates in a legal grey area and one of its problems is the reluctance of regulatory authorities in some countries to approve it as a currency (Grinberg, 2011).

A real case descripted in the article of Grinberg (2011) goes back to 1988, when Bernard von NotHaus started printing and distributing metallic and paper currency called Liberty Dollars. The currency was backed by gold, silver, or other precious metals, and it was intended to be inflation-proof, unlike the U.S. Dollar. The U.S. Mint warned consumers about the Liberty Dollar in 2006, NotHaus's offices were raided by the FBI and Secret Service in 2007 and NotHaus was indicted in 2009 and convicted in March 2011. In press releases related to the indictment and conviction, the Department of Justice made several statements that seemed extremely hostile to private currencies. Nevertheless, the statutes under which NotHaus was convicted, 18 U.S. Code §§ 485 and 486 [48], are inapplicable to Bitcoin because they only deal with metal coins or coins or bars that resemble official U.S. or foreign currency. Nevertheless, some have mused that the attack on Liberty Dollar indicate that Bitcoin will be next.

Following this issue, there are some points generating the need for Bitcoin regulation, namely to discourage of anti-money laundering, applying know-your-customer controls, and to minimize misinformation.

Money laundering is the process by which dirty money, proceeds of illegal activities, is rendered clean, allowing the money to be used for legal activities. Terrorist financing is similar, except that it allows clean money to be used for illegal activities, and is often considered under the same umbrella as money laundering (Grinberg, 2011). The Financial Action Task Force (FATF) is an intergovernmental organization that designs and promotes policies and standards to combat money laundering, creating recommendations which target is money laundering, terrorist financing and other threats to the global financial system. As of 2014 there are thirty-six members of the Financial Action Task Force. Most members are countries, though regional organizations, such as the European Commission, are also included. A large number of international organizations participate in the FATF as observers, each of which has some involvement in anti-money laundering activities, namely Interpol, the International Monetary Fund (IMF), Organization for Economic Cooperation and Development (OECD) and World Bank are observers [37].

Digital currencies are attractive vehicles for money laundering because they allow fast, anonymous, through-the-Internet transfers. Thus, there is a serious question of whether the regulations and regimes in force impose legal risk for the Bitcoin developers, exchanges, ewallet providers, individual miners, operators of mining pools, mere Bitcoin users and businesses that accept Bitcoins (Grinberg, 2011).

Additionally, like other commonly traded financial assets, information plays a major role in determining the price of Bitcoin, but unlike most other financial assets, the government cannot minimize the dissemination of misinformation. This has already hurt Bitcoin in the Mt. Gox incident where many false reports of the magnitude and cause of the failure were reported (Grinberg, 2011).

Despite these forces, regulators and law enforcement officials face difficult technical challenges in obtaining evidence for law enforcement purposes, e.g., relating to potential links between crime, sophisticated encryption and virtual currency (Harrel *et al*, 2017).

The flip side to government oversight is that governments could make Bitcoin inefficient, and even worse in the eyes of Bitcoin's creators, governments could take it over and essentially make it a fiat currency. Some legal scholars suggest that there is middle ground, suggesting that governments could take an active role in regulation without taking it over, essentially by taking a role in monitoring Bitcoin markets the way they do with stock exchanges (Carrick, 2016).

In a different note, Guadamuz *et al* (2015) constructed the following scenarios for virtual currencies:

i) <u>“Virtual sovereigns”</u>: virtual currency providers will serve as regulators by enforcing the terms of their contracts with users to prevent cyber-fraud and ensure proper behaviour.

ii) <u>Prohibition</u>: governments could try to block their citizens from using virtual currencies that do not abide by government restrictions and regulations (governments have not been able to completely block access to websites nor will total prohibition on virtual currencies succeed).

iii) <u>Selective prohibition</u>: government minimize the real-world impact of virtual currencies by, for instance, banning the sale of real-world goods for virtual currency. This section would also cover the banning and/or criminalization of the use of the currency to pay for illegal activities or for money laundering.

iv) <u>Selective regulation</u>: regulators impose some restrictions to specific aspects of virtual currencies, such as taxation and the regulation of intermediaries.

v) <u>“Real-world assisted virtual currency self-governance”</u>: governments provide support for mechanisms whereby users of virtual currencies can agree upon and enforce their own ‘community standards’ and rules of conduct.

So far, several authors have mentioned the position of the American regulatory institutions. Grinberg (2011) mentioned the statement of the Department of Justice, in a press release, that the creation of private coin or currency systems to compete with the official coinage and currency of the United States is a violation of federal law. However, organizations have been issuing a certain type of private currency in the U.S. for decades. Government officials have known about these currencies and have commented that they seem to pose no threat.

Harrel *et al* (2017) also referred that, while the U.S. Government Accountability Office (GAO) has observed that there are no legal definitions for a virtual economy or currency, the GAO also has stated that a virtual currency is generally a digital unit of exchange that is not backed by a government-issued legal tender. On the other hand, the U.S. Financial Crimes Enforcement Network (FinCEN) defines virtual currency as a medium of exchange that operates like a currency in some environments, but does not have legal tender status in any jurisdiction. So far, in the United States, the FinCEN only issued guidelines specified that decentralized currencies should comply with money laundering regulations.

Indeed, in the United States, only the U.S. Dollar is legal tender. Similarly, only the Mint and the Federal Reserve can produce coins and currency, which are the only means of legal tender. According to the Federal Bureau of Investigation (FBI), it is a violation of federal law for individuals or organizations to create private coin or currency systems to compete with the official coinage and currency of the United States. It would seem clear that local currencies that may compete with the dollar are not allowed, but the question of whether Bitcoin can be considered a currency for these purposes is not clear. On the contrary, there have been electronic payment systems in existence for over a decade and there have not been attempts to curb them by using counterfeiting legislation (Guadamuz *et al*, 2015).

According to Harrel *et al* (2017), the Bitcoin Foundation, founded by seven of the community's most instrumental individuals, such as Gavin Andresen - a core Bitcoin developer, has been registered under the U.S. Internal Revenue Code in Washington, D.C.. Its bylaws were effective as of July 23, 2012. The Foundation is governed by a board with five seats split by membership class. Two seats elected by the Individual member class, two seats by the Corporate member class and one seat by the Founding member class.

Moreover, the same authors referred that in January 2014, the Uniform Law Commission (ULC) created a Study Committee on Alternative and Mobile Payments (the Study Committee). The focus of the Study Committee is to devise an optimal licensing system for intermediaries that perform financial services for third parties relating to digital or virtual currencies. The Study Committee received extensive input from a variety of sources, including: the American Bankers Association; The Clearing House; the European Central Bank, the Senate of Canada, Standing Committee on Banking, Trade and Commerce; and the Consumer Financial Protection Bureau.

Additionally, one of the major advances in the Bitcoin regulation in the U.S.A. was also described by these authors and it had the first step in August 2013, when the New York State Department of Financial Services (DFS) announced its inquiry into the appropriate regulatory guidelines for virtual currencies. The proposal, first published in the July 23, 2014 edition of the New York State Register, triggered a series of comment periods. The final DFS rule was published in the New York State Register's June 24, 2015 edition. It may be summarized as including requirements that relate to: anti-money laundering issues, consumer protection concerns and cyber security rules. Additionally it includes requirements and provisions for Safeguarding Consumer Assets, Virtual Currency Receipts, Consumer Complaint Policies, Consumer Disclosures, Anti-money Laundering Compliance (Verification of Account holders and the Reporting of Suspected Fraud and Illicit Activity), a Cyber Security Program, a Chief Information Security Officer, Independent DFS Examinations, Books and Records, Reports and financial Disclosures, Audit Requirements, Capital Requirements, a Compliance Officer, Business Continuity and Disaster Recovery, Notification of Emergencies or Disruptions and provisions for a Transitional Period.

Following release of the rule, outlining the final DFS BitLicense requirements, the DFS announced approval of the first BitLicense application on September 22, 2015.

In contrast, the situation in Europe and the U.K. is less ambiguous than in the U.S. There is considerably more regulatory acceptance for alternative currencies to those issued by central banks authorities. While Bitcoin is larger by many degrees of magnitude, there does not seem to be any indication from regulators and central banking authorities in Europe that there will be a crackdown on Bitcoin over its legal status (Guadamuz *et al*, 2015).

On the other hand, according to Guadamuz *et al* (2015), there is a high threshold for an electronic money institution, as the electronic money institutions (EMI) would have to fulfil quite a number of requirements. The idea behind this stringent regulation is evident, as what is taking place is the issuing of value into the economy. If Bitcoins are not an EMI in Europe, then their status as currency is in doubt. The European Banking Authority (EBA) has opined that virtual currencies do not fulfil many of the requirements of a currency, and therefore should not be considered legal tender. While it does not state directly, the EBA opinion infers Bitcoin being a commodity that can be exchanged for fiat money. Despite this, the European Banking Authority issued a report on virtual currencies, as well as a detailed number of possible regulatory responses to the challenges posed by virtual currencies. However, they are only proposals.

Indeed, Europe has already in place a legal framework for the regulation of electronic money, which could be used to cover virtual currencies such as Bitcoin. The Directive 2009/110/EC, of the European Parliament and of the Council of 16 September

2009, contains rules for all sorts of electronic purses that can be used to store value in an electronic format, be it via a computer, a mobile device or online. The Directive defines electronic money thus:

i) electronically, including magnetically, stored monetary value;

ii) as represented by a claim on the issuer which is issued on receipt of funds for the purpose of making payment transactions;

iii) the transaction is an act, initiated by the payer or by the payee, of placing, transferring or withdrawing funds, irrespective of any underlying obligations between the payer and the payee;

iv) which is accepted by a natural or legal person other than the electronic money issuer.

Also in the U.K., Her Majesty's Revenue and Customs (HMRC) issued a briefing paper detailing its position on the tax treatment of income received from, and charges made in connection with, activities involving Bitcoin and other similar cryptocurrencies. The HMRC recognizes that this is an evolving regulatory area and is expecting that at some point there will be some sort of EU-wide effort to define and clarify cryptocurrencies in general. HMRC has decided to treat income from sales of goods and services through Bitcoin in the same manner as it does any other sales (Guadamuz *et al*, 2015).

For the rest of the world, Guadamuz *et al* (2015) referred that China has been the only jurisdiction to successfully attempt a major crackdown of Bitcoin. However, it must be said that while the Chinese crackdown had some adverse effects on the use of Bitcoin as a currency, it is still being traded in China and the most active exchange is Chinese.

On the other hand, Pieters *et al* (2016), mentioned that in July 2014 Ecuador banned Bitcoin, while the Isle of Mann merely clarified the application of existing tax rules.

Lastly, Harrel *et al* (2017) also stated that during recent months, blockchain technology has continued to gain validation by an announcement of a partnership including nine of the world's largest banks, proof of a concept experiment by Bank of Canada and an announcement that a Chinese digital currency will be issued as soon as possible.

2.8. Theories, Studies and Conclusions

The article of Cheung *et al* (2015) was based on the development of Phillips, Shi & Yu (2013) methodology, a procedure designed to detect stochastic of a given time series because such explosive behaviour is usually deemed as a key feature of a bubble. The selected data was daily Bitcoin prices over the period 17th July 2010 to 18th February 2014, collected from the *www.bitcoincharts.com* website, for the Mt. Gox Exchange. Their results showed a number of short-lived bubbles but most importantly, they found three huge bubbles in the latter part of the period (2011-2013) lasting from 66 to 106 days the last of which led to the demise of the Mt. Gox exchange. The bursting of these bubbles also seems to coincide with certain major events that occurred in the Bitcoin market. Therefore, this supports the theory that Bitcoin has been in a bubble over its relatively short existence.

In a different approach, Chan *et al* (2015) published another study about Bitcoin. Their work was based on the statistical analysis of the exchange rate of Bitcoin. Their main objective was to provide a formal statistical analysis of the exchange rate of Bitcoin versus the USD using a wide range of known parametric distributions in finance. The data used was daily Bitcoin Exhange Rate on *Bitstamp* (Bitcoin versus USD) from the 13th of September 2011 to the 8th of May 2014. With this information, it was possible to plot the log-returns of the exchange rate of Bitcoin and to estimate its range, mean, skewness, kurtosis, standard deviation, variance, coefficient of variance and other statistics. Through Autocorrelation and Partial Autocorrelation functions, the authors analysed what distribution is better to represent the behaviour of the Bitcoin's exchange rate to the USD. There were considered fifteen of the most popular parametric distributions in finance. The distributions were fitted to the selected data and they were compared by their log-likelihoods and five criteria – the Akaike Information, the Bayesian Information, the consistent Akaike Information, the corrected Akaike Information and the Hannan-Quinn criterion.

Overall, the result was that the generalized hyperbolic distribution gives the best fit, in opposite to the normal distribution which gives the worst fit. Through the distribution that better describes the exchange rate behaviour, the authors predicted the log-returns of the exchange-rate based on the Value at Risk (VaR) and the Expected Shortfall (ES). Their conclusions were that the log-returns will be greater than $2{,}282\times10^{-1}$ with 1 percent chance and will be less than $-2{,}043\times10^{-1}$ with 1 percent chance. For 0,1 percent chance, values will be greater and less than $4{,}539\times10^{-1}$ and $-4{,}108\times10^{-1}$, respectively.

The major lack of this analysis was to not consider the impact of volatility, this is, how the past volatility of returns impacts on the current volatility. Actually, one of conclusions from the study developed by Baek *et al* (2015) was that Bitcoins are 26 times more volatile than the S&P 500 Index. These authors based their study on Bitcoin daily prices ($US) from July 2010 to February 2014, downloaded from *www.bitcoinch-arts.com*.

The article written by Gouriéroux *et al* (2015) takes this in consideration. The authors, similarly to Cheung *et al* (2015), recognize the presence of local trends and short-lived episodes of soaring XBT/USD rates, followed by sudden almost vertical declines. In this context, the objective of their study was to examine the dynamics of the XBT/USD exchange rate and to predict its future evolution. Due to the presence of local explosive trends, depicted as bubbles, the XBT/USD exchange rate cannot be modelled by any traditional ARIMA or ARCH models (Gouriéroux *et al*, 2015).

Then, it was used the mixed causal-noncausal autoregressive process with Cauchy errors. They selected 150 observations on the daily closing values of the XBT/USD exchange rate over the period 20th February 2013 and 20th July 2013, since that includes a bubble, which bursted on April 10, 2013. The series of Bitcoin/USD exchange rates has been used as a playground for analysing the relevance of the causal-noncausal modelling to capture bubble phenomena, since it was typically an example of highly speculative emerging market. Indeed, when they applied the methodology, speculative bubbles appeared in that period.

In conclusion, Gouriéroux *et al* (2015) mentioned that, given that recently several exchange platforms have closed, temporarily or definitely, there is clearly a need of supervision to better protect the investors against theft of their Bitcoins, but also against the speculative behaviour of large Bitcoin holders. This supervision will likely make disappear the previously observed speculative bubbles and perhaps the market for this electronic currency itself.

Nonetheless, if Bitcoin usage grows, then it is expected Bitcoin volatility to drop and attract market and economic influence representing a more balanced internally and externally driven investments vehicle (Baek *et al*, 2015).

On this subject, Urquhart (2016) identified some arguments published, namely by Cheah *et al* (2015) arguing that if Bitcoin were a true unit, account or a form of store of value, it would not display such volatility expressed by bubbles and crashes. Dwyer (2014) found that the average monthly volatility of Bitcoin is higher than that for gold or a set of foreign currencies, and the lowest monthly volatilities for Bitcoin are less than the highest monthly volatility for gold and currencies. Dyhrberg (2016) showed that Bitcoin has similar hedging capabilities as gold and the dollar, and as such can be employed for risk management. Still, Cheah *et al* (2015) developed an econophyscis model to reveal that Bitcoin and Ripple (another cryptocurrency) are characterized by negative bubbles.

On the other hand, Urquhart (2016) also stated that the efficient market hypothesis (EMH) is one the key cornerstones of finance. A market is efficient if prices fully reflect all available information. Three forms of efficiency can be distinguished with the most commonly examined form the weak form, where a market is said to be weak form efficient if investors cannot use past information to predict future returns.

Therefore, the author developed a study to test the efficiency of Bitcoin. The study was based on data collected from *www.bitcoinaverage.com*, which is the first aggregated Bitcoin price index that aggregates rates from all available Bitcoin exchanges around the world and provides a volume weighted average Bitcoin price. The data consisted of daily closing prices for Bitcoin in USD from 1st August 2010 to 31st July 2016. Several tests were carried out emphasizing: (i) it was examined the autocorrelation of returns, which are assessed via the Ljung-Box test; (ii) the runs test (Wald & Wolowitz, 1940) and the Bartels test were employed to determine whether returns are independent; (iii) test if prices are predictable, employing the variance ratio test (Lo & MacKinlay, 1988); and (iv) the BDS test was employed to test the serial dependence in prices returns.

Summing up, the full sample was split into two subsamples and the results show that Bitcoin is an inefficient market over full sample period but appears to becoming less inefficient in the second subsample period. The analysis shows that the Bitcoin market is not weakly efficient over the full sample period. However, the author shows that Bitcoin may becoming more efficient with some of the tests for market efficiency suggesting that Bitcoin returns are random in the second subsample. Since it is a relatively new investment asset and still in its infancy, it is similar to an emerging market and therefore the inefficiency finding is not surprising. Consistent with this argument is that Bitcoin will become more efficient over time as more investors analyse and trade Bitcoin.

Carrick (2016) also explored the Bitcoin volatility. The author considered the period from 1st January 2011 to 31st December 2015. Through descriptive statistics and the correlation matrix, based on the Pearson correlation coefficient, of the major currencies and Bitcoin, Carrick performed the comparisons between: (i) Bitcoin relative value and volatility to the major currencies of the world; (ii) Bitcoin relative value and volatility to commonly traded emerging market currencies; and (iii) Bitcoin returns and the returns from an emerging market currency basket electronically exchange traded fund (ETF).

The conclusion was that, with the exception of the CNY, all of the emerging currencies are correlated at statistically significant levels. Conversely, it shows that Bitcoin is negatively correlated at statistically significant levels with all of the currencies, except the CNY. This is an interesting finding as currency risk is a major issue with emerging market currencies, but emerging market currencies have become a common way to diversify risk and balance both currency portfolios and general investment portfolios. Thus, because of the negative correlation of Bitcoin and most of the emerging markets currencies, it could fit in well in emerging market currency portfolios to offset risk. Although the analysis performed in the present study high-lighted Bitcoin's volatility, Bitcoin can still be a good means of conducting transactions. This is because Bitcoins can be instantaneously exchanged into other currencies. Thus, the volatility of Bitcoin can almost be eliminated.

One of the most recent studies was published by Balcilar et al (2017) in order to address the research gap on the Bitcoin volume-return paradigm. Therefore, the authors used a nonparametric causality-in-quantiles test, developed by themselves, to examine the predictability of Bitcoin returns and volatility based on trading volume. It was considered the daily data covering the period of 19th December 2011 to 25th April 2016.

The test has three main innovations: (i) the approach is robust to misspecification errors as it detects the underlying dependence structure across the variables under study; (ii) the methodology allows for the detection of not only the causality-in-mean but also for any potential causality in the tails of the joint distribution of the variables; and (iii) the nonparametric causality-in-quantiles approach allows to examine causality-in-variance and, thus, study higher-order dependency. Such an investigation is important because during some periods, causality in the conditional-mean may not exist, while, at the same time, higher-order interdependencies may turn out to be significant.

In this study, the authors used two variables, namely, the Bitcoin index and the trading volume, as measures of the level of trading activity.

Thereby, the authors' main results are summarized as follows:

i) The standard linear Granger causality test, which was conducted for comparison purposes, fails to detect any evidence of volume causing returns;

ii) The nonlinearity test indicates that returns and their relationship with volume evolve in a nonlinear manner. Additionally, tests of multiple structural breaks show evidence of regime changes in returns and in the equation relating them to volume. Evidence of nonlinearity and structural breaks suggests that the linear Granger causality is misspecified, thus, leading to unreliable results.

iii) The causality-in-quantiles approach, which emerges as a suitable choice given evidence of non-linearity, structural breaks, and fat tails, reveals that the null that volume does not Granger cause returns is rejected at the conventional levels of significance over the quantile range of 0,25 to 0,75 of the conditional distribution of returns.

However, the authors fail to reject the null that volume does not Granger cause volatility over the entire conditional distribution. The results show that volume can predict returns, but not volatility, with causality for returns non-existent in bearish (lower quantiles) and bullish (upper quantiles) phases.

To conclude, Balcilar *et al* (2017) stated that when the market is performing around the normal (median) mode, volume can indeed predict returns, by providing investors in the Bitcoin market with valuable predictive information. However, when the market is behaving well or poorly, all that matters for predicting future returns is past values and so information about volume is irrelevant.

3. Data

As it was mentioned before, one of the main goals of this dissertation is to understand how the Bitcoin's prices are related in the long term with financial and economic data and also the physical currencies main drivers of Bitcoin's prices (XBT), relating them with financial and economic data known to have some relationship with physical currencies.

Since the U.S. Dollar is commonly known as the most traded currency in the world, the study support base will be the exchange rate XBT/USD [40]. Its daily quotations are available in the Bloomberg platform since 1st January 2013 [62], based on the BGNL pricing source. Due to this, this will be the first observation date for all the collected data.

In order to analyse if the Bitcoin quotations have a long term relationship with financial and economic data, in this study it will be considered the following variables: the price per barrel of West Texas Intermediate (WTI) crude oil; the gold price; the 6-month and 10-year U.S. Treasury Yields and the S&P 500 Index. The reasons for including these variables in this study are explained below.

In terms of physical currencies, there are several studies analysing the relations between exchange rates, commodities, interest rates and stock prices.

In terms of commodities, Ameur *et al* (2016) concluded that there is a negative relationship between the U.S. Dollar/Euro returns and oil returns, which means that a U.S. Dollar appreciation tend to result in a drop in oil prices. The authors resorted to the price per barrel of West Texas Intermediate (WTI) crude oil, whereby this variable will be also considered in this study.

On the other hand, Dyhrberg (2016) performed a GARCH volatility analysis between Bitcoin, gold and the Dollar, showing that Bitcoin has many behaviour similarities to both gold and the Dollar. So, the gold price will be also considered in this dissertation.

Another variable whose relation with exchange rates has been studied by several authors is the yield curve, namely, government bond yields. Balčiūnas *et al* (2015) developed a research to explain how 2-year and 10-year U.S. and German government bond yields can determine the EUR/USD exchange rate in the short run. After estimating the linear regression, it was shown that the model can determine 5 per cent of the daily EUR/USD fluctuations. It affects the exchange rate as it is stated in the uncovered interest rate parity model – when the yield increases, the USD tend to decline against the Euro and vice versa. Another finding is that an increase in the German 10-year government bond yield tend to increase the price of the euro and the increase in the U.S. 10-year debt yield leads to an appreciation of the USD. In this sense, it will be collected the 6-month and 10-year U.S. Treasury Yields, in order to include a short-term and a long-term interest rate.

Regarding to the relationship between exchange rates and stock prices, Wong (2017) developed a study examining the relationship between real exchange rate returns and real stock price returns in Malaysia, Philippines, Singapore, Korea, Japan, United Kingdom and Germany. The constant conditional correlation or dynamic conditional correlation - multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model showed that real exchange rate return and real stock price return are found to be negative and the estimated coefficients are statistically significant for Malaysia, Singapore, Korea and the U.K. whereas to be insignificant relationship for the Philippines, Japan and Germany.

Based on these two studies, it will be included the daily quotations of the S&P 500 Index.

Resuming, this study will consider the exchange rate XBT/USD and five other variables: the price per barrel of West Texas Intermediate (WTI) crude oil (CL1:COM); the gold price (GC1:COM); the 6-month U.S. Treasury Yield (USGG6M); 10-year U.S. Treasury Yield (USGG10YR) and the S&P 500 Index (SPX:IND). All the prices are expressed in U.S. Dollar and the yields in percentages. All data were collected for the period between 1st January 2013 and 28th August 2017 and, therefore, the number of observations for each time series is 1.701. All the time series observations are graphically represented in the appendixes A to F.

4. Methodology under cointegration

In order to understand if the Bitcoin's prices are related in the long term with the selected variables, it will be performed a cointegration test. Engle & Granger (1987) stated that it is frequently of interest to test whether a set of variables are cointegrated, because of the econometric implications such as whether some system is in equilibrium in the long run. Indeed, the term cointegration was defined by these authors as a formulation of the phenomenon that nonstationary processes can have linear combinations that are stationary (Johansen, 2014).

This chapter briefly outlines the econometric specifications and cointegration procedures applied to the data mentioned before, starting by the nonstationarity issue.

4.1. Nonstationarity

According to Tsay (2010), the basis of time series analysis is stationarity. A time series $\{x_t\}$ is said to be strictly stationary if the joint distribution of $(x_{t_1}, \dots, x_{t_n})$ is identical to that of $(x_{t_{1+\tau}}, \dots, x_{t_{n+\tau}})$ for all t and τ, where the parameters which characterize the distribution of the process depend on the lag τ. This means it requires that the joint distribution of $(x_{t_1}, \dots, x_{t_n})$ is invariant under time shift, what is hard to verify because it is defined in terms of the distribution function.

Consequently, the concept of stationarity defined in terms of the moments is commonly preferred. Actually, Tsay (2010) mentioned that the process $\{y_t\}$ is said to be weak stationary if the mean and variance of y_t are constant and the covariance between y_t and y_{t-l} are time-invariant, where l is an arbitrary integer. The weak stationarity is also known as second-order, wide-sense or covariance stationary. The same author also explained that the weak stationarity implies that the time plot of the data would show the T values fluctuating with constant variation around a fixed level, where T is the observations number.

By consequence of the previous definitions, if y_t is strictly stationary and its first two moments are finite, then y_t is also weakly stationary. This is why Tsay (2010) referred that the second-order stationarity is the most commonly used form of stationarity.

Indeed, Tsay (2010) stated that, in some studies, interest rates, foreign exchange rates or the price series of an asset tend to be nonstationary. For a price series, the nonstationarity, also called unit-root nonstationary time series, is mainly due to the fact that there is no fixed level for the price.

Before enter into the unit root test, it is important to note that we may be in the presence of structural breaks in the time series under analysis in this study. Actually, looking to the Chart 1 in the appendix A, it is possible to observe some changes in the exchange rate XBT/USD behaviour, namely in the end of 2013, where it seems to occur a sharp 'fast' increase in the level of the series.

Perron (2005) developed a study about the interplay between structural change and unit root and how to differentiate between them. The author referred that, for example, allowing for structural breaks in many financial time series reduces considerably the estimates of the long-memory parameters within regimes. The working paper conclusions also mentioned that the econometrics and statistics literatures do not provide reliable tools to answer to questions such as if the reductions are statistically significant, if they can imply the process as being of a short-memory nature within regimes or if there is significant evidence of structural changes.

Although this limitation, it will be performed the Breakpoint Unit Root Test offered by the EViews, which allows to test a model for data with a one-time break [23].

This test consists in a modified augmented Dickey-Fuller test, based in the Perron methodology (2005), whose explanation follows.

The breaks can be characterized as an intercept break, a trend break or a one-time break. Like this, the following variables allow us to characterize the breaks, defined in terms of a specified break date T_b and where l(.) is an indicator function that takes the value one if the argument (.) is true, and zero if not.

- Intercept break variable – it takes the value zero for all dates prior to the break, otherwise one.

$$DU_t(T_b) = l(t \geq T_b) \qquad (1)$$

- Trend break variable – it takes the value zero for all dates prior to the break and it is a break date re-based trend for all subsequent dates.

$$DT_t(T_b) = l(t \geq T_b).(t - T_b + 1) \qquad (2)$$

- One-time break dummy variable – it takes the value one on the break date, otherwise zero.

$$D_t(T_b) = l(t = T_b) \qquad (3)$$

The test considers four different basic models, one for non-trending data and three for trending data. Additionally, the EViews offers two versions for each model that differ in their treatment of the break dynamics: the innovation outlier model and the additive outlier model.

The Innovational outlier model assumes that the break occurs gradually, with the breaks following the same dynamic path as the innovations, while the Additive outlier model assumes the breaks occur immediately. Since the break dynamics is not known, we performed the tests considering both options, where the conclusions were the same. Therefore, we will only present the test output considering the Innovational Outlier model. The following equations describe the tests hypothesis, the test equation and the four models equations for each trend and break behavior.

- Null hypothesis

$$y_t = y_{t-1} + \beta + \psi(L)(\theta D_t(T_b) + \gamma DU_t(T_b) + \epsilon_t) \quad (4)$$

where ϵ_t are independent and identically distributed innovations and $\psi(L)$ is a lag polynomial representing the dynamics of the stationary and invertible ARMA error process. The break variables enter the model with the same dynamics as the ϵ_t innovations.

- Alternative hypothesis – It assumes a trend stationary model with breaks in the intercept and trend, with the breaks again following the innovation dynamics.

$$y_t = \mu + \beta t + \psi(L)(\theta DU_t(T_b) + \gamma DT_t(T_b) + \epsilon_t) \quad (5)$$

- Dickey-Fuller test equation – It nests the null and the alternative hypotheses and use the t-statistic for comparing $\hat{\alpha}$ to 1 ($t_{\hat{\alpha}}$) to evaluate the null. Similarly to the conventional Dickey-Fuller unit root test equations, the k lagged differences of the y are included in the test equations to eliminate the effect of the error correlation structure on the asymptotic distribution of the statistic. The β, γ, θ and ω are the trend, trend break, intercept break and break dummy coefficients, respectively. This equation corresponds to the 29th equation presented in the working paper of Perron (2005).

$$y_t = \mu + \beta t + \theta DU_t(T_b) + \gamma DT_t(T_b) + \omega D_t(T_b) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \quad (6)$$

- Model 1: Non-trending data with intercept break – This model sets the trend (β) and trend break (γ) coefficients to zero, testing a random walk against a stationary model with intercept break.

$$y_t = \mu + \theta DU_t(T_b) + \omega D_t(T_b) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \quad (7)$$

- Model 2: Trending data with intercept break – This model sets the trend break coefficient (γ) to zero, testing a random walk with drift against a trend stationary model with intercept break.

$$y_t = \mu + \beta t + \theta DU_t(T_b) + \omega D_t(T_b) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \quad (8)$$

- Model 3: Trending data with intercept break and trend break – This model has no restrictions and it tests a random walk with drift against a trend stationary model with intercept and trend break.

$$y_t = \mu + \beta t + \theta DU_t(T_b) + \gamma DT_t(T_b) + \omega D_t(T_b) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \quad (6)$$

- Model 4: Trending data with trend break – This model has no restrictions and it tests a random walk with drift against a trend stationary model with intercept and trend break.

$$y_t = \mu + \beta t + \gamma DT_t(T_b) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t \quad (9)$$

In the EViews, when computing the Breakpoint Unit Root Test, we may choose between the four trend specifications described by each model. In this section, we will select the model with no restrictions (Model 3), corresponding to the Intercept and Trend for both Basic and Breaking dropdown menus. Therefore, the test will evaluate the breaks in the intercept and trend and we will be able to interpret what breaks are identified through the p-value for each one.

The test also requires to choose the number of lag terms in the Dickey-Fuller equations *k*. The EViews allows us to choose between Akaike Criterion (AIC), Schwarz Criterion (SC), Hannan-Quinn Criterion (HQC), Modified Akaike, Modified Schwarz, Hannan-Quinn, t-statistic, F-statistic and Fixed lag specifications. At this stage we will select the Schwarz Criterion (SC) which penalizes more the complex models. Indeed, Beal *et al* (1994) performed a comparison of the Akaike Information Criterion, the Schwarz Criterion and the *F* Test as guides to model selection, concluding that when the competing models are very similar or when the design is inadequate, the *F* test has a strong tendency to choose the simpler model, even when the more complex model is correct. Additionally, Koehler *et al* (1988) showed that the Schwarz Criterion is a better criterion for applications, when compared to the Akaike Information which leads to overparameterisation since AIC will frequently choose higher order models for empirical data.

In the Breakpoint Selection section we need to choose the method for determining the breakpoint date. For models with an intercept and trend break, we can decide between minimizing the *t*-statistic for α in the ADF test (Dickey-Fuller min-t), minimizing the *t*-statistic for the intercept break coefficient (Intercept break min-t), maximizing the *t*-statistic for the break coefficient (Intercept break max-t), maximizing the absolute value of the *t*-statistic for the intercept break coefficient (Intercept break max-abs-t), or providing a specific date (User-specified). In this study, we will select the Dickey-Fuller min-t, since it selects the break date providing the most evidence against the null hypothesis of a unit root and in favor of the breaking trend alternative hypothesis.

Although the Eviews allows to compute the test using the raw data (Level) or differences of the original data (1^{st} difference or 2^{nd} difference), in this study we will start by testing for unit root in “Level” since the proposal is to use the stationarity of the original data to cointegrate the variables. Therefore, if all the time series has unit root, we need to recompute the test in “1^{st} differences” of the original data to conclude if the all the time series are nonstationary and integrated of the same order. If so, we can proceed with tests of cointegration.

All the options selected for the Breakpoint Unit Root Test performed for each variable are presented in the appendix G.

4.2. Cointegration and VEC Model

The proposal of this study is to understand if the Bitcoin’s prices are related in the long term with the selected variables. Therefore, it will be performed a cointegration test.

According to Fabozzi *et al* (2007), two or more processes are said to be cointegrated if they stay close to each other even if they drift as individual processes. In this context, the authors stated that the cointegration can be understood in terms of its three key features, as follows:

i) Reduction of order of integration: Two or more stochastic processes that are integrated of order one or higher are said to be cointegrated if there are linear combinations of the processes with a lower order of integration.

ii) Regression: Two or more processes integrated of order one are said to be cointegrated if it is possible to make a meaningful linear regression of one process on the other(s).

iii) Common trends: Given *n* processes with *r* cointegrating relationships, it is possible to determine *n-r* common trends. Common trends are integrated processes such that any of the *n* original processes can be expressed as a linear regressions on the common trends.

These processes will be tested through the Johansen Test, based on a Vector Autoregressive (VAR) object, which can be computed in the EViews program [63]. EViews implemented this VAR-based cointegration test [22] according to the methodology developed by Johansen (1991, 1995). According to Johansen *et al* (1990) and Johansen (1991, 1995), both synthetized by Pacheco (2010) and Curto (2013), this methodology consists of the following:

Considering that $y_t = (y_{1t}, y_{2t}, \dots, y_{kt})'$ is a k-vector of nonstationary I(1) variables, y_t has been generated by an unrestricted VAR of order p in the level of the variables:

$$y_t = \Pi_1 y_{t-1} + \Pi_2 y_{t-2} + \cdots + \Pi_p y_{t-p} + \Phi y_t + \varepsilon_t \,, \qquad (10)$$

with t = 1, …, T, where $\Pi_1, \Pi_2, \dots, \Pi_p$ and Φ are matrices of coefficients to be estimated and ε_t is a vector of innovations.

The VAR system of equations written in error correction form is:

$$\Delta y_t = c + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + \Pi_p y_{t-p} + \varepsilon_t \,, \qquad (11)$$

where Δ is the first difference operator and

$\Gamma_i = \Pi_1 + \Pi_2 + \cdots + \Pi_i - I$, for $i = 1, 2, \dots, p-1$, $\Pi = \sum_{i=1}^{p} \Pi_i - I$.

Hence, Π is the long run 'level solution' for the VAR model. Therefore, if y_t is a vector of I(1) variables, the elements $\Gamma_1 \Delta y_{t-1}, \Gamma_2 \Delta y_{t-2}, \dots, \Gamma_{p-1} \Delta y_{t-p+1}$ are I(0) and the last element is a linear combination of I(1) variables. If the variables are cointegrated, this last element must also be I(0). From here, either y_t contains a number of cointegration vectors or Π must be a matrix of zeros. The rank of Π, r, determines how many linear combinations of y_t are stationary. If $r = k$, the variables in levels are stationary. If $r = 0$, then $\Pi = 0$ and none of the linear combinations are stationary. When $0 < r < k$, there exists r cointegration vectors or r stationary linear combinations of y_t. Here, it is possible to factorize Π: $-\Pi = \alpha\beta'$, where both α and β are $(k \times r)$ matrices and α and β contain the factor loadings and the cointegration vectors, respectively.

This methodology includes two asymptotically equivalent tests described by Johansen (1991, 1995): the Trace test and the Maximum Eigenvalue test. The cointegration test is calculated by looking at the rank of the Π matrix through its eigenvalues (characteristic roots). The rank of a matrix is equal to the number of its eigenvalues that are different from zero. So the eigenvalues (λ_i) are sorted in ascending order $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_g$. If the λ's are roots, then they must be less than one in absolute value and positive, and λ_1 will be the largest while λ_g will be the smallest, that is, the closest to one and zero, respectively. If there is no cointegration between the variables, the rank of Π will not be significantly different from zero, so $\lambda_i \approx 0, \forall i$. Actually, the test statistics incorporate $\ln(1-\lambda_i)$ rather than λ_i, however when $\lambda_i = 0$, $\ln(1-\lambda_i) = 0$.

The Trace and the Maximum Eigenvalue tests for cointegration under the Johansen approach are the following:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{g}\ln(1-\widehat{\lambda_i}) \quad \text{and} \tag{12}$$

$$\lambda_{max}(r, r+1) = -T\ln(1-\widehat{\lambda_{r+1}}) \quad , \tag{13}$$

where r is the number of cointegrated vectors under the null hypothesis and $\widehat{\lambda_i}$ is the i-th ordered eigenvalues estimates from the Π matrix. Likewise, the larger is the $\widehat{\lambda_i}$, the larger and negative will be the $\ln(1-\widehat{\lambda_i})$ and the larger will be the test value. A significantly different from zero eigenvalue directs to a significant cointegrating vector.

Regarding the distinction between the two tests, the Trace test is a joint test where the null is that the number of cointegrating vectors is lower or equal to r against the alternative of existence of more than r. It starts with g eigenvalues and, then, successively the largest is removed. If all the $\lambda_i = 0$, $\lambda_{trace}(r) = 0$, for $i = 1, 2, \ldots, g$.

On the other hand, the Maximum Eigenvalue test conducts separate tests on each eigenvalue and its null hypothesis is that the number of cointegrating vectors is r against an alternative of $r + 1$.

Moreover, Johansen *et al* (1990), as referred by Pacheco (2010) also consider that the distribution of the test statistics is non-standard and the critical values depend on the value of $g - r$, the number of nonstationary components and whether constants are included in each equation. Thereby, if the test statistic if greater than the critical value from Johansen's output, reject the null that there are $r+1$ or more than r, for λ_{trace} and λ_{max}, respectively. The test follows a sequence and under the null, for $r = 0, 1, \ldots, g - 1$, being the hypothesis for λ_{max}:

$H_o\colon r = 0$, otherwise $H_1\colon 0 < r \leq g$

$H_o\colon r = 1$, otherwise $H_1\colon 1 < r \leq g$

$\vdots \qquad\qquad\qquad\qquad \vdots$

$H_o\colon r = g - 1$, otherwise $H_1\colon r = g$

The first one tests the existence of no cointegrating vectors, that is, Π having zero rank. If the null is not rejected, it will be concluded that there are no cointegrating vectors and the test will be completed. However, if it is rejected, the null that there is one cointegrating vector ($H_o\colon r = 1$) will be tested and so on, increasing the *r* value until the null is no longer rejected.

If Π is full rank (g) this will correspond to the original series y_t being stationary. If Π has zero rank, then in the univariate case Δy_t depends only on Δy_{t-i}, and not on Δy_{t-p} (there is no long run relationship between the elements of y_{t-p}). Then, there is no cointegration. For $1 < rank(\Pi) < g$, there are *r* cointegrating vectors. Therefore, Π is defined as the product of the matrices α and β of dimension $(g \times r)$ and $(r \times g)$, respectively: $\Pi = \alpha\beta'$. Here, the matrix β gives the cointegrating vectors and the matrix α the amount of each cointegrating vector for each equation of the VEC Model (equation 11), also known as the adjustment parameters.

Additionally, Pacheco (2010) also clarifies that the Vector Error Correction Model (VECM) can be interpreted, for example, as a relationship between prices and returns in a specified market. That is, the current returns or price changes are a linear function of previous returns or price changes and historical prices. This historical prices form a long run relationship, where the included variables co-move over time independently of the existence of stochastic trends in each of them, meaning that their difference is stable. At this stage, the long run residual measure the distance of the system to equilibrium at each moment *t*, which may due to the impossibility of the economic agents to adjust instantaneously to new information or to the short run dynamics also present in the data. Then, it is important to note that the variables cointegration includes a complex adjustment process involving short-run and long-run dynamics.

Considering the previous notes, in order to perform the Johansen Cointegration test we need to choose the optimum lag number of VAR representation as well which trend assumption to use.

The optimum lag number of VAR representation was determined using information criteria. Similarly to the selection of the number of lag terms in the Dickey-Fuller equations (see section 4.1.), we will select to the VAR system lag number based on the Schwarz Criterion (SC), which penalizes more the complex models.

Regarding to the trend assumption considered in the test, since we are not certain which trend assumption to use, it is possible to choose the 'Summary of all 5 trend assumptions' Eviews option. This will indicate the number of cointegrating relations under each of the five trend assumptions. To choose between the five trend assumptions, we can use the information matrices based on Log Likelihood (LL), Akaike Information (AIC) and Schwarz information Criteria (SC). Once again, we will give preference to the Schwarz criteria.

4.3. Exogeneity

Dwivedi (2015) mentioned that economic variables are also classified as endogenous and exogenous variables, where an endogenous variable is one whose value is determined within the model under analysis while an exogenous variable is determined outside the model.

Pacheco (2010) explained these concepts, exemplifying with two variables x_t and y_t. Supposing we regress y_t on x_t, we say that x_t is weakly exogenous if y_t also does not explain x_t. On the other hand, x_t is said to be strongly exogenous if current and lagged y values do not explain, that is, there is no feedback relationship. Moreover, the author defined x_t as super-exogenous if the parameters values in the regression of y on x are invariant to changes in the values of x.

According to Johansen (1992), the weak exogeneity is a relevant condition to apply the conditional model for the estimation of the long-run parameters. The concept of weak exogeneity was introduced to justify considering some variables as given (exogenous) in the analysis of other (endogenous) variables. On the other hand, Ericsson *et al* (1998) stated that the weak exogeneity is the requirement for conditional estimation to be without loss of information from conditioning.

In a different note, Johansen *et al* (1990) referred that the factor loadings α contain information about exogeneity and, consequently, also about the price leadership. If one element in the α vector is zero, the respective price will be weakly exogenous, that is, it is determined outside of the system. In this case, if the factor loading parameter in the equation for the exchange rate XBT/USD is zero, the data will show that the exchange rate is determined outside of the system.

In order to test the existence of weak exogeneity, following the Johansen (1995) methodology, EViews allows us to impose restrictions on the adjustment coefficients, based on the (i, j)-th elements of the α matrix, referred as $A(i, j)$. Furthermore, assuming that there is only one cointegration relation in the VEC, to test whether the second endogenous variable is weakly exogenous with respect to β, we should enter the restriction: $A(2,1) = 0$.

This test will be applied to the variables combinations denoting a long-run relationship, based on the Johansen cointegration test. Then, the LR statistic will be reported in the EViews output if the degrees of freedom of the asymptotic Chi-Square-distribution is positive. If the null hypothesis is not rejected (prob. > 0,05 significance level), it will be concluded that the endogenous variable i is weakly exogenous with respect to the parameters β (Johansen, 1991). If any of the endogenous variables are considered weakly exogenous, it will be analyzed its strong exogeneity through the Granger causality.

According to Ericsson *et al* (1998), a Granger non-causality is one of the conditions required for strong exogeneity, where the Granger causality is defined as the presence of feedback from one variable to another. With Granger non-causality there is the absence of such feedback. Indeed, these authors mentioned that Granger non-causality is neither necessary nor sufficient for weak exogeneity. However, Granger non-causality combined with weak exogeneity defines strong exogeneity.

As detailed by Granger (1969) and synthetized by Pacheco (2010), this methodology is based on the following notes.

In spite of regression analysis deals with the dependence of one variable on other variables, it is not a necessary implication of causation. This means that the existence of a relationship between variables does not evidence causality or the influence direction. In time series regressions, it is also important to take into consideration that time does not goes back. This is the basis of the Granger causality test and it means that if even x happens before y, then it will be possible that x is causing y but not the contrary.

Indeed, the Granger (1969) approach to the question of whether x causes y, as explained by Curto (2013), is to see how much of the current y can be explained by past values of x and then to see whether adding lagged values of x can improved the explanation. Then, y is said to be Granger-caused by x if x helps in the prediction of y, that is, if the coefficients on the lagged x's are statistically significant. It is also frequent to see a bidirectional relationship, where x Granger causes y and y Granger causes x. However, it is important to emphasize that one condition does not imply the other.

Considering the pair of (x,y) series and the lag length k, corresponding to the reasonable longest time over which one of the variables could help to predict the other, the bivariate regressions are given as follows:

$$y_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_k x_{t-k} + \beta_1 y_{t-1} + \cdots + \beta_k y_{t-k} + \varepsilon_t \quad (14)$$

$$x_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_k y_{t-k} + \beta_1 x_{t-1} + \cdots + \beta_k x_{t-k} + \varepsilon_t \quad (15)$$

Then, the test reported F-statistics are the Wald statistics for the joint hypothesis:

$H_0: \beta_1 = \beta_2 = \cdots = \beta_k = 0$

for each equation. Therefore, the null hypothesis is that x does not Granger causes y in the first regression and that y does not Granger causes x in the second one.

Summing up, it is possible to distinguish between four causality types:

i) Unidirectional causality, where x Granger causes y, when the null hypothesis is rejected in the first regression and it is not in the second one;

ii) Unidirectional causality, where y Granger causes x, when the null hypothesis is not rejected in the first regression but it is rejected in the second one;

iii) Bilateral causality, when the null hypothesis is rejected in both regressions, meaning that x Granger causes y and y Granger causes x;

iv) Independence, when the null is not rejected in both regressions, showing that where x does not Granger causes y and y does not Granger causes x.

5. Empirical Results

As mentioned in the section 3., this study will consider the following variables: the XBT/USD exchange rate (XBTUSD), the price per barrel of West Texas Intermediate (WTI) crude oil (CL1:COM); the gold price (GC1:COM); the 6-month U.S. Treasury Yield (USGG6M); 10-year U.S. Treasury Yield (USGG10YR) and the S&P 500 Index (SPX:IND).

In order to understand if there is some long-term equilibrium between the variables, firstly it is necessary to verify if all the time series are nonstationary and if they are integrated of the same order. For this purpose, it will be computed the Breakpoint Unit Root Test for each variable, considering possible unknown structural breaks.

Therefore, for the nonstationary time series that are integrated of order one, it will be applied the Johansen Cointegration test. Since the purpose of this study is to understand if any of the time series presents some long-run relationship with the exchange rate XBT/USD, it will be applied the bivariate Johansen cointegration test. This test is performed for each two variables system, allowing to analyse those relationships, one by one, on a simpler way than the multivariate cointegration.

Lastly, if we conclude that the variables are cointegrated, it will be estimated the Vector Error Correction Model (VECM) for each cointegration relationship.

All the tests were computed in the EViews program [63] according to the methodology and approaches described in the section 4. Note that the EViews program replaces all colons (":") by underscores ("_") in the variables names.

All the conclusions presented in this section, and for statistical inference purposes, consider a 5% level of significance.

5.1. Breakpoint Unit Root Tests

Looking at the graphical representation of the daily quotations of each variable, presented in the appendixes A to F, no series shows to remain more or less constant in terms of variance and mean. Additionally, there also appears to be changes in the prices behavior, namely in the exchange rate XBT/USD where it is possible to observe some bitcoin's value triggers. Therefore, it is important to take into account the possibility of structural breaks when testing the stationarity of the series.

In order to test the stationarity of the daily prices of each variable, from 1st January 2013 to 28th August 2017, it was computed the Breakpoint Unit Root test in the Eviews program [23], where the null hypothesis is that the time series has a unit root. As described in the section 4.1., the test was computed based on the original data, without no trend restrictions (with trend and intercept), considering the innovational outlier model and using the Schwarz criterion and the Dickey-Fuller min-t for the lag length and breakpoint selections, respectively (see appendix G).

The Table 1 summarises the Breakpoint Unit Root Test for each variable, based on the EViews outputs presented in the appendixes H to M.

Variable	**Probabilities of the Dickey-Fuller Test**					
	C	**TREND**	**INCPT BREAK**	**TREND BREAK**	**BREAK DUM**	**ADF Test**
XBTUSD	0,2463	0,0459**	0,6433	0,0000**	0,1269	0,8535
CL1:COM	0,0000**	0,7315	0,0000**	0,5504	0,0841	0,1831
GC1:COM	0,0000**	0,0023**	0,0023**	0,2390	0,1196	0,2793
USGG6M	0,5111	0,8754	0,4189	0,0038**	0,0078**	0,9534
USGG10YR	0,0001**	0,0035**	0,0008**	0,0567	0,6669	0,6543
SPX:IND	0,0010**	N/A	0,0028**	N/A	0,0385**	0,5646

*Denotes rejection of the null hypothesis at the 0,05 significance level.
**Statistically significant coefficient, considering a 0,05 significance level.

Table 1 – Resume of the Breakpoint Unit Root Test outputs presented in the appendixes H to M.

All the tests show to not reject the null hypothesis (Prob. (ADF test) > 0,05 significance level) and, therefore, we can conclude that the each time series has a unit root. For the S&P 500 Index prices, since the null was firstly rejected and its trend break was not statistically significant, the test was computed only with intercept. Then, the conclusion was that the time series has a unit root.

For the remaining variable, when recomputed the tests considering only the statistically significant coefficients, without (**), in the trend specifications, the conclusions were the same. Therefore, those outputs were not included.

Once all the time series are nonstationary, in order to check if they are integrated of order one, we will recompute the Breakpoint Unit Root Test in first differences for each variable, that is, using the daily returns instead of the daily prices. Before looking to tests results, in the appendixes A to F are also graphically represented the daily returns of each time series. Comparing the two charts of each time series, despite the existence of some outliers, such as in the 6-month U.S. Treasury Yields daily returns (see Chart 8), it is possible to conclude that the first differences time series tend to remain more constant in terms of variance and mean than the original data. Thus, it is expectable that the first differences time series tend to be stationary.

Variable	Probabilities of the Dickey-Fuller Test					
	C	TREND	INCPT BREAK	TREND BREAK	BREAK DUM	ADF Test
D(XBTUSD)	0,2270	0,0073**	0,0126**	0,0062**	0,0000**	< 0,01*
D(CL1:COM)	0,1793	0,0439**	0,4189	0,0213**	0,0000**	< 0,01*
D(GC1:COM)	0,8545	0,3903	0,1514	0,3829	0,0000**	< 0,01*
D(USGG6M)	0,8316	0,8978	0,7316	0,9433	0,0000**	< 0,01*
D(USGG10YR)	0,5679	0,1524	0,0454**	0,1583	0,0000**	< 0,01*
D(SPX:IND)	0,0906	0,2958	0,7037	0,3696	0,0000**	< 0,01*

*Denotes rejection of the null hypothesis at the 0,05 significance level.
**Statistically significant coefficient, considering a 0,05 significance level.

Table 2 – Resume of the Breakpoint Unit Root Test outputs presented in the appendixes N to S.

Observing the summary of the Breakpoint Unit Root Tests for the first differences of each variable, in the Table 2, it is possible to conclude that all the ADF test results poit to reject the null hypothesis (Prob. (ADF test) < 0,05 significance level). Therefore, the time series have no unit root in first differences and we can conclude they are integrated of order one.

Once again, when recomputed the tests considering only the statistically significant coefficients, without (**), in the trend specifications, the conclusions were the same. Therefore, those outputs were not included.

Based on the previous unit root tests, it is possible to conclude that all the variables are nonstationary and integrated of order one *I(1)*. So, we can proceed with tests of cointegration.

5.2. Cointegration test

In this section we will perform a bivariate cointegration analysis, that is, we will investigate the long-run relationships between the exchange rate XBT/USD and each of the other variables considered in this study. Like this, we will test five variables combinations, considering the respective five VAR systems.

Firstly, it is necessary to choose the optimum lag number of VAR representation. This selection will be done based on information criteria, specifically based on the Schwarz Information Criterion (SC). In order to do not over-parameterize the models, we investigated the VAR lag number, for each combination of two variables, until a maximum of eight lags.

Variables	VAR Lag Order Selection Criteria		
	Akaike Information Criterion	**Schwarz Information Criterion**	**Hannan-Quinn Information Criterion**
XBTUSD – CL1:COM	2	1	2
XBTUSD – GC1:COM	2	1	2
XBTUSD – USGG6M	8	1	1
XBTUSD – USGG10YR	2	1	1
XBTUSD – SPX:IND	2	1	1

Table 3 – Resume of the VAR Lag Order Selection Criteria outputs presented in the appendixes T to X.

Based on the Schwarz Information Criteria, it was selected one lag for all the VAR representations. The Table 3 shows the optimum lag number of VAR representation, based on the Akaike, Schwarz and Hannan-Quinn information criteria.

After the lag number selection, it is necessary to choose the trend assumption to consider in each test, in the Cointegration Equation (CE) and Vector Autoregressive (VAR). In this case, we are not certain which trend assumption to consider. Therefore, it is possible to compute the Johansen cointegration test with the summary of all five trend assumptions, in the EViews program. This option indicates the number of cointegrating relations under each trend assumption. The five trend assumptions are the following:

1) No deterministic trend - No intercept or trend in CE or VAR;
2) Linear deterministic trend - Intercept (no trend) in CE and no intercept in VAR;
3) Linear deterministic trend - Intercept (no trend) in CE and VAR;
4) Linear deterministic trend - Intercept and trend in CE and no trend in VAR;
5) Quadratic deterministic trend - Intercept and trend in CE and trend in VAR.

To choose the trend assumption, we can use information criteria based on Log Likelihood (LL), Akaike Information (AIC) and Schwarz information Criteria (SC). As mentioned before, we will give preference to the Schwarz criteria. The EViews test shows the results by rank and model.

The Table 4 summarizes the best trend assumption for each variables combination based on the Information Criteria detailed in the appendixes Y to AC.

Variables	LL	AIC	SIC	Trend Assumption
XBTUSD - CL1:COM	Model 4 / Model 5	Model 1	Model 1 / Model 2	Model 1
XBTUSD - GC1:COM	Model 4 / Model 5	Model 3	Model 1 / Model 2	Model 1
XBTUSD - USGG6M	Model 4 / Model 5	Model 4	Model 1	Model 1
XBTUSD - USGG10YR	Model 4 / Model 5	Model 1	Model 1 / Model 2	Model 1
XBTUSD - SPX:IND	Model 4 / Model 5	Model 1	Model 1 / Model 2	Model 1

Table 4 – Trend assumption selection based on the Information Criteria presented in the appendixes Y to AC.

The Schwarz information Criterion shows that the Model 1, with no deterministic trend data and no intercept or trend in CE or VAR, is the best trend assumption for all the variables combinations. Excepting for the VAR system of XBTUSD and USGG6M, the Model 1 is as good as the Model 2. Then, to simplify, we will consider no deterministic trend in all the cointegration tests.

Summing up, the Johansen Cointegration Test will be performed between the exchange rate XBT/USD and each of the other variables, with no deterministic trend.

We will start with the Bivariate Johansen test for cointegration, that is, the cointegration between each two variables combination. As mentioned before, the tests will be computed for one lag and with no deterministic trend.

Once again, the results of the Trace and the Maximum Eigenvalue tests are presented in the Table 5 and detailed in the appendixes AD to AH.

Variables	Rank	Eigenvalue	Trace Statistic	Max. Eigenvalue Statistic	Prob.
XBTUSD – CL1:COM	$r = 0$	0,016290	30,82641	29,00915	0,0000*
	$r \leq 1$	0,001069	1,817253	1,817253	0,2090
XBTUSD – GC1:COM	$r = 0$	0,017235	32,87588	29,53819	0,0000*
	$r \leq 1$	0,001963	3,337687	3,337687	0,0803
XBTUSD – USGG6M	$r = 0$	0,018998	33,00490	32,58879	0,0000*
	$r \leq 1$	0,000245	0,416113	0,416113	0,5823
XBTUSD – USGG10YR	$r = 0$	0,017133	29,36205	29,36192	0,0000*
	$r \leq 1$	$7{,}61\text{x}10^{-8}$	0,000129	0,000129	0,9913
XBTUSD – SPX:IND	$r = 0$	0,017220	32,13529	29,51135	0,0000*
	$r \leq 1$	0,001543	2,623949	2,623949	0,1244

*Denotes rejection of the null hypothesis at the 0,05 significance level.

Table 4 – Bivariate Johansen test for cointegration, according to the outputs presented in the appendixes AD to AH.

Considering the 5% significance level, both Trace and Maximum Eigenvalue statistics fail to reject the null of no cointegration in each relationship (r = 0). Then, the results point for one cointegration equation for each relationship. Indeed, if it was considered the 1% significance level, the conclusion would be the same since all the probabilities are 0,0000 < significance level.

Therefore, it is possible to conclude that the cointegration analysis points to a long-run relationship between the exchange rate XBT/USD and each of the other variables, specifically the price per barrel of West Texas Intermediate (WTI) crude oil, the gold price, the 6-month U.S. Treasury Yield, the 10-year U.S. Treasury Yield and the S&P 500 Index. In other words, this implies that each times series is integrated with the exchange rate XBT/USB, where it is possible to estimate the Vector Error Correction Model for each one.

5.3. VEC Model Estimation

According to the previous tests and assumptions, the Vector Error Correction Model will be estimated for each bivariate cointegration relationship, considering one lag and no deterministic trend.

The VEC estimates are detailed in the appendixes AI to AM. In order to interpret the significance of the coefficients, it is necessary to analyse the *t*-statistics considering the *t*-statistic critical value of approximately -1,96, for a 5% significance level. The *t*-statistics are identified in the EViews outputs [63]. Hence, with 5% of significance level, the coefficient is statistically significant if the t-statistic will be lower than -1,96 or higher than 1,96.

Based on these outputs, it is possible to conclude that the estimates for the coefficients β of the long-term relationship equations are not statistically different from zero, at 5% significance level, for the relationships between XBTUSD and CL1:COM, USGG10YR and SPX:IND, respectively. Based on the bivariate cointegration tests, it was expected that there would be some long-run equilibrium between the Bitcoin prices and these variables. However, since the coefficients β are not statistically significant, we cannot conclude that there is a long-term relationship between one of these variables and the exchange rate XBT/USD.

In the appendixes AN to AR are presented five graphical representations where it is possible to compare the exchange rate XBT/USD historical prices behaviour with each of the time series behaviours.

Starting by the exchange rate XBT/USD and the Crude Price daily prices, the Chart 13 (see appendix AN) shows that these times series have different behaviours during the observation period. While the exchange rate XBT/USD tends to increase with time, the Crude price shows a decreasing tendency. Moreover, in periods that XBT/USD keeps more constant, namely in the first semester of 2015, the Crude price suffers large variations. These are in line with the absence of some long-run equilibrium between the Bitcoin and the Crude prices.

Looking at the Chart 14, the conclusion is not the same. Indeed, until the beginning of 2017, both time series do not show huge trend variations, being possible to observe small increases and decreases. Additionally, it is possible to observe that the Gold price tend to decrease, while the Bitcoin price tend to increase, mainly in 2013. This may mean that, since there is a cointegration relationship between these variables, possibly the Gold price positive variations will promote the Bitcoin prices negative variations, and vice versa.

Regarding the 6-month U.S. Treasury Yields, through the Chart 15 in the appendix AP, it is possible to see that this time series tends to have the same behaviour that the Bitcoin prices, both with an increasing trend during the observation period. This is in accordance with the conclusion of the existence of a long-term relationship between these variables and it may indicate that positive variations in the 6-month U.S. Treasury Yields will promote the Bitcoin prices positive variations, and vice versa.

Observing the Chart 16, in the appendix AQ, it is possible to identify some similarities with the Crude price. It shows that these times series have different behaviours during the observation period, where the exchange rate XBT/USD tends to increase with time, while the 10-year U.S. Treasury Yields show a decreasing trend. Moreover, in periods that XBT/USD keeps more constant, namely in the first semester of 2015, the 10-year U.S. Treasury Yields suffer large variations. These are in line with the absence of some long-run equilibrium between them.

Finally, through the Chart 17, presented in the appendix AR, it is possible to conclude that the S&P 500 Index prices tend to have a linear increase trend, without deep changes or outliers. On the other hand, the Bitcoin prices graphical representation denotes changes in behaviour over time, which also points to the inexistence of long-run equilibrium between the Bitcoin and the S&P 500 Index prices.

For the combinations showing a long-term relationships, the estimated equations for XBTUSD are given by:

$$\Delta XBTUSD_t = -0{,}073039\Delta XBTUSD_{t-1} + 0{,}008025(XBTUSD_{t-1} - 0{,}219458GC1{:}COM_{t-1})$$

$$\equiv \Delta XBTUSD_t = -0{,}073039\Delta XBTUSD_{t-1} + 0{,}008025XBTUSD_{t-1} - 0{,}00176GC1{:}COM_{t-1}$$

$$\Delta XBTUSD_t = -0{,}068004\Delta XBTUSD_{t-1} + 0{,}002365(XBTUSD_{t-1} + 3.802{,}169USGG6M_{t-1})$$

$$\equiv \Delta XBTUSD_t = -0{,}068004\Delta XBTUSD_{t-1} + 0{,}002365XBTUSD_{t-1} + 8{,}99213USGG6M_{t-1})$$

These estimations points that on average and in the short term an increase in the gold price promotes a decrease in the exchange rate XBT/USD (negative coefficient), while the increase in the 6-month U.S. Treasury Yields promotes an increase in the exchange rate XBT/USD (positive coefficient). These conclusions were those expected from the previous time series graphical analysis.

However, it is important to note that the 6-month U.S. Treasury Yields changes tends do not affect the Bitcoin prices on a significant way, since the estimate for the coefficient is 0,00176.

5.4. Exogeneity

Following Johansen (1992, 1995), a weak exogeneity test has been applied to each series, testing every element of the adjustment matrix coefficient against zero. Performing this test to the variables denoting a relation of cointegration with the exchange rate XBT/USD, the outputs are presented in the appendix AS.

Then, it is possible to conclude that the null hypothesis of weak exogeneity can be rejected in the cointegration relationship between XBT/USD and USGG6M (prob. < 0,05 significance level).

On the other hand, for the relationship between XBT/USD and GC1:COM, the null is not rejected (prob. > 0,05 significance level), so the test points to a weak exogeneity. This weak exogeneity shows an absence of significant adjustment in the long-term relationship of the corresponding VEC Model. Nevertheless, for the GC1:COM remains only a short-term relationship with the exchange rate XBT/USD, also implying that its prices cannot be used to forecast XBT/USD in the long-run. For this to be also the case in the short-run, these prices must be strongly exogenous and hence not affected by the short-run movements in XBT/USD.

Observing the Granger causality test (appendix AT), to check if there were any signs of strong exogeneity for the weak exogenous variable, a causal relationship was not found for the pair XBT/USD – GC1:COM. Therefore, there is no strong exogeneity of GC1:COM and it is possible to conclude that remains a short-term relationship with exchange rate XBT/USD.

Summing up, through the study of the dynamic relationships between Bitcoin prices and each of the five other variables, the results showed that only the 6-month U.S. Treasury Yields present a long-run relationship with the Bitcoin prices, being possible to use their rates to forecast the exchange rate XBT/USD in the short term.

6. Conclusion

The present dissertation "Virtual currency: A cointegration analysis between Bitcoin prices and economic and financial data" investigated the existence of dynamic relationships between Bitcoin prices and economic and financial data. The variables selected for this thesis were chosen taking in consideration their relationship with physical currencies, already showed on previous studies. The data included the Crude and Gold prices, the 6-month and 1-year U.S. Treasury Yields and the S&P 500 Index prices. Bitcoin as a digital currency, emerges in a specific part of the law where there is still many legal blanks, as so, it was not expected that instabilities on economic and financial data would have the same impacts or relationships as the ones in physical currencies.

In order to achieve this dissertation's proposal, it was important to (i) test the presence of non-stationarity and first-order integration in each of time series considered in this analysis, admitting the existence of structural breaks in the data; (ii) test the cointegration between the exchange rate XBT/USD and each of the remaining variables under study; (iii) estimate the vector error correction model for the variables cointegrated with the Bitcoin prices; and (iv) test the weak exogeneity, which implies the absence of significant adjustments in the long-run relationship and, consequently, the preclusion of using the model to forecast the Bitcoin prices.

As the results showed that all the considered time series are non-stationary and integrated of order one, all the data was included in the next tests. Therefore, the bivariate cointegration Johansen tests pointed to a long-run relationship between the exchange rate XBT/USD and each of the other variables, specifically the price per barrel of West Texas Intermediate (WTI) crude oil, the gold price, the 6-month U.S. Treasury Yield, the 10-year U.S. Treasury Yield and the S&P 500 Index quotations. Accordingly, it was estimated the Vector Error Correction Model for each one.

Despite the cointegration results, the estimates for the parameters of the VECM model revealed that only the long-term relationships between the exchange rate XBT/USD and the gold price and the 6-month U.S. Treasury Yield are statistically significant. For the other relationships, only the short-term relation has emerged from estimation results.

Additionally, the VEC model estimations pointed that, on average and in the short term, an increase in the gold price promotes a decrease in the exchange rate XBT/USD, while the increase in the 6-month U.S. Treasury Yields promotes an increase in the exchange rate XBT/USD. However, it is important to note that the 6-month U.S. Treasury

Yields changes tends to not affect the Bitcoin prices on a significant way, since the estimate for the coefficient is close to zero.

Then, considering these two models, it was performed the exogeneity tests, concluding that in the gold price system there was an absence of significant adjustment in the long-term relationship of the corresponding VEC Model. Nevertheless, for the gold price remains only a short-term relationship with the exchange rate XBT/USD, also implying that its prices cannot be used to forecast XBT/USD in the long-run.

Summing up, through the study of the dynamic relationships between Bitcoin prices and each of the five other variables, the results showed that only the 6-month U.S. Treasury Yields present a long-run relationship with the Bitcoin prices, being possible to use their rates to forecast the exchange rate XBT/USD in the short term.

It should be noted that the current dissertation has limitations that are important to consider. Firstly, the variables selection was based on their relationship with physical currencies, being possible that they are not the suitable variables to relate with the Bitcoin prices and to use to forecast them. On the other hand, the Johansen test assumes that there are no structural breaks and the exchange rate XBT/USD behaviour shows multiple structural changes. This could be sorted out through structural breaks identification and consequent division of the data samples into sub-samples. Lastly, in order to ensure the robustness of the model, it should be included additional related variables.

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Platforms and Softwares:

[62] Bloomberg Platform/Portal

[63] EViews 9.5 Student Version

8. Appendixes

A. Daily prices and returns of Exchange Rate XBT/USD

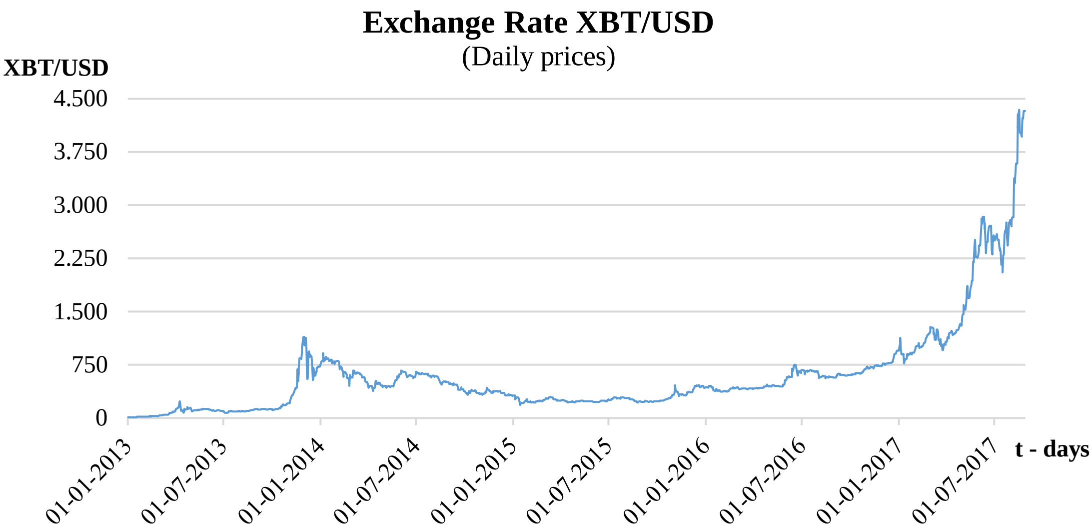


Chart 1 – Daily prices of Exchange Rate XBT/USD, between 01/01/2013 and 28/08/2017 [62].

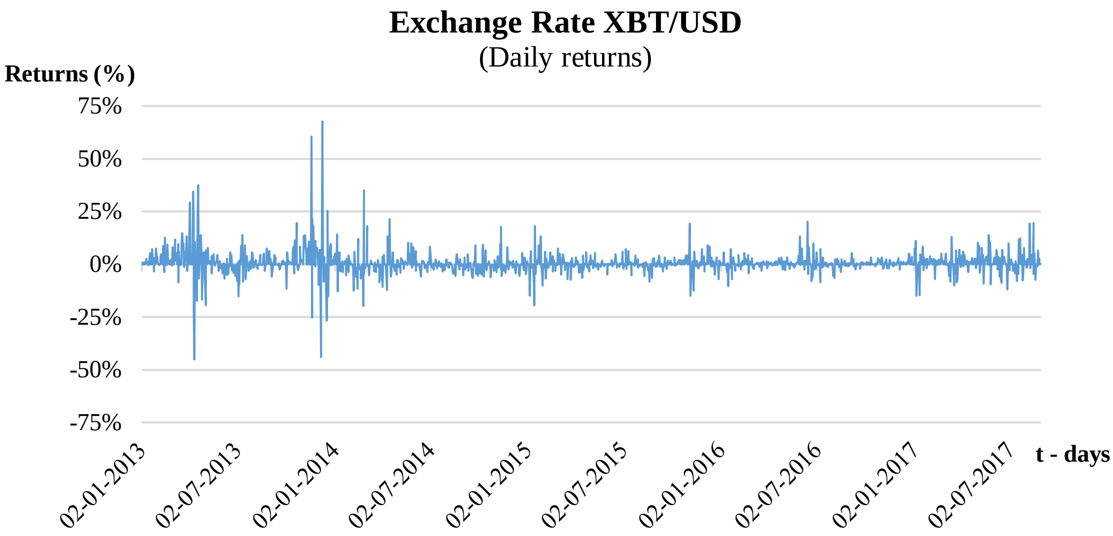


Chart 2 – Daily returns of Exchange Rate XBT/USD, between 02/01/2013 and 28/08/2017 [62].

B. Daily prices and returns of Crude Price

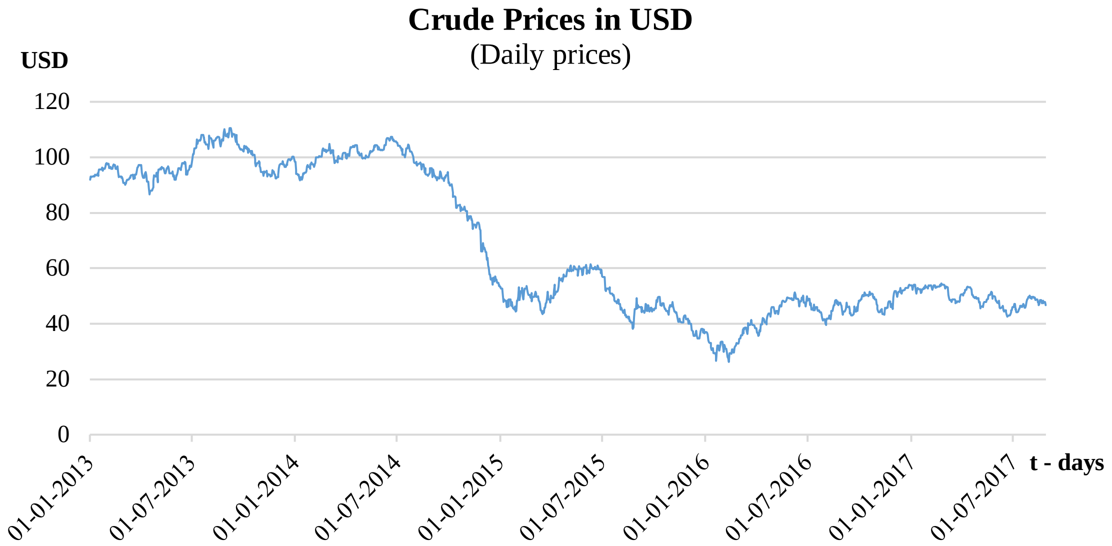


Chart 3 – Daily prices of Crude in U.S. Dollar, between 01/01/2013 and 28/08/2017 [62].

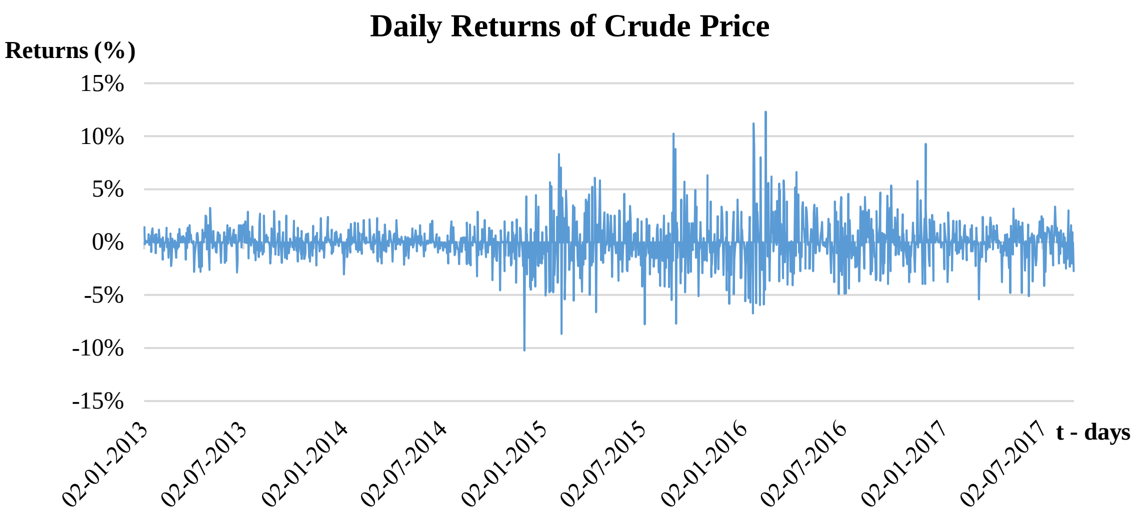


Chart 4 – Daily returns of Crude Prices in U.S. Dollar, between 02/01/2013 and 28/08/2017 [62].

C. Daily prices and returns of Gold Price

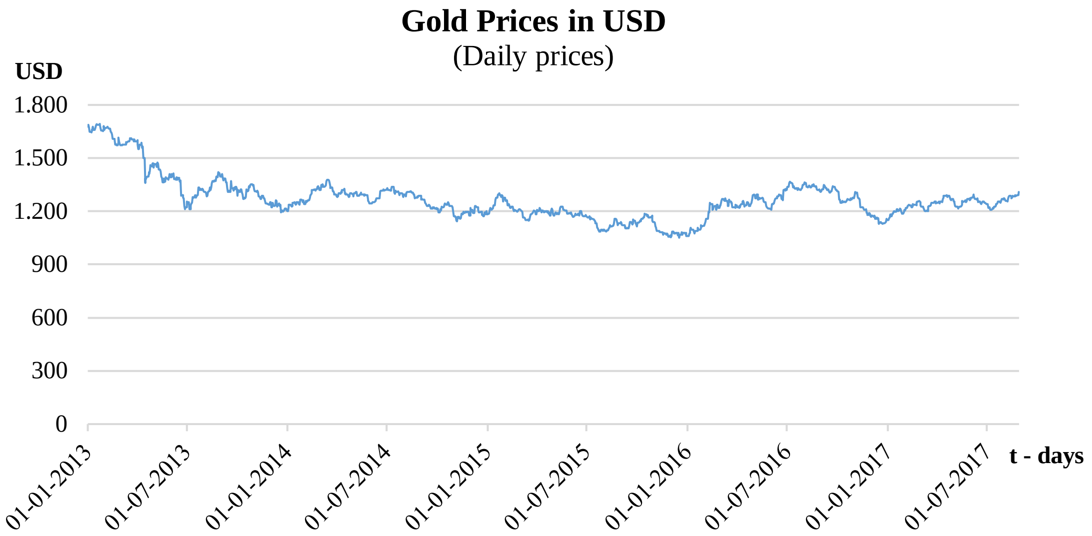


Chart 5 – Daily prices of Gold in U.S. Dollar, between 01/01/2013 and 28/08/2017 [62].

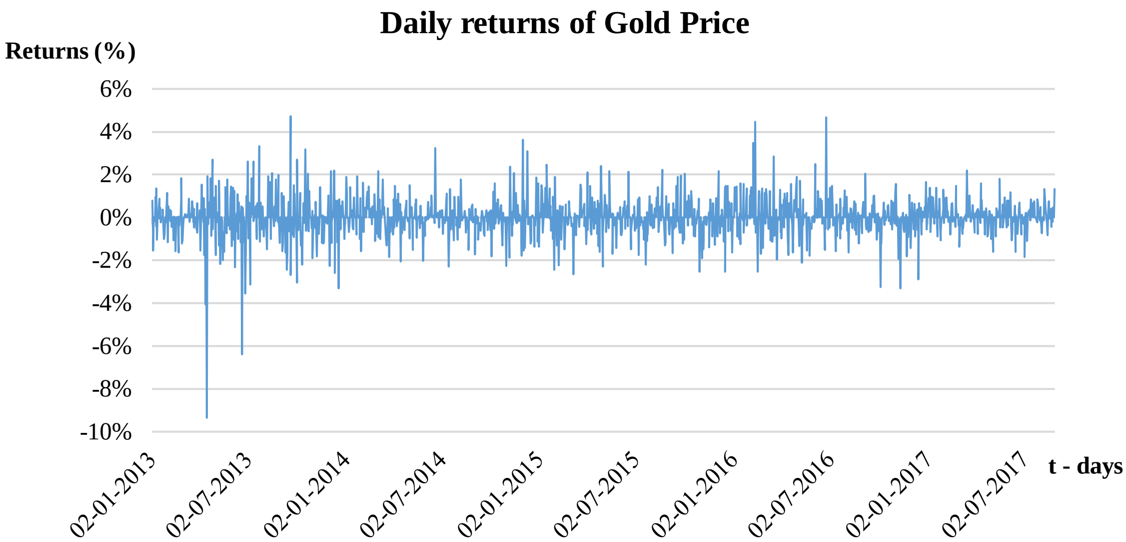


Chart 6 – Daily returns of Gold Prices in U.S. Dollar, between 02/01/2013 and 28/08/2017 [62].

D. Daily prices and returns of 6-month U.S. Treasury Yields

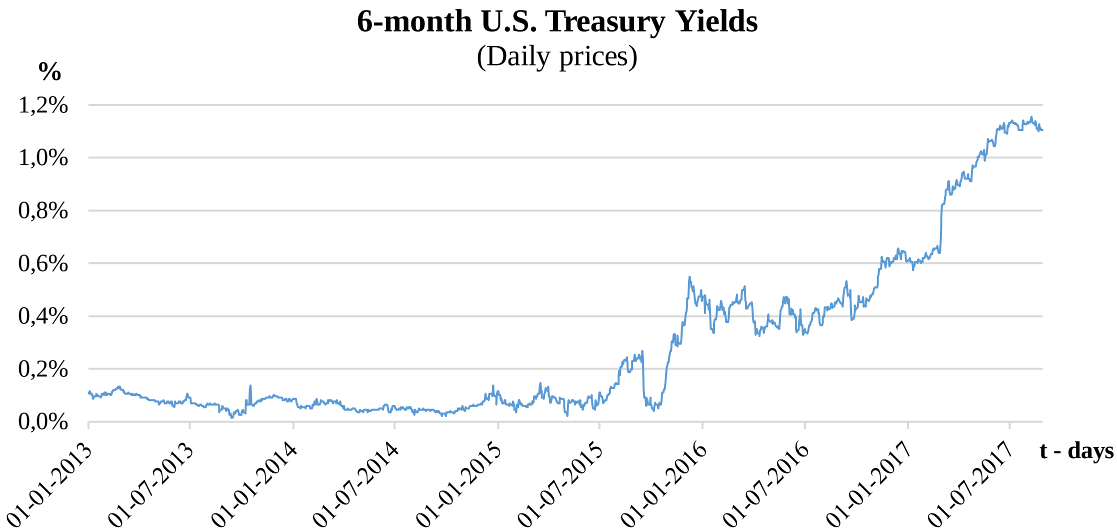


Chart 7 – Daily rates of 6-month U.S. Treasury Yields, between 01/01/2013 and 28/08/2017 [62].

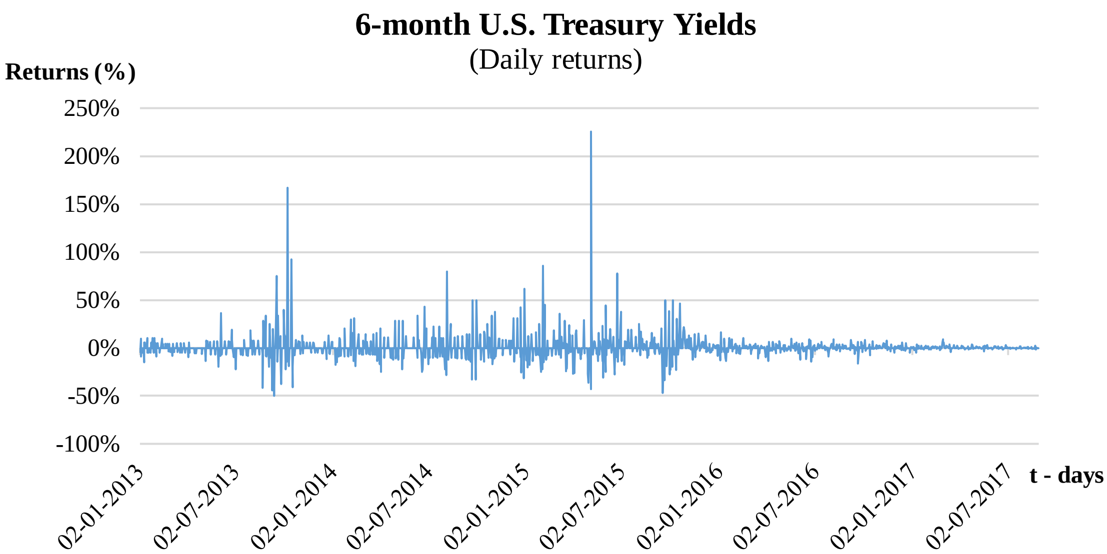


Chart 8 – Daily returns of 6-month U.S. Treasury Yields, between 02/01/2013 and 28/08/2017 [62].

E. Daily prices and returns of 10-year U.S. Treasury Yields

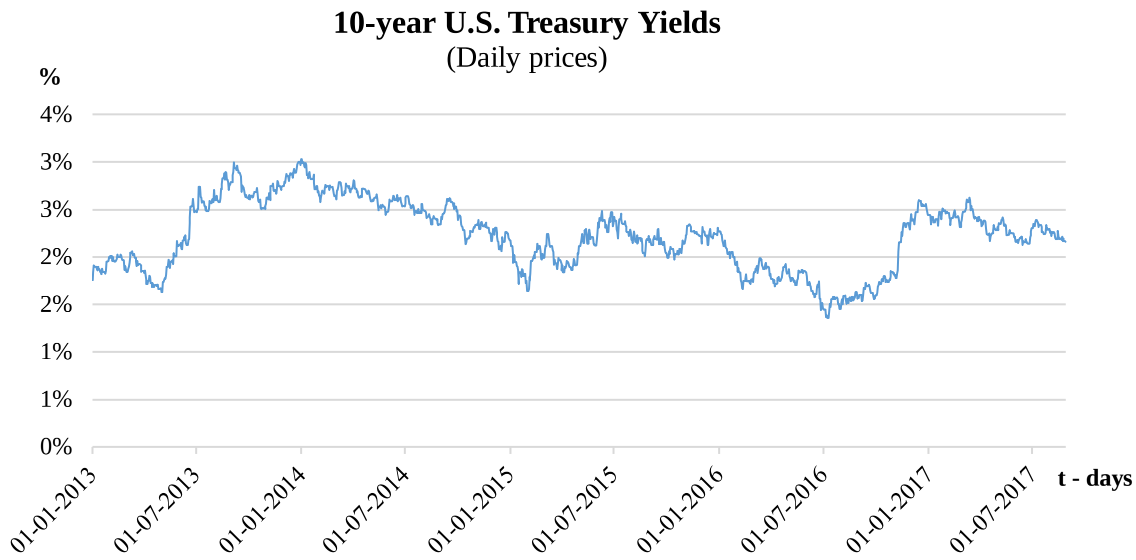


Chart 9 – Daily rates of 10-year U.S. Treasury Yields, between 01/01/2013 and 28/08/2017 [62].

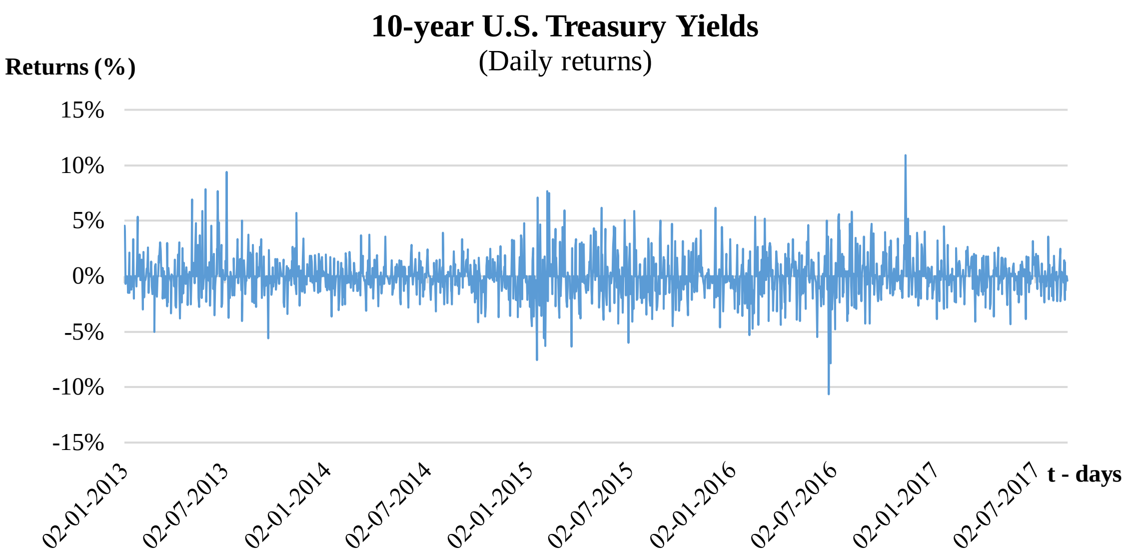


Chart 10 – Daily returns of 10-year U.S. Treasury Yields, between 02/01/2013 and 28/08/2017 [62].

F. Daily prices and returns of the S&P 500 Index

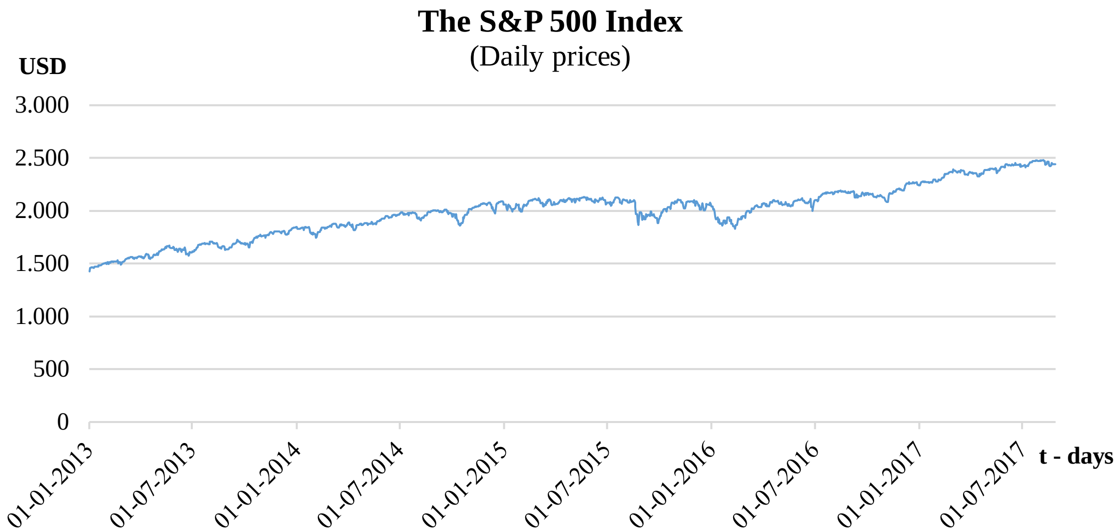


Chart 11 – Daily prices of the S&P 500 Index, between 01/01/2013 and 28/08/2017 [62].

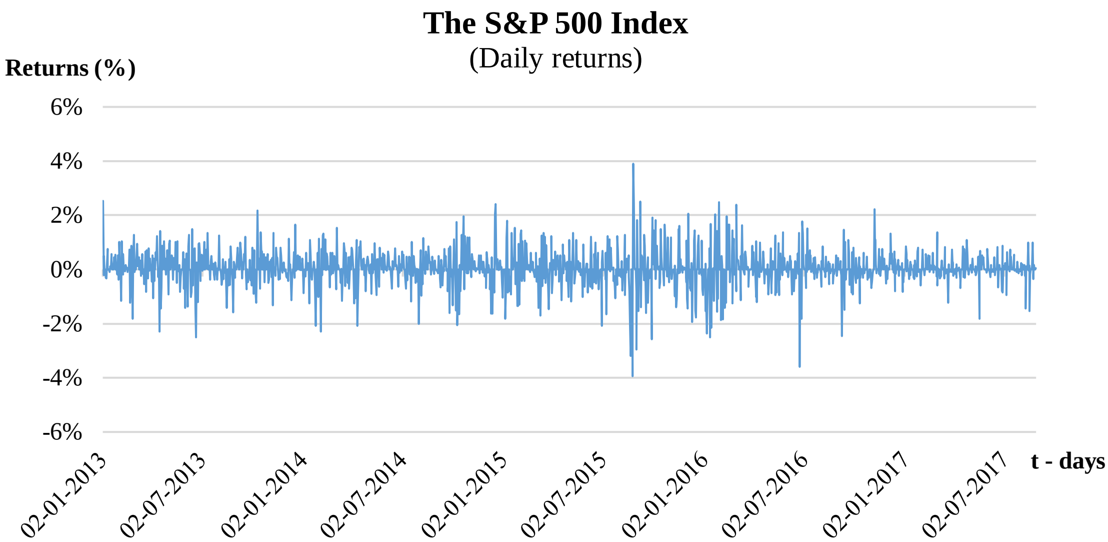
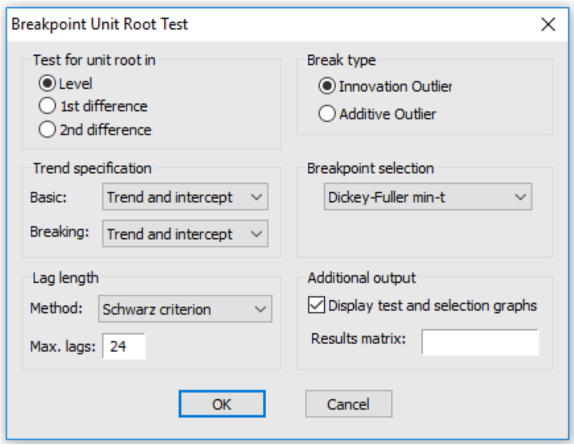


Chart 12 – Daily returns of the S&P 500 Index, between 02/01/2013 and 28/08/2017 [62].

G. Breakpoint Unit Root Test



H. Breakpoint Unit Root Test – XBTUSD

Null Hypothesis: XBTUSD has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 3/21/2017
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.410537	0.8535
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: XBTUSD
Method: Least Squares
Date: 09/18/17 Time: 15:28
Sample (adjusted): 1/02/2013 8/28/2017
Included observations: 1700 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
XBTUSD(-1)	0.984333	0.004594	214.2747	0.0000
C	2.716625	2.342176	1.159872	0.2463
TREND	0.005912	0.002960	1.997514	0.0459
INCPTBREAK	3.412204	7.367446	0.463146	0.6433
TRENDBREAK	0.487829	0.109919	4.438072	0.0000
BREAKDUM	67.56582	44.23890	1.527294	0.1269

R-squared	0.995612	Mean dependent var	596.7340
Adjusted R-squared	0.995599	S.D. dependent var	658.4309
S.E. of regression	43.67885	Akaike info criterion	10.39513
Sum squared resid	3231885.	Schwarz criterion	10.41432
Log likelihood	-8829.859	Hannan-Quinn criter.	10.40223
F-statistic	76876.15	Durbin-Watson stat	2.126104
Prob(F-statistic)	0.000000		

I. Breakpoint Unit Root Test – CL1:COM

Null Hypothesis: CL1_COM has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 9/29/2014
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 1 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.625228	0.1831
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: CL1_COM
Method: Least Squares
Date: 09/18/17 Time: 19:15
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CL1_COM(-1)	0.986522	0.002914	338.5399	0.0000
D(CL1_COM(-1))	-0.073138	0.024085	-3.036602	0.0024
C	1.355504	0.291475	4.650495	0.0000
TREND	-7.36E-05	0.000214	-0.343226	0.7315
INCPTBREAK	-0.730697	0.164318	-4.446832	0.0000
TRENDBREAK	0.000145	0.000242	0.597327	0.5504
BREAKDUM	1.712537	0.990750	1.728526	0.0841

R-squared	0.998520	Mean dependent var	67.75364
Adjusted R-squared	0.998515	S.D. dependent var	25.50338
S.E. of regression	0.982859	Akaike info criterion	2.807409
Sum squared resid	1634.492	Schwarz criterion	2.829813
Log likelihood	-2377.894	Hannan-Quinn criter.	2.815704
F-statistic	190263.8	Durbin-Watson stat	1.997258
Prob(F-statistic)	0.000000		

J. Breakpoint Unit Root Test – GC1:COM

Null Hypothesis: GC1_COM has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 1/14/2016
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.411778	0.2793
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: GC1_COM
Method: Least Squares
Date: 09/18/17 Time: 19:14
Sample (adjusted): 1/02/2013 8/28/2017
Included observations: 1700 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GC1_COM(-1)	0.982542	0.003957	248.3011	0.0000
C	24.82171	5.913921	4.197166	0.0000
TREND	-0.005552	0.001817	-3.054742	0.0023
INCPTBREAK	4.051541	1.326550	3.054194	0.0023
TRENDBREAK	0.003817	0.003241	1.177942	0.2390
BREAKDUM	-17.24747	11.07659	-1.557110	0.1196

R-squared	0.991423	Mean dependent var	1266.500
Adjusted R-squared	0.991397	S.D. dependent var	118.8304
S.E. of regression	11.02164	Akaike info criterion	7.641122
Sum squared resid	205781.4	Schwarz criterion	7.660316
Log likelihood	-6488.954	Hannan-Quinn criter.	7.648228
F-statistic	39160.15	Durbin-Watson stat	2.112670
Prob(F-statistic)	0.000000		

K. Breakpoint Unit Root Test – USGG6M

Null Hypothesis: USGG6M has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 3/16/2015
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.059785	0.9534
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: USGG6M
Method: Least Squares
Date: 09/18/17 Time: 18:51
Sample (adjusted): 1/02/2013 8/28/2017
Included observations: 1700 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
USGG6M(-1)	0.989692	0.003369	293.7787	0.0000
C	0.000585	0.000889	0.657296	0.5111
TREND	2.85E-07	1.82E-06	0.156835	0.8754
INCPTBREAK	-0.000961	0.001189	-0.808457	0.4189
TRENDBREAK	1.36E-05	4.70E-06	2.901727	0.0038
BREAKDUM	0.031735	0.011923	2.661693	0.0078

R-squared	0.998573	Mean dependent var	0.289903
Adjusted R-squared	0.998569	S.D. dependent var	0.314268
S.E. of regression	0.011887	Akaike info criterion	-6.023187
Sum squared resid	0.239371	Schwarz criterion	-6.003993
Log likelihood	5125.709	Hannan-Quinn criter.	-6.016081
F-statistic	237161.3	Durbin-Watson stat	1.994959
Prob(F-statistic)	0.000000		

L. Breakpoint Unit Root Test – USGG10YR

Null Hypothesis: USGG10YR has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 11/06/2016
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.807081	0.6453
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: USGG10YR
Method: Least Squares
Date: 09/18/17 Time: 18:52
Sample (adjusted): 1/02/2013 8/28/2017
Included observations: 1700 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
USGG10YR(-1)	0.988138	0.003116	317.1394	0.0000
C	0.032314	0.008256	3.913766	0.0001
TREND	-8.81E-06	3.01E-06	-2.928373	0.0035
INCPTBREAK	0.017894	0.005306	3.372404	0.0008
TRENDBREAK	-5.04E-05	2.65E-05	-1.907085	0.0567
BREAKDUM	-0.016710	0.038822	-0.430426	0.6669

R-squared	0.988609	Mean dependent var	2.224741
Adjusted R-squared	0.988575	S.D. dependent var	0.360250
S.E. of regression	0.038506	Akaike info criterion	-3.672503
Sum squared resid	2.511661	Schwarz criterion	-3.653309
Log likelihood	3127.628	Hannan-Quinn criter.	-3.665397
F-statistic	29404.18	Durbin-Watson stat	2.071927
Prob(F-statistic)	0.000000		

M. Breakpoint Unit Root Test – SPX:IND

Null Hypothesis: SPX_IND has a unit root
Trend Specification: Intercept only
Break Specification: Intercept only
Break Type: Innovational outlier

Break Date: 2/11/2016
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.203574	0.5646
Test critical values:	1% level	-4.949133	
	5% level	-4.443649	
	10% level	-4.193627	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: SPX_IND
Method: Least Squares
Date: 09/18/17 Time: 19:06
Sample (adjusted): 1/02/2013 8/28/2017
Included observations: 1700 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SPX_IND(-1)	0.994533	0.001707	582.7710	0.0000
C	10.65374	3.229860	3.298515	0.0010
INCPTBREAK	2.622452	0.876547	2.991798	0.0028
BREAKDUM	-25.93191	12.51799	-2.071571	0.0385

R-squared	0.997335	Mean dependent var	1996.399
Adjusted R-squared	0.997331	S.D. dependent var	241.7533
S.E. of regression	12.49038	Akaike info criterion	7.890145
Sum squared resid	264592.2	Schwarz criterion	7.902941
Log likelihood	-6702.623	Hannan-Quinn criter.	7.894882
F-statistic	211595.8	Durbin-Watson stat	2.068680
Prob(F-statistic)	0.000000		

N. Breakpoint Unit Root Test – D(XBTUSD)

Null Hypothesis: D(XBTUSD) has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 8/14/2017
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-46.48855	< 0.01
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(XBTUSD)
Method: Least Squares
Date: 09/19/17 Time: 16:24
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(XBTUSD(-1))	-0.050581	0.022599	-2.238234	0.0253
C	-2.401877	1.987218	-1.208663	0.2270
TREND	0.005498	0.002046	2.687507	0.0073
INCPTBREAK	-64.22159	25.70350	-2.498555	0.0126
TRENDBREAK	7.438895	2.714345	2.740586	0.0062
BREAKDUM	748.3700	46.89505	15.95840	0.0000

R-squared	0.155767	Mean dependent var	2.541798
Adjusted R-squared	0.153274	S.D. dependent var	44.27656
S.E. of regression	40.74229	Akaike info criterion	10.25594
Sum squared resid	2810268.	Schwarz criterion	10.27514
Log likelihood	-8706.417	Hannan-Quinn criter.	10.26304
F-statistic	62.47413	Durbin-Watson stat	1.935685
Prob(F-statistic)	0.000000		

O. Breakpoint Unit Root Test – D(CL1:COM)

Null Hypothesis: D(CL1_COM) has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 11/28/2014
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-45.03709	< 0.01
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CL1_COM)
Method: Least Squares
Date: 09/19/17 Time: 16:33
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CL1_COM(-1))	-0.073311	0.023832	-3.076212	0.0021
C	0.099385	0.073975	1.343490	0.1793
TREND	-0.000372	0.000185	-2.016345	0.0439
INCPTBREAK	0.077683	0.096082	0.808503	0.4189
TRENDBREAK	0.000491	0.000213	2.304534	0.0213
BREAKDUM	-7.458964	0.974780	-7.651945	0.0000

R-squared	0.041715	Mean dependent var	-0.027398
Adjusted R-squared	0.038885	S.D. dependent var	0.992323
S.E. of regression	0.972838	Akaike info criterion	2.786327
Sum squared resid	1602.279	Schwarz criterion	2.805530
Log likelihood	-2360.985	Hannan-Quinn criter.	2.793436
F-statistic	14.73968	Durbin-Watson stat	2.007351
Prob(F-statistic)	0.000000		

P. Breakpoint Unit Root Test – D(GC1:COM)

Null Hypothesis: D(GC1_COM) has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 4/15/2013
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-46.13517	< 0.01
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GC1_COM)
Method: Least Squares
Date: 09/19/17 Time: 16:32
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GC1_COM(-1))	-0.065081	0.023086	-2.819070	0.0049
C	-0.385177	2.100468	-0.183377	0.8545
TREND	-0.030437	0.035418	-0.859378	0.3903
INCPTBREAK	3.067516	2.137095	1.435367	0.1514
TRENDBREAK	0.030915	0.035423	0.872740	0.3829
BREAKDUM	-139.9782	10.54212	-13.27799	0.0000

R-squared	0.100580	Mean dependent var	-0.223131
Adjusted R-squared	0.097924	S.D. dependent var	11.08567
S.E. of regression	10.52891	Akaike info criterion	7.549653
Sum squared resid	187682.6	Schwarz criterion	7.568856
Log likelihood	-6407.430	Hannan-Quinn criter.	7.556762
F-statistic	37.86489	Durbin-Watson stat	1.969660
Prob(F-statistic)	0.000000		

Q. Breakpoint Unit Root Test – D(USGG6M)

Null Hypothesis: D(USGG6M) has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 10/15/2013
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-41.51954	< 0.01
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(USGG6M)
Method: Least Squares
Date: 09/19/17 Time: 16:31
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(USGG6M(-1))	-0.001164	0.024113	-0.048267	0.9615
C	-0.000299	0.001408	-0.212624	0.8316
TREND	1.10E-06	8.53E-06	0.128414	0.8978
INCPTBREAK	-0.000527	0.001536	-0.343057	0.7316
TRENDBREAK	6.09E-07	8.57E-06	0.071072	0.9433
BREAKDUM	0.061412	0.011869	5.174134	0.0000

R-squared	0.018527	Mean dependent var	0.000588
Adjusted R-squared	0.015628	S.D. dependent var	0.011946
S.E. of regression	0.011852	Akaike info criterion	-6.029060
Sum squared resid	0.237829	Schwarz criterion	-6.009856
Log likelihood	5127.686	Hannan-Quinn criter.	-6.021950
F-statistic	6.391626	Durbin-Watson stat	2.004687
Prob(F-statistic)	0.000007		

R. Breakpoint Unit Root Test – D(USGG10YR)

Null Hypothesis: D(USGG10YR) has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 7/05/2013
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-43.36572	< 0.01
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(USGG10YR)
Method: Least Squares
Date: 09/19/17 Time: 16:31
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(USGG10YR(-1))	-0.040002	0.023982	-1.667986	0.0955
C	-0.003239	0.005669	-0.571273	0.5679
TREND	7.65E-05	5.35E-05	1.431748	0.1524
INCPTBREAK	-0.011935	0.005961	-2.002027	0.0454
TRENDBREAK	-7.55E-05	5.35E-05	-1.411440	0.1583
BREAKDUM	0.237066	0.038239	6.199548	0.0000

R-squared	0.025800	Mean dependent var	0.000188
Adjusted R-squared	0.022923	S.D. dependent var	0.038634
S.E. of regression	0.038189	Akaike info criterion	-3.689024
Sum squared resid	2.469045	Schwarz criterion	-3.669820
Log likelihood	3139.826	Hannan-Quinn criter.	-3.681914
F-statistic	8.967365	Durbin-Watson stat	2.006618
Prob(F-statistic)	0.000000		

S. Breakpoint Unit Root Test – D(SPX:IND)

Null Hypothesis: D(SPX_IND) has a unit root
Trend Specification: Trend and intercept
Break Specification: Trend and intercept
Break Type: Innovational outlier

Break Date: 8/21/2015
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=24)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-43.57814	< 0.01
Test critical values:	1% level	-5.719131	
	5% level	-5.175710	
	10% level	-4.893950	

*Vogelsang (1993) asymptotic one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SPX_IND)
Method: Least Squares
Date: 09/19/17 Time: 16:32
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(SPX_IND(-1))	-0.050662	0.024110	-2.101285	0.0358
C	1.357901	0.802027	1.693086	0.0906
TREND	-0.001511	0.001445	-1.045865	0.2958
INCPTBREAK	0.462646	1.216290	0.380375	0.7037
TRENDBREAK	0.002320	0.002586	0.897378	0.3696
BREAKDUM	-67.43346	12.48367	-5.401734	0.0000

R-squared	0.019324	Mean dependent var	0.577881
Adjusted R-squared	0.016427	S.D. dependent var	12.50825
S.E. of regression	12.40509	Akaike info criterion	7.877615
Sum squared resid	260529.3	Schwarz criterion	7.896819
Log likelihood	-6686.034	Hannan-Quinn criter.	7.884725
F-statistic	6.671927	Durbin-Watson stat	2.004932
Prob(F-statistic)	0.000004		

T. VAR Lag Order Selection Criteria – XBTUSD and CL1:COM

VAR Lag Order Selection Criteria
Endogenous variables: XBTUSD CL1_COM
Exogenous variables: C
Date: 09/20/17 Time: 10:34
Sample: 1/01/2013 8/28/2017
Included observations: 1693

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-21205.02	NA	2.60e+08	25.05259	25.05901	25.05497
1	-11202.54	19969.51	1930.019	13.24104	13.26030*	13.24817
2	-11193.56	17.91511	1918.689*	13.23515*	13.26725	13.24704*
3	-11190.50	6.089218	1920.827	13.23627	13.28120	13.25290
4	-11188.42	4.126594	1925.202	13.23854	13.29632	13.25993
5	-11185.93	4.952793	1928.634	13.24032	13.31094	13.26647
6	-11178.80	14.16156	1921.503	13.23662	13.32007	13.26752
7	-11177.73	2.115731	1928.172	13.24008	13.33638	13.27574
8	-11172.92	9.515932*	1926.338	13.23913	13.34826	13.27954

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

U. VAR Lag Order Selection Criteria – XBTUSD and GC1:COM

VAR Lag Order Selection Criteria
Endogenous variables: XBTUSD GC1 COM
Exogenous variables: C
Date: 09/20/17 Time: 10:36
Sample: 1/01/2013 8/28/2017
Included observations: 1693

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-23831.67	NA	5.79e+09	28.15554	28.16196	28.15792
1	-15278.97	17075.08	238211.6	18.05667	18.07593*	18.06380
2	-15270.68	16.53067	237007.4*	18.05160*	18.08370	18.06349*
3	-15267.84	5.652583	237333.0	18.05297	18.09791	18.06961
4	-15264.51	6.632927	237519.8	18.05376	18.11154	18.07515
5	-15263.81	1.395078	238447.0	18.05766	18.12827	18.08380
6	-15256.56	14.37705*	237535.0	18.05382	18.13728	18.08473
7	-15255.56	1.991107	238377.1	18.05736	18.15366	18.09302
8	-15252.77	5.512934	238719.8	18.05880	18.16793	18.09921

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

V. VAR Lag Order Selection Criteria – XBTUSD and USGG6M

VAR Lag Order Selection Criteria
Endogenous variables: XBTUSD USGG6M
Exogenous variables: C
Date: 09/20/17 Time: 10:38
Sample: 1/01/2013 8/28/2017
Included observations: 1693

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-12921.08	NA	14628.52	15.26648	15.27290	15.26886
1	-3718.343	18372.85	0.279136	4.399697	4.418956*	4.406828*
2	-3713.146	10.36456	0.278741	4.398282	4.430380	4.410167
3	-3710.513	5.243266	0.279192	4.399897	4.444835	4.416537
4	-3707.726	5.544513	0.279592	4.401330	4.459107	4.422724
5	-3707.089	1.266468	0.280705	4.405303	4.475919	4.431450
6	-3700.482	13.11196	0.279842	4.402223	4.485679	4.433125
7	-3691.879	17.05306	0.278325	4.396786	4.493081	4.432442
8	-3675.611	32.20920*	0.274320*	4.382293*	4.491428	4.422704

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

W. VAR Lag Order Selection Criteria – XBTUSD and USGG10YR

VAR Lag Order Selection Criteria
Endogenous variables: XBTUSD USGG10YR
Exogenous variables: C
Date: 09/20/17 Time: 10:44
Sample: 1/01/2013 8/28/2017
Included observations: 1693

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-14057.25	NA	55989.95	16.60868	16.61510	16.61106
1	-5703.598	16677.70	2.913027	6.744947	6.764206*	6.752078*
2	-5697.549	12.06060	2.905987*	6.742527*	6.774626	6.754413
3	-5695.364	4.351825	2.912225	6.744671	6.789609	6.761311
4	-5694.092	2.531888	2.921623	6.747893	6.805670	6.769287
5	-5691.868	4.417736	2.927762	6.749992	6.820609	6.776140
6	-5685.565	12.50898	2.919809	6.747272	6.830728	6.778174
7	-5684.697	1.720827	2.930633	6.750972	6.847267	6.786628
8	-5679.154	10.97487*	2.925296	6.749149	6.858283	6.789559

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

X. VAR Lag Order Selection Criteria – XBTUSD and SPX:IND

VAR Lag Order Selection Criteria
Endogenous variables: XBTUSD SPX_IND
Exogenous variables: C
Date: 09/20/17 Time: 10:46
Sample: 1/01/2013 8/28/2017
Included observations: 1693

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-24559.13	NA	1.37e+10	29.01492	29.02134	29.01730
1	-15492.52	18101.08	306567.2	18.30895	18.32821*	18.31608*
2	-15486.41	12.19136	305802.7*	18.30645*	18.33855	18.31833
3	-15483.58	5.641408	306224.8	18.30783	18.35277	18.32447
4	-15479.26	8.584514	306110.8	18.30746	18.36523	18.32885
5	-15477.57	3.358585	306947.3	18.31019	18.38080	18.33633
6	-15471.37	12.30573*	306150.5	18.30759	18.39104	18.33849
7	-15470.24	2.251040	307188.3	18.31097	18.40726	18.34663
8	-15466.53	7.337223	307295.2	18.31132	18.42045	18.35173

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion

Y. Trend Assumption – XBTUSD and CL1:COM

Date: 09/20/17 Time: 16:32
Sample: 1/01/2013 8/28/2017
Included observations: 1699
Series: XBTUSD CL1_COM
Lags interval: 1 to 1

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	1	1	1	0	0
Max-Eig	1	1	1	1	0

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	-11242.88	-11242.88	-11239.16	-11239.16	-11234.09
1	-11228.38	-11228.24	-11227.64	-11227.55	-11227.50
2	-11227.47	-11227.26	-11227.26	-11226.49	-11226.49
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	13.23942	13.23942	13.23739	13.23739	13.23377
1	13.22705*	13.22806	13.22854	13.22961	13.23072
2	13.23069	13.23279	13.23279	13.23424	13.23424
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	13.25222*	13.25222*	13.25659	13.25659	13.25938
1	13.25266	13.25687	13.26054	13.26481	13.26913
2	13.26910	13.27760	13.27760	13.28545	13.28545

Z. Trend Assumption – XBTUSD and GC1:COM

Date: 09/20/17 Time: 16:37
Sample: 1/01/2013 8/28/2017
Included observations: 1699
Series: XBTUSD GC1 COM
Lags interval: 1 to 1

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	1	2	2	2	2
Max-Eig	1	2	2	2	0

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	-15344.72	-15344.72	-15341.13	-15341.13	-15334.58
1	-15329.95	-15329.89	-15328.81	-15328.71	-15327.15
2	-15328.28	-15322.94	-15322.94	-15322.41	-15322.41
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	18.06795	18.06795	18.06607	18.06607	18.06071
1	18.05527	18.05638	18.05628	18.05734	18.05668
2	18.05801	18.05408	18.05408*	18.05581	18.05581
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	18.08075*	18.08075*	18.08528	18.08528	18.08632
1	18.08087	18.08518	18.08829	18.09254	18.09509
2	18.09642	18.09888	18.09888	18.10702	18.10702

AA. Trend Assumption – XBTUSD and USGG6M

Date: 09/20/17 Time: 16:37
Sample: 1/01/2013 8/28/2017
Included observations: 1699
Series: XBTUSD USGG6M
Lags interval: 1 to 1

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	1	1	1	1	1
Max-Eig	1	1	1	1	1

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	-3739.476	-3739.476	-3734.670	-3734.670	-3727.578
1	-3723.182	-3722.189	-3721.387	-3720.697	-3717.804
2	-3722.974	-3721.144	-3721.144	-3717.760	-3717.760
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	4.406682	4.406682	4.403378	4.403378	4.397385
1	4.392209	4.392218	4.392450	4.392816	4.390587*
2	4.396673	4.396873	4.396873	4.395245	4.395245
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	4.419484	4.419484	4.422582	4.422582	4.422989
1	4.417814*	4.421023	4.424456	4.428023	4.428994
2	4.435080	4.441681	4.441681	4.446454	4.446454

AB. Trend Assumption – XBTUSD and USGG10YR

Date: 09/20/17 Time: 16:38
Sample: 1/01/2013 8/28/2017
Included observations: 1699
Series: XBTUSD USGG10YR
Lags interval: 1 to 1

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	1	1	2	1	2
Max-Eig	1	1	2	1	0

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	-5731.341	-5731.341	-5728.226	-5728.226	-5723.058
1	-5716.660	-5716.640	-5716.535	-5716.464	-5716.464
2	-5716.660	-5714.038	-5714.038	-5713.039	-5713.039
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	6.751431	6.751431	6.750119	6.750119	6.746389
1	6.738858*	6.740012	6.741065	6.742159	6.743336
2	6.743567	6.742834	6.742834	6.744013	6.744013
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	6.764234*	6.764234*	6.769323	6.769323	6.771994
1	6.764463	6.768817	6.773071	6.777365	6.781743
2	6.781974	6.787642	6.787642	6.795222	6.795222

AC. Trend Assumption – XBTUSD and SPX:IND

Date: 09/20/17 Time: 16:38
Sample: 1/01/2013 8/28/2017
Included observations: 1699
Series: XBTUSD SPX IND
Lags interval: 1 to 1

Selected (0.05 level*) Number of Cointegrating Relations by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	1	1	1	1	2
Max-Eig	1	1	1	1	0

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	-15553.63	-15553.63	-15548.71	-15548.71	-15543.60
1	-15538.87	-15538.85	-15537.06	-15537.05	-15537.04
2	-15537.56	-15535.71	-15535.71	-15532.00	-15532.00
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	18.31386	18.31386	18.31043	18.31043	18.30677
1	18.30120*	18.30236	18.30143	18.30258	18.30376
2	18.30437	18.30454	18.30454	18.30253	18.30253
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	18.32667*	18.32667*	18.32963	18.32963	18.33238
1	18.32681	18.33116	18.33344	18.33779	18.34216
2	18.34277	18.34935	18.34935	18.35374	18.35374

AD. Johansen Cointegration Test – XBTUSD and CL1:COM

Date: 09/20/17 Time: 16:35
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Trend assumption: No deterministic trend
Series: XBTUSD CL1_COM
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.016929	30.82641	12.32090	0.0000
At most 1	0.001069	1.817253	4.129906	0.2090

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.016929	29.00915	11.22480	0.0000
At most 1	0.001069	1.817253	4.129906	0.2090

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

AE. Johansen Cointegration Test – XBTUSD and GC1:COM

Date: 09/20/17 Time: 16:37
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Trend assumption: No deterministic trend
Series: XBTUSD GC1_COM
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.017235	32.87588	12.32090	0.0000
At most 1	0.001963	3.337687	4.129906	0.0803

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.017235	29.53819	11.22480	0.0000
At most 1	0.001963	3.337687	4.129906	0.0803

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

AF. Johansen Cointegration Test – XBTUSD and USGG6M

Date: 09/20/17 Time: 16:37
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Trend assumption: No deterministic trend
Series: XBTUSD USGG6M
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.018998	33.00490	12.32090	0.0000
At most 1	0.000245	0.416113	4.129906	0.5823

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.018998	32.58879	11.22480	0.0000
At most 1	0.000245	0.416113	4.129906	0.5823

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

AG. Johansen Cointegration Test – XBTUSD and USGG10YR

Date: 09/20/17 Time: 16:38
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Trend assumption: No deterministic trend
Series: XBTUSD USGG10YR
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.017133	29.36205	12.32090	0.0000
At most 1	7.61E-08	0.000129	4.129906	0.9913

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.017133	29.36192	11.22480	0.0000
At most 1	7.61E-08	0.000129	4.129906	0.9913

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

AH. Johansen Cointegration Test – XBTUSD and SPX:IND

Date: 09/20/17 Time: 16:39
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Trend assumption: No deterministic trend
Series: XBTUSD SPX_IND
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.017220	32.13529	12.32090	0.0000
At most 1	0.001543	2.623949	4.129906	0.1244

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.017220	29.51135	11.22480	0.0000
At most 1	0.001543	2.623949	4.129906	0.1244

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

AI. Vector Error Correction Estimates – XBTUSD and CL1:COM

Vector Error Correction Estimates
Date: 09/20/17 Time: 10:51
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	
XBTUSD(-1)	1.000000	
CL1 COM(-1)	-2.922598	
	(1.97567)	
	[-1.47929]	
Error Correction:	D(XBTUSD)	D(CL1_COM)
CointEq1	0.007452	-1.34E-05
	(0.00138)	(3.1E-05)
	[5.39987]	[-0.43131]
D(XBTUSD(-1))	-0.071930	-0.000331
	(0.02444)	(0.00055)
	[-2.94299]	[-0.60138]
D(CL1_COM(-1))	0.715910	-0.070212
	(1.07509)	(0.02424)
	[0.66591]	[-2.89659]
R-squared	0.016294	0.004452
Adj. R-squared	0.015134	0.003278
Sum sq. resids	3274543.	1664.584
S.E. equation	43.94024	0.990695
F-statistic	14.04647	3.792301
Log likelihood	-8836.304	-2393.392
Akaike AIC	10.40530	2.820944
Schwarz SC	10.41490	2.830545
Mean dependent	2.541798	-0.027398
S.D. dependent	44.27656	0.992323
Determinant resid covariance (dof adj.)		1892.046
Determinant resid covariance		1885.370
Log likelihood		-11228.38
Akaike information criterion		13.22705
Schwarz criterion		13.25266

AJ. Vector Error Correction Estimates – XBTUSD and GC1:COM

Vector Error Correction Estimates
Date: 09/20/17 Time: 15:13
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	
XBTUSD(-1)	1.000000	
GC1 COM(-1)	-0.219458	
	(0.10350)	
	[-2.12046]	
Error Correction:	D(XBTUSD)	D(GC1_COM)
CointEq1	0.008025	0.000336
	(0.00149)	(0.00037)
	[5.39472]	[0.89622]
D(XBTUSD(-1))	-0.073039	0.004569
	(0.02445)	(0.00616)
	[-2.98769]	[0.74204]
D(GC1 COM(-1))	-0.009395	-0.063084
	(0.09624)	(0.02424)
	[-0.09762]	[-2.60277]
R-squared	0.016039	0.004448
Adj. R-squared	0.014879	0.003274
Sum sq. resids	3275392.	207742.5
S.E. equation	43.94593	11.06751
F-statistic	13.82304	3.788995
Log likelihood	-8836.524	-6493.694
Akaike AIC	10.40556	7.647668
Schwarz SC	10.41516	7.657270
Mean dependent	2.541798	-0.223131
S.D. dependent	44.27656	11.08567
Determinant resid covariance (dof adj.)		236483.0
Determinant resid covariance		235648.6
Log likelihood		-15329.95
Akaike information criterion		18.05527
Schwarz criterion		18.08087

AK. Vector Error Correction Estimates – XBTUSD and USGG6M

Vector Error Correction Estimates
Date: 09/20/17 Time: 15:14
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	
XBTUSD(-1)	1.000000	
USGG6M(-1)	3802.169	
	(998.537)	
	[3.80774]	
Error Correction:	D(XBTUSD)	D(USGG6M)
CointEq1	0.002365	2.49E-07
	(0.00044)	(1.2E-07)
	[5.36094]	[2.07259]
D(XBTUSD(-1))	-0.068004	7.06E-06
	(0.02428)	(6.6E-06)
	[-2.80062]	[1.06870]
D(USGG6M(-1))	64.24729	0.000268
	(89.3821)	(0.02430)
	[0.71879]	[0.01103]
R-squared	0.016534	0.001237
Adj. R-squared	0.015374	0.000059
Sum sq. resids	3273745.	0.242018
S.E. equation	43.93488	0.011946
F-statistic	14.25656	1.050459
Log likelihood	-8836.097	5112.852
Akaike AIC	10.40506	-6.015128
Schwarz SC	10.41466	-6.005527
Mean dependent	2.541798	0.000588
S.D. dependent	44.27656	0.011946
Determinant resid covariance (dof adj.)		0.275428
Determinant resid covariance		0.274457
Log likelihood		-3723.182
Akaike information criterion		4.392209
Schwarz criterion		4.417814

AL. Vector Error Correction Estimates – XBTUSD and USGG10YR

Vector Error Correction Estimates
Date: 09/20/17 Time: 15:14
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	
XBTUSD(-1)	1.000000	
USGG10YR(-1)	-113.9649	
	(59.0034)	
	[-1.93150]	
Error Correction:	D(XBTUSD)	D(USGG10YR)
CointEq1	0.008021	-4.71E-07
	(0.00148)	(1.3E-06)
	[5.43182]	[-0.36268]
D(XBTUSD(-1))	-0.072824	1.01E-05
	(0.02444)	(2.1E-05)
	[-2.97926]	[0.47073]
D(USGG10YR(-1))	22.83660	-0.037688
	(27.5709)	(0.02424)
	[0.82829]	[-1.55478]
R-squared	0.016613	0.001590
Adj. R-squared	0.015453	0.000412
Sum sq. resids	3273482.	2.530405
S.E. equation	43.93312	0.038626
F-statistic	14.32585	1.350061
Log likelihood	-8836.029	3118.972
Akaike AIC	10.40498	-3.668007
Schwarz SC	10.41458	-3.658405
Mean dependent	2.541798	0.000188
S.D. dependent	44.27656	0.038634
Determinant resid covariance (dof adj.)		2.878362
Determinant resid covariance		2.868206
Log likelihood		-5716.660
Akaike information criterion		6.738858
Schwarz criterion		6.764463

AM. Vector Error Correction Estimates – XBTUSD and SPX:IND

Vector Error Correction Estimates
Date: 09/20/17 Time: 15:14
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	
XBTUSD(-1)	1.000000	
SPX_IND(-1)	-0.111833	
	(0.06618)	
	[-1.68971]	
Error Correction:	D(XBTUSD)	D(SPX_IND)
CointEq1	0.007942	0.000355
	(0.00147)	(0.00042)
	[5.38737]	[0.84517]
D(XBTUSD(-1))	-0.073113	-0.000599
	(0.02443)	(0.00696)
	[-2.99226]	[-0.08603]
D(SPX_IND(-1))	0.087471	-0.036732
	(0.08495)	(0.02421)
	[1.02973]	[-1.51755]
R-squared	0.016711	-0.000379
Adj. R-squared	0.015551	-0.001559
Sum sq. resids	3273156.	265763.6
S.E. equation	43.93093	12.51800
F-statistic	14.41162	-0.321332
Log likelihood	-8835.944	-6702.932
Akaike AIC	10.40488	7.893976
Schwarz SC	10.41448	7.903578
Mean dependent	2.541798	0.577881
S.D. dependent	44.27656	12.50825
Determinant resid covariance (dof adj.)		302418.3
Determinant resid covariance		301351.2
Log likelihood		-15538.87
Akaike information criterion		18.30120
Schwarz criterion		18.32681

AN. Daily prices of Exchange Rate XBT/USD and Crude Price

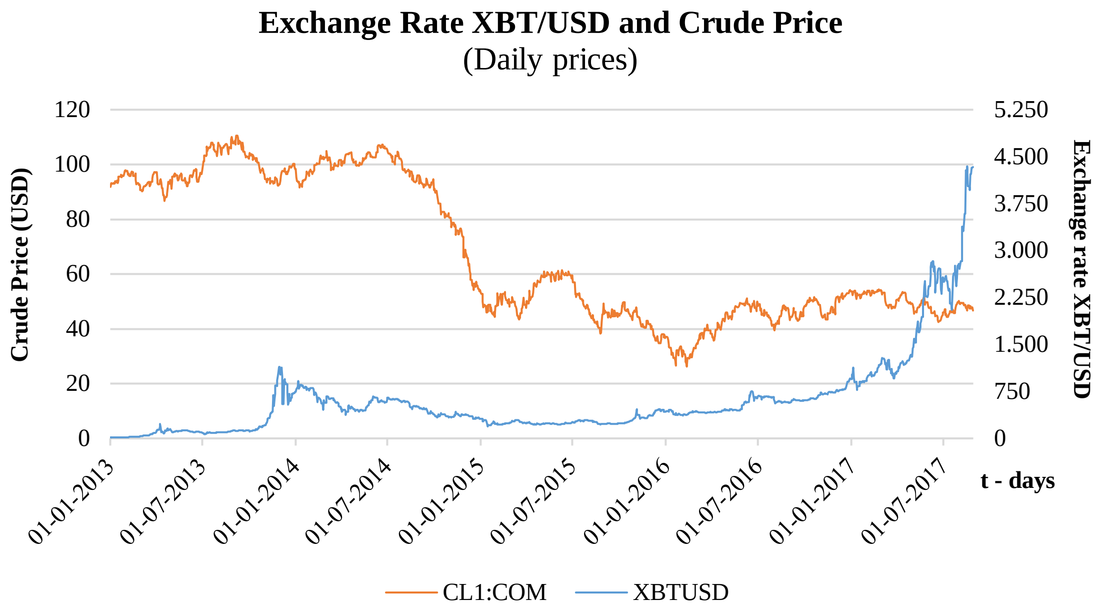


Chart 13 – Daily prices of exchange rate XBT/USD and Crude price, between 01/01/2013 and 28/08/2017 [62].

AO. Daily prices of Exchange Rate XBT/USD and Gold Price

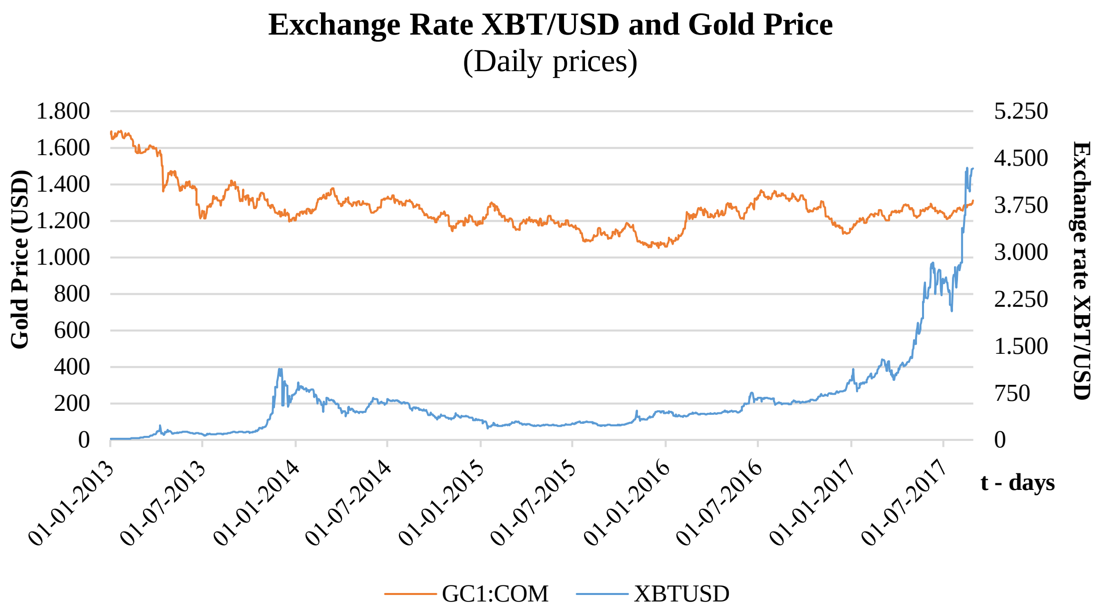


Chart 14 – Daily prices of exchange rate XBT/USD and Gold price, between 01/01/2013 and 28/08/2017 [62].

AP. Daily prices of Exchange Rate XBT/USD and 6-month U.S. Treasury Yields

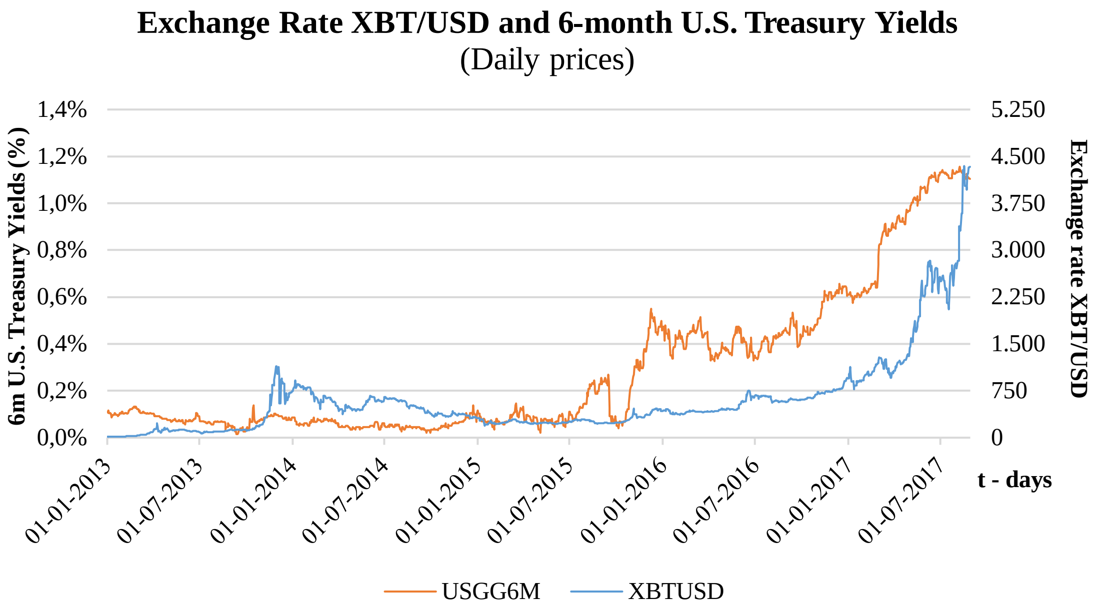


Chart 15 – Daily prices of exchange rate XBT/USD and 6-month U.S. Treasury Yields, between 01/01/2013 and 28/08/2017 [62].

AQ. Daily prices of Exchange Rate XBT/USD and 10-year U.S. Treasury Yields

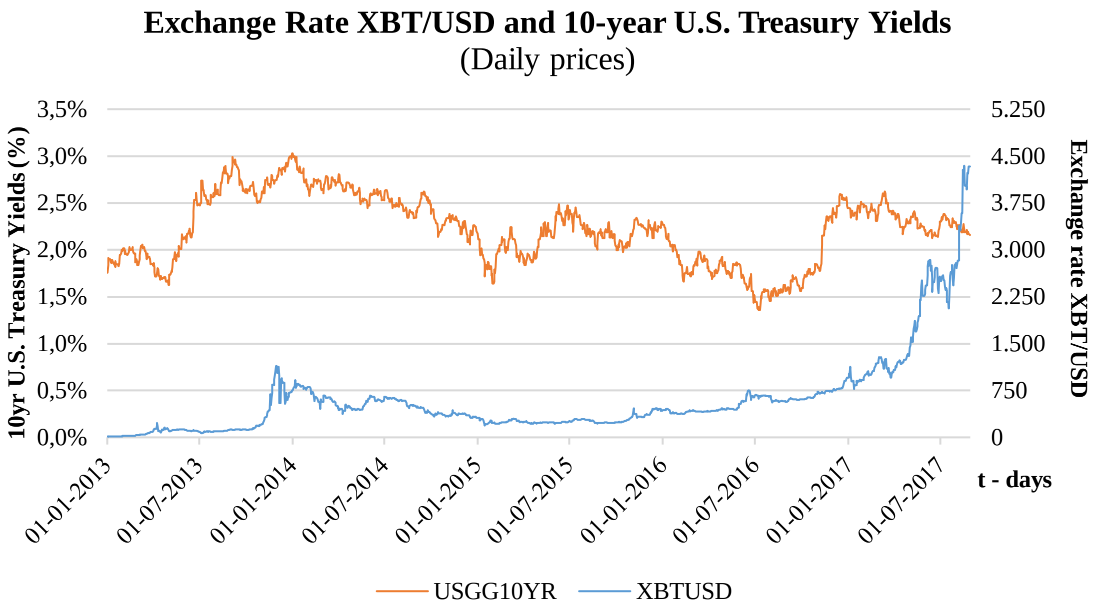


Chart 16 – Daily prices of exchange rate XBT/USD and 10-year U.S. Treasury Yields, between 01/01/2013 and 28/08/2017 [62].

AR. Daily prices of Exchange Rate XBT/USD and the S&P 500 Index

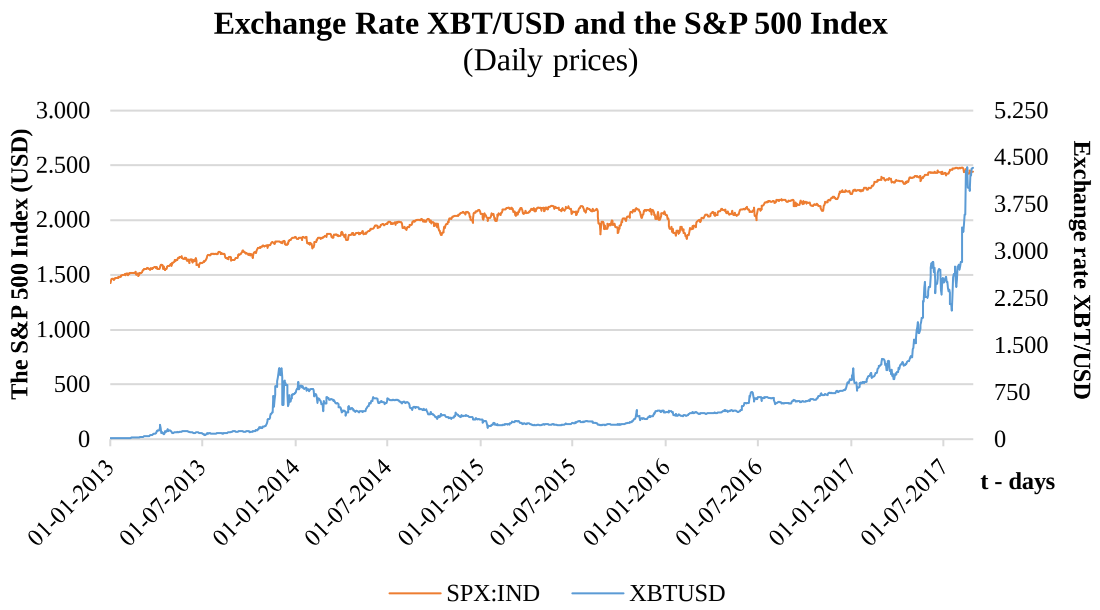


Chart 17 – Daily prices of exchange rate XBT/USD and the S&P 500 Index, between 01/01/2013 and 28/08/2017 [62].

AS. Weak Exogeneity Tests

Vector Error Correction Estimates
Date: 09/24/17 Time: 11:51
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
A(2,1)=0
Convergence achieved after 1 iterations.
Not all cointegrating vectors are identified
LR test for binding restrictions (rank = 1):

Chi-square(1)	0.714222	
Probability	0.398046	
Cointegrating Eq:	CointEq1	
XBTUSD(-1)	-0.001360	
GC1_COM(-1)	0.000250	
Error Correction:	D(XBTUSD)	D(GC1_COM)
CointEq1	-5.734657	0.000000
	(1.06431)	(0.00000)
	[-5.38814]	[NA]
D(XBTUSD(-1))	-0.072887	0.004687
	(0.02444)	(0.00616)
	[-2.98225]	[0.76146]
D(GC1_COM(-1))	-0.008561	-0.063020
	(0.09624)	(0.02424)
	[-0.08896]	[-2.60003]
R-squared	0.016080	0.004348
Adj. R-squared	0.014920	0.003173
Sum sq. resids	3275255.	207763.6
S.E. equation	43.94502	11.06807
F-statistic	13.85893	3.702784
Log likelihood	-8836.489	-6493.780
Akaike AIC	10.40552	7.647769
Schwarz SC	10.41512	7.657371
Mean dependent	2.541798	-0.223131
S.D. dependent	44.27656	11.08567
Determinant resid covariance (dof adj.)		236494.3
Determinant resid covariance		235659.9
Log likelihood		-15330.31
Akaike information criterion		18.05569
Schwarz criterion		18.08129
Number of coefficients		8

Vector Error Correction Estimates
Date: 09/24/17 Time: 11:55
Sample (adjusted): 1/03/2013 8/28/2017
Included observations: 1699 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
A(2,1)=0
Convergence achieved after 2 iterations.
Not all cointegrating vectors are identified
LR test for binding restrictions (rank = 1):

Chi-square(1)	4.243358	
Probability	0.039404	
Cointegrating Eq:	CointEq1	
XBTUSD(-1)	-0.000526	
USGG6M(-1)	-1.349641	
Error Correction:	D(XBTUSD)	D(USGG6M)
CointEq1	-5.695038	0.000000
	(1.06485)	(0.00000)
	[-5.34818]	[NA]
D(XBTUSD(-1))	-0.068634	7.02E-06
	(0.02430)	(6.6E-06)
	[-2.82472]	[1.06226]
D(USGG6M(-1))	65.75116	0.000477
	(89.3605)	(0.02430)
	[0.73580]	[0.01962]
R-squared	0.016564	0.001169
Adj. R-squared	0.015404	-0.000009
Sum sq. resids	3273645.	0.242035
S.E. equation	43.93421	0.011946
F-statistic	14.28294	0.992425
Log likelihood	-8836.071	5112.794
Akaike AIC	10.40503	-6.015060
Schwarz SC	10.41463	-6.005458
Mean dependent	2.541798	0.000588
S.D. dependent	44.27656	0.011946
Determinant resid covariance (dof adj.)		0.275438
Determinant resid covariance		0.274467
Log likelihood		-3725.303
Akaike information criterion		4.394707
Schwarz criterion		4.420312
Number of coefficients		8

AT. Granger Causality Test

Pairwise Granger Causality Tests
Date: 09/24/17 Time: 11:58
Sample: 1/01/2013 8/28/2017
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
GC1_COM does not Granger Cause XBTUSD	1700	0.24403	0.6214
XBTUSD does not Granger Cause GC1_COM		0.80933	0.3684