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Thesis

"A Granger Causality analysis between the bitcoin and the stock market returns of countries related to money laundering"

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Contents

Abstract.

The purpose of this paper is to investigate the causal relationship between various stock markets and the bitcoin. The selection of the stock market under scrutiny is not random. Many media outlets, researchers, international and public organizations, accuse the Bitcoin, and other cryptocurrencies being used for money laundering and illicit activities. This paper examines the existence of Granger causality-in-mean and in-variance between the bitcoin and stock indices of countries, that are traditionally associated with illegal activities. The methodology was based on the test from (Cheung, 1996) and Ng, which allows for the analyses of Granger causality in-mean and in-variance. The results suggest that there is in fact a relationship from bitcoin to some of the stock indices under inspection, and the causality is uni-directional from bitcoin to the other stock indices. The empirical findings show that Bitcoin is the Granger cause in-mean to CSE(Cyprus) , FTSE100(U.K.) , LuxX (Luxembourg) and China's SHCOMP. Although rare there are cases of volatility spillover from Bitcoin to some stock indices. The test conducted reveal that there is a Granger causality in-variance from Bitcoin to German DAX and FTSE100.

1.Introduction.

Since societies transitioned from a barter economy to using a money as a medium of exchange, individuals have tried to devise systems that allow for rational ways to exchange value. In order to help make goods and services commensurable the Greek philosopher Aristotle came up with four criteria that help to dictate what is considered to be ‘good money’ (Lee, 2009)

1. It must be durable

2. It must be portable

3. It must be divisible

4. It must have intrinsic value

Originally the preferred medium of exchange was gold as it was able to fulfill all four of these criteria. As economies grew and the demand for a medium of exchange increased, governments were forced to create a more accessible medium of exchange that they could control and regulate. This was the birth of fiat currency. Coming from the Latin and is often translated as the decree "it shall be" or "let it be done." this medium of exchange has been adopted worldwide. So, fiat money is currency that a government has declared to be legal tender but is not backed by a physical commodity. The value of fiat money is derived from the relationship between supply and demand rather than the value of the material that the money is made of.

However, it has come with its own set of issues.
Price Instability — Fiat currencies require relatively insignificant physical, economic inputs to be produced. The lack of production requirements means that the value of fiat currencies holds no direct relationship to the economic reality of the physical world.
Currency Debasement — Fiat currencies issued by governments or central banks represent intangible concepts of value like “full faith and credit.” However, the currency itself holds no enduring value. Specifically, fiat currencies have a built-in inclination to decrease in purchasing power over time as more currency is produced. This inevitable depreciation is even more prevalent in fractional reserve and debt-based fiat currencies.

“Paper money eventually returns to its intrinsic value — zero.”

-Voltaire

"The one thing that's missing but that will soon be developed is a reliable e-cash, a method whereby on the internet you can transfer funds from A to B without A knowing B or B knowing A, the way in which I can take a twenty-dollar bill and hand it over to you and there is no record of where it came from and you may get that without knowing who I am."

- Milton Friedman, interviewed in 1999 (Friedman, 2012)

1.1 ENTER BITCOIN.

In October 2008 a hacker (or group of hackers) name Satoshi Nakamoto publics a white paper laying out the found work of a new payment system, the paper name was *"Bitcoin: A Peer-to-Peer Electronic Cash System"* (Nakamoto, 2008) and was about to change the world.

To understand the bitcoin market, it helps to have a good understanding of the chain-block system and what makes these transactions so unique. Roughly speaking Bitcoin is a new form of currency that doesn't need a bank or government agency or middlemen to operate. The people are using it just carry out transactions among themselves in what is called a decentralized network or block-chain. Essentially, blockchain is a suit of distributed ledger technology that can be programed to record financial transaction. Unlike the age-old ledger method, originally a book, blockchain was designed to be decentralized and distributed in a large network of computers reducing the ability for data tempering.

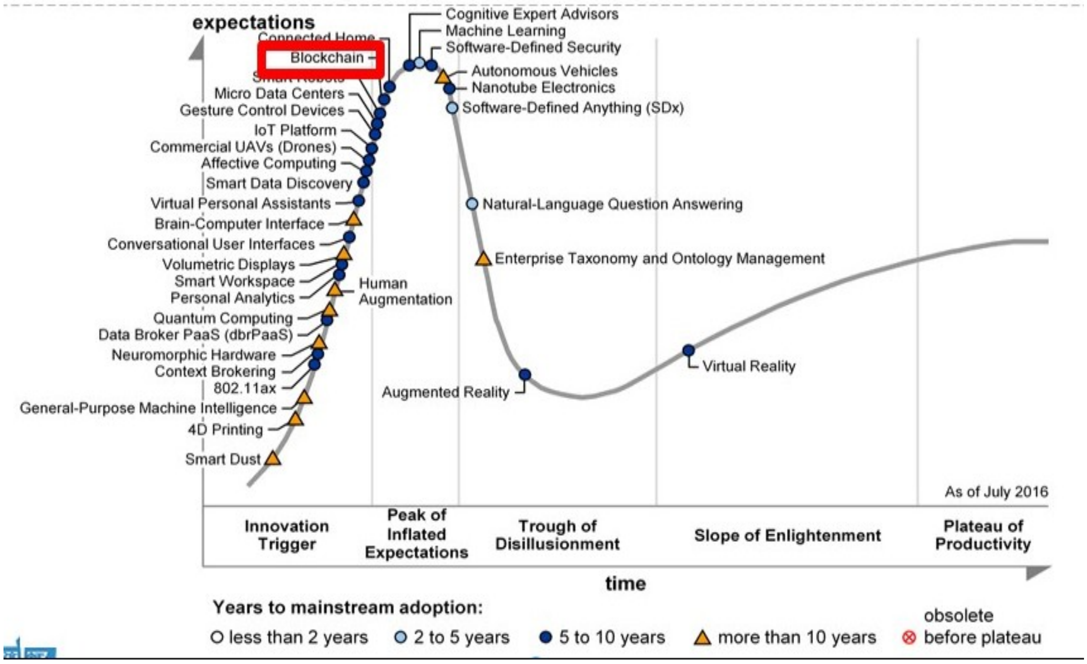
The backbone underlying this technology is not a bank that verifies transactions, but a clever system of trusted verifications based of some mathematics born from cryptography such as digital signatures and cryptographic hash function and two unique codes , the private key and public key given to each user. The combination of all 4 of them (digital signatures, hash function, private and public key) assign to each transaction, an inimitable signature making each transaction unique and more to the point of this paper *anonymous*.

There are 2^{256} combination, since the signature consists of only 1s and 0s and has 256 bytes. In perspective, a large PC would need approximately 0.6 billion years to crack a signature[1].

Unlike fiat currency, which has been declared to be legal tender by a government even though it has no intrinsic value and is not backed by reserves, the Bitcoin scheme has no centralized issuing authority. The network is programmed to increase the money supply in a slowly increasing geometric series until the total number of

[1] Considering the revised Moore's Law, Bitcoins are safe for the next 60 years.

bitcoins reaches an upper limit of about 21 million BTC's. Bitcoins are awarded to Bitcoin "miners" for solving increasingly difficult proof-of-work problems which confirm transactions and prevent double-spending. The network currently requires over one million times more work for confirming a block and receiving an award (currently 50 BTC's) than when the first blocks were confirmed. To this day, the real identity of Satoshi is unknown. But whether is Elon Musk[2] or a group of hackers or as some claim a drug cartel [3] at this point is irrelevant to the impact it has in the financial markets. In fact the famous *Gartner Hype Cycle*, which tracks new technologies as they move toward broad adoption, has placed blockchain in its "peak of inflated expectations" phase since 2016 and sits today on the edge of the cycle's "trough of disillusionment" phase, when interest wanes, implementations fail, and investment continues only if products improve enough to satisfy early adopters.



In the same year (Vigna michael, 2016) in their paper stated that a company may implement a better payment system benefiting from a wide range of clients pre-established network and better mobile technologies. Three years later with the rise of 5G networks the colossal social platform FACEBOOK, despite the criticism by central banks and financial institutions alike , decides to create LYBRA, a cryptocurrency based on the blockchain technology.[4] It's worth to mention that In America Facebook's Messenger app already allows peer-to-peer transfers, but only in existing currencies and between accounts linked to bank-issued payment cards. But the new blockchain-based money would be a currency on its own.

1.2 Advantages/Disadvantages

In this section I will try to emphasize the main advantages and disadvantages of bitcoin and in general the block-chain ecosystem. It's a product of academic research

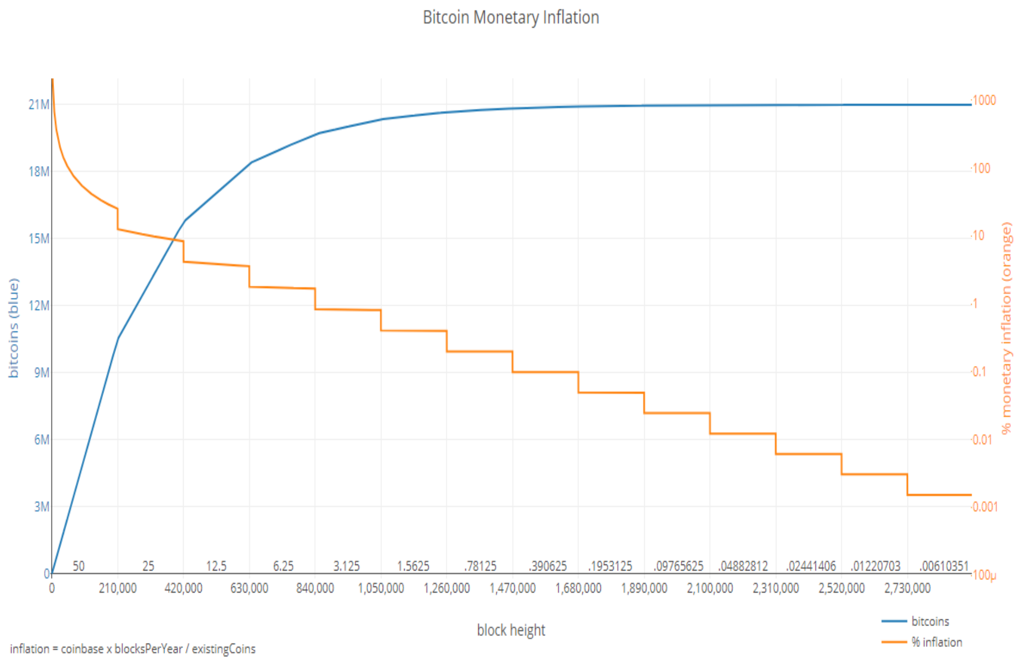
[2] https://medium.com/hackernoon/elon-musk-probably-invented-bitcoin-9d6c7b7f9c3b
[3] https://www.wired.com/story/was-bitcoin-created-by-this-international-drug-dealer-maybe/
[4] https://www.economist.com/finance-and-economics/2019/05/30/facebooks-planned-new-currency-may-be-based-on-a-blockchain

papers which in addition with those in literature review help us have a better understanding of the dangers that looms over cryptocurrencies and the potential they have. This consensus to some of those topics is still debatable between researchers, political figures and media alike.

Advantages

- *Lower transaction fees:*
  It is estimated that a bitcoin transaction costs 5 times lower than those that are made with credit cards[5]. And business that accept bitcoin saves up to 5% of the transaction cost than those who don't.[6] Although (Franco, 2014) these fees could go much higher if bitcoin transactions, include the cost of theft protection the compliance and regulatory cost that currently does not have.
- *Transaction speed.* Although banks can transfer money sometimes up to days a bitcoin transaction will need 10 to 30 minutes. This means that merchants can check whether the transaction was made thus eliminating the risk of charge-back. In a report (Anon., 2016) , it is estimated that every US$ of fraud cost the merchant 2,40$ in e-commerce industry and 71% of them was due to charge-back.
- *Transparency.* Blockchain -the spinal cord that bitcoin is based- is an essential continuous chain of blocks containing every history of transaction that have ever taken place. Due to the open nature of the bitcoin, every transaction that was ever made is logged and accessible by everyone, every time. [7]
- *Protection of privacy/Anonymity.* Despite the transparency of the system, there is no way of information disclosure between the users. Unlike credit cards there is no access to the information of the sender nor the recipient. (Tyler Moore, 2013)
- *Immune to Inflation.* The main advantage Bitcoin has against the traditional fiat currencies is that it is entirely decentralized and relies in the POW (proof of work) algorithm in order to produce money. Today arounds 18 million bitcoins have been mined through this procedure further leading us to 21 million which is the upper limit and it is estimated to be reached at 2140. Consequently, since there are no political figures and finance institution that can change that order the money supply is contained and there is no possibility for inflation. Fiat currencies, on the other hand, can have wildly fluctuating supplies that are impossible to predict. Since 2008, the average supply increase for the US Dollar has been 36% per year, and 129% per year for the embattled Argentine peso. In comparison, Bitcoin's annual supply increase is currently 3.7%, and will fall next year to 1.7%. Similar in spirit to hard commodities such as gold, Bitcoin is a popular alternative to those who fear that "quantitative easing" policies might trigger runaway inflation.

[5] https://www.investopedia.com/articles/company-insights/090916/how-square-cash-works-and-makes-money-sq.asp
[6] https://www.investopedia.com/articles/forex/042215/bitcoin-transactions-vs-credit-card-transactions.asp
[7] https://www.blockchain.com/el/charts/n-transactions



Disadvantages.

- *51% attack*
  This can be a major threat for bitcoin and other cryptocurrencies. It occurs when more than 50% of the network computing power is controlled by one group. If that happens then they can manipulate the network in such a way so false transactions are accepted as correct by the consensus. A study in the Cornel university (Malhotra, 2013) examines such an attack and highlights that it is feasible since mining pools in the network often controls 25-33% of the mining power. On the other hand, for a 51% attack to take place someone should have a $18,107,485,082 worth of hardware mining equipment and consumes at daily basis 93 million KWh[8].
- Double spending
  Another serious threat arises when in “fast payment mode”. This attack is most likely to occur with 'Fast payment' mode. In this attack, an attacker with coin A makes a transaction to the receiver and at the same time the transaction with the same coin is made to another address that might be in the control of attacker or it may be another receiving node. The Bitcoin cryptocurrency offered a solution by implementing a proof of work consensus. However, (Chiu, 2017) argues that the intensive work that is needed leads to a welfare loss of consumption.
- No-Legal Tender. Because of their lack of legal tender status very small group of merchants and institutions accept them as payment.
- *Losses due to fraudulent or non-genuine exchanges.* A risk related to hacking or identity theft. The Bitcoin foundation[9], the Financial Action Task Force

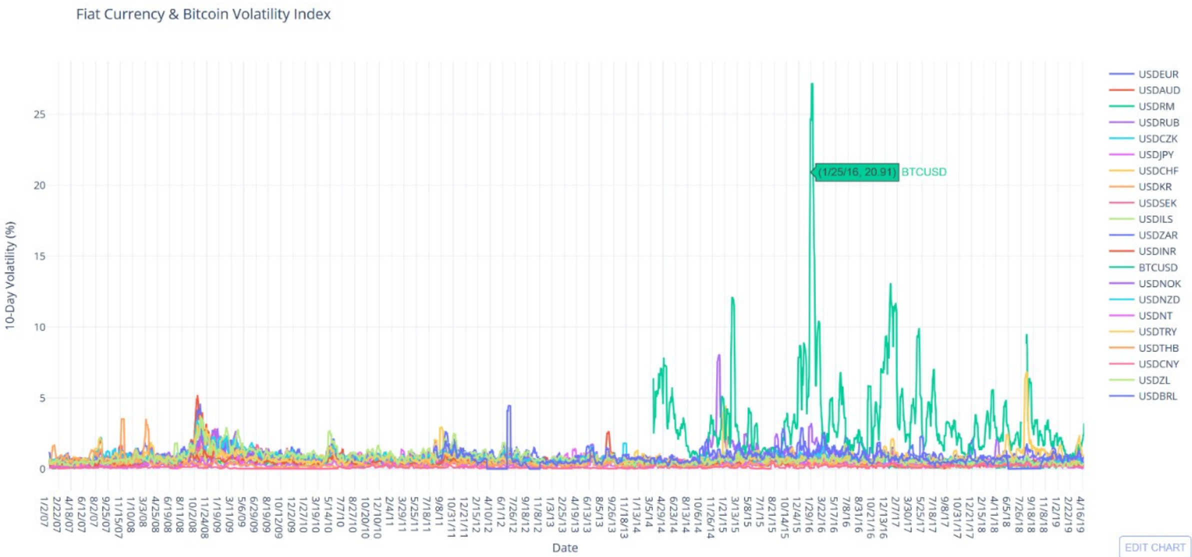
[8] https://gobitcoin.io/tools/cost-51-attack/

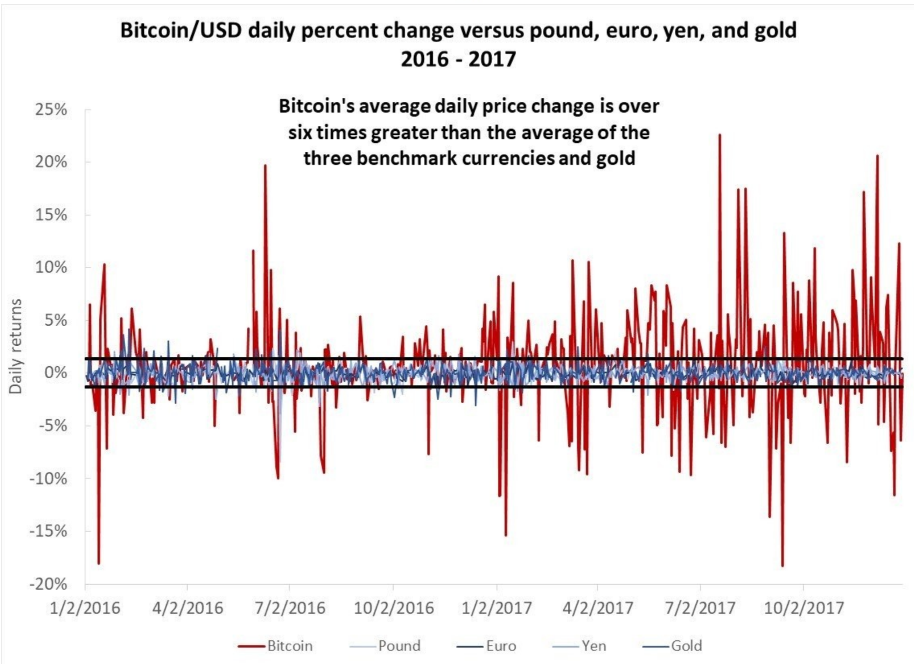
[9] Jim Harper, ‘Removing Impediments to Bitcoin’s Success: A Risk Management Study’ [2014] Bitcoin Foundation Research Brief 1, 25

(FATF)[10] and the European banking Authority after conducting a risk assessment exercise has concludes that this threat has high probability to materialize and have high impacts [11]

- *High Volatility*

  While risk is inherited to investments the risk of high volatility in cryptocurrencies market are considerable much higher than those in fiat currencies. These markets are relatively opaque, not regulated and not working with enough warnings and information to the users leaving investors exposed.





[10] Financial Action Task Force, 'Virtual Currencies: Key Definitions and Potential AML/CFT Risks' (FATF 2014)

[11] European Banking Authority, "Opinion on 'virtual currencies'" (EBA/Op/2014/08 2014) 21–22 and 31.

- *What about deflation.*
  Cryptocurrencies like bitcoin might be immune to inflation but they might be subject to deflation since a build in cap on the number of units in circulation is present (21 million). Forecast estimate that in 2140 all bitcoins will be mined and maybe resulting in a deflationary spiral. A study by Chain analysis show that approximately between 3.79 (high estimate)—and 2.78 million (on moderate one) are lost forever due to theft [12]. Be that as it may, Satoshi mined some 1 million bitcoins, they are on the ledges, so we know that he (she, they) haven't touch it. That represent the 5-7% of total supply. Satoshi might be dead, and those coins are forever lost but given that he is smart enough he might have employed some time-delaying mechanism to distribute his bitcoins in an increasingly exponential rate.

1.3 Some interesting infographics and statistics that highlights the bitcoin-cryptocurrency

Figure 1. The 10 largest Cryptocurrencies Market Capitalizations on the 28th of January 2020[13]

#	Name	Market Cap	Price	Volume (24h)	Circulating Supply
1	Bitcoin	$164,508,214,346	$9,045.73	$32,164,231,348	18,186,275 BTC
2	Ethereum	$18,832,863,046	$172.05	$11,363,887,187	109,464,540 ETH
3	XRP	$10,196,496,873	$0.233407	$1,816,143,436	43,685,558,183 XRP *
4	Bitcoin Cash	$6,713,719,732	$367.92	$3,650,422,252	18,247,575 BCH
5	Bitcoin SV	$5,488,797,804	$301.21	$3,328,829,434	18,222,577 BSV
6	Tether	$4,656,126,669	$1.00	$41,175,852,442	4,642,367,414 USDT *
7	EOS	$3,799,438,937	$4.00	$4,102,723,392	950,603,004 EOS *
8	Litecoin	$3,799,001,242	$59.40	$4,032,538,458	63,955,761 LTC
9	Binance Coin	$2,759,663,468	$17.74	$229,823,043	155,536,713 BNB *
10	Cardano	$1,324,320,491	$0.051079	$168,167,883	25,927,070,538 ADA

[12] https://fortune.com/2017/11/25/lost-bitcoins/?utm_campaign=JM-305&utm_content=v3867p&utm_medium=ED&utm_source=for
[13] https://coinmarketcap.com/

Figure 2. Annual Electricity consumption in 2019 [14]

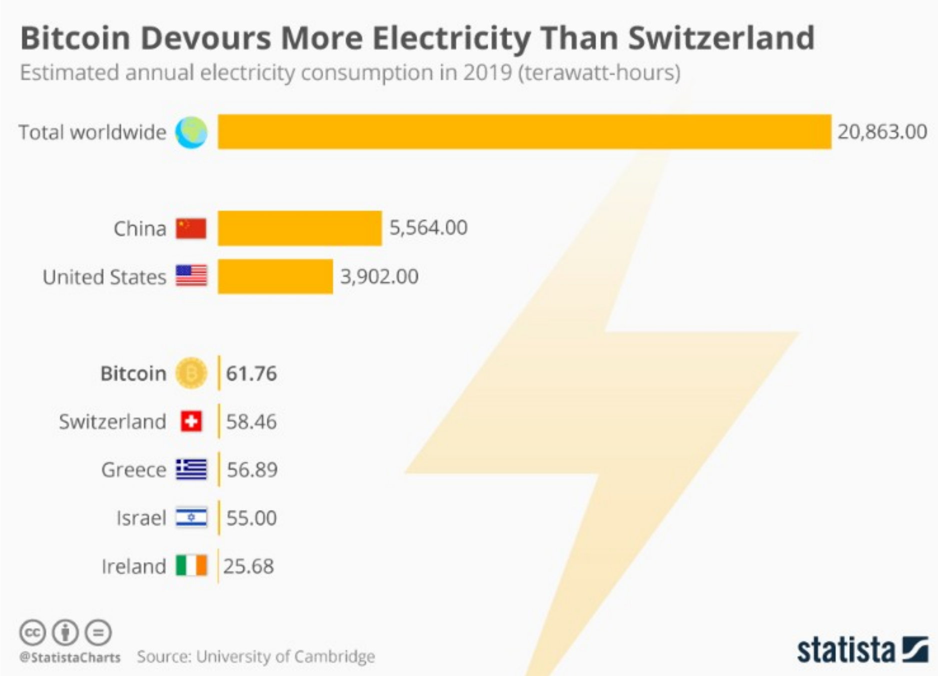


Figure 3. Bitcoin Market capitalization 28th of January 2020 [15]

In sheer number alone, Bitcoin Market capitalization reach over 300 billion U.S. dollars in 2018, surpassing the traditional financial institutions such as the Bank of America and nearly JP Morgan.[16] Subsequently, its price decreased substantially and as of August 2018 remains around $7000 USD.

Figure 4. Bitcoin survey conducted by Harris interactive, in 2014

[14] https://www.cam.ac.uk/
[15] https://coinmarketcap.com/currencies/bitcoin/
[16] https://coinmarketcap.com/currencies/bitcoin/

Shows that support for bitcoin increases with income and education Decline with age, and that men are slightly more supportive.

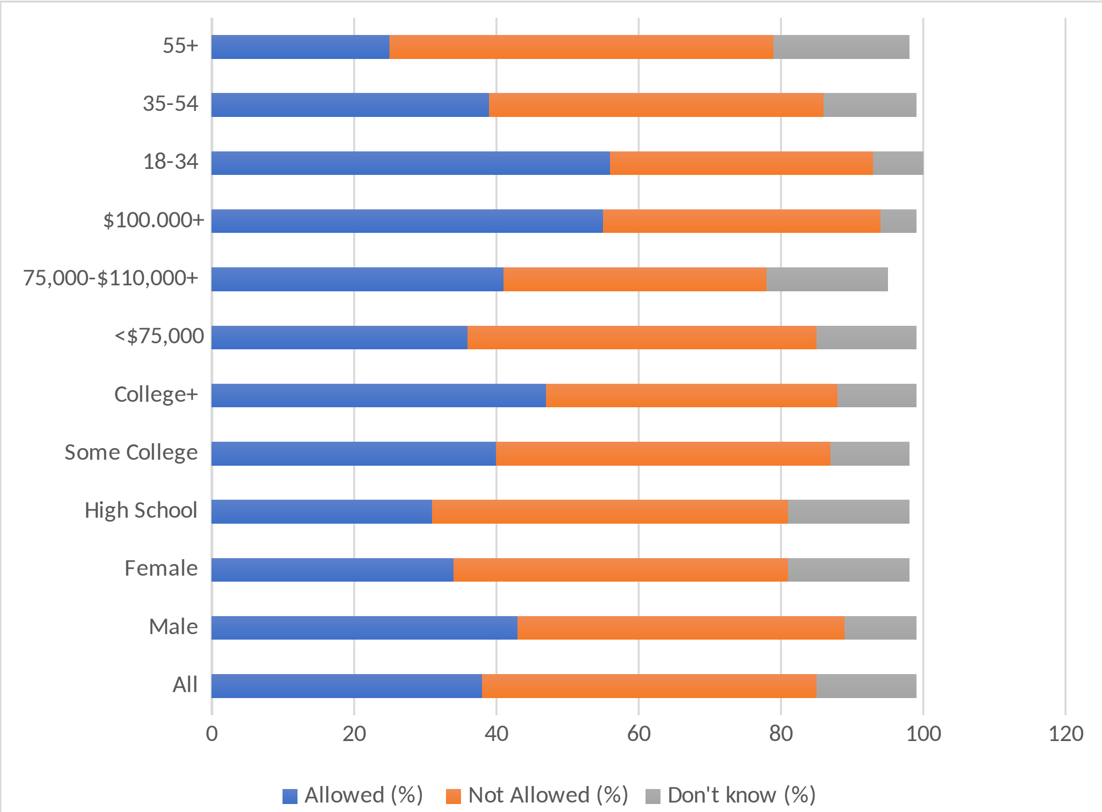
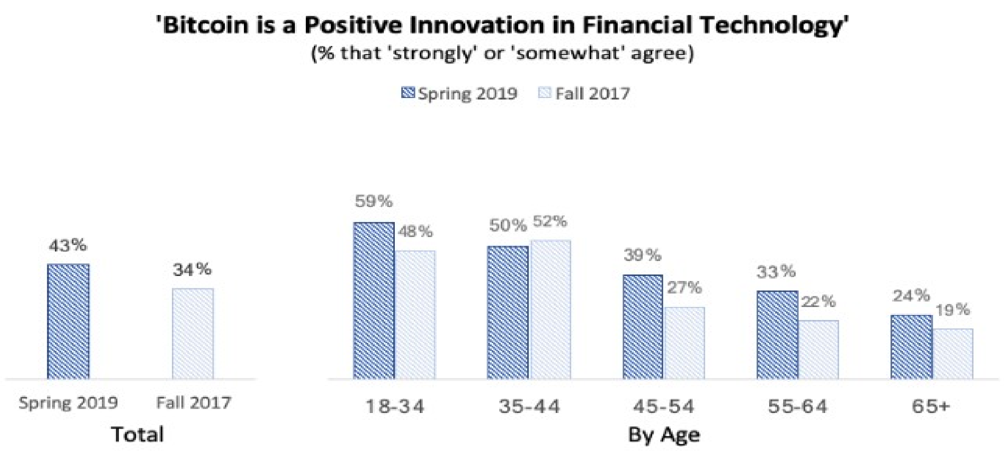


Figure 5. Bitcoin survey conducted by the Harris Poll, on behalf of Blockchain Capital in 2019



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ounger demographics were most inclined to have a positive view of Bitcoin: 59% of those aged 18–34 ‘strongly’ or ‘somewhat’ agree that ‘Bitcoin is a positive innovation in financial technology — up 11 percentage points from October 2017.

1.4. Status Quo

Since its creation, was hailed as the “new internet” by some, accused as a medium of criminal activity and a potential threat to our traditional “stable” monetary system by others. Even though Bitcoin (and other cryptocurrencies) has not been officially recognized as a currency by any government, it is being observed by central banks and legislative agencies and experts. The report "Regulation of Bitcoin in Selected Jurisdictions" in 2014 by the (The Law Library of Congress, Global Legal Research Center, 2014)[17] reveals that, Bitcoin is met with distrust and a few countries have a prohibitive stance on it, China, Thailand, and Iceland having the toughest stance. In China, banks and payment institutions are not allowed to deal bitcoins while in Thailand and Iceland there is a strict ban on the use of bitcoin. Central banks of Cyprus, Finland, France, India, Netherlands, Portugal, Singapore, and Taiwan together with the European Banking Authority issued warnings on bitcoin use due to its unregulated and unprotected nature. After the report Russia has also taken a prohibitive stance on cryptocurrencies including Bitcoin (Foley, 2014)

It is the unregulated nature that can potentially cause turmoil in the monetary system and the element of anonymity that can be used in illegal activities that makes -the main regulatory bodies i.e. the Central banks and the Treasury Departments- to be so skeptical about the new technology

Some characteristic quotes from political leaders, voicing concerns in the World Economic forum of 2018.

> *"My number one focus on cryptocurrencies and whether that be digital currencies or bitcoin or other things, is that we want to make sure they are not used for illicit activities"*[18]

Steven Mnuchin
(U.S. Secretary of Treasury)

> *"The anonymity, the lack of transparency and the way it conceals and protects money laundering, financing of terrorism and all sorts of dark trades is just unacceptable"*[19]

Christine Lagarde
(former Director, International Monetary fund.)

After a surge in combined market capitalization value of all cryptocurrencies, from less than 10 bn USD to more than 500bn USD the phenomenon has been impossible to ignore. The world's largest financial institutions are fighting with the cryptocurrency dilemma

[17] https://www.loc.gov/law/help/bitcoin-survey/regulation-of-bitcoin.pdf
[18] https://www.weforum.org/agenda/2018/01/macron-merkel-mnuchin-ma-davos-day-2/
[19] https://www.weforum.org/agenda/2018/04/fix-the-roof-now-three-priorities-for-the-global-economy/

Should they denounce the technology or join and start investing in it? This question is examined in a recent paper published by the Federal Reserve Bank of Boston. The paper "Beyond Theory: Getting Practical With Blockchain" (boston., n.d.) concludes that cryptocurrency despite having some advantages, is not mature enough to be adopted by the institutions nor is to cast away since it possesses characteristics and capabilities that will make viable the implementation of cryptocurrency in the monetary system providing it a supervisory node.

Rank	Friendly countries	Official position	Unfriendly states	Official position
1	Malta	Maltese government have formed the Malta Digital Innovation Authority encourage cryptocurrency and blockchain businesses. That's the reason Binance, one of the world's biggest crypto exchanges, has decided to set up their HQ in Malta.	Algeria	The purchase, sale, use, and holding of so-called virtual currency is prohibited. Virtual currency is that used by internet users via the web. It is characterized by the absence of physical support such as coins, notes, payments by cheque or credit card. Any breach of this provision is punishable in accordance with the laws and regulations in force
2	Estonia	Estonia's government does not regulate cryptocurrencies. They are even looking forward to implementing the blockchain technology for healthcare.	Egypt	Dar al-Ifta, the primary Islamic legislator in Egypt, has issued a religious decree classifying commercial transactions in bitcoin as haram (prohibited under Islamic law
3	Switzerland	Unlike other European countries the government is very welcoming of cryptocurrencies. This has earned it the title of CryptoValley, something similar to Silicon. The Bitcoin trading is allowed and if you are a trader there you need to pay the capital gains taxes. If you are not, you are just liable to pay income taxes if you receive your salary in crypto.	Bolivia	Absolute ban. In 2014 the Central Bank of Bolivia issued a resolution banning bitcoin and any other currency not regulated by a country or economic zone
4	Sweden	The Swedish Financial Supervisory Authority (Finansinspektionen) declared Bitcoin and other cryptocurrencies as a means of payment.	Ecuador	In 2015, The National Assembly of Ecuador banned bitcoins including other decentralized digital/crypto currencies
5	Hong-Kong	BTC is considered as a virtual commodity in Hong Kong. Hong Kong's exchange regulations are	Nigeria	As of 17 January 2017, The Central Bank of Nigeria (CBN) has passed a circular to inform

		clear and easy to understand and that is why some of the big crypto exchanges operate from there.		all Nigerian banks that bank transactions in bitcoin and other virtual currencies have been banned in Nigeria
6	Denmark	Danish Central Bank declared that Bitcoin is not a currency, stating that it will not regulate its use in the country. Danish Financial Supervisory Authority suggests that Bitcoin is an electronic service and the earnings from its use would, therefore, be taxable. Denmark aims to digitalize its currency 100%.	Nepal	Absolute ban. On 13 August 2017 Nepal Rastra Bank declared bitcoin as illegal
7	Belarus	In December 2017 when Bitcoin was at its all-time-high. Belarus legalized BTC and cryptocurrencies in the country. Not only this, ICOs and smart contracts were also put in the same category. Belarus aims, cryptocurrency mining, trading, and capital gains on any crypto or ICO to be tax-free until January 1, 2023.	The Russian Federation	As of November 2016, bitcoins are "not illegal" according to the Federal Tax Service of Russia. A bill on digital financial assets was introduced on 20 March 2018. In the bill, bitcoins are classified as property and are not considered legal tender.
8	U.S.A.	According to the U.S. Treasury, bitcoin is a convertible decentralised virtual currency (Forexsq, 2017).	China	Although China is home to the world's largest digital payment systems. WeChatPay and AliPay share as many transactions a day as the United States in nine months, Bitcoin and other cryptocurrencies are ban..
9	U.K .	Bitcoin is currently unregulated and treated as foreign currency (private money). The Bank of England is analyzing the possibility to implement Bitcoin technologies to improve its monetary system.	Vietnam	The State Bank of Vietnam has declared that the issuance, supply and use of bitcoin and other similar virtual currency is illegal as a mean of payment and subject to punishment ranging from 150 million to 200 million VND
10	Australia	Australian citizens are allowed to use Bitcoin freely as any other currency (Scott, 2016)	Colombia	Bitcoin is illegal in Colombia as of the end of 2016.

1.5 Crypto-Laundering.

As long as dirty money has been around, so has money-laundering. The United Nations Office of Drugs and Crime estimates that between $800bn and $2trn, or

2-5% of global GDP, is washed annually.[20] Criminals have swapped money for precious metals, mis-stated invoices, washed cash through casinos or simply strapped it to their bodies and flown to places where banks don't ask questions. Now they have a new detergent: crypto currencies.

Money laundering is the process of converting illegal earnings or any kind of sources into legal, following particular actions that transforming money origin and the status of the initial parts of criminal transactions like drug or weapon dealing and human trafficking operations. These kinds of processes exist many years now, always adjusting their flexibility to the existing financial regulations and evolutions that technology can offer to make criminal efforts even easier through years. Many things have changed into the global financial system through last decades, forcing initially all interested parts of legal or illegal transactions to create new ways of hiding paths of money travelling through it. Technology is now the path of creating profits. Last decade trend in financial market, using tools of technology and mathematics is the use of cryptocurrencies. Known also as virtual currencies, this new form of online currency is offering new ways of making transactions universally, enjoying particular advantages like anonymity, speed, low costs to use and the highly-attractive privilege of the difficulty to track the source of any parts of any transaction using them. The way the system of cryptocurrencies is functioning is merely based on unique codes created online and correspond to a specific value of the in-search cryptocurrency. Each value, between many kinds of cryptocurrencies existing now, applying to demand and supply county meaning that the quantity of cryptocurrencies existing defying their real money value in the market. The most recognizable cryptocurrency of our days is called Bitcoin and its existence includes all the characteristics mentioned above

Mr. Wainwright head of the Europol has estimated that 3-4% of the continent's annual criminal takings ($4.2bn-5.6bn), are crypto-laundered. He thinks the problem will get worse.: "They're not banks and governed by a central authority so the police cannot monitor those transactions. And if they do identify them as criminal, they have no way to freeze the assets unlike in the regular banking system."

Another problem Europol has identified involves the method that criminals use to launder money. Proceeds from criminal activity are being converted into bitcoins, split into smaller amounts and given to people who are seemingly not associated with the criminals but who are acting as "money mules" These money mules then convert the bitcoins back into hard cash before returning it to the criminals.

> "It's very difficult for the police in most cases to identify who is cashing this out,"
>
> **Mr. Wainwright.**[21]

Authorities are slowly catching up Europol recently uncovered how European crime bosses used crypto to pay a Colombian drug cartel for cocaine. European henchmen visited crypto exchanges to convert euros into anonymous virtual currencies. These

[20] https://www.unodc.org/unodc/en/money-laundering/globalization.html
[21] https://www.bbc.com/news/technology-43025787

were sent to a digital wallet registered in Colombia and swapped into pesos on an online exchange. The pesos were withdrawn in cash, which local “money mules” spread over dozens of bank accounts, in sums small enough to avoid suspicion. The cartel bosses got the money by withdrawing the cash or by e-transfer.

In addition to warnings issued by head of institutions and political leaders there are a number of academic papers-that I am about to review in chapter 2- that search for money-laundering technics with the use of cryptocurrencies. Most of them claim that although there is an obvious danger the use of cryptocurrencies for that specific reasons are not so widespread.

> “Sticking £10,000 down your underpants and flying to Zurich is still quite a common and easy way to launder money,” [22]
>
> **-Mr McGuire.**
>
> **University of Surrey**

Nevertheless, evolution of online financial transactions using these types of currencies have created an anxiety between governments and existing financial representatives. The anonymity behind online buying and selling and the difficulty on defying the source behind each transaction is creating a strong tool for criminals to use. Money laundering or funding terrorism is the main reason of concern due to the flexibility of cryptocurrency usage. These concerns are imprinted into nations’ efforts to encounter further development of criminality by creating departments that will deal only with virtual exchanges of major amounts of money, like United States’ effort with the establishment of the US Treasury department which reports to the Treasury Undersecretary for Terrorism and Financial Intelligence and the Money Laundering Regulations via the Third Money Laundering Directive, implemented in the United Kingdom. In order to fully understand and respond fast and widely to the challenge of the use of virtual currencies for financing terrorism and criminality governments should build strong teams of experts and train them to analyze details that track illegal actions despite anonymity. Furthermore, single people should apply due diligence in any occasion that indicates criminality and inform authorities like the Financial Action Task Force which is specialized in online money laundering situations.

1.6 Goal of this paper.

Despite the warnings and the skepticism by big international institutions and head political figures the integration of cryptocurrency in the financial system is a fact. Advancement in information and technology and the increase flow of capital is driving globalization. A seemingly unrelated phenomenon in one market affects another in a different setting or geography. Having an idea and understanding of the relationships between these markets is becoming more and more important for investors and researchers. Driven by the advantages of new technologies, the potentials they have for advancing the current monetary system but also the risk they possess, if they are used for illicit activities, I wanted to examine if there is any connection between the biggest of the cryptocurrencies , Bitcoin and stock indices

[22] https://www.economist.com/finance-and-economics/2018/04/26/crypto-money-laundering

around the world. The choice of the indices was made under the scope that if in fact cryptocurrencies where used for money laundering then there must be a connection between the mean and variance of Bitcoin and the chosen indices. So, the scope of this paper is to investigate for Granger causality in-mean and in-variance between Bitcoin and stock indices of countries accused or traditionally associated with money laundering. Regardless of my motives behind the choice of countries and my hypothesis, the examination for Granger causality in-mean and in-variance is of high importance. In recent years there has been a growing interest among portfolio managers in the contagion effects of financial markets. This effect has cause portfolio managers and investors to become more cautious in their investment decisions and try to diversify their investment options.

2. LITERATURE REVIEW.

The literature review is organized in 3 sub-sections. The first one underlines some key characteristics of the Bitcoin and how it is associated with criminal activities. The second highlights econometric research associated with the bitcoin. Lastly, I focus on articles that study Granger Causality between indices and articles using the Cross-Correlation Function methodology, the one I am about to use to test for causality in-mean and in-variance.

2.1 BITCOIN PAPERS

(Nakamoto, 2008) In the founding paper of Bitcoin Satatoshi Nakomoto claims that money exchanged anywhere depends on the "trust-based model": A payment is never final because a bank can reverse that sum if it's in dispute, even if it's for an already rendered service. Because banks' involvement has a cost, low-value transactions end up being uneconomical. Also, fraud is inherent in the system, so checking for creditworthiness adds even more expense.

> *"A purely peer-to-peer version of electronic money would allow online payments to be sent directly from one party to another without going through a financial institution."*

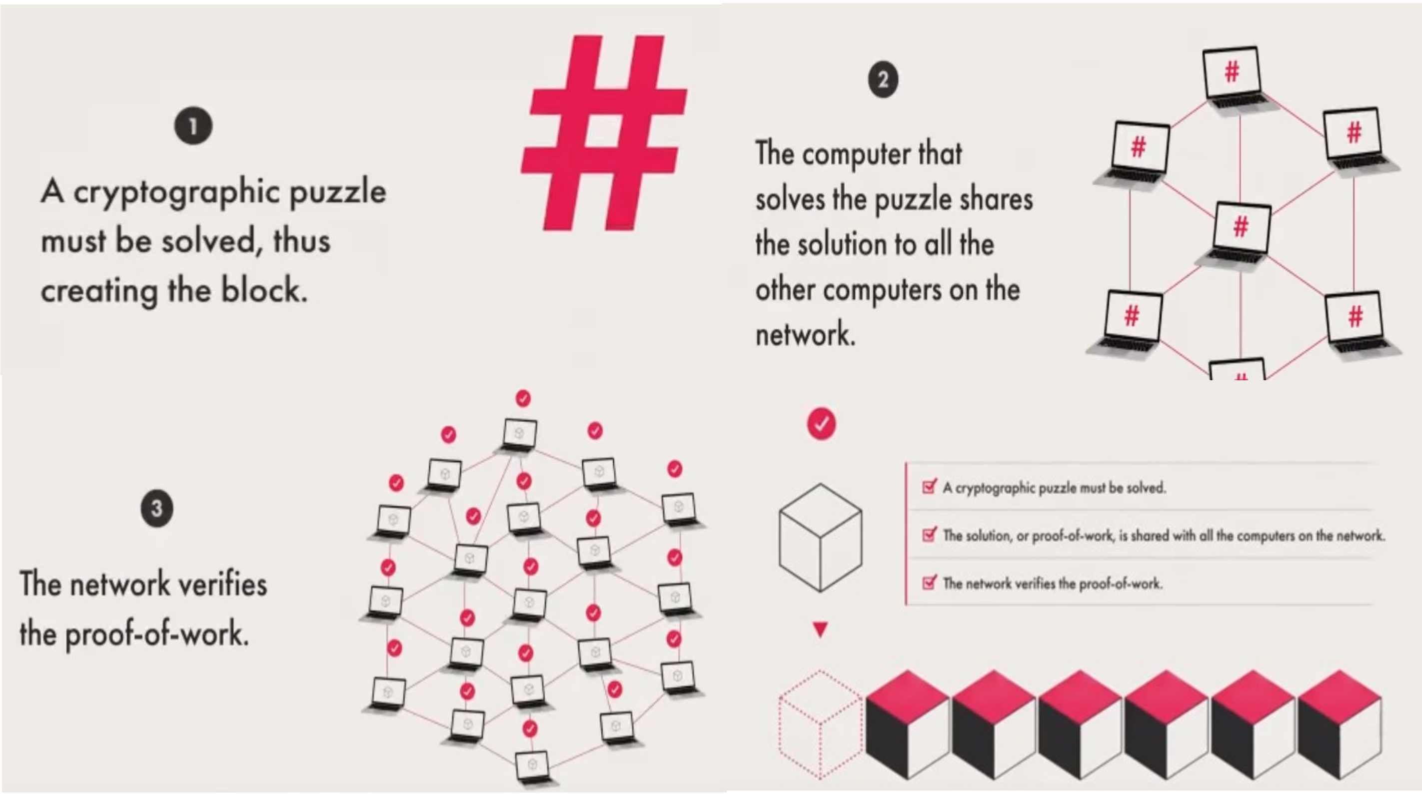
A "peer-to-peer" system that doesn't need a third party operates on "cryptographic proof" rather than trust. A bitcoin, a unit of electronic money, is "a chain of digital signatures." These unique signatures can prove a specific individual or entity owns a particular coin. With bitcoins as electronic currency, sellers would gain from receiving payments that are irreversible, and escrow accounts would assure purchasers.

> *"The system is secure as long as honest nodes collectively control more CPU power than any cooperating group of attacker nodes."*

In real life, you exchange objects, but, in online life, you copy data – be it a document, a music file or a photo. With other e-coins, that could result in "double-spending" if the data were code that represents a unit of currency. With bitcoins, digital signatures of the coin owner along with the "public key" of the next owner added to the string of code creates a "chain of ownership" that anyone can track to verify that the coin hasn't been double spent. A "time-stamp server" establishes the chronology of the transaction. A "proof-of-work" protocol furnishes a public record of bitcoin transactions that hackers would find "computationally impractical" to modify. Multiple bitcoin transaction make a block and as a reward for the verification of the block users called "miners" are awarding a small amount of bitcoins. Adding new bitcoins into the supply takes the energy of CPU processing and electrical power, much like "gold miners expending resources to add gold to circulation."

The nature of the open source code means all bitcoin dealings must be visible, but secret public keys keep individual trans actors' identities confidential; that's similar to stock exchange transactions, where you know the size and timing of securities trades, just not who the buyers and sellers are.

Bitcoins support electronic sales and purchases through unique digital signatures, thus removing trust and intermediaries from the online commercial equation. Eliminating the possibility of double-spending with complex proof-of-work chains makes for a viable currency that operates on a "consensus mechanism."



A common theme of Bitcoin-related studies is searching for what role Bitcoin really plays as a cryptocurrency. This balancing act between being purely a medium of exchange and an opportunity for investment is a central question in much of the literature on Bitcoin markets.

(Luther, 2013) William J. Luther acknowledge that Cryptocurrencies like Bitcoin are fiat money that use cryptography to ensure their integrity. Unlike more well-known currencies such as the dollar, yen or euro, cryptocurrencies don't have the backing of governments and central banks but rely on the security of underlying software algorithms to prevent counterfeiting and double spending. The existence of cryptocurrencies poses two significant questions: First, why wouldn't everyone adopt a cryptocurrency? And second, why would anyone adopt one? A sizable part of the value of a currency is the extent to which others use it. Clearly a currency with only one user has no application, whatever its other merits. Adopting a currency also involves costs – for example, in programming vending machines and cash registers, as well as in becoming familiar with denominating values in the new currency. For a new money to take off – that is, without the assistance of an outside agency like a government – it must have a broad network of users and offer benefits greater than the costs of transferring to the new money. In practice, these are high barriers to entry. "Successful switching" has occurred only in cases of national sponsorship or of high inflation in an incumbent currency – as in, for example, Ecuador's 2000 "official dollarization" or the widespread parallel use of US dollars in Peru and Bolivia during periods of hyperinflation in the 1980s. In such cases, the troubled currency loses its utility and value, and everyone knows it, prompting them to seek an alternative. Bitcoin competes with well-regarded and stable currencies. In the absence of third-party support from governments, Bitcoin is unlikely to benefit from the spontaneous coordination among users necessary to secure its adoption. Given its weak prospects, why would anyone switch to Bitcoin? Most adopters see it as a store of value or as a speculative investment, rather than as a medium of exchange. Active users may have lower switching costs than the broad population due to a technological bent that lowers their individual costs of adoption. Others may choose bitcoins for "political and philosophical" motives, for use in online games that recognize bitcoins as a medium of exchange, or for illicit transactions that benefit from Bitcoin's near anonymity in transactions. These factors simultaneously account for Bitcoin's success to date and describe the limits of its appeal to the broader population.

In the article written by (Malte Möser, 2014) the authors try to test Bitcoin's leading and starting principle of anonymity. By using reverse – engineering methods and by employing, several services offering increased transaction anonymization that have emerged in the Bitcoin ecosystem, such as Bitcoin Fog, Bit Laundry, and the Send Shared functionality of Blockchain.info, try to investigate the relations between the inputs and outputs given by the underlying systems. Their econometric results indicate that two of the three systems (Bitcoin Fog and Blockchain.info) are quite reliable and it is difficult for any external source to intervene and combine any input with its related output. Especially Blockchain info seems to be more secure in the manner that underlying analysis could not find any connection evidence. On the other hand, Bit laundry had an easier accessibility leading to the conclusion that there are quite a lot of connections linked with each other and thus the experiment revealed any connection of the transactions. In this case, anonymity is violated for anyone, even an attacker that is willing to interfere and stole the bitcoin information. By all means, this research indicates that there are ways of controlling and monitoring the Bitcoin environment, especially for law enforcements of serious crime related transactions

(Yermack, 2014) provides preliminary academic, analysis into viewing Bitcoin as an asset or currency. His work also gives perspective to how far the cryptocurrencies have develop in modern markets. Yermack concluded that Bitcoin failed to satisfy the three criteria that currencies have:

- medium of exchange,
- unit of account and
- store of value.

This analysis was based on a recent hack of the most prominent exchange, Mt. Gox, and the observation that most other exchanges experienced low volume and liquidity.

(Jonathan Chiu, 2017) develop a general equilibrium monetary model of Bitcoin and find that the resource intensive Proof-of-Work process yields a welfare loss of consumption. The authors argue that a prominent alternative, the Proof-of-Stake (POS) process could be implemented by Bitcoin to utilize resources more efficiently. Indeed, the annual amount of electricity consumed by the Bitcoin network is comparable to Denmark and larger than Greece. This is due to the computationally difficulty task miners undertake when finding the solution to the hashing function. Specialized mining rigs, known as Application-Specific, Integrated Circuits (ASICs), have been developed to reduce the immense energy consumption used in the mining process. Alternately, POS proposes to allow for more weighting for validating transactions to be proportional to how much holdings one has. Proponents of PoW argue that the energy consumption trade-off should be favored over POS, as POS concentrates the consensus mechanism at the top of the income distribution. Consequently, smaller users and adopters are at the mercy of trusting these large holders to maintain the network, rather than POW relying on competition despite high energy consumption

(Kellerman, 2017) has a tougher stance. The expansion of digital financial services around the globe could add $3.7 trillion, or 6%, to developing economies' collective GDP. The downside of this growth is the growing specter of cybercrime. Officials estimate that, each year, cybercrime slashes world economic output by $445 billion. Much of this nefarious activity – money laundering, "child pornography, weapons and drug sales, hackers and murder for hire, zero-day exploits and false identity documents" – ties directly to the increasing prevalence of cryptocurrencies. The world of virtual currencies provides a strategic and tactical resource for criminals, particularly in terms of the storage, exchange and transportation of illegal products and services. Decentralized digital currencies, such as bitcoin, do not depend on central bank clearing houses for recordkeeping and transfers; rather, they rely on distributed ledgers. Thus lawbreakers can far more easily bypass antimony laundering and "know your customer" protections. Clearly, the governance of these digital currencies and platforms often runs far behind the innovation driving their growth. The proliferation of not just digital currencies but also alternative platforms and “mobile and stored value systems” in the emerging economies offers great promise and serious challenges. For example, fully “43% of Kenya’s GDP flows through M-Pesa, a mobile phone-based platform for the transfer of money and financial services” that facilitates 237 million personal transactions. Despite their benefits, these technologies allow criminal elements to flow through the dark web and conduct illegal transactions. Experts indicate that money laundering operations account for up to $2 trillion per year globally. Because “50% of all crimes now have a cyber component,” international efforts must coordinate and spearhead more effective controls. To stay ahead of financial felons, global leaders should insist on the creation of an “international e-forfeiture fund” that would harness, and leverage dollars captured from criminal enterprises to strengthen global financial protection mechanisms.

(Roubini, 2018) Highlights that depending on your viewpoint, blockchain and the cryptocurrencies stemming from the distributed ledger design are either the next transformative technology or will soon vanish into the junkyard of failed enterprises. In 2018, investors long in digital currencies have taken a beating, with high-profile names such as Ether, EOS, Litecoin and XRP giving up more than 80% of their valuations. Second- and third-tier cryptocurrencies have fared even worse, falling between 90% and 99%. Moreover, 80% of initial coin offerings are frauds. Against this backdrop, proponents of blockchain declare that the technology stands on its own merits, regardless of the trajectory of digital tenders. Blockchain advocates herald the software as a liberating egalitarian tool that disseminates information of all kinds through open, “permission-less” and “trustless” networks, as opposed to through centralized government and institutional channels. The irony of this paean to financial democratization is that a few main actors largely control blockchain’s operations and wealth. A handful of firms operating in China, Russia and Georgia direct 66% to 75% of all blockchain and crypto-mining traffic, while reaping enormous profits. Cryptocurrency markets also pose tangible risks. Hackers routinely crack cryptocurrency platforms and make off with considerable sums. And the currency creators can at any time alter blockchain information and digital monies, so these are far from being immutable. Blockchain and its roster of cryptocurrencies are in fact stores of wealth for the elite and powerful. Consider the Gini coefficient, a measure of financial equality in which a value of 1.0 represents the 100% ownership of a nation’s wealth by one individual or entity. The Gini coefficient of North Korea, one of the world’s most impoverished and statist regimes, is 0.86, while Bitcoin’s ranking is 0.88. It is worth noting that the US Gini coefficient is 0.41, even as many politicians rail against the country’s rising inequality. Legitimate users of distributed ledger technology exist; however, these organizations rely on permission-based networks with only private access. Individuals who believe blockchain can transform the world or even their own fortunes are in for a rude awakening.

According to the article of (Campbell-Verduyn, 2018) Bitcoin and other cryptocurrencies, better known as Altcoins, have induced by their quick implementation, a tremendous swift in the electronic transactions system. The altcoins' fastest implementation and broader acceptance led to a struggle by the regimes and governments globally in order to control and delimit their ongoing power. Analyzing in depth the above paper, the author explains the money laundering characteristics provided by the altcoins due to their anonymity but insists that there is little evidence of actual money laundering situation that is revealed by the Media. Furthermore, the author insists more on CC's opportunity rather than threat caused by laundering practices. Besides that, the Paris-based Financial Action Task Force (FATF) which is an intergovernmental organization officially comprised of thirty-five member-states and two regional organizations, based on a risk-based approach, examined the altcoins gap in regimes regulation but it fails to approve these allegations, due to the fact that risk based approaches do not implement in decentralized – driven networks.

(Liao, 2017) claims that despite most people associate blockchain with cryptocurrencies such as bitcoin, blockchain can serve a larger purpose by furthering global trade. Businesses are already using the technology to enable digital contracts and bookkeeping, and to do away with financial go-betweens. Companies can execute safe, immediate cross-border transactions without the need for prior mutual relationships. While their use of blockchain could potentially save financial institutions hundreds of millions of dollars annually by getting rid of physical contracts, eliminating clearinghouses and engaging in speedier transactions, the industry has so far resisted such changes. More immediate prospects exist for blockchain in the area of trade finance – the facilitation of international trade through the handling of instruments such as letters of credit and bills of lading. Participants in trade finance are linked to one another through a supply chain, and this gives them incentives to cooperate. Although the value of the worldwide trade finance sector was about $2.8 billion in 2015, estimates suggest that the actual market capacity is 10 times that amount. But regulations crimp banks' willingness to fund this activity, thus keeping some firms, particularly small ones, from accessing trade credit. The cost of the financing can also be high. Blockchain could allow more businesses to participate in international trade, which would enhance economic growth. The distributed ledger technology reduces "performance risk (the risk that a party will fail to fulfill its contractual obligations)" through the real-time digital tracking of goods. The ability to see a firm's blockchain history of meeting contract terms helps trading partners and banks minimize their "counterparty risk (the risk that a buyer or seller is not financially sound)." In October 2016, blockchain facilitated its first global trade deal, in which an exporter, a US bank and an Australian bank collaborated to ship cotton to China. Now and in the future, blockchain can aid in "narrowing the trade finance gap."

Buclish (2018) develops conditions to study the mining incentives and the susceptibility of the Bitcoin network to a majority attack. This occurs when over 51% of the network's computing power is controlled by one group and an alternate version of the Blockchain, with false transactions, is accepted by consensus as correct. This allows for double spending, as multiple recipients will be waiting for the same funds to arrive. The double-spending problem is a serious drawback of the decentralized network, as a similar attack happened to Bitcoin Gold in May 2018, the 26th largest cryptocurrency at the time. Other smaller cryptocurrencies that have experienced a majority attack in the past year are Verge and Krypton. With that said, Bitcoin has a much deeper mining network and estimates suggest that one would need over $6.8 billion in mining equipment and would have to service a daily electricity bill of 93 million kWh'S. Together, these immense costs align the incentives of the attacker to maintain the network and preserve the value of Bitcoin, rather than manipulating the blockchain to steal Bitcoin and cause the community to devalue it.

2.2. Econometric Research.

(Bouoiyour, 2014) described Bitcoin value by regressing its market price against several independent variables like, the market price of gold, the occurrences of the word 'bitcoin' in Google searches, the number of transactions and so on. Generally, the variables when regressed, at the 5% level of significance, they were not statistically significant. As for lags on the price of Bitcoin itself, they have some weight. Lagged Google search results were the only variable significant at the 1% level.

At their paper (Paolo Giudici, 2018) The authors Paolo Giudice and Iman Abu-Hashish try to capture the dynamics of cryptocurrencies exchange market and how information affects them. Based on a correlation network Var process they try to model the connections between different crypto and classic assets. They confirm that bitcoin price are in most cases unrelated with classical market prices and bring diversification in a portfolio of financial products.

An article (Dirk G.Baur, 2015) focuses on the balance between acting as a currency and investment. Baur et al. determine that bitcoin is uncorrelated with traditional investments and has little to no correlation with other asset classes such as stocks or bonds. This gives it some serious benefits as an investment opportunity. Bitcoin is described in this article as a hybrid between commodity backed assets and fiat currency backed by monetary authority, and they believe its usage as a currency holds more potential than as an investment.

(Briere, 2013)) hold a much different belief as their paper touts the potential for diversification and higher returns when including bitcoin in a diversified portfolio. However, it should be noted this study was carried out over a period of surging growth in the bitcoin bubble of 2013 and it would be of interest to see if these results hold true for 2014 and beyond as the value is still volatile yet showing no consistent positive trends.

(Dyhrberg, 2016)applied the asymmetric GARCH methodology to explore the hedging capabilities of Bitcoin. The data used for this paper include daily observations from the 19th of July 2010 to 22nd of May 2015 of the dollar-euro and dollar-sterling exchange rates as well as the Financial Times Stock Exchange Index (FTSE) yielding 1769 observations. It was shown that Bitcoin can be used as a hedge against stocks in the Financial Times Stock Exchange Index and against the American dollar in the short term

In another paper the same author (Dyhrberg, 2016) use daily closing bitcoin price from 19th July 2010 to 22nd of May2015 and gold bullion USD/troy ounce rate (GoldCash), the CMX gold futures 100 ounce rate in USD (Gold Future), the dollar-euro and dollar-pound exchange rates and the financial times stock exchange index (FTSE Index) and applying GARCH models tries to explore the financial asset capabilities of Bitcoin. Using GARCH (1,1) has shown that Bitcoin has a place on the financial markets and in portfolio management as it can be classified as something in between gold and the American dollar, on a scale from pure medium of exchange advantages to pure store of value advantages

(Letra, 2016)) used a GARCH (1, 1) model to analyze daily Bitcoin prices and search trends on Google, Wikipedia and tweets on Twitter. They found that Bitcoin prices were influenced by popularity, but also that web content and Bitcoin prices had some predictable power.

(Ziaul Haque Munum, 2019) analyze the forecasting capabilities of Bitcoin. They use daily returns from January 1st, 2012 to October 4th, 2018, in total 2466 observations. They test whether ARIMA model have more predictive capabilities than NNAR (neuro network autoregressive). They found that for forecasting next-day Bitcoin prices the classical ARIMA model with 4 lags outperforms the NNAR model.

(Mobeen Ur Rehman, 2018) tries to measure causality in quantiles between commodity futures and cryptocurrency. They use daily returns for Bitcoin and Ethereum and Gold, Silver, Cooper, Wheat, Crude oil and natural gas for commodities futes from February 2012 to December 31, 2017. The conclude that there is a significant causal relationship running from cryptocurrency markets to commodity future, both in terms of mean and variance. They also imply that future diversification of portfolios or research in the behavior of cryptocurrencies must consider the commodities futures.

2.3 The Cross-Correlation Function for causality in-mean and in-variance literature.

As far as my research no academic paper applies CCF methodology to test causality in mean and in variance between cryptocurrencies and stock indices. There are some papers that utilize the method but for commodities, other indexes and macroeconomic indicators

(jihn wei-Shan hu, 1997) Among the first who implement this method are the authors of this paper and they do so without the established prejudice that the direction of the causation in from big markets such as the US to smaller ones. So, they examine for causality in mean and in variance between US and Japanese stock markets and the south China Growth triangular. Their data spans from October 5, 1992 to February 15, 1996. They use six indices of the most important markets in the SCGT region and the US Dow Jones and Nikkei225. They find evidence of volatility spill over from the Japanese to the US market and vice versa. The US market is also correlated with the Hong Kong market with the strongest connection from Hong Kong to the US. Contemporaneously there is an effect from the US to all 5 markets (Japan, Hong Kong, Taiwan, Shanghai and Shenzhen) It is interesting that the Hong Kong and Taiwan markets are not correlated with the rest of Chinese markets Shanghai and Shenzhen. This might be due the special relationship Hong Kong and Taiwan have with the rest of the China.

(V.T. Alaganar, 2003) In this article the authors examine the causality between interest rates and 3 financial sectors, the banking, insurance and the financial sector of the G7 countries, so in total 21 combinations. Using daily closing values, the calculate the weakly returns of each sector and the weekly holding period returns for a 10-year bonds. In total they cover a decade from January 1990 to December 2000. Out of all combinations they found that in the case of Canada, France, Germany and the U.S., the financial sector, the banking and insurance industries show a two-way causality in mean level. Likewise, the banking and insurance industries exhibit causality in mean among all countries with the exception of Japan.

(Neaime, 2012) focuses his research in the same (MENA) region but he splits the countries between oil producing and non-oil producing. After analyzing the characteristics of different MENA regions countries -such as the fact that FDI is relatively low – he argues that trade agreements such as GAFTA might have a palliative effect determining the size of the spillover. Using daily data of the national indices of U.S., U.K. and France and 7 other MENA regions countries he examines for causality. The results indicate that the United Arab Emirates are highly corelated with the U.S. and the U.K. and that markets of Kuwait and Saudi Arabia are correlated in variance with the other markets in the region and the US, the UK and France. Causality is uni-directional from the U.S. to the oil producing countries.

(Gonzales., 2015) is using the CCF method to Investigate for causality between equity markets from 3 geographical regions, *America*, Europe and Asia. He also takes into account asymmetry in the causal relationships. Asymmetry could be interpreted as nonlinear causality i.e. if the causality has the same effect for good news and bad news. He uses daily data from January 1997 to December 2014 for the closing prices of the most important stock markets indexes in each region. The analyses show that the Chinese SSA and the Indian SENSEX are the main drives for causality in Asia whilst Europe has the highest number of asymmetric causality.

(Bouri, 2016) Driven by the resent change of highly regulated rules of oil pricing in China this particular paper is searching for causality in mean and in variance between stock market and the price of oil. The data covers the period from January

4, 2005 to June 30, 2015. It consists of daily returns of Brent oil prices and also 10 sectoral indices (Energy and Gas, Financials Industrials, etc.) . They estimate different types of ARMA models all with the GARCH specification so they can acquire the residuals of each model. The found that in the first period, before the abolish of regulations, there is causality in variance from oil to all sectors of the economy except communications. After the ending of the regulation, causality does not exist and the only causal relationship present, is from financials to Brent oil price suggesting there is a positive impact lifting the regulations.

(Nouira, 2017) examine the effect of oil fluctuations on the exchange rate in the MENA region. (middle east and north Africa) using Daily data for a period of 17 years. Searching for causality in mean they found statistical important results for only two countries Tunisia and Saudi Arabia. In addition, the found that when oil prices are rising there is a change in the exchange rate of all countries, but when oil prices are falling the cause only the exchange rate of Saudi Arabia to fall. For all countries there is evidence for causality in variance. They claim that their findings are a call for MENA regions to diversify their economies.

3.Methodology

3.1 The Cross-Correlation Function Methodology

Co-movements across international stock markets has attracted much attention from both academia and investors. That is, if realized movements in one market (past) might influence the decision of participants in another (future). One approach to determine causal relationship that involve one action (cause) and the subsequent (not contemporary) reaction is to examine if the prediction of one series can be improved by incorporating information from the other. Specifically, if the variance of the predictive error of one time series can be reduced if we include past movements of the other in a regression model. Then the first time series it said to have Granger causality in mean with the other.

But since the research deals with financial time series we must take into account the stylized facts of financial time series such as heavy tails, heteroskedasticity and volatility clustering. These stylized facts determine the relevant methodologies. The methodologies in question are grouped into two types. Fist, those using multivariable vector autoregressive models (mean equations) with autoregressive heteroskedasticity (variance equation) also known as VAR-GARCH models. Others use the cross-correlation function (CCF) to analyze if a time series has significant effects on another. The VAR-GARCH methodology allows us to jointly estimate the causality in mean and variance for a set of assets but has some drawbacks, such as computational complexity when the number of assets increases. Meanwhile with the CCF methodology we can’t examine causality in mean and in variance at the same time, if the causality in mean is present, since the results obtained from causality in variance tests are affected (Theologos Pantelidis, 2004.). This work is not a analysis of which method is better, but in this context the CCF method was preferred.

According to the approach used by Cheung and Ng (1996), testing for the causality in mean and variance is based on the CCF of the standardized residuals and the squared standardized residuals extracted from the estimation of univariate GARCH-type models. According to this view, the CCF procedure is straightforward and thus does not require the simultaneous modeling as with multivariate GARCH-based tests. The CCF procedure is applied in two steps. First, a univariate GARCH-based specification is used to model the returns series. Then the standardized residuals are extracted from the GARCH-based model and are used to check the null hypothesis of no causality in mean and the squared residuals for causality in variance.

Let Z_{it} be a stationary ***i*** financial time series, in our case these are the log returns of indexes and bitcoin. For each time series an **AR(p)-GARCH (1,1)** model is estimated the number of lags p is chosen by the Akaike information criterion. In general, the GARCH model can be specified as :

$$Z_{it} = \mu_{it} + \sigma_{it} \cdot e_{it}$$

where μ_{it} the conditional mean equation, the σ_{it} is the conditional variance of Z_{it} time series and e_{it} is an independent white nose process with zero mean and unit variance. All limitations and properties of an GARCH models are present.

3.2 Causality in mean test

The test statistic proposed by Chung and Ng is the following.
Consider the univariate AR-GARCH models

$$Z_{1,t} = \mu_{i,t} + \sigma_{i,t} \cdot e_{i,t}$$

$$Z_{2,t} = \mu_{i,t} + \sigma_{i,t} \cdot e_{i,t}$$

For causality in mean we use the standardized residuals from each model. The standardized residuals are defined as

$$\hat{u}_{1,t} = \left(z_{1,t} - \hat{\mu}_{1,t}\right) / \hat{\sigma}_{1,t} = \hat{e}_{l,t}$$

$$\hat{u}_{2,t} = \left(z_{2,t} - \hat{\mu}_{2,t}\right) / \hat{\sigma}_{2,t} = \hat{e}_{2,t}$$

Then, the cross-correlation function of $\hat{u}_{1t} \wedge \hat{u}_{1t}$ is used with the formula

$$\hat{\rho}_{1,2}(k) = \frac{\hat{C}_{1,2}(k)}{\sqrt{\hat{C}_{1.1}(0) \cdot \hat{C}_{1.1}(0)}} \qquad \text{eq.1}$$

where

$$\hat{C}_{1,2}(k) = \frac{1}{T} \sum_{t=k+1}^{T} \left[\left(\hat{u}_{1,t} - \acute{u}_{1t}\right)\left(\hat{u}_{2,t-k} - \acute{u}_{2,t-k}\right)\right], k \geqq 0$$

eq.2

$$\hat{C}_{1,2}(k)=\frac{1}{T}\sum_{t=-k+1}^{T}\left[\left(\hat{u}_{1,t+k}-\acute{u}_{1t}\right)\left(\hat{u}_{2,t}-\acute{u}_{2,t-k}\right)\right],k<0$$

where T is the sample size, $\acute{u}_{it}$ is the sample mean of $u_{it} \wedge \hat{C}_{ii}(0)\, is\, the\, sample\, variance\, of\, u_{it}, i=1,2$

For the second stage we have to calculate the sum of the squared cross correlations of the standardized residuals and multiply it with the sample size T.

$$S=T\cdot\sum_{k=j}^{M}\hat{\rho}_{1,2}^{2}(k)$$

The S statistic asymptotically follows a X_{M-j+1}^{2} distribution where M is the number of sample cross correlations. For j=1 we can check whether z_{2t} Granger causes z_{1t} in mean, under the null hypothesis, there is no Granger causality from z_{2t} to z_{1t}.

On the other hand, we can use

$$S=T\cdot\sum_{k=-M}^{-1}\hat{\rho}_{1,2}^{2}(k)$$

To test whether z_{1t} Granger causes z_{2t} in mean.

3.3 Causality in variance test

The specification of the conditional mean is crucial when testing for Granger causality in the variance. In the case that causality in mean is present, then the conditional mean should be modified accordingly to account for these additional dynamics. If not, the causality-in-variance tests are likely to suffer from size distortions especially when the causality in mean is strong (Theologos Pantelidis, 2004.). Therefore as (Bartoz Gebka, 2007) suggested an new AR-GARCH model were re-estimated including in them the lagged return series, which were the granger cause (causality in mean) of a given variable. The re-[2]estimation of the model allowed eliminated the influence of causality-in-mean on the values of the causality-in-variance test.

For the causality in variance we use the squared standardized residuals retrieved form from the GARCH models.

$$u_{1t}^{2}=\left(z_{1t}-\mu_{1,t}\right)^{2}/\hat{\sigma}_{1,t}^{2}=\hat{e}_{1t}$$

$$u_{2t}^{2}=\left(z_{2t}-\mu_{2,t}\right)^{2}/\hat{\sigma}_{1,t}^{2}=\hat{e}_{2t}$$

Using equation 1 and equation 2 we estimate the sample cross covariance function of $\hat{e}_{1t}$ and $\hat{e}_{2t}$.

Finally we can compute Cheung and Ng's test statistic, S, which is based on the first M squared sample cross correlations This test statistic is asymptotically $X^2(M)$, under the null hypothesis of no causality in variance between the two series.

4. Data and Empirical Results

4.1 Country selection and data preparation.

As mentioned in the introduction, the choice of the countries was made, based on the connectiveness of the market with money laundering. For this reason, the selected countries were chosen using the financial secrecy index[23]. The Financial Secrecy Index (FSI)[24] uses a combination of qualitative data and quantitative data to create a measure of each jurisdiction's contribution to the global problem of financial secrecy. Qualitative data based on laws, regulations, cooperation with information exchange processes and other verifiable data sources, is used to prepare a secrecy score for each jurisdiction. Secrecy jurisdictions with the highest secrecy scores are opaquer in the operations they host, less engaged in information sharing with other national authorities and less compliant with international norms relating to combating money-laundering. Lack of transparency and unwillingness to engage in effective information exchange makes a secrecy jurisdiction a more attractive location for routing illicit financial flows and for concealing criminal and corrupt activities. Quantitative data is then used to create a global scale weighting, for each jurisdiction, according to its share on financial services activity in the global total.

Their 2018 list is given below.

Rank	Country or territory	FSI Value	FSI Share	Secrecy Score	Global Scale Weight
1	Switzerland	1,589.57	5.01%	76	4.50%
2	United States	1,298.47	4.09%	60	22.30%
3	Cayman Islands	1,267.68	4.00%	72	3.79%
4	Hong Kong	1,243.68	3.92%	71	4.17%
5	Singapore	1,081.98	3.41%	67	4.58%
6	Luxembourg	975.92	3.08%	58	12.13%
7	Germany	768.95	2.42%	59	5.17%
8	Taiwan	743.38	2.34%	76	0.50%
9	United Arab Emirates	661.15	2.08%	84	0.14%

Since the Cayman islands don't have any stock market index and also due to the fact that many commonwealth countries are featured heavily on the list , the United

[23] https://fsi.taxjustice.net/en/

[24] : The Secrecy Scores are calculated based on 20 indicators. For full explanation of the methodology and data sources, FSI Methodology, here: www.financialsecrecyindex.com/PDF/FSI-Methodology.pdf

Kingdom was included due it's connection with satellite states ,such as Cayman islands and British Virgin Islands, very familiar places if we consider the recent money laundering scandals of paradise papers or panama papers. In addition, due to its connectiveness with Taiwan and Hong Kong, China was included in the analysis and Cyprus as well for the connection it has with money-laundering [25]

In general, the countries that are included in the analysis and their stock market indexes are

- **Cyprus , CSE General** from 2016/02/24 to 2020/02/03 , total 963 observations
- **China, SHCOMP** from 2015/12/30 to 2020-02-10 total 860 observations
- **Germany, DAX** from 2016/02/24 to 2020/02/03, total 963 observations
- **Hong Kong, Hang Seng** from 2016/02/01 to 2020/02/03, total 999 observations
- **Luxembourg, LuxX** from 2016/02/24 to 2020/02/03, total 1029 observations
- **Switzerland, SMI** from 2016/02/24 to 2020/02/03, total 1029 observations
- **U.S.A., SP500** from 2015/02/03 to 2020/02/03, total 1259 observations
- **United Kingdom, FTSE100** from 2016/02/24 to 2020/02/03, total 963 observations
- **Taiwan, TWSE** 2016/01/11 to 2020/02/03 total 995 observations

All the indices were gathered from trading economics[26] database and they include daily closing prices from 2016 to 2020. There are approximately 1000 observation for each index, with only exception SP500 where the years expand from 2015 to 2020 (approximately1250 observations). All indices are based on local currencies, thus eliminating possible correlations due to a common factor such as a common currency appreciation or depreciation

Data for bitcoin was collected from Coinbase. We use the daily exchange rates between Bitcoin and US dollar, and we include observations from 2015 to 2020. The closing prices and the returns for all indices can be shown in **graph 1-10** and **graph 11-21**

For each index and the bitcoin exchange rate, their daily returns were calculated using the logarithmic formula

$$r_t = \log (P_t / P_{t-1}) = \log(P_t) - \log(P_{t-1})$$

where P_t is the price of the asset at time t. The formula of first logarithmic differences were chosen instead of the arithmetic differences because logs and exponents are easier to manipulate with calculus and theoretical models tend to assume, unrealistically but conveniently, continuously compounded rates of return.

[25] https://www.bloomberg.com/news/articles/2019-01-10/cyprus-loses-luster-as-mediterranean-haven-for-russian-business

[26] https://tradingeconomics.com

4.2 Data Analyses

Table 1 shows summary statistics on the daily data for all series including the mean median , maximum, minimum, standard deviation (St.Dev.) , skewness, kurtosis , Jarque Bera test statistics and the corresponding probability of each series. The highest mean observed in the bitcoin returns which also has the highest volatility making it a risky investment. The skewness coefficient is negative in all cases with the exception of Bitcoin and the Cyprus stock market. Furthermore, all series demonstrate high kurtosis and tend to have fatter tails. In addition to volatility clustering showing in **graph 11-21** a simple kernel density-based analysis **Graph 22-32** reveals that all the returns series display critical deviations (of the leptokurtic type) from a Gaussian benchmark, and fat tails – that may be induced by the presence of volatility clustering indication of heteroskedasticity and GARCH dynamics. The stylized facts for indices in the financial sector are present in our series. (Karthik Jilia, 2018)

Table 1 (descriptive statistics)

	bitcoin	CSE	DAX	FTSE100	LuxX
Mean	0.003208	1.38E-05	0.000367	0.000231	0.000216
Median	0.003217	-0.000139	0.000815	0.000481	0.000481
Maximum	0.240606	0.043743	0.034457	0.03515	0.03515
Minimum	-0.241059	-0.036796	-0.070673	-0.039324	-0.032839
Std. Dev.	0.047244	0.007717	0.00959	0.007749	0.00732
Skewness	0.230212	0.388656	-0.612785	-0.207198	-0.078504
Kurtosis	6.800426	5.54165	7.166961	5.461301	5.388676
Jarque-Bera	587.4303	283.1566	756.1955	249.7082	245.4531
Probability	0	0	0	0	0
Sum	3.086272	0.013257	0.352722	0.222098	0.222098
Sum Sq. Dev.	2.14496	0.057229	0.088373	0.057707	0.055035
Observations	962	962	962	962	1028

	SMI	TWSE	SHCOMP	Hang Seng	SP500

Mean	0.000318	0.0004	-0.0000438	0.000297	0.000366
Median	0.00053	0.000766	0.000507	0.0008	0.000503
Maximum	0.028111	0.028563	0.054495	0.041251	0.048403
Minimum	-0.03499	-0.065206	-0.088087	-0.05252	-0.04184
Std. Dev.	0.007316	0.007914	0.011646	0.010301	0.008409
Skewness	-0.185347	-1.332199	-0.848603	-0.36192	-0.55163
Kurtosis	4.78184	12.87788	11.35457	4.636144	7.017624
Jarque-Bera	141.8797	4335.144	2601.314	132.9714	909.8735
Probability	0	0	0	0	0
Sum	0.327099	0.397127	-0.037666	0.296433	0.460468
Sum Sq. Dev.	0.054976	0.062194	0.116361	0.105692	0.088882
Observations	1028	994	859	997	1258

To examine whether the stock indexes returns are stationary, unit root test were conducted. The Augmented Dickey Fuller (ADF) test and the Philips Peron (PP) test were used. ADF and the PP were conducted for the closing dates with trend, with trend and intercept and without trend and intercept, as well as in the first logarithmic differences i.e the returns of the indices. The test results are shown in table 2. With the exception of the United Kingdom (FTSE100 index) the prices are not stationary whereas the returns show no long-term memory. For the unit root test, the null hypothesis of having a unit root is rejected showing that all returns are stationary.

Table 2. part 1 (PP unit root test)

	At Level	BIT2	CHINA	CYPRUS	DAX	FTSE100
With Constant	t-Statistic	-1.6932	-2.4248	-2.3942	-2.4305	-3.2731
	Prob.	***0.4345***	***0.1352***	***0.1436***	***0.1336***	***0.0164***
		n0	n0	n0	n0	**
With Constant & Trend	t-Statistic	-2.3037	-2.5074	-2.4444	-2.4293	-3.1391
	Prob.	***0.4310***	***0.3245***	***0.3562***	***0.3640***	***0.0978***
		n0	n0	n0	n0	*
Without Constant & Trend	t-Statistic	-0.4627	-0.1258	-0.0761	1.0229	0.7280
	Prob.	***0.5149***	***0.6402***	***0.6572***	***0.9199***	***0.8719***
		n0	n0	n0	n0	n0
	At First Difference	d(BIT2)	d(CHINA)	d(CYPRUS)	d(DAX)	d(FTSE100)
With Constant	t-Statistic	-31.2556	-29.5306	-30.0570	-31.4737	-30.4349
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***
With Constant & Trend	t-Statistic	-31.2418	-29.5124	-30.0490	-31.4766	-30.4689
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***
Without Constant & Trend	t-Statistic	-31.2585	-29.5481	-30.0726	-31.4298	-30.4088
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***

		At Level				
			HONG_KONG	LUX	SP500	SWITZ.	TAIWAN
With Constant	t-Statistic	-2.1112	-3.2772	-0.8222	-0.8299	-2.0820
	Prob.	***0.2404***	***0.0162***	***0.8119***	***0.8097***	***0.2521***
		n0	**	n0	n0	n0
With Constant & Trend	t-Statistic	-1.7261	-3.1345	-2.8842	-2.5453	-2.7392
	Prob.	***0.7392***	***0.0988***	***0.1681***	***0.3060***	***0.2209***
		n0	*	n0	n0	n0
Without Constant & Trend	t-Statistic	0.5041	0.7308	1.0687	1.5697	1.3410
	Prob.	***0.8243***	***0.8724***	***0.9260***	***0.9718***	***0.9551***
		n0	n0	n0	n0	n0

	At First Difference					
		d(HONG_KONG)	d(LUX2)	d(SP500)	d(SWIT2)	d(TAIWAN)
With Constant	t-Statistic	-31.1142	-30.1844	-32.5440	-31.4465	-32.7981
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***
With Constant & Trend	t-Statistic	-31.1491	-30.2140	-32.5300	-31.4494	-32.7956
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***
Without Constant & Trend	t-Statistic	-31.1167	-30.1698	-32.5123	-31.3095	-32.7314
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***

Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant
*MacKinnon (1996) one-sided p-values.

Table 2 part 2 (ADF Unit root test)

	At Level					
		BIT2	CHINA	CYPRUS	DAX	FTSE100
With Constant	t-Statistic	-1.8179	-2.3695	-2.2418	-2.0431	-3.2902
	Prob.	***0.3720***	***0.1508***	***0.1917***	***0.2684***	***0.0156***
		n0	n0	n0	n0	**
With Constant & Trend	t-Statistic	-2.5892	-2.4990	-2.2958	-2.1188	-3.1647
	Prob.	***0.2854***	***0.3286***	***0.4353***	***0.5341***	***0.0923***
		n0	n0	n0	n0	*
Without Constant & Trend	t-Statistic	-0.5647	-0.3361	-0.0681	0.9022	0.6770
	Prob.	***0.4726***	***0.5641***	***0.6599***	***0.9022***	***0.8619***
		n0	n0	n0	n0	n0

	At First Difference					
		d(BIT2)	d(CHINA)	d(CYPRUS)	d(DAX)	d(FTSE100)
With Constant	t-Statistic	-8.1865	-13.9156	-30.0474	-16.8859	-30.3496
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***
With Constant & Trend	t-Statistic	-8.1826	-13.9038	-30.0393	-16.8887	-30.3666
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***
Without Constant & Trend	t-Statistic	-8.1628	-13.9270	-30.0631	-16.8501	-30.3468
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***

	At Level					
		HONG_K	LUX	SP500	SWITZ	TAIWAN

		ONG				
With Constant	t-Statistic	-2.4383	-2.7668	-0.8837	-0.3870	-2.1474
	Prob.	***0.1315***	***0.0635***	***0.7936***	***0.9088***	***0.2262***
		n0	*	n0	n0	n0
With Constant & Trend	t-Statistic	-1.8683	-2.7177	-2.9243	-1.9857	-2.8178
	Prob.	***0.6702***	***0.2295***	***0.1551***	***0.6079***	***0.1911***
		n0	n0	n0	n0	n0
Without Constant & Trend	t-Statistic	0.6813	0.5379	1.0006	1.6588	1.2792
	Prob.	***0.8627***	***0.8321***	***0.9168***	***0.9768***	***0.9495***
		n0	n0	n0	n0	n0

At First Difference

		d(HONG_ KONG)	d(LUX)	d(SP500)	d(SWITZ)	d(TAIWAN)
With Constant	t-Statistic	-13.7661	-10.9038	-8.2042	-11.2454	-21.6260
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***
With Constant & Trend	t-Statistic	-13.8608	-10.9400	-8.2172	-11.2605	-21.6297
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***
Without Constant & Trend	t-Statistic	-13.7310	-10.8857	-12.2699	-11.1067	-21.5620
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***

Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant
*MacKinnon (1996) one-sided p-values.

Autocorrelation is present in all series. The selection of lag lengths in AR models can sometimes be guided by economic theory. However, there are statistical methods that are helpful to determine how many lags should be included as regressors. In general, too many lags inflate the standard errors of coefficient estimates and thus imply an increase in the forecast error while omitting lags that should be included in the model may result in an estimation bias.
A common way to choose the lag order that minimizes one of the following two information criteria:

- The *Bayes information criterion* (BIC):

$$BIC(p) = \log\left(\frac{SSR(p)}{T}\right) + (p+1)\frac{\log(T)}{T}$$

- The *Akaike information criterion* (AIC):

$$AIC(p) = \log\left(\frac{SSR(p)}{T}\right) + (p+1)\frac{2}{T}$$

Both criteria are estimators of the optimal lag length p. The lag order p that minimizes the respective criterion is called the *BIC estimate* or the *AIC estimate* of the optimal model order. The basic idea of both criteria is that the SSR decreases as additional lags are added to the model such that the first term decreases whereas the second increases as the lag order grows. In this study the preferred information criterion is AIC and the maximum lag order is set to 10. **Table 3** reports the lag order chosen by AIC. We can see that autocorrelation and partial autocorrelation has been filtered out from each series observing the correlogram of ***p-1 lags*** in comparison with the **p lag** **(table 4)**

Our initial suspicion for heteroskedasticity (due to periods of volatility clustering in the graphs of the returns in each time series) is strengthened by observing the correlogram of square residuals **-table 5-** for each model and confirmed when executing ARCH test for heteroskedasticity with the appropriate lags for each time-series. We must reject the null hypothesis that our time-series are homoscedastic for all indices except Cyprus and Taiwan. In **Table 6** there are the results from ARCH test with the F statistic and the corresponding p-value.

TABLE 3 (AIC information criterion)

AIC	LuxX	SM1	SP500	SHCOMP	HANG-SENG
0	-7.0097	-7.002658	-6.710618	-6.134423	-6.338732
1	-7.01305	-7.001702	-6.7095	-6.134221	-6.336757
2	-7.01152	-7.000161	-6.710900*	-6.133216	-6.336216
3	-7.01225	-7.000529	-6.709386	-6.130865	-6.338127
4	-7.0178	-7.005129*	-6.70917	-6.131744	-6.338849
5	-7.01649	-7.00436	-6.70861	-6.129933	-6.337558
6	-7.01497	-7.002683	-6.70699	-6.13299	-6.339103*
7	-7.0165	-7.002803	-6.706869	-6.131919	-6.337173
8	-7.019238*	-7.000863	-6.709602	-6.129698	-6.33563
9	-7.01735	-7.000754	-6.708038	-6.142292*	-6.33026

* indicates lag order selected by the criterion

AIC	FTSE100	CSE	BITCOIN	DAX
0	-6.89008	-1 402856	2 226794	-6.460637
1	-6.88876	-11 08709*	ι 681066*	-6.458538
2	-6.88676	-11 08096	-1.678901	-6.456588
3	-6.88742	-1107800	-1 674141	-6.454525
4	-6.890975*	-11 07548	-1.667503	-6.465529*
5	-6.88997	-11 07269	-1.662859	-6.46427
6	-6.88806	-11 06867	-1.658442	-6.462179
7	-6.89003	-11 07150	-1.653375	-6.460207
8	-6.88853	-11 06581	-1.647814	-6.458508

Table 4 (part 1) autocorrelation and partial autocorrelation with p-1 and p lags , the Q-stat. and the corresponding p-value for each lag.

DAX(Germany) 3 / 4 lags

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0007	0.979
		2	-0.003	-0.003	0.0083	0.996
		3	-0.005	-0.005	0.0334	0.998
		4	-0.115	-0.115	12.799	0.012
		5	-0.031	-0.031	13.708	0.018
		6	0.003	0.002	13.715	0.033
		7	0.013	0.012	13.880	0.053
		8	-0.006	-0.019	13.910	0.084
		9	-0.026	-0.034	14.570	0.103
		10	-0.045	-0.046	16.528	0.085

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.005	-0.005	0.0282	0.867
		2	0.001	0.001	0.0291	0.986
		3	-0.002	-0.002	0.0334	0.998
		4	-0.003	-0.003	0.0415	1.000
		5	-0.033	-0.033	1.0814	0.956
		6	-0.002	-0.002	1.0844	0.982
		7	0.019	0.019	1.4220	0.985
		8	-0.030	-0.030	2.2876	0.971
		9	-0.037	-0.038	3.6311	0.934
		10	-0.047	-0.049	5.8090	0.831

luxX (Luxembourg) 7 / 8 lags

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0012	0.973
		2	0.002	0.002	0.0053	0.997
		3	0.004	0.004	0.0207	0.999
		4	0.009	0.009	0.1022	0.999
		5	0.003	0.003	0.1114	1.000
		6	-0.009	-0.009	0.1893	1.000
		7	0.052	0.052	2.9770	0.887
		8	0.067	0.067	7.6349	0.470
		9	0.007	0.007	7.6864	0.566
		10	-0.034	-0.035	8.8917	0.542

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.001	-0.001	0.0013	0.972
		2	0.005	0.005	0.0236	0.988
		3	-0.002	-0.002	0.0291	0.999
		4	0.003	0.003	0.0416	1.000
		5	0.002	0.002	0.0444	1.000
		6	0.002	0.002	0.0474	1.000
		7	0.010	0.010	0.1475	1.000
		8	0.002	0.002	0.1515	1.000
		9	0.006	0.006	0.1930	1.000
		10	-0.035	-0.035	1.4247	0.999

Table 4 (part 2) autocorrelation and partial autocorrelation with p-1 and p lags, the Q-stat. and the corresponding p-value for each lag.

SMI (SWITZERLAND) , 3 / 4 lags

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.002	-0.002	0.0030	0.956
		2	-0.002	-0.002	0.0064	0.997
		3	-0.004	-0.004	0.0229	0.999
		4	-0.076	-0.076	5.9218	0.205
		5	-0.037	-0.037	7.3144	0.198
		6	-0.021	-0.021	7.7548	0.257
		7	0.045	0.044	9.8431	0.198
		8	0.003	-0.002	9.8543	0.275
		9	0.027	0.022	10.608	0.304
		10	-0.083	-0.088	17.700	0.060

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.006	-0.006	0.0359	0.850
		2	0.001	0.001	0.0381	0.981
		3	-0.000	-0.000	0.0383	0.998
		4	0.001	0.001	0.0399	1.000
		5	-0.032	-0.032	1.1014	0.954
		6	-0.026	-0.026	1.7809	0.939
		7	0.039	0.039	3.3541	0.850
		8	-0.005	-0.005	3.3851	0.908
		9	0.021	0.021	3.8431	0.921
		10	-0.086	-0.087	11.493	0.320

FTSE100 (U.K) 3 / 4 lags

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.003	-0.003	0.0113	0.915
		2	-0.005	-0.005	0.0309	0.985
		3	-0.003	-0.003	0.0387	0.998
		4	-0.072	-0.072	4.9915	0.288
		5	-0.034	-0.034	6.0760	0.299
		6	-0.014	-0.016	6.2771	0.393
		7	0.067	0.066	10.569	0.159
		8	0.034	0.029	11.678	0.166
		9	-0.004	-0.008	11.698	0.231
		10	0.016	0.013	11.932	0.290

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.003	-0.003	0.0069	0.934
		2	-0.002	-0.002	0.0105	0.995
		3	0.001	0.001	0.0123	1.000
		4	0.006	0.006	0.0436	1.000
		5	-0.031	-0.031	0.9870	0.964
		6	-0.015	-0.015	1.2056	0.977
		7	0.067	0.067	5.5072	0.598
		8	0.023	0.023	6.0181	0.645
		9	-0.010	-0.010	6.1182	0.728
		10	0.014	0.013	6.3199	0.788

Table 4 (part 3) autocorrelation and partial autocorrelation with p-1 and p lags, the Q-stat. and the corresponding p-value for each lag.

SP500 (U.S.) 1 / 2 lags

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.001	-0.001	0.0007	0.978
		2	-0.050	-0.050	3.1935	0.203
		3	0.012	0.012	3.3767	0.337
		4	-0.035	-0.038	4.9662	0.291
		5	-0.030	-0.029	6.0908	0.297
		6	0.005	0.001	6.1178	0.410
		7	0.040	0.038	8.1879	0.316
		8	-0.066	-0.067	13.725	0.089
		9	-0.008	-0.006	13.810	0.129
		10	-0.021	-0.030	14.372	0.157

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0013	0.971
		2	-0.001	-0.001	0.0036	0.998
		3	0.008	0.008	0.0894	0.993
		4	-0.038	-0.038	1.9184	0.751
		5	-0.028	-0.028	2.9233	0.712
		6	-0.001	-0.001	2.9250	0.818
		7	0.039	0.039	4.8056	0.684
		8	-0.067	-0.068	10.522	0.230
		9	-0.006	-0.008	10.570	0.306
		10	-0.024	-0.026	11.310	0.334

Hang-Seng (Hong Kong) 5/6 lags

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.007	-0.007	0.0544	0.816
		2	0.010	0.010	0.1623	0.922
		3	0.009	0.009	0.2479	0.970
		4	-0.010	-0.010	0.3393	0.987
		5	0.012	0.011	0.4768	0.993
		6	-0.064	-0.064	4.6024	0.596
		7	0.008	0.007	4.6689	0.700
		8	0.022	0.023	5.1485	0.742
		9	0.008	0.010	5.2185	0.815
		10	-0.035	-0.037	6.4688	0.774

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.005	0.005	0.0253	0.874
		2	0.015	0.015	0.2606	0.878
		3	0.003	0.003	0.2698	0.966
		4	-0.007	-0.007	0.3197	0.989
		5	0.010	0.010	0.4202	0.995
		6	-0.002	-0.002	0.4238	0.999
		7	0.007	0.007	0.4749	1.000
		8	0.023	0.023	1.0030	0.998
		9	0.010	0.010	1.1132	0.999
		10	-0.034	-0.035	2.3018	0.993

Table 4 (part 4) autocorrelation and partial autocorrelation with p-1 and p lags, the Q-stat. and the corresponding p-value for each lag.

TWSE (Taiwan) 1 / 2 lags

		1	0.050	0.050	2.4500	0.118
		2	0.038	0.035	3.8728	0.144
		3	0.060	0.056	7.4266	0.059
		4	0.024	0.017	8.0069	0.091
		5	0.043	0.038	9.8789	0.079
		6	0.012	0.004	10.035	0.123
		7	-0.003	-0.009	10.043	0.186
		8	0.035	0.030	11.262	0.187
		9	-0.005	-0.010	11.283	0.257
		10	0.038	0.035	12.700	0.241

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0012	0.973
		2	-0.000	-0.000	0.0012	0.999
		3	-0.017	-0.017	0.2926	0.961
		4	0.006	0.006	0.3243	0.988
		5	-0.045	-0.045	2.3384	0.801
		6	-0.014	-0.014	2.5318	0.865
		7	-0.004	-0.004	2.5506	0.923
		8	0.057	0.055	5.7913	0.671
		9	-0.014	-0.014	5.9855	0.741
		10	0.020	0.018	6.3937	0.781

SHCOMP (China) 8/9

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.006	0.006	0.0300	0.862
		2	0.006	0.006	0.0620	0.969
		3	-0.013	-0.013	0.2069	0.976
		4	-0.003	-0.003	0.2139	0.995
		5	0.015	0.016	0.4189	0.995
		6	0.006	0.005	0.4474	0.998
		7	-0.019	-0.019	0.7556	0.998
		8	0.010	0.010	0.8354	0.999
		9	0.119	0.119	12.953	0.165
		10	0.030	0.028	13.735	0.185

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.006	-0.006	0.0305	0.861
		2	0.013	0.013	0.1756	0.916
		3	-0.012	-0.012	0.2994	0.960
		4	-0.011	-0.011	0.4012	0.982
		5	0.006	0.006	0.4310	0.994
		6	0.010	0.010	0.5190	0.998
		7	-0.008	-0.008	0.5678	0.999
		8	0.005	0.004	0.5866	1.000
		9	-0.007	-0.007	0.6310	1.000
		10	0.033	0.033	1.5922	0.999

table 5 (part 1) correlogram of the ***square*** residuals for an AR(p) model, the Q-stat. and the corresponding p-value.

DAX(Germany)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.144	0.144	19.925	0.000
		2	0.069	0.049	24.529	0.000
		3	0.060	0.044	27.950	0.000
		4	0.107	0.092	39.029	0.000
		5	0.004	-0.028	39.048	0.000
		6	0.041	0.033	40.696	0.000
		7	0.006	-0.012	40.726	0.000
		8	0.051	0.042	43.290	0.000
		9	0.004	-0.008	43.308	0.000
		10	0.105	0.098	54.065	0.000

luxX (Luxembourg)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.280	0.280	80.370	0.000
		2	0.172	0.102	110.93	0.000
		3	0.161	0.098	137.76	0.000
		4	0.171	0.101	167.78	0.000
		5	0.092	0.001	176.59	0.000
		6	0.088	0.029	184.66	0.000
		7	0.102	0.045	195.36	0.000
		8	0.080	0.015	201.95	0.000
		9	0.037	-0.017	203.39	0.000
		10	0.077	0.045	209.53	0.000

SMI (SWITZERLAND)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.195	0.195	38.919	0.000
		2	0.210	0.179	84.111	0.000
		3	0.159	0.098	110.17	0.000
		4	0.131	0.059	127.77	0.000
		5	0.049	-0.026	130.21	0.000
		6	0.113	0.069	143.44	0.000
		7	0.058	0.010	146.91	0.000
		8	0.051	0.006	149.65	0.000
		9	0.050	0.014	152.25	0.000
		10	0.067	0.032	156.84	0.000

FTSE100 (U.K)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.231	0.231	51.234	0.000
		2	0.126	0.077	66.483	0.000
		3	0.145	0.106	86.666	0.000
		4	0.114	0.057	99.274	0.000
		5	0.053	-0.002	101.99	0.000
		6	0.052	0.016	104.55	0.000
		7	0.047	0.014	106.73	0.000
		8	0.046	0.020	108.74	0.000
		9	0.008	-0.019	108.81	0.000
		10	0.040	0.030	110.35	0.000

table 5 (part 2) correlogram of the ***square*** residuals for a AR(p) model, the Q-stat. and the corresponding p-value.

SP500 (U.S.)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.287	0.287	103.97	0.000
		2	0.214	0.143	161.44	0.000
		3	0.216	0.137	220.54	0.000
		4	0.202	0.103	272.09	0.000
		5	0.113	-0.005	288.25	0.000
		6	0.218	0.148	348.37	0.000
		7	0.140	0.012	373.06	0.000
		8	0.096	-0.008	384.67	0.000
		9	0.098	0.013	396.96	0.000
		10	0.127	0.043	417.49	0.000

Hang-Seng (Hong Kong)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.029	0.029	0.8134	0.367
		2	-0.003	-0.004	0.8221	0.663
		3	0.087	0.087	8.2758	0.041
		4	0.011	0.006	8.3964	0.078
		5	0.054	0.055	11.301	0.046
		6	0.062	0.052	15.184	0.019
		7	0.097	0.095	24.594	0.001
		8	0.030	0.017	25.472	0.001
		9	0.075	0.068	31.119	0.000
		10	0.028	0.007	31.910	0.000

TWSE (Taiwan)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.051	0.051	2.6003	0.107
		2	0.026	0.024	3.2904	0.193
		3	0.059	0.056	6.7165	0.082
		4	0.023	0.017	7.2382	0.124
		5	0.045	0.041	9.2510	0.099
		6	0.011	0.003	9.3699	0.154
		7	-0.005	-0.010	9.3945	0.226
		8	0.033	0.029	10.493	0.232
		9	-0.004	-0.009	10.511	0.311
		10	0.034	0.032	11.646	0.309

CSE(Cyprus)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.049	0.049	2.3275	0.127
		2	0.012	0.010	2.4734	0.290
		3	0.078	0.077	8.3643	0.039
		4	0.014	0.006	8.5487	0.073
		5	-0.040	-0.043	10.136	0.071
		6	0.011	0.009	10.248	0.115
		7	0.017	0.016	10.533	0.160
		8	0.004	0.008	10.546	0.229
		9	0.061	0.060	14.169	0.116
		10	-0.006	-0.017	14.208	0.164

table 5 (part 3) correlogram of the ***square*** residuals for a AR(p) model

SHCOMP (China)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.008	0.008	0.0566	0.812
		2	0.040	0.040	1.4125	0.493
		3	0.104	0.103	10.581	0.014
		4	0.030	0.027	11.348	0.023
		5	0.112	0.105	22.097	0.001
		6	0.025	0.013	22.646	0.001
		7	0.153	0.143	42.691	0.000
		8	0.063	0.042	46.113	0.000
		9	0.037	0.023	47.296	0.000
		10	0.050	0.009	49.447	0.000

Table 6 (ARCH heteroskedasticity test for p lags)

	LuxX	SMI	SP500	SHCOMP	HANG-SENG
ARCH test					
F-statistic	36.346	22.3433	70.49857	8.1463	2.31
p-value	0.000	0.000	0.000	0.000	0.032
	***	***	***	***	**

	FTSE100	CSE	BITCOIN	DAX	TWSE
ARCH test					
F-statistic	18.64	2.319	21.973	8.16032	1.573
p-value	0.000	0.12	0.000	0.000	0.207
	***		***	***	

4.3 GARCH MODELS

For each time-series a AR(p)-Garch(1,1) model was calculated with p lags chosen by the AIC information criterion. The results for each time series are reported in the following pages together with the correlogram of squared residuals. We can see in all cases that the conditional variance was capture by applying the GARCH methodology in contrast with **table 6** (correlogram of squared residuals before applying GARCH methodology).

- BITCOIN: AR(1)-GARCH (1,1)

BITR = C(1) + C(2)*BITR(-1)

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002364	0.001199	1.971808	0.0486
BIT2R(-1)	0.041983	0.033535	1.251888	0.2106
		Variance Equation		
C	7.05E-05	9.99E-06	7.058717	0.0000
RESID(-1)^2	0.095129	0.012547	7.581621	0.0000
GARCH(-1)	0.876643	0.013911	63.01896	0.0000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.025	0.025	0.8085	0.369
		2	-0.014	-0.015	1.0561	0.590
		3	-0.008	-0.007	1.1377	0.768
		4	0.035	0.036	2.7095	0.608
		5	-0.031	-0.034	3.9551	0.556
		6	0.002	0.005	3.9616	0.682
		7	-0.040	-0.041	6.0365	0.535
		8	-0.020	-0.020	6.5654	0.584
		9	-0.003	-0.000	6.5741	0.681
		10	0.067	0.064	12.195	0.272

- USA, SP500: AR(2)-GARCH(1,1)

SP500R = C(1) + C(2)*SP500R(-1) + C(3)*SP500R(-2)

GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000898	0.000176	5.094775	0.0000
SP500R(-1)	-0.075417	0.033016	-2.284267	0.0224
SP500R(-2)	-0.023181	0.031824	-0.728416	0.4664
		Variance Equation		
C	4.16E-06	5.05E-07	8.244347	0.0000
RESID(-1)^2	0.209130	0.020531	10.18621	0.0000
GARCH(-1)	0.741135	0.022377	33.12050	0.0000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.018	0.018	0.3143	0.575
		2	0.010	0.009	0.4056	0.816
		3	0.023	0.023	0.9191	0.821
		4	0.084	0.083	7.7047	0.103
		5	-0.021	-0.024	8.1280	0.149
		6	0.043	0.042	9.9043	0.129
		7	-0.023	-0.028	10.410	0.167
		8	0.039	0.033	11.847	0.158
		9	-0.026	-0.026	12.517	0.186
		10	0.074	0.069	17.831	0.058

- GERMANY, DAX: AR(4)-GARCH(1,1)

DAXR = C(1) + C(2)*DAXR(-1) + C(3)*DAXR(-2) + C(4)*DAXR(-3) + C(5)*DAXR(-4)

GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000348	0.000612	0.568480	0.5697
DAXR(-1)	0.002611	0.070872	0.036846	0.9706
DAXR(-2)	0.012909	0.066149	0.195151	0.8453
DAXR(-3)	-0.002290	0.061228	-0.037398	0.9702
DAXR(-4)	-0.114340	0.063949	-1.787985	0.0738
Variance Equation				
C	5.84E-05	3.70E-05	1.576395	0.1149
RESID(-1)^2	0.150000	0.091846	1.633177	0.1024
GARCH(-1)	0.600000	0.236615	2.535767	0.0112

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.018	0.018	0.3143	0.575
		2	0.010	0.009	0.4056	0.816
		3	0.023	0.023	0.9191	0.821
		4	0.084	0.083	7.7047	0.103
		5	-0.021	-0.024	8.1280	0.149
		6	0.043	0.042	9.9043	0.129
		7	-0.023	-0.028	10.410	0.167
		8	0.039	0.033	11.847	0.158
		9	-0.026	-0.026	12.517	0.186
		10	0.074	0.069	17.831	0.058

- United Kingdom, FTSE100 AR(4)-GARCH(1,1)

FTSE100R = C(1) + C(2)*FTSE100R(-1) + C(3)*FTSE100R(-2) + C(4)*FTSE100R(-3) + C(5)*FTSE100R(-4)

GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000325	0.000229	1.422718	0.1548
FTSE100R(-1)	0.007432	0.038886	0.191129	0.8484
FTSE100R(-2)	0.004928	0.035335	0.139458	0.8891
FTSE100R(-3)	-0.043181	0.032960	-1.310121	0.1902
FTSE100R(-4)	-0.053712	0.031458	-1.707409	0.0877
		Variance Equation		
C	1.37E-05	3.22E-06	4.262399	0.0000
RESID(-1)^2	0.185441	0.036129	5.132760	0.0000
GARCH(-1)	0.585420	0.078473	7.460116	0.0000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.011	-0.011	0.1074	0.743
		2	-0.030	-0.030	0.9567	0.620
		3	0.005	0.004	0.9783	0.807
		4	0.025	0.024	1.5759	0.813
		5	0.001	0.001	1.5762	0.904
		6	-0.003	-0.001	1.5836	0.954
		7	-0.025	-0.026	2.2084	0.947
		8	-0.004	-0.005	2.2255	0.973
		9	-0.031	-0.033	3.1729	0.957
		10	0.002	0.001	3.1768	0.977

▪ Cyprus, CSE AR(1)-GARCH(1,1)

CYPRUSR = C(1) + C(2)*CYPRUS(-1)

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.011175	0.004436	2.519226	0.0118
CYPRUS(-1)	-0.000163	6.44E-05	-2.533427	0.0113
		Variance Equation		
C	2.40E-06	1.07E-06	2.244962	0.0248
RESID(-1)^2	0.051678	0.014442	3.578323	0.0003
GARCH(-1)	0.908961	0.026795	33.92273	0.0000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.049	0.049	2.3275	0.127
		2	0.012	0.010	2.4734	0.290
		3	0.078	0.077	8.3643	0.039
		4	0.014	0.006	8.5487	0.073
		5	-0.040	-0.043	10.136	0.071
		6	0.011	0.009	10.248	0.115
		7	0.017	0.016	10.533	0.160
		8	0.004	0.008	10.546	0.229
		9	0.061	0.060	14.169	0.116
		10	-0.006	-0.017	14.208	0.164

- Luxembourg, LuxX : AR(8)-GARCH(1,1)

LUX2R = C(1)*LUX2R(-1) + C(2)*LUX2R(-2) + C(3)*LUX2R(-3) + C(4)*LUX2R(-4) + C(5)*LUX2R(-5) + C(6)*LUX2R(-6) + C(7)*LUX2R(-7) + C(8)*LUX2R(-8) + C(9)

GARCH = C(10) + C(11)*RESID(-1)^2 + C(12)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LUX2R(-1)	0.035360	0.035750	0.989080	0.3226
LUX2R(-2)	-0.014500	0.035567	-0.407677	0.6835
LUX2R(-3)	-0.037450	0.033152	-1.129636	0.2586
LUX2R(-4)	-0.070350	0.030992	-2.269919	0.0232
LUX2R(-5)	0.006338	0.031084	0.203914	0.8384
LUX2R(-6)	-0.039381	0.033257	-1.184149	0.2364
LUX2R(-7)	0.042290	0.029154	1.450584	0.1469
LUX2R(-8)	0.034976	0.030150	1.160051	0.2460
C	0.000405	0.000197	2.059602	0.0394
		Variance Equation		
C	8.76E-06	2.24E-06	3.910741	0.0001
RESID(-1)^2	0.176438	0.028477	6.195762	0.0000
GARCH(-1)	0.655617	0.060479	10.84047	0.0000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.004	0.004	0.0127	0.910
		2	-0.053	-0.053	2.9405	0.230
		3	-0.020	-0.019	3.3408	0.342
		4	0.036	0.033	4.6506	0.325
		5	0.014	0.012	4.8585	0.433
		6	0.001	0.004	4.8589	0.562
		7	0.014	0.017	5.0671	0.652
		8	-0.035	-0.036	6.3229	0.611
		9	0.007	0.008	6.3676	0.703
		10	0.025	0.022	7.0049	0.725

- Switzerland, SCE :AR(4)-GARCH(1,1)

SWITZ2R = C(1) + C(2)*SWITZ2R(-1) + C(3)*SWITZ2R(-2) + C(4)*SWITZ2R(-3) + C(5)*SWITZ2R(-4)

GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000601	0.000203	2.957858	0.0031
SWITZ2R(-1)	0.024184	0.034893	0.693077	0.4883
SWITZ2R(-2)	-0.004313	0.034350	-0.125576	0.9001
SWITZ2R(-3)	-0.051069	0.031918	-1.600011	0.1096
SWITZ2R(-4)	-0.048490	0.033833	-1.433217	0.1518
Variance Equation				
C	4.98E-06	1.21E-06	4.122985	0.0000
RESID(-1)^2	0.137374	0.022657	6.063128	0.0000
GARCH(-1)	0.769563	0.038327	20.07877	0.0000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.000	-0.000	7.E-05	0.993
		2	-0.012	-0.012	0.1369	0.934
		3	0.030	0.030	1.0720	0.784
		4	-0.006	-0.006	1.1109	0.893
		5	-0.029	-0.028	1.9854	0.851
		6	0.043	0.042	3.8738	0.694
		7	-0.029	-0.029	4.7321	0.693
		8	-0.022	-0.019	5.2351	0.732
		9	-0.014	-0.017	5.4247	0.796
		10	-0.011	-0.010	5.5528	0.851

- HONK KONG, HANG SENG: AR(6)-GARCH(1,1)

HKR = C(1) + C(2)*HKR(-1) + C(3)*HKR(-2) + C(4)*HKR(-3) + C(5)*HKR(-4) + C(6)*HKR(-5) + C(7)*HKR(-6)

GARCH = C(8) + C(9)*RESID(-1)^2 + C(10)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000518	0.000309	1.674556	0.0940
HKR(-1)	0.016634	0.035633	0.466823	0.6406
HKR(-2)	0.003828	0.034658	0.110449	0.9121
HKR(-3)	0.071726	0.033062	2.169445	0.0300
HKR(-4)	-0.048288	0.034442	-1.401992	0.1609
HKR(-5)	-0.025002	0.031403	-0.796152	0.4259
HKR(-6)	-0.054255	0.033113	-1.638471	0.1013
		Variance Equation		
C	1.62E-06	6.31E-07	2.568616	0.0102
RESID(-1)^2	0.033091	0.008381	3.948122	0.0001
GARCH(-1)	0.950618	0.011044	86.07766	0.0000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.026	-0.026	0.6741	0.412
		2	-0.033	-0.034	1.7810	0.410
		3	0.026	0.024	2.4319	0.488
		4	-0.024	-0.024	3.0251	0.554
		5	0.030	0.030	3.9128	0.562
		6	0.007	0.006	3.9641	0.682
		7	0.052	0.055	6.6271	0.469
		8	-0.026	-0.025	7.3020	0.504
		9	0.010	0.013	7.3954	0.596
		10	0.017	0.013	7.7015	0.658

- China, SCHCOMP: AR(9)-GARCH(1,1)

CHINAR = C(1) + C(2)*CHINAR(-1) + C(3)*CHINAR(-2) + C(4)*CHINAR(-3) + C(5)*CHINAR(-4) + C(6)*CHINAR(-5) + C(7)*CHINAR(-6) + C(8)*CHINAR(-7) + C(9)*CHINAR(-8) + C(10)*CHINAR(-9)

GARCH = C(11) + C(12)*RESID(-1)^2 + C(13)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	6.68E-05	0.000311	0.215171	0.8296
CHINAR(-1)	-0.018275	0.041140	-0.444219	0.6569
CHINAR(-2)	-0.023849	0.040782	-0.584792	0.5587
CHINAR(-3)	0.030542	0.040411	0.755786	0.4498
CHINAR(-4)	-0.041818	0.041075	-1.018101	0.3086
CHINAR(-5)	-0.032044	0.033762	-0.949122	0.3426
CHINAR(-6)	-0.001878	0.040903	-0.045925	0.9634
CHINAR(-7)	0.002908	0.035546	0.081799	0.9348
CHINAR(-8)	0.007706	0.040386	0.190806	0.8487
CHINAR(-9)	0.112526	0.038116	2.952154	0.0032
Variance Equation				
C	7.05E-07	1.94E-07	3.639267	0.0003
RESID(-1)^2	0.049104	0.007239	6.783467	0.0000
GARCH(-1)	0.944280	0.006378	148.0586	0.0000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.017	-0.017	0.2451	0.621
		2	-0.009	-0.009	0.3075	0.857
		3	0.019	0.019	0.6191	0.892
		4	-0.027	-0.026	1.2402	0.871
		5	0.066	0.065	4.9343	0.424
		6	-0.012	-0.011	5.0547	0.537
		7	0.027	0.029	5.6997	0.575
		8	0.006	0.003	5.7268	0.678
		9	-0.008	-0.004	5.7888	0.761
		10	0.018	0.012	6.0600	0.810

- TAIWAN, TWSE : AR(2)-GARCH(1,1)

TAIWANR = C(1) + C(2)*TAIWANR(-1) + C(3)*TAIWANR(-2)

GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000645	0.000248	2.604215	0.0092
TAIWANR(-1)	-0.016236	0.034991	-0.463997	0.6426
TAIWANR(-2)	-0.001103	0.036485	-0.030227	0.9759
		Variance Equation		
C	5.65E-06	1.66E-06	3.402575	0.0007
RESID(-1)^2	0.101128	0.010632	9.511650	0.0000
GARCH(-1)	0.818119	0.031864	25.67492	0.0000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.013	-0.013	0.1774	0.674
		2	-0.012	-0.012	0.3218	0.851
		3	0.012	0.012	0.4622	0.927
		4	0.006	0.006	0.4974	0.974
		5	0.009	0.010	0.5850	0.989
		6	-0.001	-0.001	0.5872	0.997
		7	-0.016	-0.016	0.8296	0.997
		8	0.005	0.004	0.8545	0.999
		9	-0.004	-0.005	0.8746	1.000
		10	-0.005	-0.005	0.8997	1.000

The coefficients on both the lagged squared residual and lagged conditional variance terms in the conditional variance equation are highly statistically significant in all the models. Also, the sum of the coefficients on the lagged squared error and lagged conditional variance is very close to unity in all models. This implies that shocks to the conditional variance will be highly persistent. Furthermore, the large sum of these coefficients imply that a large positive or negative return will lead future forecasts of the variance to be high for a protracted period. In all cases the individual conditional variance coefficients are also as one would expect.

4.4 Causality-in-mean tests

The causality in mean test -explained in section 2.1- was made using the first 5 and 10 lags of the cross-correlation function. Table 7 highlights the results for causality in mean with the S statistic and the corresponding p-value. None of the 9 sets show bi-directional causation. All the causality runs from bitcoin to the stock indices. There is strong evidence of Granger causality in mean from bitcoin to the Chinese SHCOMP for both 5 and 10 lags, from Bitcoin to the FTSE 100 in both lags. Relatively weak, is the effect from bitcoin to LuxX (Luxembourg) and to CSE (Cyprus).

4.4 Causality in variance tests

The analyses for causality in variance was conducted for 5 and 10 lags as in causality in-mean tests. Table 7 presents the results for Causality in-variance. There are strong evidence for volatility spillover between Bitcoin, Germany's DAX, U.K's FTSE100. Specifically, Bitcoin is the reason for volatility contagion in DAX at any confidence level and at both lags, the reverse is not occurring. Similar is the results between Bitcoin and FTSE100. Whilst there is a volatility spillover from Bitcoin to the FTSE100 the later doesn't cause any congestion. Thus, Bitcoin and FTSE100 are connected both in mean and in variance. The only set of variables where there is a bi-directional causality in variance is between TWSE and Bitcoin i.e. Bitcoin is Granger causes in-variance TWSE and vice versa, although it seems that TWSE effect in BITCOIN is much stronger.

TABLE 7 (part1-from bitcoin to indexes)

bitcoin	*Granger causes in mean*	CSE	DAX	FTSE100	HANG-SENG
lag length	*5*	11.66603 0.039 **	4.76938 0.5180	13.4686 0.01 ***	5.48031 0.3960
	10	20.61106 0.0239 **	9.1489 0.446	18.569 0.046 **	9.9670 0.360
bitcoin	***Granger causes in variance***	**CSE**	**DAX**	**FTSE100**	**HANG-SENG**
lag length	*5*	3.543 0.616	17.558 0.003 ***	10.433 0.0638 *	5.904 0.315
	10	10.8588 0.3686	38.757 2.8E-05 ***	14.737 0.1473	7.739 0.654

bitcoin	*Granger causes in mean*	luxX	SHCOMP	SMI	SP500	TWSE
lag length	*5*	9.059 0.10 *	13.87474 0.01 ***	2.859 0.721	7.666 0.175	2.724 0.742
	10	14.917 0.13508 *	16.335 0.090 **	9.608 0.475	13.201 0.212	4.974 0.892
bitcoin	***Granger causes in Variance***	**luxX**	**SHCOMP**	**SMI**	**SP500**	**TWSE**
lag length	*5*	3.543 0.616	0.662 0.984	0.5497 0.990	4.368 0.497	8.067 0.15
	10	10.858 0.336	3.925 0.950	0.997 0.999	11.464 0.322	10.119 0.430

Note a) (*) Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1%

b) In each cell there is the S-statistic form Cheung and Ng test and the corresponding p-value

Table 7 (part2- from indexes to bitcoin)

CSE	**DAX**	**FTSE100**	**HANG-SENG**	**Granger causes in mean**	***bitcoin***
6.810 0.235	2.562 0.766	2.406 0.790	3.582 0.611	*5 lags*	*lag length*
9.094 0.523	4.461 0.924	6.126 0.80	11.207 0.325	*10 lags*	
CSE	**DAX**	**FTSE100**	**HANG-SENG**	**Granger causes in Variance**	***bitcoin***
1.122 0.952	4.469 0.48	5.339 0.375	2.176 0.824	*5 lags*	*lag length*
5.389 0.69	6.569 0.765	7.343 0.375	3.068 0.979	*10 lags*	

luxX	**SHCOMP**	**SMI**	**SP500**	**TWSE**	**Granger causes in mean**	***bitcoin***
3.606 0.607	3.138 0.678	7.799 0.167	3.372 0.642	8.067 0.150	*5 lags*	*lag length*
12.131 0.270	13.035 0.21	13.146 0.215	9.522 0.482	10.1199 0.430	*10 lags*	
luxX	**SHCOMP**	**SMI**	**SP500**	**TWSE**	**Granger causes in Variance**	***bitcoin***
6.159 0.291	2.558 0.767	6.014 0.304	3.233 0.660	9.97 0.076 **	*5 lags*	*lag length*
9.34 0.499	9.503 0.485	9.64 0.472	5.922 0.821	13.360 0.20	*10 lags*	

Note a) (*) Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1%
b) In each cell there is the S-statistic form Cheung and Ng test and the corresponding p-value

5.Conclusion and Discussion

The goal of the study is to examine the connection between bitcoin and various stock markets from countries related to money laundering and illicit activities. We use daily returns from 2016 to 2020 of the stock indices and the bitcoin/USD exchange rate. The methodology was based on a two-step procedure proposed by (Yin-Wong Cheung, 1996) which include developing AR-GARCH model for prices returns , which allows us to correct the so-called stylized facts that are present in financial returns. Once the sample cross correlations of standardized and squared standardized residuals are calculated we apply two types of test, one to examine for causality in mean and one to check for causality in variance.

The results show that there is in fact a causality in mean but not in variance from bitcoin to FTSE100 justifying the inclusion of the index although is not highlighted in the financial secrecy index. The U.K. has the largest number of financial paradises with high secrecy and low regulations and controls. The connection was to be expected. That being said, the UK exchange is also the world greatest FOREX center and that might have played a crucial role since bitcoin's value measured -in quantified terms- as the exchange rate with US dollar. Interestingly and despite the high regulations and the tough stance in China there is strong evidence for a causal relationship in-mean from bitcoin to the China's index SHCOMP. This might have something to do with China monetary policy and the accusation for as currency manipulation [27]. Since Bitcoin is essentially an exchange rate a rise of bitcoin would mean depression of U.S dollar. That would lead China to depreciate Chinese Yen even more.

Being the center of financial scandals Germany[28] and Luxembourg[29] is also included in the list of countries under investigation. The only country, along with the U.K that bitcoin granger causes in-variance is the Germany's DAX index. DAX's volatility spillover is even greater than that of FTSE100, while Luxembourg's LuxX has a strong causal relationship in mean with bitcoin i.e Bitcoin is Granger causes in mean in LuxX. Some would argue that Bitcoin is so much integrated as a financial asset that these connections are to be expected. If that was the case then someone would expect SP500 index belonging to the biggest stock market in the world to have some sort of causal relationship, but according to our analysis this is not the case.

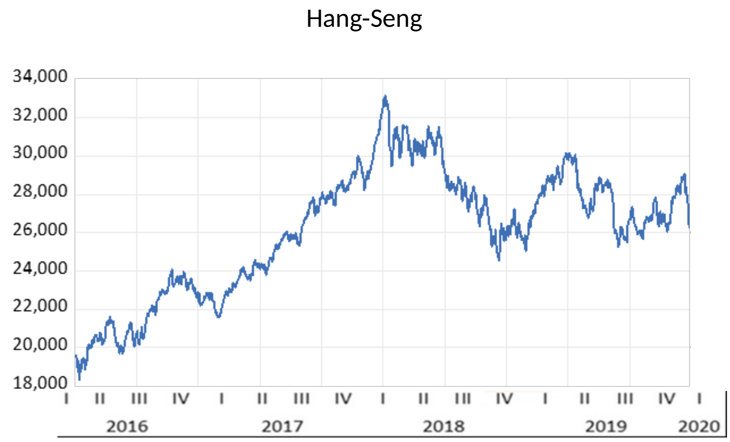
[27] https://www.nytimes.com/2019/08/06/business/economy/china-currency-manipulator.html

[28] https://the-european.eu/story-14871/danske-bank-mired-in-money-laundering-scandal.html

[29] https://luxtimes.lu/economics/35995-luxembourg-faces-very-high-inherent-threat-from-money-laundering

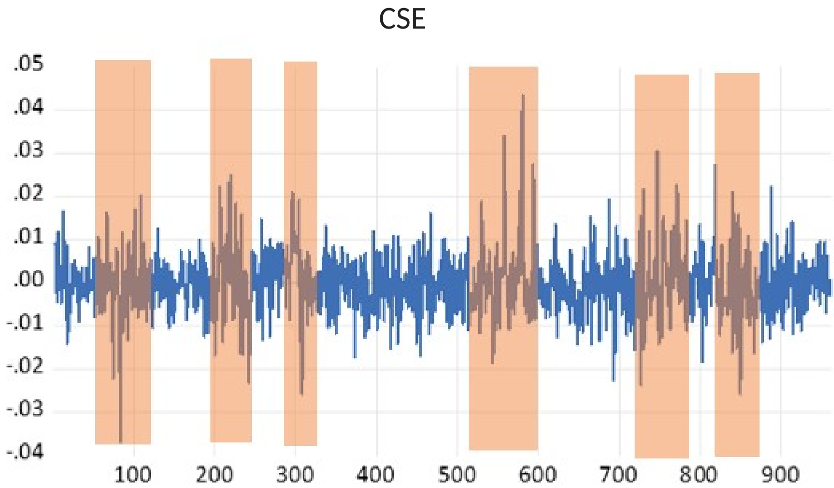
6.Appendix

Graphs 1-10 Closing prices of stock indices and bitcoin

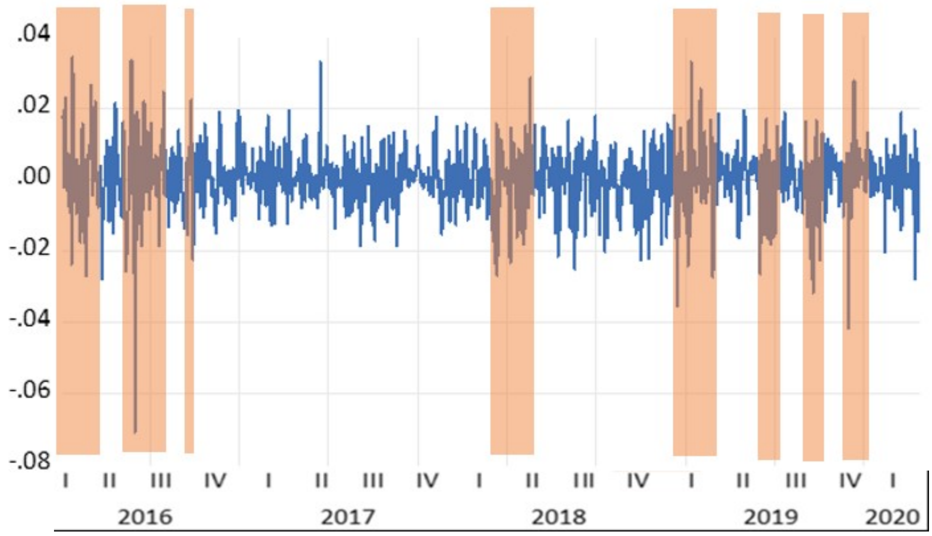


Graphs 11-21, Stock indices and bitcoin returns

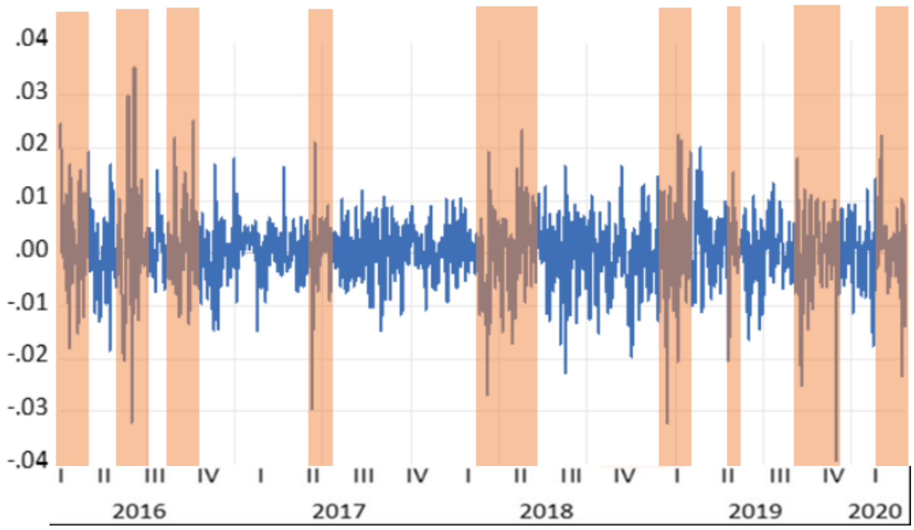
(periods highlighted with orange indicate volatility clustering)



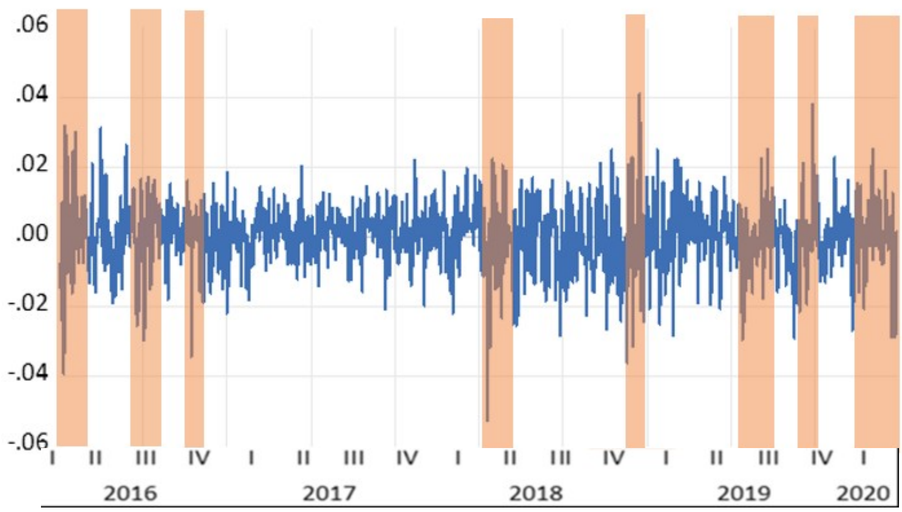
DAXR



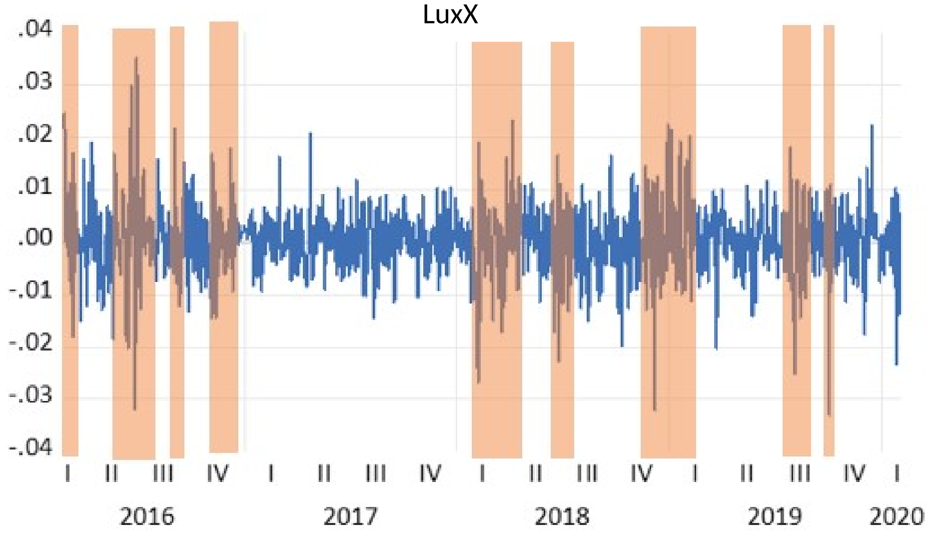
FTSE100R



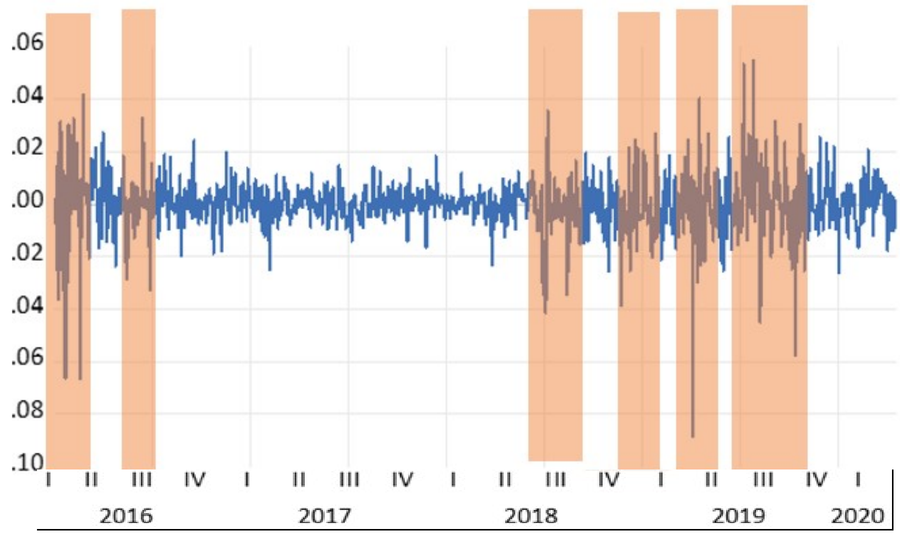
Hang-Seng



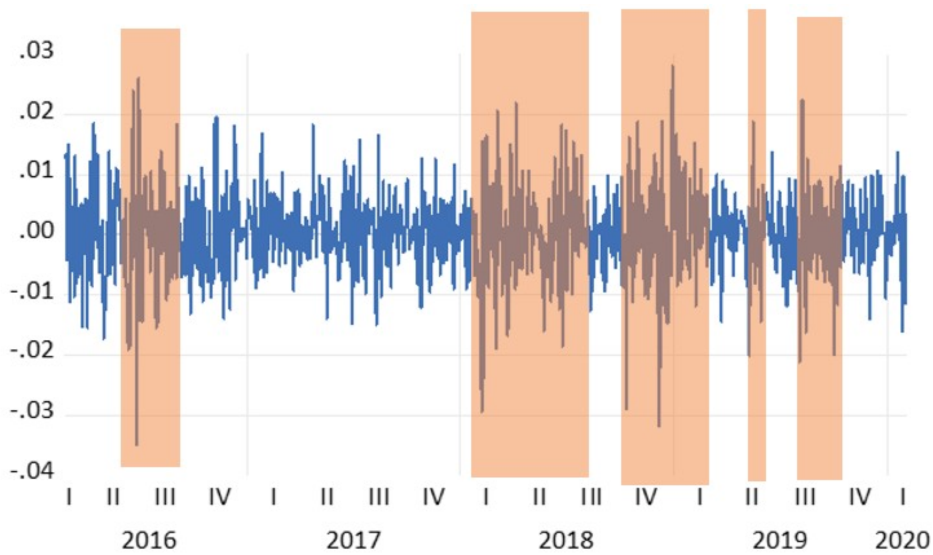
LuxX



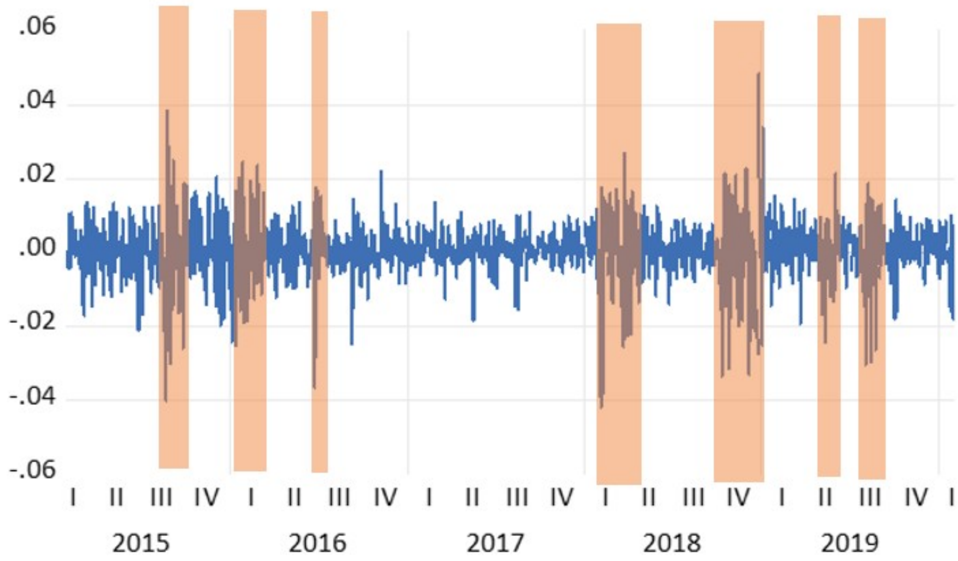
SHCOMP



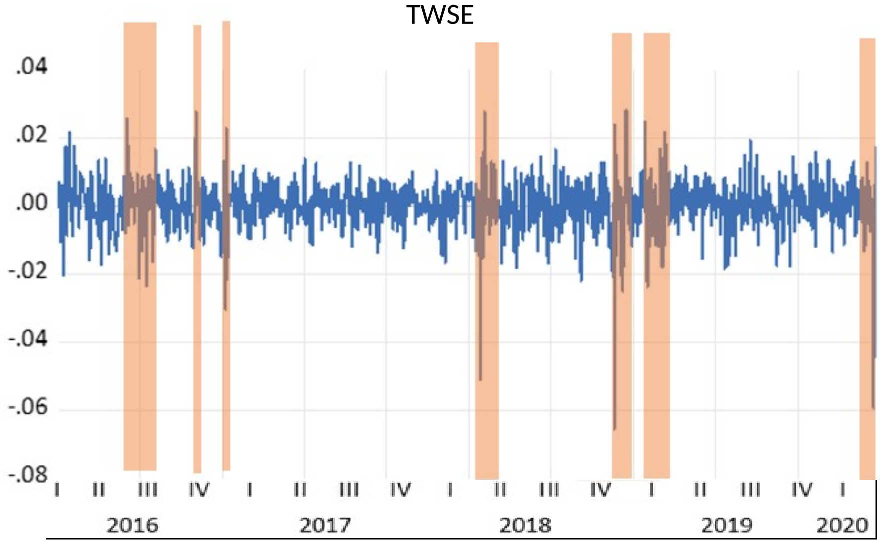
SMI



SP500

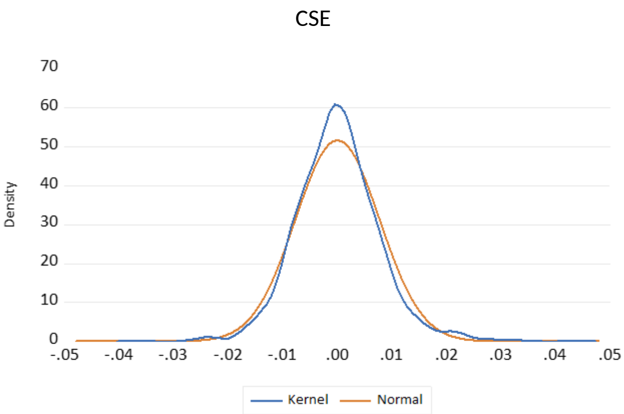


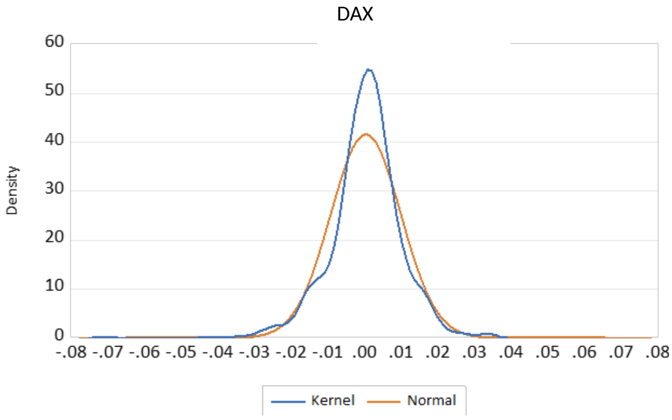
TWSE

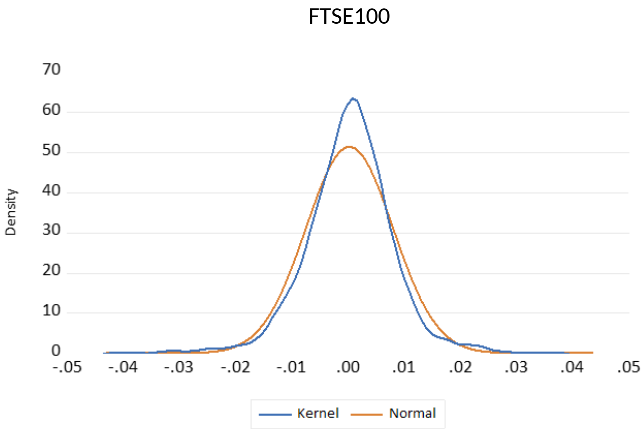


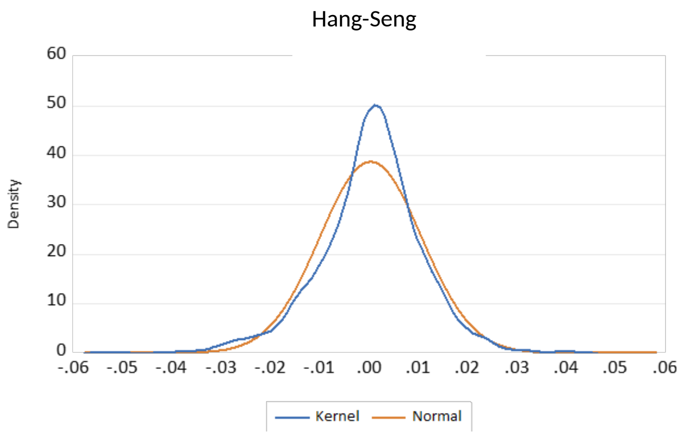
Bitcoin

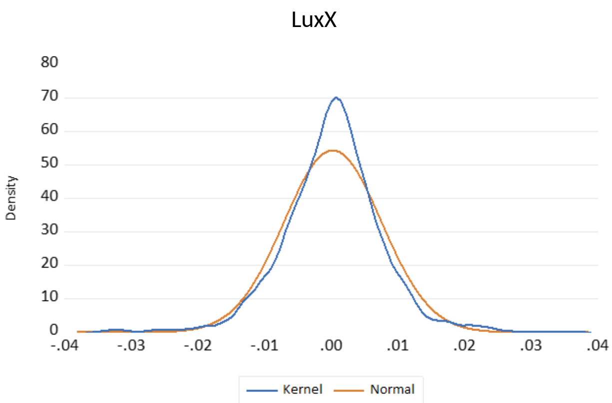
Graph 22-32 (Kernel distribution and theoretical distribution)

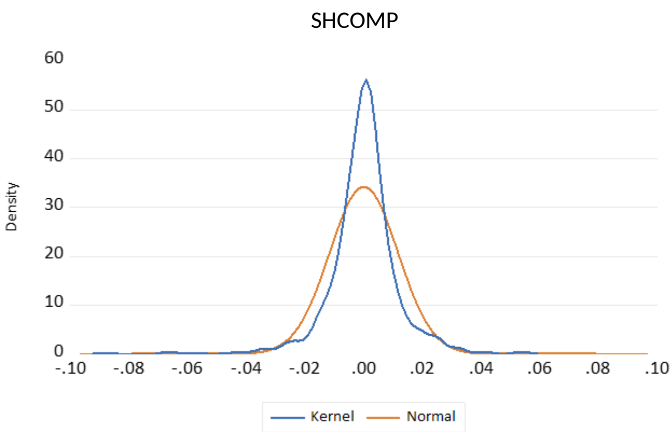


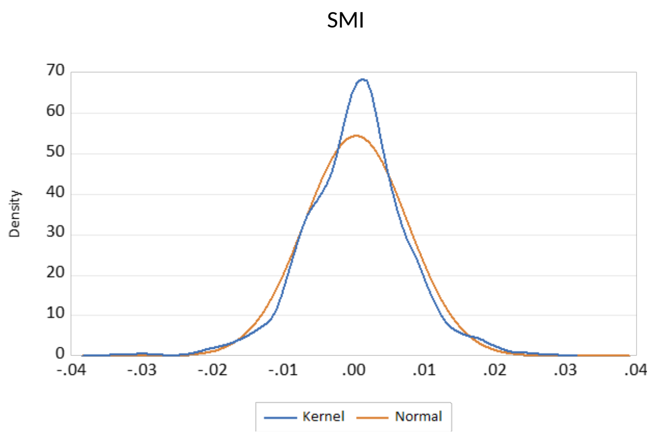


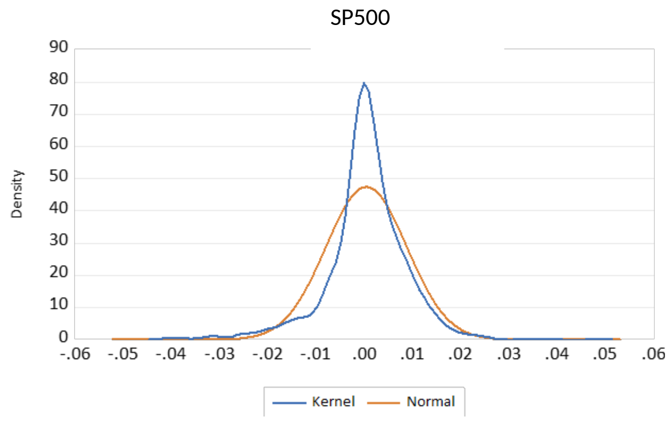


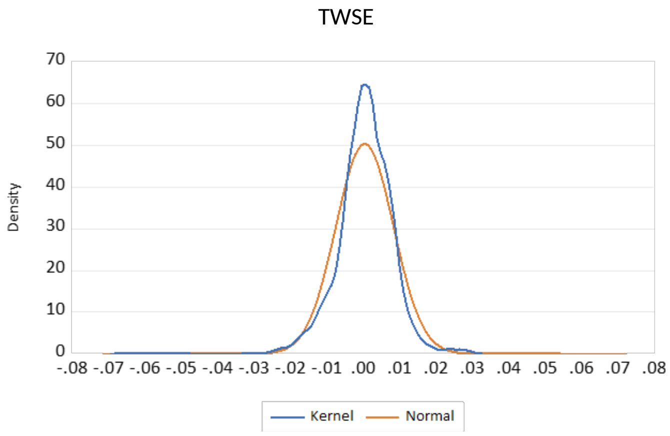


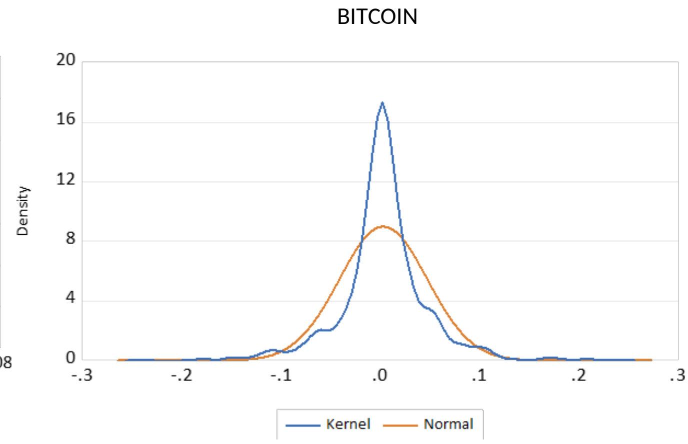












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