The Dark Currency: An Analysis of the Relationship Between Dark Market Activity and Bitcoin Returns

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This body of research aims to study the relationship between two distinct disruptive technologies, Bitcoin, and the Dark Market, as both entities are used in tandem and are not mutually exclusive Dark Market consumers have adopted Bitcoin as the primary tender used for transactions, with circa 46% of all Bitcoin transactions being related to the sale of goods on the dark web. This study aims to determine a causal relationship between Dark Market activity and Bitcoin returns in an attempt to legitimise Bitcoin as a credible asset, determine Bitcoin price formation and aid in regulation formation and oversight. The results highlight no causal relationship between Dark Market activity and Bitcoin returns, however, an interesting takeaway of this study in terms of regulation is the causal relationship between Dark Market activity and the privacy coin, Monero. The contribution to the literature is noted in chapter five. The economic and regulatory significance of these results are also presented, which discuss Bitcoin price formation, and suggestions for a cryptocurrency regulatory trajectory.

Keywords: Bitcoin, dark market, cryptocurrency regulation, cryptocurrency crime

INTRODUCTION

Executive Summary

Bitcoin and its use as a virtual currency has become somewhat of a striking phenomenon since its creation in 2009. The revolutionary technology adopted by Bitcoin as well as its independence from government control have contributed to the popularity of the coin, in both positive and negative ways. The government cannot control the monetary policy of Bitcoin, thus having no input during inflationary or deflationary environments, making it an attractive investment asset. Bitcoin has no association or commitment to a higher authority, unlike conventional assets such as stocks and bonds (Corbet et al., 2015). The anonymity of Bitcoin makes it tax exempt, as tax collection is essentially impossible (Kubát, 2015). Furthermore, Bitcoin poses risks to financial intermediaries as it decentralises payment systems, allowing for peer-to-peer low-cost payments, often referred to as "removing the middleman". These features of Bitcoin have led to a surge in price, volatility, trading volume and appearances in the mainstream news (Corbet et al., 2019). Bitcoin price formation is based on a variety of determinants - supply and demand, news sources and geopolitical events - all of which have individual effects on the cryptocurrencies price. Bitcoin's price movements between October 2016 and October 2017 saw Bitcoin price climb from $616 to $4800 (Corbet et al., 2019), as political earthquakes in both the UK and the US in the form of Brexit and Trump's presidential win sent the price of Bitcoin soaring (Kubát, 2019). These events effectively created the opportunity for a 680% return on investment per year (Corbet et al., 2019). Following these events in

2017, the Chicago Mercantile Exchange (CME) and the Chicago Board Option Exchange (CBOE) accepted Bitcoin as part of their derivatives strategies, legitimising Bitcoin as an investment asset (Luu Duc Huynh, 2019). As the popularity of Bitcoin increased, the cryptocurrency arena grew, with new coins such as Ethereum or Monero being created which currently contributes to a total market capitalization of circa $1.26 trillion.

A fascinating phenomenon that has arisen alongside the growth of cryptocurrency, and more specifically Bitcoin, is cryptocurrency crime and the Dark Market. Both merit significant regulatory intervention as the frequency of dark web use and ransomware attacks increases. It is curious as to whether these events cause mispricing of Bitcoin, which merits this research. The Dark Market encapsulates anonymity via technologies such as traffic encryption and obfuscation which has led to the dark web becoming the main platform for the sale and distribution of illegal goods and harmful content (Zhang & Zou, 2020). When there is a shift in the classification of a product from legal to illegal, there is a shift in its marketplace from the surface web, such as Amazon and eBay, to the dark web, such as Sci-Hub or Dark Lair (Kermitsis et al., 2017). The Dark Market is based on anonymity and trust, with many dark marketplaces having a vendor rating system in place in order to evaluate vendors and enforce a reputational sales system. According to the Serious and Organised Crime Threat Assessment in 2017, the top 1% of all vendors are responsible for circa 51.5% of all sales on the Dark Market (Europa 2017; Kermitsis et al., 2017). Over 100,000 dark web vendors accept cryptocurrencies, and it is evident that as the value of the cryptocurrency grows, there is an increased number of vendors accepting them (Kermitsis et al., 2017). The common factors fostering this Dark Market cryptocurrency relationship is the anonymity associated with both entities. Anonymity creates a conducive environment for Dark Market activity and transactions, and aids in evading detection.

Following the 1358% price appreciation of Bitcoin in 2017, a cryptocurrency called Monero enhanced its privacy features, to an "always-on" privacy mechanism, a mechanism where the user's private information is never displayed. Monero is known as a "privacy coin", as it employs alternative technologies to Bitcoin to ensure anonymity. Monero alters from Bitcoin as it does not publish the amounts being sent or the receiving accounts (Kermitsis et al., 2017). Monero rapidly replaced Bitcoin as the preferred tender on the dark web due to these additional anonymity features built into its payment system (Jung et al., 2022). In 2018, Monero reached an all-time high of $542 as dark web vendors and buyers pivoted currency preferences away from Bitcoin in order to increase privacy. However, Monero is not offered on conventional cryptocurrency exchanges such as coinbase, and US regulators dislike the asset due to the enhanced anonymity feature. Hence, this shift from Bitcoin to Monero reverted shortly after as Monero's accessibility declined. Nevertheless, the coin has gained popularity from Dark Market activists since its creation in 2017, and Monero now has a market cap of circa $3.07 billion.

Jawaheri et al., (2020) explored the aforementioned privacy differences between Bitcoin and privacy coins such as Monero. Bitcoin lacks operational security, suggesting that one piece of historical information relating to a transaction allows authorities to trace the payment to its origin, as blockchain is a public ledger of information. Thus, the literature is divided on the exact direction of the relationship between Tor Brower use and Bitcoin, as blockchains traceability may enable the deanonymization of the dark web transactions. By carefully analysing blockchain nodes and the associated Bitcoin addresses, information can be leaked about dark marketplaces services and their consumers. Hence, this study aims to uncover whether Bitcoin returns are affected by activity on the dark market, while including Monero returns as a variable to assess the power of cryptocurrency privacy and anonymity. Chapter four discusses the interesting takeaways of this research, highlighting a significant causal relationship between Dark Market activity and Monero returns, and finding an absence of a relationship between Dark Market activity and Bitcoin Returns.

Purpose and Motivation of Study

> ***"Bitcoin & other cryptocurrency have as much of a future as the internet itself"***
>
> ***- Christine Lagarde* (Thakur and Banki, 2018)**

The issuance of new cryptocurrencies has grown at an exponential rate since the birth of Bitcoin in 2009, with over 2000 Bitcoin-like cryptocurrencies now in circulation (White et al., 2020). This astonishing growth rate highlights the pace of technological advancements in the financial industry, with which, regulators cannot keep up. These multifaceted assets, although legal, are often used as a medium of exchange in the dark market to facilitate e-commerce on the dark web. Studies have shown that 46% of Bitcoin transactions are related to illicit or illegal activities (Sutanrikulu, Czajkowska & Grossklags, 2020). Given this fact, this study aims to determine the relationship between a change in Dark Market activity and the subsequent effect on Bitcoin returns. This investigative research will aim to uncover the extent to which both Bitcoin returns, and Dark Market activity are reliant on each other, and determine a causal relationship. In determining the complementary effects of the darknet on Bitcoin pricing, a regulatory trajectory can be determined in an attempt to combat cybercrime.

Bitcoin, a revolutionary technological innovation, was created with sound intentions to decentralise and digitise payment systems, facilitating peer-to-peer transactions. However, the characteristics of Bitcoin not only make it an attractive digital currency in the financial industry, but in criminal markets too. The very design of Bitcoin (identity flexibility, anonymity, digitised and decentralised) makes it a fruitful tool for criminal activity (Kethineni, Cao & Dodge, 2017). The motivation for this study is to uncover the effect of activity in the Dark Market on the performance of Bitcoin, which fills a gap in the cybercrime and cryptocurrency literature.

The value of Bitcoin is subjective, based on supply and demand, as both increase, so does the price of Bitcoin (Kethineni, Cao & Dodge, 2017). Studies have attempted to uncover the exact factors that cause shocks to the price of Bitcoin (Nguyen et al., 2018), finding that the Bitcoin economy is affected by “speculative demand"; Bitcoin miner supply, media attention, or the price of other cryptocurrencies. Further studies confirm that Bitcoin follows the efficient market hypothesis as it reacts almost immediately to the publication of related information (Bartos, 2015). This study filters media attention down to more specifically, Dark Market media attention, in order to determine an exact link between the two entities. The extensiveness of previous research in this field is hindered by Dark Market data limitations, however, this research compiles data in an innovative way in order to fill this gap in the literature and produce meaningful results.

Research Question

The research question posed in this study is.

“Did the level of activity in the Dark Market influence Bitcoin returns over the period of March 2022 to March 2023?”.

The three hypotheses posed with the objective of determining the “relationship between Dark Market Activity and Bitcoin Returns” are:

Hypothesis 1: *An increase in Dark Market activity had a positive effect on Bitcoin Return*

Hypothesis 2: *An increase in Dark Market activity had a negative effect on Bitcoin Return*

Hypothesis 3: *A change in the level of Dark Market had no effect on Bitcoin Return*

Despite the large body of literature published discussing the topic of Bitcoin and its closely linked relationship with the Dark Market and cyber criminality, there has been no direct result generated to confirm or deny a relationship between both entities. The results of this research will be effective in determining, more specifically, the reasons for changes in the price of Bitcoin, which has often proved ambiguous since its creation in 2008. In determining a relationship, this study aims to provide increased levels of legitimacy and credibility to Bitcoin as a tradable asset, which conforms to the efficient market hypothesis. Furthermore, an invaluable result of this research is to attempt to increase transparency and accessibility in a seemingly anonymous, and to many, unpopular entity. Finally, this study has the meaningful objective of influencing a regulatory trajectory for the cryptocurrency ecosystem based on results.

Overview of Study

In quest of comprehensiveness, this study is divided into six chapters.

Chapter One introduces the topic of discussion, providing a description of the topic and research question, as well as rationale for the research.

Chapter Two reviews the previous literature concerning the topic.

Chapter Three considers the data collection and analysis procedure as well as the methodology.

Chapter Four discusses the results, as well as limitations of the results found.

Chapter Five considers the economic and regulatory significance of the results. The study concludes with a summary of the findings, a note on contribution to existing literature and potential for further research.

LITERATURE REVIEW

Introduction

Chapter One mentions, in brevity, the gap in existing literature providing motivation for this study, as well as other elements of current research in the field of cryptocurrency. Chapter Two will therefore provide a comprehensive review of current literature, with the aim of addressing the gaps mentioned. In doing so, I will introduce Bitcoin as a cryptocurrency and discuss the coin's characteristics. Furthermore, chapter two investigates literature discussing the Dark Market, as well as the relationship between Bitcoin and the Dark Web.

Introduction to Bitcoin

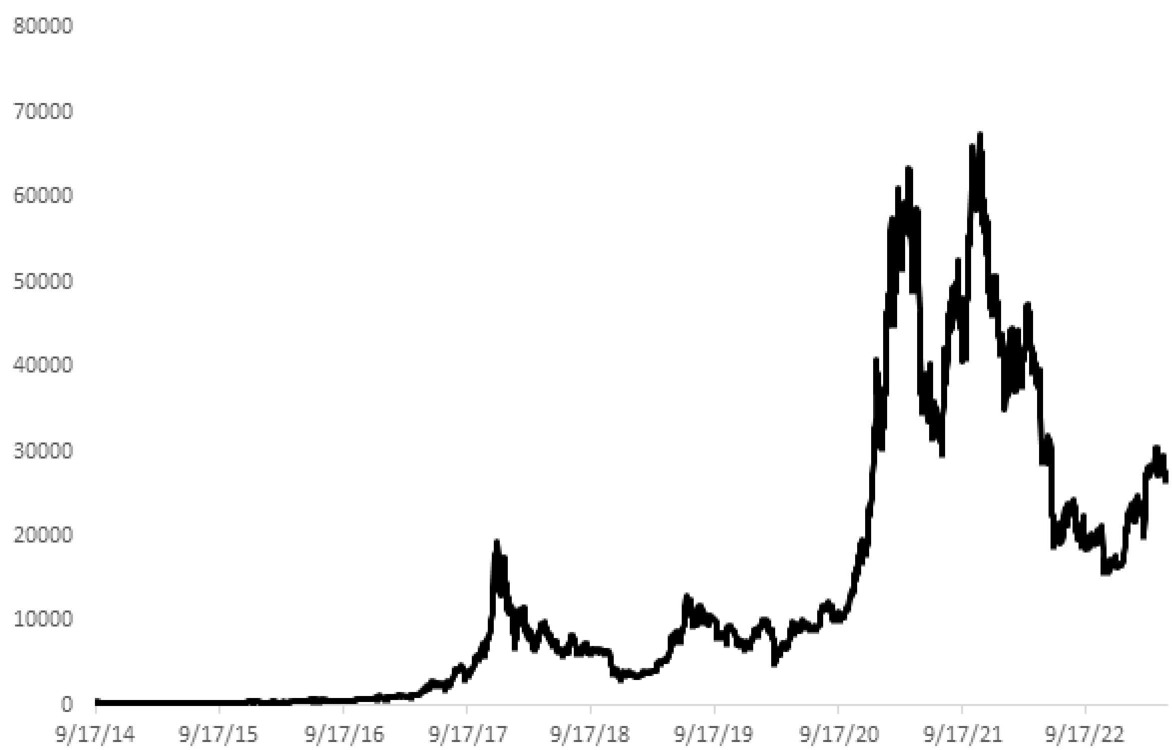
Bitcoin is one of many cryptocurrencies, and a cryptocurrency is a subset of digital currencies which adopt the "cryptography" technique, which verifies transactions and identifies ownership (Pietras and Vivanco, 2017). Bitcoin was first conceived in 2008 by Satoshi Nakamoto (2008) and is the world's most traded and transferred cryptocurrency. It is referred to as a "peer-to-peer network" that enables commerce to occur independent of banks and governments (Segendorf, 2014; Hu et al., 2019). Users digitally create value without the oversight of a third party with the use of a combined network of computers to verify transactions (DeVries, 2016). According to DeVried (2016), Bitcoin is the pacemaker in the disruptive technological revolution that is cryptocurrency, and is expected to change the way that traditional, long standing, financial systems of fiat currency operate.

Bitcoin has attracted attention from technologists, consumers, retail investors, regulators, and Dark Market retailers. It derived its popularity from the price increases witnessed in its nascent stage of trading from 2009 to 2015, where researchers such as Bouri et al., (2017) explore Bitcoin as a hedging tool, or a safe-haven for major stock-indices. During this period Bitcoin began to proliferate financial markets, growing to a market capitalization of circa $6 billion. The volatility of Bitcoin was highlighted during 2013, with prices fluctuating from a low of $13.60, to a high of $217 (Wolfson, 2015). Research from Bouri et al., 2017 found an inverse relationship between Bitcoin volatility and the VIX index in 2013, to which Bitcoin prices reacted positively as the asset became an equity hedge in portfolios. Corbet et al., (2020) created a sentiment index based on news publications of four economic indicators such as GDP, CPI, unemployment, and durable goods. They found an increase in negative sentiment surrounding these indicators lead to a rise in Bitcoin returns. This enforces the idea that Bitcoin can be an efficient hedging tool as negative sentiment results in a reduction in returns in equity markets, often referred to as "risk-off". Yermack (2015) highlights Bitcoin's use not only as a hedging tool during an equity downturn, but as a speculative investment to generate capital gains. Bitcoin has reached as high as $68,789.63 per coin, compared to a price of $4.81 per coin only twelve years ago (Fig.1) (Wolfson, 2015) and has a current market capitalization of circa $591.85 billion.

Bitcoin is unlike any other financial asset as it does not derive its value from an underlying tangible asset, and does not produce any income, only capital gains. Furthermore, Bitcoin is not a fiat currency, thus, does not adhere to regulation from governments or central banks, it has its own monetary policy system, combining some features of cash and some of online payment systems (Meiklejohn et al., 2016). Bitcoin's ambiguous state poses an ideological challenge to conventional money, according to Bjerg (2015). The literature is divided on whether Bitcoin poses risks to the current monetary system. Murali (2013) states that bitcoin is a reserve currency for when generations ahead lose confidence in fiat currency, suggesting it is the precursor to a new monetary system. McCallum (2015) does not believe that Bitcoin is not a quantitatively important monetary system and does not accurately reflect the standard definition of "money"; *medium of exchange, store of value and unit of account*. Bank of America (2013) stated that Bitcoin's role as a store of value is highly compromised by its high volatility levels, caused by speculative trading, which hinders its acceptance. Thus, the entity cannot serve as a reserve monetary system. Weber (2013) enforces these findings, concluding that Bitcoin value is coupled with economic production, while monetary systems are not, and thus Bitcoin as a monetary system would pose large risks to value.

Bitcoin is traded 24 hours a day, 7 days a week, 365 days a year globally. Bitcoin also has a mining supply cap of 21 million coins. Therefore, according to Barber et al., (2012), in capped supply, Bitcoin has no option but to appreciate tremendously. The creation of Bitcoin has arguably caused one of the largest disruptions in the financial arena and has led to the establishment of a new and complex financial ecosystem of cryptocurrencies (Hu, 2019). Pseudonymous software developer Satoshi Nakamoto designed bitcoin so that it acquires four specific properties: *decentralised, distributed, immutable* and *transparent* (Fanusie and Robinson, 2018; Hellani et al., 2018). To put in the vernacular, Bitcoin does not require a mediator to facilitate transactions, any change in data is traceable, and a record of each transaction is public.

FIGURE 1
BITCOIN PRICE HISTORY (SOURCE: BLOOMBERG)



Bitcoin Characteristics & Users

Bitcoin's anonymity factor prevents the publication of user data. However, Yelowitz & Wilson (2015) completed an analysis of Bitcoin characteristics to determine the audience that utilise Bitcoin to categorise from where it derives its economic value. Primarily, Bitcoin is largely unregulated, and transactions are referred to as “decentralised” and “peer-to-peer” (P2P), creating significant demand from the libertarian political belief system. Dallyn (2016) states that libertarianism underpins the entire Bitcoin ecosystem. Satoshi Nakamoto actively cites the ills of nation-state control of money and central bank’s ability to adjust monetary policy, thus Bitcoin is depicted as the utopian ideal future of currency systems (Nakamoto, 2009; De Fillipi, 2014). Additionally, Dallyn (2016) suggests that the libertarian ideology associated with Bitcoin adds an additional dimension of economic value, which is the existence of Dark Markets. The anti-government, anti-regulation ethos associated with Bitcoin largely supports its use in funding the sale of illicit goods and services.

Wilde (2013) questions the “decentralised” attributes of Bitcoin, reporting that 927 individuals own circa 50% of the number of coins in circulation, making the concentration of ownership amongst a small number of wealthy people. This is contradictory to the decentralised arguments. Furthermore, according to the IMF (2022), the decentralised blockchain technology cannot facilitate large volumes of transactions without dramatically altering the market value. For example, Elon Musk’s Tesla purchased $1.5 billion worth of Bitcoin in 2021, which caused the price to rise by 25% (Gerken, 2023). Thus, it seems necessary for an intermediary such as an investment bank to streamline decentralised services (Allen, 2022).

Bitcoin’s popularity is in part derived from its traceability and transparency, as all transactions are logged on a public ledger, and blockchain uses a “proof-of-work” trust model to confirm the existence of transactions (Kumar et al., 2017). Bitcoin opposes the less transparent traditional monetary policy structures, with Bartos (2015) stating that the peer-to-peer mechanism facilitates real time transactions, and transparency via open algorithm and store of history. The traceability of Bitcoin proves the greatest threat to user anonymity, as Greenberg (2015) noted, Bitcoin does not reveal user identifying information but utilises blockchain technology to trace transactions to its origin. The traceability characteristic thus provides the largest risk to illegal Dark Market users. Privacy worries were calmed in April 2014, when a new cryptocurrency was created called “Monero”, which according to Kumar at al. (2017), addresses the privacy issues in the following ways.

Unlinkability: For any two transactions, no trail will exist making it impossible to link them to the same person, by means of a “single use” address in the blockchain.

Untraceability: For any one transaction input, the output redeemed is anonymous among a set of alternative outputs. Transaction amounts are disguised behind complex cryptographic mechanics, making currency flows difficult to trace.

A privacy update of Monero in 2017 introduced a “Ring confidential transactions”, which not only hides real output, but the transaction value (Kumar et al., 2017), resulting in a shift in popularity in the Dark Market crypto world from the use of Bitcoin to Monero (Bahamazava & Nanda, 2022). Monero traded higher than Bitcoin from December 2017 until June 2018 yet has not reached a price higher than Bitcoin since.

In terms of financial characteristics, the literature is relatively torn on the classification of Bitcoin. Baur et al., (2018) present arguments to suggest that Bitcoin is a hybrid between a fiat currency and a commodity currency such as gold. In Popper’s (2015) book “Digital Gold: The Untold Story of Bitcoin”, he suggests that Bitcoin is a digital version of gold and a safe haven. However, Kyriazis (2020) suggests that Bitcoin regulation must advance before it can acquire the same characteristics as a safe-haven asset such as gold, stating that Bitcoins characteristics make it an efficient hedge against oil and stock market indices movements, but to a lesser extent than gold. O’Conner et al., (2015) highlight that gold's unique features, such as malleable, dense, ductile, globally accepted, and beautiful render its intrinsic value. Bitcoin does not constitute any of these characteristics. Alternatively, Eisl et al., (2014) suggest that Bitcoins characteristics offer diversification benefits to a portfolio, as their research finds that Bitcoin is lowly correlated with conventional assets, and lead to superior risk-return ratios.

Bitcoin and Blockchain

Blockchain Architecture

The blockchain technology underlying Bitcoin is said to be seen as the "heralded as the harbinger of the new economy" (White et at., 2020) and has the power to disrupt the world of banking through smart contracts, automated banking ledgers and digital assets (Peters and Panayi, 2015). Some researchers recognize Bitcoin and cryptocurrencies as a "technology" rather than a currency (Maurer, Nelms & Swartz, 2013) due to the complex blockchain technology Bitcoin utilises. Blockchain is a globally distributed database often referred to as a ledger. It consists of an order of nodes, each node storing information, and connected through a chain (Gorkhali, 2020). This node and chain structure acts as a public ledger of all transactions, thus, in the occurrence of a digital event, it is shared amongst participants, and participant majority consensus is used to verify transactions (Crosby et al., 2016). This system of participant consensus created by blockchain allows participants to be certain that the event occurred (Crosby et al., 2016). Once data is entered into the blockchain, it can never be erased. Blockchain is used to perform the accurate and irreversible transfer of data in a decentralised peer-to-peer network (Zile and Strazdina, 2018). Public blockchain technology is arguably superior to modern monetary systems, such as banking, where actors are required to put their trust and confidence in the system (Monrat et al., 2019). Blockchain however is a faithful system, where a network of nodes and a consensus system address trust and security issues.

Bitcoin Technology

Blockchain operates in a decentralised environment, which is facilitated by a complex combination of technologies, including digital signatures, cryptographic hash, and distributed consensus algorithms for proof-of-work trust models (Monrat et al., 2019). Bitcoin is defined by a chain of digital signatures (Wright, 2008). Owners of Bitcoin transfers the cryptocurrency onwards by digitally signing the hash of the previous transaction, as well as signing the public key of the future owner which creates a chain attached to the coin, thus enforcing the verification system of the blockchain network. The Bitcoin hashrate is simply defined as the number of computations completed by Bitcoin miners (Fantazzini & Kolodin, 2020). A higher hash rate corresponds to increased computing power of mining rigs, and according to Rehman & Kang (2020), increases the level of completion of Bitcoin code. Miners with greater efficiency and computational power will have a higher hashrate, and miners are compensated with newly issued Bitcoins as they validate and post transactions on the blockchain (Rehman & Kang, 2020). A higher hashrate enforces security against an attack on the blockchain as it elevates the level of computing power needed to gain control of the network. A "51% attack" occurs when a miner has enough computing power to control more than 50% of the hashrate of the blockchain (Serena et al., 2022). This undermines the integrity of blockchain as it can result in misbehaviours such as double spending. Rosenfeld (2014) defines a double spending attack as convincing the Bitcoin merchant that the transaction occurred, and convince the blockchain network to accept the transaction, while the attacker remains in ownership of the Bitcoins and product sold by the merchant. Thus, a high hashrate is invaluable to Bitcoin miners as a source of revenue, and for blockchain security.

The Future of Blockchain

Research on the benefits of blockchain provides the enhanced attraction to the use of Bitcoin due to data quality and integrity, minimization of human error, information accessibility, security, privacy, reliability, and anonymity (Ali et al., 2020). Blockchain technology is gaining recognition in fields outside of cryptocurrency, such as healthcare and banking (Abu-elezz et al., 2020; Garg et al., 2021). However, social acceptance of blockchain is limited due to fears of security, data breaches and confidentiality, making Bitcoin the protagonist of the blockchain success story.

Bitcoin Regulation

Regulatory & Classification Overview

The rising popularity of Bitcoin has attracted regulatory attention from the Financial Accounting Standards Board and International Accounting Standards Board. Regulating Bitcoin requires authoritative interpretation of the relevant accounting standards and the in-depth knowledge of the economics of Bitcoin

(Tan and Low, 2017). Magnuson (2018) argues that current financial regulation is inadequate in addressing the issues created by Bitcoin and other cryptocurrencies. A high degree of ambiguity lies around the asset classification of Bitcoin, whether it is cash, a cash equivalent, an intangible asset, or an investment (Raiborn and Sivitanides, 2015).

Research confirms that there is no national or international consensus on Bitcoin regulation (Tu and Meredith, 2015). For example, The US Department of Justice classifies Bitcoin as a "legal means of exchange", taking a positive approach to Bitcoin integration and acceptance. Bitcoin has entered derivative markets in the US further enforcing its legitimacy (Thakur and Banik, 2018). In contrast, The People's Bank of China has banned all cryptocurrencies, appearing as the most stringent cryptocurrency regulator (Jani, 2018). Kaiser et al's., (2018) research concludes that China has strong motives and capabilities to perform a variety of attacks on Bitcoin in an attempt to curtail financial crime and tax evasion. In Europe, Germany classifies Bitcoin as an asset that is taxed, rather than a currency (Kethineni, Cao and Dodge, 2017). The United Kingdom classifies and regulates Bitcoin as a property rather than legal tender (Tambe & Jain, 2023). In India, cryptocurrencies are used as a payment medium and are not regulated by a central authority (Tambe & Jain, 2023).

European Regulation

The European Commission drafted its Digital Finance Strategy in 2020, with the main topic of legislation being Markets in Crypto-Assets (MiCA), which aims to draft a legal framework for digital asset use in the EU (Zetsche et al., 2020). The aim of MiCA is to ensure consumer protection, cryptocurrency financial stability and support technological innovation. The regulation distinguishes between a cryptocurrency and a crypto "token". Oliveira et al., (2018) define crypto tokens as an artefact that represents assets, utility or holds an inherent claim to something specific to blockchain. Furthermore, MiCA sets requirements for cryptocurrency issuers and crypto asset service providers (BBVA, 2023). According to Nelson (2023), crypto asset trading platforms, exchanges and those providing crypto asset advice will be subject to a clear regulatory framework, whereby authorisation needs to be granted to operate in the EU. According to the Central Bank of Ireland (2023), MiCA also prohibits unlawful disclosures of information that enable insider trading, or manipulation of crypto asset prices.

Regulation of Bitcoin will thus differ among regions due to alternative asset classifications, and central authority legislation. According to Miriam Dunne, head of Investment Firm and Client Asset Supervision at the Central Bank of Ireland, these differences may result in regulatory arbitrage in cryptocurrency trading (2023). The Minister of State Finance in India reinforced this, stating "Crypto assets are, by definition, borderless and require international collaboration to prevent regulatory arbitrage. Therefore, any legislation on the subject can be effective only with significant international collaboration" (Chaudhary, 2023). Thus, on an international level, Bitcoin's status remains relatively enigmatic.

Cryptocurrency Crime

It is well cited across cryptocurrency literature that the Bitcoin anonymity factor enables criminality (Engle, 2016; Reid & Harrigan, 2012). The anonymization tools facilitate illicit activity in Dark Markets and other illegal marketplaces, and according to Stroukal & Nedvědová, 2016, led to the opening of the first ever Dark Market in 2011, called Silk Road, which will be discussed in the preceding section.

Cryptocurrency miscreants exploit the anonymity of Bitcoin, creating a growing threat of malicious cyber-attacks, and increase the risk to banks, businesses, and other institutions of ransomware (Meinert, 2022). Ransomware attacks are perhaps one of the most known criminal uses of Bitcoin, which effectively prevent users from accessing devices or files until the ransom (in the form of crypto) is paid in exchange for a decryption key to unlock and restore the files (Paquet-Clouston et al., 2019). In the absence of Bitcoin or other crypto coins, ransomware would be less desirable as alternative forms of payment have increased transparency, and the risk is considerably higher for the hackers (Kshetri & Voas, 2017). Khazar et al., (2015) analysed a set of Bitcoin ransom payment addresses stemming from the "Cryptolocker" ransomware group and found that 69% Bitcoin addresses were active for 10 days or less and 84% of the addresses had only 6 transactions or less. Thus, transaction flows to the ransomware families are difficult to trace, identify and quantify (Paquet-Clouston et al., 2019). Several high-profile cases of ransomware include the (1) US Pipeline Operator Colonial Pipeline, and (2) JBS USA, both of which occurred in May 2021.

1. Colonial Pipeline, May 7th, 2021

An Eastern European cybercriminal hacking group named "Darkside" conducted a ransomware attack on the US based Colonial Pipeline which forced a shutdown of the daily delivery of 2.5 million barrels of refined petroleum products such as gasoline and jet fuel (Bradley, 2022). The shutdown led to a 4 cents-per-gallon increase in gasoline prices in affected areas across the west coast of the USA (Tsvetanov & Slaria, 2021). On May 12th, Joseph Blount, CEO of Colonial Pipeline paid a ransom of $4.4 million (75 Bitcoin at the time) to the hacker group, who then provided a decrypting tool in order to restore the computer network (Turton, Riley & Jacobs, 2021).

2. JBS USA, May 30th, 2021

The notorious "REvil" ransomware gang attacked the US's largest meat company by sales, JBS Foods, which processes roughly one fifth of meat in the USA (Bunge, 2021). The cyberattack disabled operations in slaughterhouses across the US for five days, resulting in a threat to food security in the US, Canada, and Australia. Although legal, the Federal Bureau of Investigation strongly discourages paying ransoms to hackers, however, JBS paid $11 million to REvil (301 Bitcoin at the time) to prevent compromise of consumer data (Kshetri, 2022).

It is noteworthy for the purpose of this study that the first ever cryptocurrency crash occurred in May 2021, when both the above crimes occurred. As highlighted in Fig.1, there was a large depreciation in the price of Bitcoin in May of 2021, when both these crimes occurred.

Cryptocurrency crime is not only witnessed inside the vacuum of cyberspace, rather it can facilitate crime beyond the digital realm (Stroukal & Nedvědová, 2016). Cryptocurrency has been utilised to motivate and enable white collar crime in the financial industry, with a contemporary example being the run-on Sam Bankman-Fried's cryptocurrency exchange, 'FTX'. Bankman-Fried highlighted the array of criminal activity facilitated by actively utilising cryptocurrency as a financial instrument. The former FTX CEO and founder is now facing charges for money laundering, bribery, and fraud (Alter, 2023). FTX used a trading apparatus, called "Alameda research", to funnel circa $8 billion of consumer deposits off FTX's balance sheet, and proceeded to conduct ill-judged investments into "FTT", which is the crypto token emitted by FTX (Chohan, 2023). Researchers Jalan and Matkovskyy found that this FTX crisis was not caused by an inherent issue with cryptocurrency structure or design, rather the lack of regulatory oversight and clear accounting and auditing guidelines resulting in a system lacking robust control (2023).

The Dark Market

Technological advancement is a double-edged sword. It enhances the efficiency of communication, healthcare, finance, politics, and society. However, it is a zero-sum game in which there must be losers to be winners (Moran, 2007). The Dark Market is an innovation directly stemming from technological advancements, and facilitates the commerce of human trafficking, drug supply, gun transactions, hackers, terrorism, certificate fraud and several other illicit activities (Zhang and Zou, 2020). The dark market is an anonymous platform that cyber criminals use to trade illicit goods and services (Europa, 2018).

The dark web is an encrypted network built as part of the Dark Market, which is only accessible through dedicated software and a private or a peer-to-peer network (Zhang and Zou, 2020). The most used private network browser is TOR, which was ironically created by the US government in 2002 to protect military communications (Macrina & Phetteplace, 2015; Raeesi, 2013). Today, TOR is used by circa four million Dark Market enthusiasts to avoid surveillance, which allows users to anonymously browse blocked internet sites (Macrina & Phetteplace, 2015). The TOR Browser masks the location, identity, and browsing history of the user, which is referred to as "onion routing", where there are three layers of encryption (Macrina & Phetteplace, 2015). Macrina & Phetteplace, 2015 affirm that the TOR browser is not only celebrated by criminals, but libertarians who are committed to intellectual freedom, and view the TOR browser as a means to enforce their commitment to democratic values. The dark web exists underneath the surface web, which is the conventional web service enabled by search engines such as Google or Yahoo. The dark web is estimated to make up 96% of The World Wide Web (Finlea, 2015). The dark web cannot be accessed through the surface web browser, maintaining the anonymity of the user (Zhang and Zou, 2020).

One of the more commonly known dark web sites is “Silk Road”, launched in February 2011, and reached a transaction volume of $1.2 billion in 2013, until it was shut down in October of that year, with the FBI seizing $3.6 millions of funds in escrow (Lacson and Jones, 2016).

> ***“The rise and fall of Silk Road stands as one of the most unique stories in the history of the Internet.”***
>
> ***- Lacon and Jones, 2013***

Silk Road, a military-grade private web browser, was the platform through which over 4000 illegal merchants took advantage of the vulnerabilities of unregulated technological advancement to facilitate illegal trade (Lacson and Jones, 2016). Christin (2013) conducted research on the intricacies of Silk Road dark web, finding that users felt a sense of community through anonymity and used the site to share information and discuss important issues. Pace (2016) believes that silk road was an aggressively capitalist mode of exchange, with a clear absence of state regulation, and resulted in blackmail, scam, coercion, and monopoly. The “Silk Road Charter” found on the website landing screen states “We provide systems and platforms that allow our customers to defend their basic human rights” (Ormsby, pg. 1, 2014). Thus, dark web users believe it is their inherent right to utilise these illegal platforms.

The largest darknet marketplace in the world was “Hydra”, which was shut down in April 2022, and covered 69% of the Russian population. Hydra, launched in 2015, traded a wide variety of illegal drugs, and when shutdown by the FBI, $25 million worth of Bitcoin was seized (Department of Justice, 2022). Hydra used a more sophisticated level of digitization than Silk Road for the wholesale of illicit goods (Goonetilleke at al., 2022). Hydra succeeded in lasting longer than any other darknet due to its use of cryptocurrency as a means of payment and used rating systems to ensure trust in suppliers (Goonetilleke, Knorre and Kuriksha, 2022).

The Dark Web & Bitcoin

Even in its nascent stage, Bitcoin has proved to be risky in nature, hence the aggressive position taken by China in opposition to Bitcoin (Grant and Hogan, 2015). One of Bitcoins more pronounced risks is its anonymity factor, which provides a platform for cybercriminals to engage in illegal e-commerce, using Bitcoin as the medium of exchange. Gandal et al., highlights the predominant issues associated with technological innovations such as cryptocurrency and Bitcoin (2018), concluding that Bitcoin’s anonymity feature facilitates a marketplace for criminals. Van Mieghem (2015) notes that the combination of Tor browser and Bitcoin contain the most lucrative characteristics to achieve anonymity, with Bitcoin historically being the most popular choice for purchasing Dark Market services (Jawaheri et al., 2020)

Bitcoin is the primary enabling mechanism of the dark web. Analysts Yellin et al., (2015) go so far as to define Bitcoin as an “illegitimate dark market currency”, with no government regulation. A common characteristic both entities share is anonymity, which is frequently referred to in this research. In fact, 90% of Bitcoin transactions are not tied to economically meaningful activities (Makarov, 2021). Furthermore, the US Department of Justice estimates that in 2021, 80% of all Dark Market cryptocurrency transactions were on Hydra (2022).

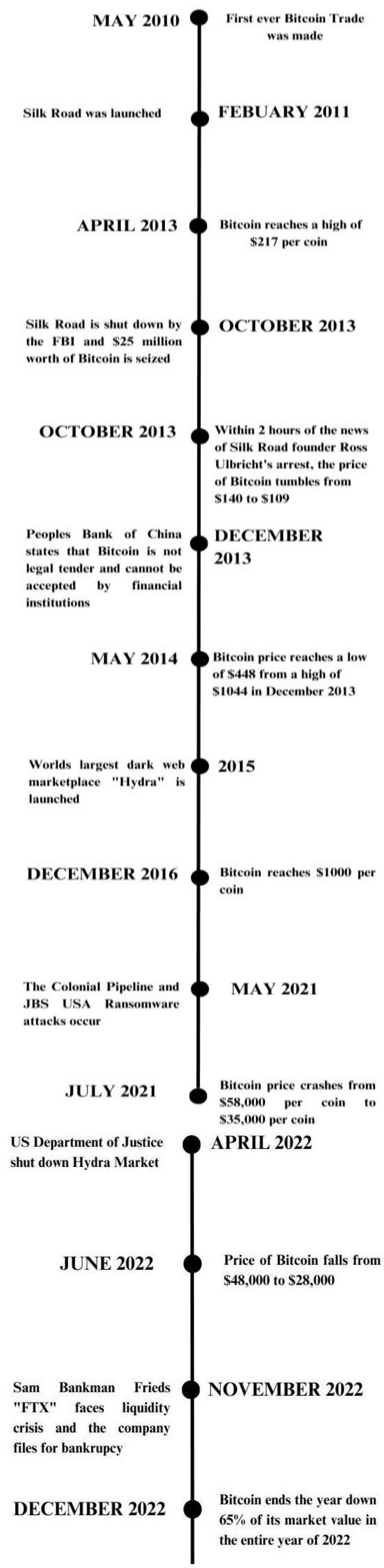
Janze (2017) finds an indication of a positive relationship between the number of goods and services sold on the darknet and the time-delayed usage of Bitcoin. Lord et al., (2018) discusses how this relationship deters attraction from Bitcoin investments as evidence of its misuse on the dark web surfaces. Hiramoto and Tsuchiya (2020) highlight the extent to which Bitcoin was used for trading on Silk Road, noting that when it was undertaken by the FBI in 2013, investigators seized circa 177,991 Bitcoin worth around $25 million, confirming that Bitcoin was the preferred cryptocurrency used by cyber criminals on the dark web (Wolfson, 2015). Hydra facilitated the use of Bitcoin by incorporating a currency exchange service for buyers to exchange fiat currency for Bitcoin (Meylakhs and Saidashev, 2021). Corbet et al., (2019) suggest that there are two forms of cyber criminality, one of which is cybercrime that stems from the use of crypto assets, and the other is cybercrime that influences the structure of crypto assets. Silk Road is an example of cyber criminality stemming from Bitcoin, and the two entities were intrinsically linked. Upon closure of Silk Road in 2013, the price of Bitcoin fell from $145 to $109 (Corbet et al., 2019). Abramova & Böhme (2021) found statistically significant abnormal Bitcoin returns following the shutdown of both Silk Road and Hydra.

Concluding Remarks

The purpose of this literature review was to provide a thematic outline of Bitcoin, as well as detail Bitcoins role in facilitating a Dark Market for criminal activity. Fig. 2 presents a timeline to summarise some of the key Bitcoin events mentioned in the literature review, and a note of how the price of Bitcoin changed throughout that period.

In the realm of Bitcoin literature, research surrounding Bitcoin characterization, regulation, technology, and criminal activity is predominant. However, there is a gap in the literature with regards to (1) The direct effect of Dark Market activity on the daily price of Bitcoin, (2) The incorporation of the Bitcoin and Dark Markets relationship into regulatory efforts such as MiCA and (3) an analysis of whether dark market activity has a greater impact on the price of a private coin, such as Monero. Therefore, this research will aim to capture this gap by encompassing both Bitcoin and Monero into my analysis, as well as formulating a regulatory trajectory which incorporates the results of such analysis.

FIGURE 2
TIMELINE OF LITERATURE REVIEW EVENTS



DATA AND METHODOLOGY

Introduction

Chapter Three discusses the processes used for data collection of each variable and a brief justification of the variables. The database used to obtain news mentions data is outlined, followed by a breakdown of the financial data sources. The data is defined as Time Series data, which contains observations of a single variable over the 365-day period. Time Series is used for the purpose of forecasting future values, analysing trends, and detecting patterns to make predictions. The mining of financial data was completed using Bloomberg, and Excel was used to prepare the data for testing and modelling. The second half of this chapter will discuss the econometric processes employed to analyse the data with the intention of exploring the under-researched question, whilst highlighting the processing techniques as completed on STATA.

Data Collection

Bitcoin Data

Daily closing Bitcoin returns data is the chosen dependent variable to be analysed. According to Corbet et al., (2020), Bitcoin itself is an emerging market, and there are many price series available for Bitcoin at any one time, and prices may differ across exchanges. To maintain homogeneity in data collection, daily Bitcoin data was accessed through Bloomberg using the ticker symbol XBT, which is Bitcoin price against USD. Data was downloaded for the period March 8th, 2022, to March 7th, 2023. Bitcoin returns are used in my empirical analysis from this period and were calculated using the below formula (Zhang et al., 2021):

$$XBT\ Returns\ (i)\ =\ [ln\frac{Bitcoin\ Price\ (Pi)}{Bitcoin\ Price\ (Pi-1)}]x\ 100\%\ ^{*} \tag{1}$$

Where XBT returns refers to the returns of Bitcoin for period i; Bitcoin price (i) and Bitcoin price (i-1) represents the price in period i and the period beforehand respectively.

The first difference of the logarithm of Bitcoin price data is used as according to Zhang et al., (2021), as often logarithm data has better characteristics of skewness and Kurtosis.

News Mentions Data

"News Mentions" data is used in this study as a proxy for Dark Market activity data. A limitation associated with studying Dark Market activity is that by nature, the dark market is private, and data is not publicly available. A surface web search for dark market activity presents literature on Dark Market crimes, and levels of cryptocurrency seized due to closures of Dark Markets, which is discussed previously in the literature review. Surface web searches provide no empirical results or data on the translation flows or revenues of dark web marketplaces. Thus, an innovative approach was taken to achieve a sufficient proxy variable for dark market activity.

Daily Dark Market news mentions were collected using the LexisNexis News and Business database, as performed by Corbet et al., (2020). The period from which data is obtained is March 8th, 2022, to March 7th, 2023. Articles from six news sources were scanned to include the following eleven key terms: "Dark Market", "Dark Net", "Dark Web", "Cybercrime", "Silk Road", "Tor", "Hydra", "Dark economy", "Bitcoin", "Bitcoin Fraud" and "Monero". The headlines of each article had to allude or directly allude to one of the above themes to be included in the sample. A key term must explicitly be included in the headline of the article, as Corbet et al., (2020) stated, it creates the strongest image in the reader's mind and may produce a more pronounced effect on the price of the dependent variable. The sentiment of the articles could be negative or positive, assuming positive sentiment increases Dark Market activity and the antithesis for negative news sentiment. Results were omitted that contained a vague reference to the topic, such as an article containing the key term "Bitcoin fraud" but did not refer to the dark web.

The news sources facilitating this search were Bloomberg, The New York Times, The Financial Times, The Times, The Times of India, and India Express. In order to accurately reflect the global nature of Bitcoin, the news sources must be diversified across the US, Europe and Asia. Thus, two news sources from North America, Great Britain and India were chosen, one business related and the other general.

The rationale for choosing the US, UK and India as the sample countries is derived from the general level of Bitcoin acceptance in each country, as well as the level of Dark Market use experienced there. Bitcoin use, although classified alternatively, is legal in all three countries. Furthermore, Dark Market and dark web daily reports are numerous in each national news source, which will enhance the reliability and robustness of the data. Table 1 documents a breakdown of the data derived from LexisNexis, with a total of 264 articles accounted for over the 365 days study period.

TABLE 1
DARK MARKET ACTIVITY DATA BREAKDOWN

USA	Bloomberg	27
	The New York Times	38
UK	The Financial Times	38
	The Times	25
India	The Times India	87
	India Express	49
Total		**264**

Financial Data

When identifying the control variables, asset pricing theory is considered, as completed in the Birz et al., (2011) analysis. Asset pricing theory states that variables that affect asset investment or consumption should affect the asset price (Merton, 1973). Variables are thus chosen which are shown to previously affect the price of Bitcoin. The price of altcoins, which is any digital asset alternative to Bitcoin, is an example of such variables. Hence, Ethereum returns is independent variables that can be considered as asset pricing theory states they affect Bitcoin returns. Monero returns are also included as an independent variable as it is fitting to include a privacy coin to test for the power of anonymity. Prices of both assets were downloaded from Bloomberg for the aforementioned period. Beneki et al., (2019) stated that the volatility of Bitcoin and Ethereum are positively correlated, with a delayed response in Bitcoin volatility being witnessed due to a positive Ethereum volatility shock. Meynkhard, (2020) confirmed this relationship, finding an absolute correlation between Bitcoin and the price of altcoins. The inclusion of two altcoins ensures a balanced availability of data, and avoids missing observations (Luu Duc Huynh, 2019).

Bitcoin miners' revenue data is taken from NASDAQ and represents an important control variable as it is directly affected by the market value of Bitcoin. Finally, non-crypto asset returns are used in this study as control variables. The market value of the S&P 500, as well as gold price data are downloaded from Bloomberg for the set period. They are proven to be inversely correlated with Bitcoin returns and can be used as diversification tools.

Methodology

Introduction

The Methodology section to proceed explains the several steps involved in the econometric tests being carried out, following the framework proposed by Luu Duc Huynh (2019). This research will pay head to previous frameworks in establishing a methodology with the aim of answering the aforementioned research question *"Did the level of activity in the Dark Market influence Bitcoin returns over the period of March 2022 to March 2023?"*. A rich set of quantitative techniques are employed, including Shapiro-Wilk Test (normality), The Pearson Correlation, The Augmented Dickey-Fuller (stationarity), Optimal Lag selection and Vector autoregressive Granger Causality.

Correlation Coefficient

To test the influence of Dark Market activity on Bitcoin returns, a correlation between the two variables must be distinguished by applying the Pearson correlation and the Granger Causality tests. The Pearson test will measure the strength of the linear relationship between Bitcoin returns and Dark Market activity (Medina-González et al., 2019). The Shapiro-Wilk test is used to identify if the data is normally distributed and linear, which is assumed in the Pearson correlation. The W statistic represents a probability value under the assumption that the data is normal. A probability greater than the tabulated 50% point suggests that there is no evidence of non-normality in the data (Shaprio & Wilk, 1965). The Shapiro-Wilk "W" statistic is calculated by the following formula (Shapiro & Wilk, 1965):

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_i(i)\right)^2}{\sum_{i=1}^{n} (xi - x)^2} \qquad (2),$$

where a_i are constants made from means, variances and covariances of the statistics from sample size n which are normally distributed, x_i are ordered sample values.

The Null and alternative hypotheses are set up as follows:

***H*$_0$**: *The data is normally distributed.*

***H*$_A$:** *The data is not normally distributed.*

TABLE 2
SHAPIRO-WILK TEST RESULTS

Variable	Shapiro-Wilk Test
Bitcoin Returns	W = 0.915
News Mentions	W = 0.879
Ethereum	W = 0.939
Monero	W = 0.940
Gold	W = 0.985
S&P 500	W = 0.968
Miner Revenue	W = 0.858

Upon measuring the normality of the distribution using the "swilk" command in STATA, I fail to reject the null hypothesis, as the W statistic is greater than the 50% point, concluding that the data is normally distributed (see Appendix i). Thus, a linear regression remains a statistically sound technique due to the normality of the data set.

The Pearson correlation coefficient is used to measure the strength of the linear relationship between Dark Market activity and Bitcoin Returns. The Pearson correlation coefficient takes a value between -+1.0 to -1.0, with a value of -1.0 representing a perfect negative linear correlation between both variables, a value of 0.0 representing no correlation, and a value of +1.0 representing a perfect positive linear correlation (Medina-González et al., 2019). The formula for the Pearson Correlation Coefficient is:

$$rxy = \frac{\Sigma(xi-\bar{x})(yi-\bar{y})}{\sqrt{\Sigma(xi-\bar{x})^2\Sigma(yi-\bar{y})^2}} \tag{3}$$

where x and x̄ refers to the values and mean of the x variable respectively, and y and ȳ refer to the values and mean of the y variable respectively.

Augmented Dickey-Fuller

The test to follow is the Augmented Dickey-Fuller, which is a commonly used unit root test. Testing for stationarity is critical when researching time-based variables (Mushtaq, 1995). Data that is characterised by unit roots can lead to spurious regressions as they contain a stochastic trend and are thus non-stationary. The Augmented Dickey-Fuller addresses serial correlation through the inclusion of lagged changes in the variables. However, the inclusion of the aforementioned lags can lead to a reduction in the power of the test. On the advice of econometricians, one should include enough lags to remove autocorrelation in the residuals (Jalil & Rao, 2019). A unit root exists if the absolute value of the t-statistic is lower than the critical value. In the event that a unit root does exist, and the nature of the data is stochastic, the data will be differenced to ensure it is suited to the model. Stationary data is a critical prerequisite for the Granger causality test.

The null and alternative hypotheses are set up as follows:

***H₀*:** *A unit root exists* $(\Theta = 0)$

***H_A*:** *The time series is stationary* $(\Theta \neq 0)$

Optimal Lag

The remaining requirement for the Granger causality test is optimal lag selection. This is a crucial step in time series research as it facilitates analysis of temporal patterns or dependencies in the data without overfitting or underfitting the model. The most commonly used information criterion for model selection is Akaike Information Criteria (AIC) and Final Prediction Error (FPE). Both tests are recommended by Khim-Sen Liew (2004) for the estimation of autoregressive lag length. AIC and FPE are superior to other criteria as they minimise the chances of underestimation while maximising the chances of recovering the true lag length (Khim-Sen Liew, 2004). The implementation of both tests will aid the determination of optimal lag length in order to perform the following Granger causality test.

Granger Causality

The final test to complete is the VAR Granger Causality test. Granger Causality is a statistical method of measuring the direct influence of time series data. Roebroeck (2015) dissects Granger causality by stating that a variable "y" G-causes an alternative variable "x" if when predicting "x" values, past "y" variables improve predictability. Granger Causality testing is a popular and common technique when modelling the co-movement of Bitcoin and specific variables (Sarker & Wang, 2022; Zhang, 2021, Dastgir et al., 2019). In using the Granger Causality test, I will determine if Dark Market activity is causal to changes in Bitcoin returns. This test is critical to the study as determining causation between both variables will provide fruitful regulatory and economic insights.

The null and alternative hypotheses are set up as follows:

H_0: *Lagged Dark Market activity does not Granger-cause Bitcoin returns*

H_A: *Lagged Dark Market activity does Granger-cause Bitcoin returns*

Data Analysis Implementation

The tests mentioned above are critical in answering the research question of "Did the level of activity in the Dark Market influence Bitcoin returns over the period of March 2022 to March 2023?". The data was organised and prepared in Excel and exported into STATA, where the aforementioned tests were completed. The results of testing the below hypotheses are provided in Chapter four:

Hypothesis 1: *An increase in Dark Market activity had a positive effect on Bitcoin Return*

Hypothesis 2: *An increase in Dark Market activity had a negative effect on Bitcoin Return*

Hypothesis 3: *A change in the level of Dark Market had no effect on Bitcoin Return*

RESULTS & DISCUSSION

Introduction

Chapter four presents a breakdown of the results derived from the aforementioned tests in Chapter three. Table 3 shows the descriptive statistics of the model to aid understanding of the properties of the time series data. The results of the augmented Dickey-Fuller tests are then presented, which, as mentioned in chapter 3.2.3, is critical to progressing in modelling the data. Subsequently, the results of the Pearson correlation are shown, which provide interesting insights into the co-relationships of the variables. The following analysis of optimal lag selection is invaluable to the study as it is an essential prerequisite to the Granger Causality test. Finally, a breakdown of the causality test results is discussed, with results indicating an absence of a causal relationship between Bitcoin returns and Dark Market activity. Chapter four concludes with a note on the limitations that may hinder the strength of the model and provide an avenue for future research.

Results

Descriptive Statistics

With the data organised and prepared, the descriptive statistics for the dataset are presented in Table 3 to initially evaluate how the variables are distributed. The test was carried out in STATA. The data includes 365 observations over a year period. Ethereum represents the highest loss level out of the crypto assets in the data set (-19.18441%), and Monero returns are the highest (21.42057%) over the 365 days. Both Bitcoin and Ethereum returns experience a left-skewed trait, while the remaining variables are skewed to the right. Dark market activity news mentions have the heaviest value on the fat tail (2.308897). The positive Kurtosis across the dataset suggests a leptokurtic distribution exists, meaning there is a higher probability of extreme values or outliers to appear in the data, and the tails are heavier than in a normal distribution. It is possible to have a high kurtosis, yet pass the Shapiro-Wilk test, as has occurred in this study due to the sample size and skewness of the data. Thus, the assumption of normality of the dataset still holds (see Appendix i). The closeness of the mean and median of the variables suggests the data is relatively symmetric given the maximum and minimum values. The standard deviation for each variable is substantial, indicating a large spread in the data.

TABLE 3
DESCRIPTIVE STATISTICS

Variable	Minimum	Maximum	Mean	Median	Standard Dev.	Skewness	Kurtosis
Bitcoin Returns	-17.405	10.204	-0. 153	-0.098	3.172	-0.845	8.052
News Mentions	0	7	0.721	0	0.721	2.309	12.026
Ethereum Returns	-19.184	16.649	-0.133	-0.135	4.302	-0.462	6.567
Monero Returns	-11.190	21.421	0.100	-0.226	4.174	0.929	6.563
S&P 500	3577.03	4631.6	4015.682	3991.01	222.92	0.555	3.125
Gold	1633.4	2000.4	1813.126	1818.8	92.653	0.021	2.315
Miner Revenue	988,6180	4.75e+07	2.32e+07	2.05e+07	8116940	1.178	3.388

Test for Stationarity

The results for the Augmented Dickey-Fuller unit root test are presented below, as completed in line with Luu Duc Huynh's (2019) methodology. As mentioned in chapter 3.2.4, the null hypothesis is that a unit root exists. In order to ensure stationarity in the data, the null hypothesis must be rejected. The test was carried out using the "adf (variable), lags(n)" function in STATA. The results demonstrate that all variables are stationary to the 1% significance level. The ADF test statistic is greater than the ADF critical value at the respective degrees of freedom. The presence of stationarity in the data ensures that the statistical properties of the data are constant over time, allowing for meaningful comparisons across all elements of time series testing. The inclusion of 4 lags is to ensure that autocorrelation and serial correlation is accounted for in the data (Cheung & Lai, 1998). Including lags thus captures any memory effect in the data.

TABLE 4
AUGMENTED DICKEY-FULLER RESULTS

Variable	P Value	Lag Order	ADF Value	Hypothesis
Bitcoin Returns	0.000***	4	-7.960 ***	*Reject the Null*
News Mentions	0.000***	4	-7.828***	*Reject the Null*
Ethereum Returns	0.000***	4	-8.142***	*Reject the Null*
Monero Returns	0.000***	4	-8.753***	*Reject the Null*
S&P 500	0.0001***	4	-3.695***	*Reject the Null*

Gold	0.0071***	4	-2.463 ***	*Reject the Null*
Miner Revenue	0.0042***	0	-3.691***	*Reject the Null*

Symbols *, **, *** represent the significance at the 10%, 5%, and 1% level respectively.

The Pearson Correlation

A basic, however necessary analysis of the data is to test the correlations. As found in Luu Duc Huynh's (2019) study, Ethereum and Bitcoin returns have a strong and significant correlation to the 1% level (coefficient of 0.8985). Intuitively, this suggests that the coins have dependence in linearity, with a change in one coin's returns having a positive relationship with the returns on the other coins. Monero returns however are lowly, yet positively correlated to Ethereum and Bitcoin returns, which is due to the difference in the underlying technologies and characteristics, as mentioned in chapter 2.2. An additional variable is added to this test to highlight the positive relationship between Bitcoin and Miner Revenue. Bitcoin returns are lowly correlated with Miner Revenue; however, the price of Bitcoin is strongly correlated with Miner Revenue, with a coefficient of 0.9627. An important finding in the Pearson correlation is the very weak or negligible negative correlation of -0.0425 between Bitcoin Returns and Dark Market activity News Mentions. The correlation between Monero returns and News Mentions is slightly stronger yet remains a weak positive correlation (0.1212). This initial test to determine structural dependence will be further quantitatively investigated in the following section.

TABLE 5
PEARSON CORRELATION MATRIX

	Bitcoi~e	MinerR~e	Bitcoi~s	NewsMe~s	Ethereum	SP500	Monero	Gold
BitcoinPrice	1.0000							
MinerRevenue	0.9627	1.0000						
BitcoinRet~s	0.0222	-0.0329	1.0000					
NewsMentions	0.0139	-0.0108	-0.0425	1.0000				
Ethereum	0.0205	-0.0315	0.8985	-0.0575	1.0000			
SP500	0.7936	0.7649	0.0727	0.0798	0.0696	1.0000		
Monero	-0.0166	-0.0142	0.1139	0.1212	0.1150	0.0228	1.0000	
Gold	0.6782	0.6617	0.0159	0.1356	-0.0022	0.6907	0.0254	1.0000

Optimal Lag Selection

The optimal lag selection for the VAR Granger Causality was completed using the "varsoc" command in STATA. When selecting the information criterion to determine optimal lag length, lower values indicate a superior model of fit. The optimal lag selection conforms to the findings of Khim-Sen Liew (2004), as Akaike Information Criterion (AIC) is chosen as the superior information criteria. The optimal lag length (n) is presented in Table 6. AIC uses a penalty term (2*K), which encourages the selection of simpler models as the penalty term increases as parameters are added to the model, discouraging excessive complexity in the model (Boykin et al., 2023). Determining the optimal lag is an invaluable prerequisite for the Granger Causality test as estimation bias may arise if too little lags are included, while too many lags can cause spurious causality results through overfitting.

TABLE 6
OPTIMAL LAG SELECTION FOR ALL VARIABLES

Variable	AIC (n)	HQIC(n)	SBIC(n)	FPE(n)
Bitcoin Returns	0	0	0	0
News Mentions	1	1	0	1
Ethereum Returns	0	0	0	0
Monero Returns	2	2	1	2
S&P 500	1	1	1	1
Gold	3	2	1	4
Miner Revenue	4	3	3	4

Vector Autoregressive Granger Causality Test

The VAR Granger Causality test results are presented in Table 7. The first section in Table 7 determines whether Dark Market Activity (News Mentions data) is efficient in predicting Bitcoin Returns when the past and current information of Dark Market Activity can be used to accurately predict Bitcoin Returns. The second section highlights whether Bitcoin Returns data is efficient in predicting Dark Market Activity. The null hypothesis of the Granger Causality test is that the lagged value of the origin does not accurately predict the receiver values. The VAR Granger Causality test was carried out in STATA by primarily using the Multivariate Time Series VAR test, followed by the "vargranger" command. The lag length was determined by the optimal lag length test carried out in chapter 4.1.4. The results below show several key takeaways.

Primarily, only two of the independent variables show a statistically significant relationship with the Dark Market Activity and Bitcoin Returns. In this case, an important finding for the study is that I fail to reject the null hypothesis in the case for a G-causal relationship between Dark Market activity and Bitcoin Returns. However, there appears to be a causal relationship between Dark Market Activity and Monero Returns to the 10% significance level. Furthermore, an intuitive finding shows a strongly significant causal relationship between Bitcoin Returns and Bitcoin Miner Revenue which is useful in providing a baseline comparison point for discussing the results of other variables. Interestingly, there is no bidirectional Granger Causality between Bitcoin Returns and Miner Revenue (appendix iii), suggesting that only lagged values of Bitcoin Returns can accurately predict Miner Revenue. Despite the scarcity of results, the relationships above provide several important insights, and create a path for further research.

TABLE 7
VAR GRANGER CAUSALITY RESULTS

Origin	Receiver	Lag	F Value	P Value	Significance	Null Hypothesis
News Mentions	Bitcoin Returns	1	0..00065	0.9796		Fail to Reject the null
News Mentions	Monero Returns	2	1.447	0.0991	*	Reject the null
News Mentions	Ethereum Returns	1	0.64363	0.4229		Fail to Reject the null
News Mentions	S&P500	1	0.04147	0.8387		Fail to Reject the Null
News Mentions	Gold	3	0.91626	0.4564		Fail to Reject the Null
News Mentions	Miner Revenue	4	0.20142	0.9375		Fail to Reject the Null
Bitcoin Returns	News Mentions	1	0.17025	0.6801		Fail to Reject the Null
Bitcoin Returns	Monero Returns	2	0.71141	0.4916		Fail to Reject the Null
Bitcoin Returns	Ethereum Returns	1	1.0664	0.3024		Fail to Reject the Null
Bitcoin Returns	S&P500	1	0.04628	0.8298		Fail to Reject the Null
Bitcoin Returns	Gold	3	0.49434	0.4825		Fail to Reject the Null
Bitcoin Returns	Miner Revenue	4	18.52	0.0000	***	Reject the null

Symbols *, **, *** represent the significance at the 10%, 5%, and 1% level respectively

Summary of Findings

The tests above were completed with the goal of answering this study's research question of "*Did the level of activity in the Dark Market influence Bitcoin returns over the period of March 2022 to March 2023?"*. The results of the descriptive statistics analysis depict symmetry in the data, as well as a large spread. The Shapiro-Wilk test finds that the data is normally distributed as the W statistic is greater than the 50% point for all variables. The Augmented Dickey-Fuller test finds that the data is stationary and thus no differencing of variables had to occur. Additionally, the Akaike Information Criterion (AIC) was the chosen criterion for the optimal lag selection, and the results were utilised in the Granger Causality test as the lag value. As a general rule of the optimal lag selection, the criterion with the lowest value must be chosen (Hatemi-J & S. Hacker, 2009). Finally, the results of the Granger Causality test are presented, which provide meaningful results for this research. The three hypotheses of this research, as presented in chapter 1.3 and 3.2.6 are statistically answered below in Table 8. To summarise these results, the VAR Granger causality test highlighted that a change in the level of dark market activity does not have a significant positive or negative on Bitcoin Returns. Nevertheless, a meaningful takeaway from this test is the significance of the causal relationship between Dark Market activity and Monero Returns, which will be mentioned in the proceeding chapter.

TABLE 8
HYPOTHESES RESULTS

Hypothesis	Result
An increase in Dark Market activity had a positive effect on Bitcoin Returns	Reject the hypothesis
An increase in Dark Market activity had a negative effect on Bitcoin Returns	Reject the hypothesis
A change in the level of Dark Market had no effect on Bitcoin Returns	Fail to reject the hypothesis

CONCLUSION

Introduction

Chapter five will conclude this body of research by noting the limitations associated with alternative aspects of this study's methodology and data set. These limitations, if built upon, will open various avenues for future research into the relationship between cryptocurrency and the Dark Market. Additionally, this study fills a gap in the cryptocurrency literature which has not yet been explored, thus acting as a noteworthy contribution to existing research. The results mentioned above justify the rationale and motivation of this study, mentioned in chapter 1.2, with several meaningful takeaways being drawn from the model about the characteristics of cryptocurrencies most attractive for use on the dark web. The objective of this study was to determine a relationship between Dark Market activity and Bitcoin returns. In the quest to define this relationship an alternative yet important relationship regarding Monero and the Dark Market was uncovered. This chapter will define the significance of the study's findings through a regulatory and economic lens and conclude with a summary of the study.

Limitations & Future Research

The limitations of this study provide motive for further research, which make it possible to outperform. Primarily, the data set constructed in this study was limited as it only examined the variables over a 365-day period. Furthermore, the proxy used for Dark Market activity could be strengthened by broadening the search by geographically diversifying, as well as the inclusion of more news sources to improve the strength of data. Broadening the data set would provide more representative statistical results. Due to the limited time available to complete this research, increasing the data period, as well as Dark Market activity data was not feasible, and thus provides an avenue for further research. The inclusion of Altcoins such as Ripple, Litecoin and Dogecoin as well as privacy coins such as Dash, and Zcash in the study would enhance results as meaningful comparisons could be made between altcoins and privacy coins relationship with the Dark Market.

Additionally, as mentioned in research completed by Luu Duc Huynh (2019), this study also does not capture the spatial spillover effects, which suggests that a shock to Bitcoin is more likely to affect neighbouring countries than countries that are separated. The countries chosen in this study are the United States, Great Britain, and India, all of which do not capture spatial spillover effects due to their geographical location. I suggest further research to analyse neighbouring countries' Dark Market activity to capture these effects.

There are several limitations associated with the modelling techniques involved in this study, which can be overcome in future research. Primarily, Mushtaq (1995) notes that a critique of the Augmented Dickey-Fuller test is that it is often not considered a suitable test when carried out in isolation, with the test having low stationarity explanation power (circa 30% explanatory power). Future research should combine the Augmented Dickey-Fuller with a test for structural breaks in the data, such as the Zivot-Andrew's test. Furthermore, the VAR Granger Causality test has several well documented weaknesses that may affect the integrity of this study due to the restrictive assumptions, which Granger himself admitted has led to false conclusions being drawn (Shojaie & Fox, 2022). Nevertheless, it is noteworthy that the correct prerequisite testing has taken place in this study to ensure the data adheres to these restrictions. This study uses sufficient and appropriate methodologies without overwhelming econometric rigour. A drawback of the Granger Causality test is that it does not specify the direction in which the relationship is causal. To determine directionality, additional models must be used, which creates an additional pathway for future research. This is a model that can be enhanced and built upon in further research. To combat the restrictiveness of the VAR Granger Causality test, an event study may act as a suitable alternative methodology to test whether Dark Market activity causes abnormal Bitcoin returns.

Contribution to Existing Literature

Cryptocurrency literature is abundant, with researchers actively exploring the intricacies of these complex and nascent assets. Researchers such as Corbet et al., (2019) have investigated cryptocurrencies as a financial asset, discussing Bitcoins characteristics and price formation. Yelowitz & Wilson (2015) further discuss the characteristics of Bitcoin to determine the audience that is attracted to the crypto asset. Both studies briefly mention the use of Bitcoin as a Dark Market currency, however, this relationship is not explored any further. This study builds upon the previously mentioned research by embarking on an in-depth exploration of the characteristics of cryptocurrencies that enhances their attractiveness for use on the Dark Market. Furthermore, this study contributes to the body of regulatory literature surrounding Bitcoin and cryptocurrency. The results of this research will aid in formulating a comprehensive regulatory framework as it highlights the differences between Bitcoin, altcoins such as Ethereum and privacy coins such as Monero. Furthermore, this study reinforces the findings of Gandal et al., (2018), stating that characteristics anonymity facilitates a marketplace for dark web criminals. Although Janze (2017) finds a relationship between the amount of goods and services sold on the darknet and the time delayed usage of Bitcoin, this study highlights that this relationship has no effect on Bitcoin returns. Abramova & Böhme (2021) found that the closure of Silk Road in 2013, as well as the closure of Hydra in 2022 resulted in abnormal returns of Bitcoin, however these events may be taken as outliers which exist in the data according to the descriptive statistics, and over the last year, Dark Market activity had no statistically significant effect on Bitcoin Returns. Hence, this study fills a gap in the cryptocurrency literature as well as enforcing or disproving results of alternative research.

Economic and Regulatory Significance

The primary contribution of this research is that there is no statistically significant causal relationship between Dark Market activity and Bitcoin returns. Although it is a widely accepted and proven fact that cybercriminals misuse Bitcoin for the sale of illicit goods, this research has uncovered that there is no link between the level of such financial misuse and the performance of Bitcoin. In an economic sense, this result allows the inference that Bitcoin price formation is not affected by Dark Market activity. According to findings by Ciaian et al. (2015), demand side variables (number of transactions) have a more pronounced effect on Bitcoin price formation than supply side (number of Bitcoins). Intuitively, this study facilitates the inference that levels of Dark Market activity have no significant effect on the demand for Bitcoin. When paired in conjunction with the findings of Ciaian et al., (2015), the empirical results of this study suggest that the price formation of Bitcoin conforms to the conventional currency price formation of supply and demand. Thus, macroeconomic global factors such as the value of the S&P 500, exchange rates, gold price and Dark Markets do not affect Bitcoin price or returns. Due to Bitcoins rapidly growing market capitalization, price and volatility, the results of this study are of interest to economists in fully understanding the Bitcoin ecosystem.

As previously mentioned in this study, disruptive technologies such as blockchain and cryptocurrency have rendered financial regulation challenging since the creation of Bitcoin in 2009. The disruptive speed of technological innovation thus poses serious risks to governmental decision making and regulation, as if not effectively regulated, issues of citizen safety, privacy and security will persist (Taeihagh et al., 2021). An intrinsic issue associated with policymaking and disruptive technologies is that it is often characterised by asymmetric information, meaning that although information is available on technological disruption, policymakers may be uninformed. Hence, the purpose of this investigative research is to uncover statistical facts which when incorporated into government regulation, can aid in decreasing harmful activity taking place on the Dark Market.

A key takeaway of this study is the 10% significance level causal relationship between Dark Market activity and Monero returns. Monero's characteristics differ from those of Bitcoin due to the crypto asset's unlinkability and untraceability (Kumar et al., 2017). For crypto regulatory efforts - such as MiCA - the significance of this result is useful in determining specific characteristics of crypto assets that must be targeted directly in regulation. MiCA currently defines a crypto asset as "*a digital representation of value or rights which may be transferred and stored electronically, using distributed ledger technology or similar technology*" (Hidalgo et al., 2023). A broad definition of an intricate and complex technological asset is insufficient for effective regulation. Thus, given the results of this study, the scope of this definition should be narrowed down to define the cryptographic technology employed by the crypto asset. This study has proven that cryptocurrencies with strong anonymisation and privacy features such as Monero may be more susceptible to illicit use, as they employ complex anonymity enforcing cryptography. Henceforth, the trajectory of crypto regulation must include a strong definition of the cryptography techniques used to achieve anonymity as internet privacy and anonymity are becoming more critical than ever (Jawaheri et al., 2020). In regulating anonymity, the pool of currency available for use on the Dark Market will decline, and the risks associated with using cryptocurrency as a form of payment will increase.

Conclusion

Disruptive technologies such as Bitcoin and the Dark Market are studied in tandem in this thesis, with the motive of dissecting the relationship between both entities. Uncovering a causal relationship between Dark Market activity and the return on specific crypto coins fills a gap in the cryptocurrency literature. Understanding the relationship between Bitcoin returns and Dark Markets is crucial for regulators, investors, and researchers alike as it opens new avenues for future research, while attempting to legitimise this relatively new and topical form of asset class. Filling the literature gap in cryptocurrency research will aid in the push to legitimise major cryptocurrencies such as Bitcoin, which Miriam Dunne, head of Investment Firm and Client Asset Supervision at the Central Bank of Ireland has stated that it is a prominent issue when formulating a regulatory trajectory (2023). The results of this investigative research will create a pathway for regulators to uncover the pricing dynamics between cryptocurrency and privacy coins, as well as highlight the specific characteristics of cryptocurrency that Dark Market users prefer. The results of this study suggest that many Monero owners are Dark Market users, and thus Dark Market activity has an effect on Moreno's market capitalisation. Bitcoins clientele varies amongst Dark Market customers, retail investors, traders, sceptics, and hedgers and thus Dark Market activity has no effect on Bitcoin returns due to Bitcoins high market capitalisation. To conclude, in the quest to define a causal relationship between Dark Market activity and Bitcoin returns, this study has uncovered several key takeaways about the alternative characteristics of crypto coins. These key takeaways may be of interest to regulators as the understanding of cryptocurrencies enhances. Furthermore, this research has opened several avenues for future research which may enforce these findings. Research in the field of cryptocurrency must continue in order to gain an in-depth of these complex, fascinating digital assets.

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REFERENCES

Abramova, S., & Böhme, R. (2021, December). Out of the Dark: The Effect of Law Enforcement Actions on Cryptocurrency Market Prices. In *2021 APWG Symposium on Electronic Crime Research (eCrime)*, (1–11). IEEE.

Abu-elezz, I., et al. (2020). The benefits and threats of blockchain technology in Healthcare: A scoping review. *International Journal of Medical Informatics*, *142*, 104246. https://doi.org/10.1016/j.ijmedinf.2020.104246.

Ali, O., Jaradat, A., Kulakli, A., & Abuhalimeh, A. (2021). A comparative study: Blockchain technology utilization benefits, challenges and functionalities. *Ieee Access*, *9*, 12730–12749.

Allen, H. (2022a). *The superficial allure of crypto*. IMF. Retrieved from https://www.imf.org/en/Publications/fandd/issues/2022/09/Point-of-View-the-superficial-allure-of-crypto-Hilary-Allen

Alter, A. (2023) The rise of FTX, and Sam Bankman-Fried, was a great story. its implosion is even better. *The New York Times*. Retrieved from https://www.nytimes.com/2023/05/16/books/michael-lewis-ftx-bankman-fried-going-infinite.html#:~:text=On%20Dec.%2012%2C%20Bankman%2D,of%20bribing%20a%20foreign%20official. (Accessed: 16 May 2023).

Baek, C., & Elbeck, M. (2014) Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters*, *22*(1), 30–34. doi:10.1080/13504851.2014.916379.

Barber, S., Boyen, X., Shi, E., & Uzun, E. (2012, Februray 27-March 2). Bitter to better—how to make bitcoin a better currency. In *Financial Cryptography and Data Security: 16th International Conference, FC 2012, Kralendijk, Bonaire. Revised Selected Papers*, *16*(399–414). Springer Berlin Heidelberg.

Bartos, J.A.K.U.B. (2015). Does bitcoin follow the hypothesis of efficient market? *International Journal of Economic Sciences*, *4*(2), 10–23. Retrieved from https://doi.org/10.20472/es.2015.4.2.002.

Baur, D.G., Hong, K., & Lee, A.D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, *54*, 177–189. doi:10.1016/j.intfin.2017.12.004

Beneki, C. *et al.* (2019). Investigating volatility transmission and hedging properties between Bitcoin and Ethereum. *Research in International Business and Finance*, *48*, 219–227. doi:10.1016/j.ribaf.2019.01.001

Birz, G., & Lott, J.R. (2011). The effect of macroeconomic news on Stock returns: New evidence from newspaper coverage. *Journal of Banking and Finance*, *35*(11), 2791–2800. doi:10.1016/j.jbankfin.2011.03.006.

Bjerg, O. (2016). How is bitcoin money? *Theory, Culture & Society*, *33*(1), 53–72.

Bloomberg. (2012). *Bloomberg Professional*. [Online]. Retrieved from Subscription Service.

Bouri, E. et al. (2017). On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? *Finance Research Letters*, *20*, 192–198. doi:10.1016/j.frl.2016.09.025
Bouri, E., Azzi, G., & Dyhrberg, A.H. (2017). On the return-volatility relationship in the bitcoin market around the price crash of 2013. *Economics*, *11*(1). doi:10.5018/economics-ejournal.ja.2017-2.
Boykin, A.A., Ezike, N.C., & Myers, A.J. (2023). Model-data fit evaluation: Posterior checks and Bayesian model selection. *International Encyclopedia of Education (Fourth Edition)*, 279–289. doi:10.1016/b978-0-12-818630-5.10038-7
Bradley, L.P. (2023). Was the Colonial Cyberattack the First Act of Cyberwar Against the US? Finding the Threshold of War for Ransomware Attacks. *St. John's Law Review*, *96*(2), 8.
Broadhurst, R., Lord, D., Maxim, D., Woodford-Smith, H., Johnston, C., Chung, H.W., . . . Sabol, B. (2018). *Malware trends on 'darknet'crypto-markets: Research review*. Retrieved from SSRN 3226758.
Bunge, J. (2021). *JBS Paid $11 Million to Resolve Ransomware Attack; Meat supplier's U.S. chief says firm paid cybercriminals in bitcoin to avoid more disruptions*. New York, N.Y.
Central Bank of Ireland. (2023). *Markets in Crypto Assets (MiCA) Regulation*. Central Bank of Ireland. Retrieved from https://www.centralbank.ie/regulation/markets-in-crypto-assets-regulation
Chaudhary, S.P. (n.d.). *Crypto assets are borderless, require international collaboration to prevent regulatory arbitrage*. Press Information Bureau. Retrieved from https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1896722
Cheung, Y.-W., & Lai, K.S. (1995). LAG order and critical values of the Augmented Dickey–Fuller Test. *Journal of Business & Economic Statistics*, *13*(3), 277–280. doi:10.1080/07350015.1995.10524601.
Cheung, Y.W., & Lai, K.S. (1998). Power of the augmented dickey-fuller test with information-based lag selection. *Journal of Statistical Computation and Simulation*, *60*(1), 57–65.
Chohan, U.W. (2023). *FTX, Sam Bankman-Fried, and the Cryptoexchange Problem*. Retrieved from SSRN 4326161.
Christin, N. (2013). May. Traveling the Silk Road: A measurement analysis of a large anonymous online marketplace. In *Proceedings of the 22nd international conference on World Wide Web* (pp. 213–224).
Christin, N. (2013). May. Traveling the Silk Road: A measurement analysis of a large anonymous online marketplace. In *Proceedings of the 22nd international conference on World Wide Web* (pp. 213–224).
Ciaian, P., Rajcaniova, M., & Kancs, D. (2015). The economics of Bitcoin Price Formation. *Applied Economics*, *48*(19), 1799–1815. doi:10.1080/00036846.2015.1109038.
Corbet, S. et al. (2020). The impact of macroeconomic news on Bitcoin returns. *SSRN Electronic Journal* [Preprint]. doi:10.2139/ssrn.3550842.
Corbet, S., et al. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, 182–199. doi:10.1016/j.irfa.2018.09.003.
Crosby, M., Pattanayak, P., Verma, S., & Kalyanaraman, V. (2016). Blockchain technology: Beyond bitcoin. *Applied Innovation*, *2*(6–10), 71.
Dallyn, S. (2017). Cryptocurrencies as market singularities: The strange case of bitcoin. *Journal of Cultural Economy*, *10*(5), 462–473. doi:10.1080/17530350.2017.1315541.
Darknet Markets Ecosystem. (2018). Lifetimes and reasons for closure of over 100 global darknet markets offering drugs. *European Monitoring Centre for Drugs and Drug addication*. Retrieved from https://www.emcdda.europa.eu/publications/posters/2018/darknet-markets-ecosystem_en#:~:text=Summary,darknet%20markets%20are%20drug%2Drelated.
Dastgir, S., et al. (2019). The causal relationship between bitcoin attention and Bitcoin returns: Evidence from the copula-based Granger causality test. *Finance Research Letters*, *28*, 160–164. doi:10.1016/j.frl.2018.04.019.
De Filippi, P. (2014). Bitcoin: A regulatory nightmare to a Libertarian dream. *Internet Policy Review*, *3*(2). doi:10.14763/2014.2.286.

DeVries, P.D. (2016). An analysis of cryptocurrency, bitcoin, and the future. *International Journal of Business Management and Commerce*, *1*(2), 1–9.
Dunne, MD. (2023). *Gender Diversity in Finance.* Trinity College Dublin Business School.
Eisl, A., Gasser, S.M., & Weinmayer, K. (2015). Caveat emptor: Does bitcoin improve portfolio diversification? *SSRN Electronic Journal* [Preprint]. doi:10.2139/ssrn.2408997.
Engle, E. (2015). Is bitcoin rat poison: Cryptocurrency, crime, and counterfeiting (CCC). *J. High Tech. L.*, *16*, 340.
Fantazzini, D., & Kolodin, N. (2020). Does the Hashrate affect the bitcoin price? *SSRN Electronic Journal* [Preprint]. doi:10.2139/ssrn.3720039.
Fanusie, Y., & Robinson, T. (2018, January). *Bitcoin laundering: An analysis of illicit flows into digital currency services.* Centre on Sanctions and Illicit Finance memorandum.
Finklea, K.M. (2015). Dark Web. *Proc. Congressional Res. Service*, 1–16.
Gandal, N., Hamrick, J.T., Moore, T., Oberman, T. (2018). Price manipulation in the Bitcoin ecosystem. *Journal of Monetary Economics*, *95*, 86–96. https://doi.org/10.1016/j.jmoneco.2017.12.004.
Gantiva Hidalgo, C., Fontecha Mejía, J.F., & Escobar, S. (2023) *New Comprehensive Regulation on crypto-assets in Europe: Insights*, *Holland & Knight*. Retrieved from https://www.hklaw.com/en/insights/publications/2023/05/nueva-regulacin-integral-sobre-criptoactivos-en-europa#:~:text=The%20MiCA%20Regulation%20defines%20crypto,ledger%20technology%20or%20similar%20technology.%22
Garg, P., Gupta, B., Chauhan, A.K., Sivarajah, U., Gupta, S., & Modgil, S. (2021). Measuring the perceived benefits of implementing blockchain technology in the banking sector. *Technological Forecasting and Social Change*, *163*, 120407. Retrieved from https://doi.org/10.1016/j.techfore.2020.120407
Gerken, T. (2023). *Elon Musk's Tesla lost $140m on Bitcoin in 2022.* BBC News. Retrieved from https://www.bbc.com/news/technology-64428257
Goonetilleke, P., Knorre, A., & Kuriksha, A. (n.d.). *Hydra: Lessons from the World's Largest Darknet Market*.
Gorkhali, A., Li, L., & Shrestha, A. (2020). Blockchain: A literature review. *Journal of Management Analytics*, *7*(3), 321–343. Retrieved from https://doi.org/10.1080/23270012.2020.1801529.
Grant, G., & Hogan, R. (2015). Bitcoin: Risks and controls. *Journal of Corporate Accounting & Finance*, *26*(5), 29–35.
Greenberg, A. (2015). *Prosecutors Trace $13.4 M in Bitcoins From the Silk Road to Ulbricht's Laptop*. Retrieved from https://www. wired. com/2015/01/prosecutors-trace-13-4-million-bitcoins-silk-road-ulbrichts-laptop
Hatemi-J, A., & Hacker, S.R. (2009). Can the LR test be helpful in choosing the optimal LAG order in the VAR model when information criteria suggest different lag orders? *Applied Economics*, *41*(9), 1121–1125. doi:10.1080/00036840601019273.
Hellani, H., Samhat, A.E., Chamoun, M., El Ghor, H., & Serhrouchni, A. (2018, November). On blockchain technology: Overview of bitcoin and future insights. In *2018 IEEE International Multidisciplinary Conference on Engineering Technology (IMCET)*, (pp. 1–8). IEEE.
Hiramoto, N., & Tsuchiya, Y. (2020). Measuring dark web marketplaces via bitcoin transactions: From birth to Independence. *Forensic Science International: Digital Investigation*, *35*, 301086. Retrieved from https://doi.org/10.1016/j.fsidi.2020.301086.
Hu, Y., Seneviratne, S., Thilakarathna, K., Fukuda, K., & Seneviratne, A. (2019). Characterising and detecting money laundering activities on the bitcoin network. arXiv preprint arXiv:1912.12060.
Ian Nelson, A.S. (2023). *Markets in crypto-assets.* KPMG. Retrieved from https://kpmg.com/ie/en/home/insights/2023/04/mica.html
Jalan, A., & Matkovskyy, R. (2023). Systemic risks in the cryptocurrency market: Evidence from the FTX collapse. *Finance Research Letters*, *53*, 103670. doi:10.1016/j.frl.2023.103670.

Jalil, A., & Rao, N.H. (2019). Time Series Analysis (stationarity, cointegration, and causality). *Environmental Kuznets Curve (EKC)*, 85–99. doi:10.1016/b978-0-12-816797-7.00008-4.
Jani, S. (2018). *The growth of cryptocurrency in India: Its challenges & potential impacts on legislation* Research gate publication.
Janze, C. (2017). *Are cryptocurrencies criminals best friends? Examining the co-evolution of bitcoin and darknet markets.*
Jawaheri, H.A., Sabah, M.A., Boshmaf, Y., & Erbad, A. (2020). Deanonymizing Tor hidden service users through Bitcoin transactions analysis. *Computers & Security*, *89*, 101684. doi:10.1016/j.cose.2019.101684
Kethineni, S., Cao, Y., & Dodge, C. (2018). Use of bitcoin in darknet markets: Examining facilitative factors on bitcoin-related crimes. *American Journal of Criminal Justice*, *43*, 141–157.
Kharraz, A., Robertson, W., Balzarotti, D., Bilge, L., & Kirda, E. (2015). Cutting the gordian knot: A look under the hood of ransomware attacks. *Detection of Intrusions and Malware, and Vulnerability Assessment*, 3–24. doi:10.1007/978-3-319-20550-2_1.
Kshetri, N., & Voas, J. (2017). Do crypto-currencies fuel ransomware? *IT Professional*, *19*(5), 11–15. doi:10.1109/mitp.2017.3680961.
Kshetri, N., & Voas, J. (2022). Ransomware: Pay to play? *Computer*, *55*(3), 11–13. doi:10.1109/mc.2021.3126529.
Kubát, M. (2015). Virtual currency bitcoin in the scope of money definition and store of value. *Procedia Economics and Finance*, *30*, 409–416. doi:10.1016/s2212-5671(15)01308-8.
Kumar, A., et al. (2017). A traceability analysis of Monero's blockchain. *Computer Security – ESORICS*, 153–173. doi:10.1007/978-3-319-66399-9_9.
Kyriazis, N.A. (2020). Is bitcoin similar to gold? An integrated overview of empirical findings. *Journal of Risk and Financial Management*, *13*(5), 88. doi:10.3390/jrfm13050088.
Lacson, W., & Jones, B. (2016). The 21st century darknet market: lessons from the fall of Silk Road. *International Journal of Cyber Criminology*, *10*(1), 40.
Liew, V.K.-S. (2004). Which Lag Length Selection Criteria Should We Employ? *Economics Bulletin*, *3*(33), 1−9. Retrieved from https://ssrn.com/abstract=885505
Luu Duc Huynh, T. (2019). Spillover risks on cryptocurrency markets: A look from Var-SVAR Granger causality and student's-T copulas. *Journal of Risk and Financial Management*, *12*(2), 52. doi:10.3390/jrfm12020052.
Macrina, A., & Phetteplace, E. (2015). The Tor browser and intellectual freedom in the digital age. *Reference and User Services Quarterly*, *54*(4), 17–20.
Magnuson, W. (2018). Financial regulation in the Bitcoin era. *Stan. JL Bus. & Fin.*, *23*, 159.
Makarov, I., & Schoar, A. (2021). *Blockchain analysis of the bitcoin market* (No. w29396). National Bureau of Economic Research.
Maurer, B., Nelms, T.C., & Swartz, L. (2013). When perhaps the real problem is money itself!': The practical materiality of Bitcoin. *Social Semiotics*, *23*(2), 261–277. https://doi.org/10.1080/10350330.2013.777594
McCallum, B.T. (2015). The bitcoin revolution. *Cato J.*, *35*, 347.
Medina-González, S., Gkioulekas, I., Dua, V., & Papageorgiou, L.G. (2019). A novel scenario aggregation framework based on Network Community Detection Methods. *Computer Aided Chemical Engineering*, 811–816. doi:10.1016/b978-0-12-818634-3.50136-3.
Meiklejohn, S., Pomarole, M., Jordan, G., Levchenko, K., McCoy, D., Voelker, G.M., & Savage, S. (2016). A fistful of Bitcoins. *Communications of the ACM*, *59*(4), 86–93. Retrieved from https://doi.org/10.1145/2896384.
Meinert, M.C. (2022). The Realities of Ransomware. *American Bankers Association. ABA Banking Journal*, *114*(2), 32–34.
Merton, R.C. (1973). An intertemporal capital asset pricing model. *Econometrica*, *41*(5), 867. doi:10.2307/1913811.

Meylakhs, A., & Saidashev, R. (2021). A qualitative analysis of the Russian cryptomarket Hydra. *Kriminologisches Journal*, *3*, 169–185.
Meynkhard, A. (2020). Effect of bitcoin volatility on Altcoins pricing. *Software Engineering Perspectives in Intelligent Systems*, 652–664. doi:10.1007/978-3-030-63322-6_55
Monrat, A.A., Schelen, O., & Andersson, K. (2019). A survey of blockchain from the perspectives of applications, challenges, and opportunities. *IEEE Access*, *7*, 117134–117151. doi:10.1109/access.2019.2936094
Moran, M.E. (2007). The zero sum game. *Journal of Endourology*, *21*(8), 803–806.
Murali, J. (2013). A New Coinage. *Economic and Political Weekly*, *48*(38).
Nakamoto, S. (2008). *Bitcoin: A peer-to-peer electronic cash system.* Retrieved from https://Bitcoin.org/Bitcoin.pdf.
Nasdaq. (n.d.). *Nasdaq Data Link.* data.nasdaq.com. Retrieved from https://data.nasdaq.com/data/BCHAIN/MIREV-bitcoin-miners-revenue.
NEWS BBVA. (2023). *Mica regulation: What is it and why does it matter?* Retrieved from https://www.bbva.com/en/innovation/eu-markets-in-cryptoassets-mica-regulation-what-is-it-and-why-does-it-matter/
Nguyen, T., De Bodisco, C., & Thaver, R. (2018). Factors Affecting Bitcoin Price in The Cryptocurrency Market: An Empirical Study. *International Journal of Business & Economics Perspectives*, *13*(1).
O'Connor, F.A. et al. (2015). The Financial Economics of Gold — A Survey. *International Review of Financial Analysis*, *41*, 186–205. doi:10.1016/j.irfa.2015.07.005.
Oliveira, L., Zavolokina, L., Bauer, I., & Schwabe, G. (2018, December). *To token or not to token: Tools for understanding blockchain tokens.* ICIS.
Ormsby, E. (2014). *Silk Road*. Macmillan Publishers Aus.
Pace, J. (2016). Exchange relations on the dark web. *Critical Studies in Media Communication*, *34*(1), 1–13. doi:10.1080/15295036.2016.1243249.
Paquet-Clouston, M., Haslhofer, B., & Dupont, B. (2019). Ransomware payments in the Bitcoin ecosystem. *Journal of Cybersecurity*, *5*(1). doi:10.1093/cybsec/tyz003
Peters, G.W., & Panayi, E. (2015). Understanding modern banking ledgers through blockchain technologies: Future of transaction processing and smart contracts on the Internet of Money. *SSRN Electronic Journal [Preprint]*. Retrieved from https://doi.org/10.2139/ssrn.2692487.
Pieters, G., & Vivanco, S. (2017). Financial regulations and price inconsistencies across Bitcoin markets. *Information Economics and Policy*, *39*, 1–14. Retrieved from https://doi.org/10.1016/j.infoecopol.2017.02.002.
Raiborn, C., & Sivitanides, M. (2015). Accounting issues related to Bitcoins. *Journal of Corporate Accounting & Finance*, *26*(2), 25-34.
Reid, F., & Harrigan, M. (2013). *An analysis of anonymity in the bitcoin system* (197-223). Springer New York.
Roebroeck, A. (2015). Granger causality. *Brain Mapping*, 593–597. doi:10.1016/b978-0-12-397025-1.00337-7.
Rosenfeld, M. (2014). Analysis of hashrate-based double spending. *arXiv preprint arXiv:1402.2009*.
Sarker, P.K., & Wang, L. (2022). Co-movement and Granger causality between Bitcoin and M2, inflation and economic policy uncertainty: Evidence from the U.K., & Japan. *Heliyon*, *8*(10). doi:10.1016/j.heliyon.2022.e11178.
Segendorf, B. (2014). What is bitcoin? *Sveriges Riksbank Economic Review*, 2–71.
Serena, L., D'Angelo, G., & Ferretti, S. (2022). Security analysis of distributed ledgers and blockchains through agent-based simulation. *Simulation Modelling Practice and Theory*, *114*, 102413. doi:10.1016/j.simpat.2021.102413.
Shojaie, A., & Fox, E.B. (2022). Granger causality: A review and recent advances. *Annual Review of Statistics and Its Application*, *9*(1), 289–319. doi:10.1146/annurev-statistics-040120-010930.

Stroukal, D., & Nedvědová, B. (2016). Bitcoin and other cryptocurrency as an instrument of crime in Cyberspace. *Proceedings of 4th Business & Management Conference* [Preprint]. doi:10.20472/bmc.2016.004.018.

Sutanrikulu, A., Czajkowska, S., & Grossklags, J. (2020, November). Analysis of darknet market activity as a country-specific, socio-economic and technological phenomenon. In 2020 *APWG Symposium on Electronic Crime Research* (eCrime) (1-10). IEEE.

Taeihagh, A., Ramesh, M., & Howlett, M. (2021). Assessing the regulatory challenges of emerging disruptive technologies. *Regulation & Governance*, *15*(4), 1009–1019. doi:10.1111/rego.12392.

Tambe, N., & Jain, A. (2023). *All you need to know about India's crypto bill.* Forbes. Retrieved from https://www.forbes.com/advisor/in/investing/cryptocurrency/crypto-bill/

Tan, B.S., & Low, K.Y. (2017). Bitcoin–its economics for financial reporting. *Australian Accounting Review*, *27*(2), 220-227.

Thakur, K.K., & Banik, G.G. (2018). Cryptocurrency: Its risks and gains and the way ahead. *IOSR Journal of Economics and Finance*, *9*(2), 38-42.

The United States Department of Justice. (2022). *Justice Department investigation leads to shutdown of largest online darknet marketplace.* Retrieved from https://www.justice.gov/opa/pr/justice-department-investigation-leads-shutdown-largest-online-darknet-marketplace (Accessed: 24 May 2023).

Tsvetanov, T., & Slaria, S. (2021). The effect of the colonial pipeline shutdown on gasoline prices. *Economics Letters*, *209*, 110122. doi:10.1016/j.econlet.2021.110122.

Tu, K.V., & Meredith, M.W. (2015). Rethinking virtual currency regulation in the Bitcoin age. *Wash. L. Rev*., *90*, 271.

Turton, W., Riley, M., & Jacobs, J. (2021). *Colonial pipeline paid hackers nearly $5 million in ransom*. Bloomberg.com. Retrieved from https://www.bloomberg.com/news/articles/2021-05-13/colonial-pipeline-paid-hackers-nearly-5-million-in-ransom.

Weber, B. (2014). Can Bitcoin compete with money? *Journal of Peer Production*, *4*.

White, R., et al. (2020). Is bitcoin a currency, a technology-based product, or something else?. *Technological Forecasting and Social Change*, *151*, 119877. Retrieved from https://doi.org/10.1016/j.techfore.2019.119877.

White, R., Marinakis, Y., Islam, N., & Walsh, S. (2020). Is Bitcoin a currency, a technology-based product, or something else? *Technological Forecasting and Social Change*, *151*, 119877.

Wolfson, S.N. (2015). Bitcoin: The early market. *Journal of Business & Economics Research*, *13*(4), 201. doi:10.19030/jber.v13i4.9452.

Yellin, T., Aratari , D., & Pagliery, J. (n.d.). What is bitcoin?. *CNNMoney*. Retrieved from https://money.cnn.com/infographic/technology/what-is-bitcoin/

Yermack, D. (2013). Is bitcoin a real currency? an economic appraisal. *NBER Working Paper Series* (No. w19747) [Preprint]. doi:10.3386/w19747.

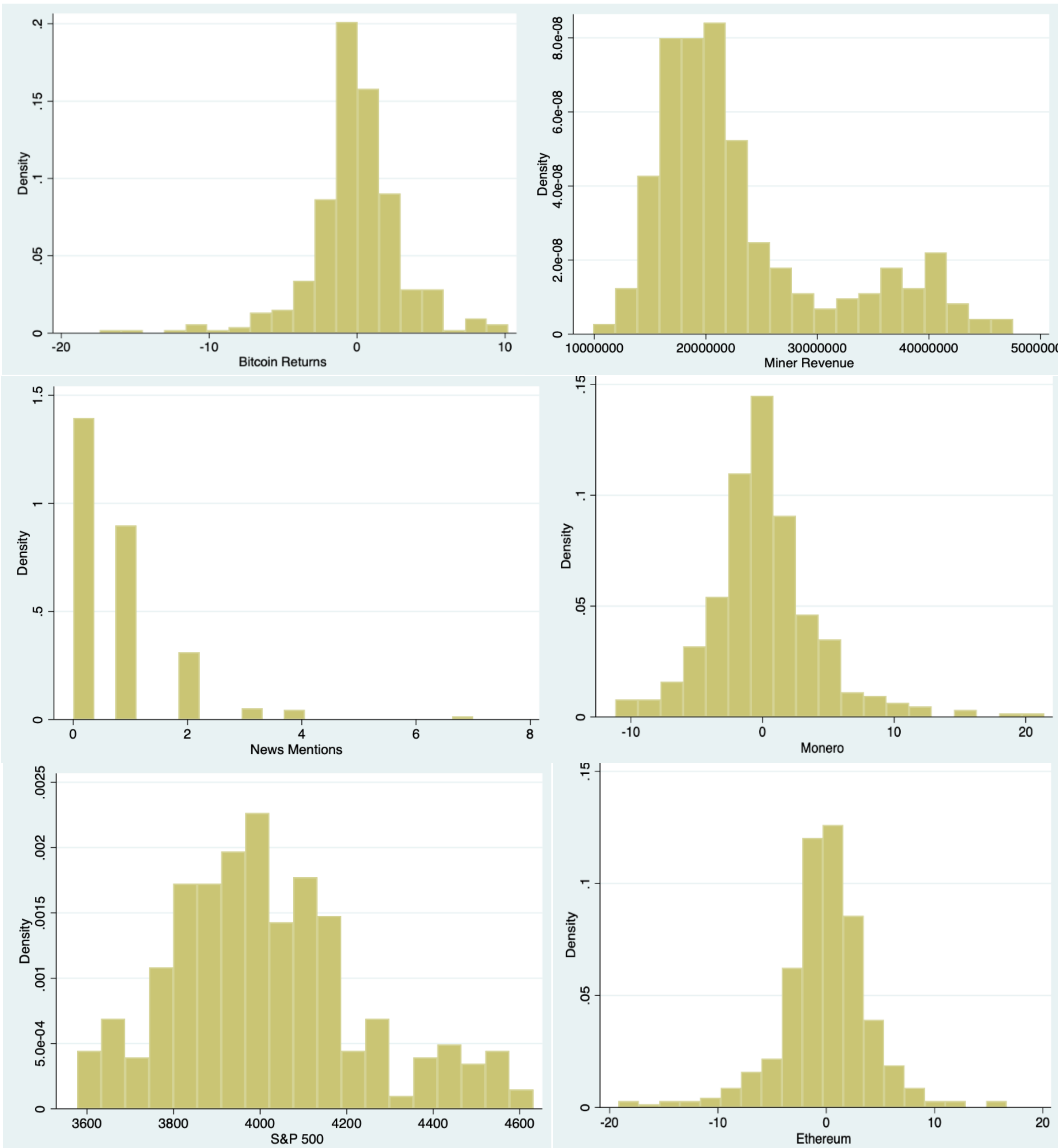
Zetzsche, D.A., Annunziata, F., Arner, D.W., & Buckley, R.P. (2021). The Markets in Crypto-Assets regulation (MiCA) and the EU digital finance strategy. *Capital Markets Law Journal*, *16*(2), pp.203-225.

Zhang, H., & Zou, F. (2020, December). A survey of the dark web and dark market research. In *2020 IEEE 6th international conference on computer and communications (ICCC)* (1694-1705). IEEE.

Zhang, X., et al. (2021). The time-varying causal relationship between the bitcoin market and internet attention. *Financial Innovation*, *7*(1). doi:10.1186/s40854-021-00275-9.

APPENDIX

FIGURE I
SHAPIRO-WILK NORMALITY HISTOGRAMS



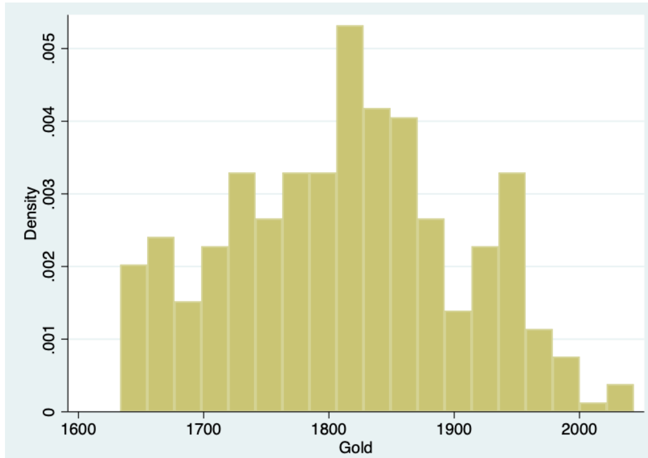


FIGURE II
SHAPIRO-WILK TEST RESULTS

```
. swilk BitcoinReturns NewsMentions Ethereum SP500 MinerRevenue Monero Gold
```

Shapiro–Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
BitcoinRet~s	366	0.91507	21.596	7.281	0.00000
NewsMentions	366	0.87941	30.665	8.111	0.00000
Ethereum	366	0.93933	15.426	6.483	0.00000
SP500	366	0.96786	8.172	4.978	0.00000
MinerRevenue	366	0.85797	36.115	8.499	0.00000
Monero	366	0.93981	15.305	6.465	0.00000
Gold	366	0.98481	3.864	3.203	0.00068

FIGURE III
AUGMENTED DICKEY FULLER RESULTS

Variable: **BitcoinReturns** Number of obs = **360**
Number of lags = **4**

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	-7.960	-3.451	-2.876	-2.570

MacKinnon approximate *p*-value for Z(t) = **0.0000**.

Variable: **NewsMentions** Number of obs = **360**
Number of lags = **4**

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	**-7.828**	**-3.451**	**-2.876**	**-2.570**

MacKinnon approximate *p*-value for Z(t) = **0.0000.**

Variable: **Ethereum** Number of obs = **360**
Number of lags = **4**

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	**-8.142**	**-3.451**	**-2.876**	**-2.570**

MacKinnon approximate *p*-value for Z(t) = **0.0000.**

Variable: **SP500** Number of obs = **360**
Number of lags = **4**

H0: Random walk without drift, d = 0

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	**-2.240**	**-3.451**	**-2.876**	**-2.570**

MacKinnon approximate *p*-value for Z(t) = **0.1922.**

Dickey–Fuller test for unit root Number of obs = **364**
Variable: **MinerRevenue** Number of lags = **0**

H0: Random walk with drift, d = 0

	Test statistic	t-distribution critical value 1%	5%	10%
Z(t)	**-3.695**	**-2.337**	**-1.649**	**-1.284**

p-value for Z(t) = **0.0001**

```
Variable: Monero                                  Number of obs  = 360
                                                  Number of lags =   4

H0: Random walk without drift, d = 0

                                       Dickey-Fuller
                   Test        ──────── critical value ────────
              statistic             1%           5%          10%
───────────────────────────────────────────────────────────────
 Z(t)            -8.753         -3.451       -2.876       -2.570
───────────────────────────────────────────────────────────────
MacKinnon approximate p-value for Z(t) = 0.0000.
```

```
Variable: Gold                                    Number of obs  = 360
                                                  Number of lags =   4

H0: Random walk with drift, d = 0

                                      t-distribution
                   Test        ──────── critical value ────────
              statistic             1%           5%          10%
───────────────────────────────────────────────────────────────
 Z(t)            -2.463         -2.337       -1.649       -1.284
───────────────────────────────────────────────────────────────
p-value for Z(t) = 0.0071
```

FIGURE IV
OPTIMAL LOG SELECTION

```
. varsoc NewsMentions

Lag-order selection criteria

   Sample: 3/12/2022 thru 3/8/2023                     Number of obs = 362
```

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-508.428				.976911	2.81452	2.81879	2.82527*
1	-506.447	3.9621*	1	0.047	.97163*	2.8091*	2.81764*	2.8306
2	-506.447	.00015	1	0.990	.977013	2.81462	2.82744	2.84687
3	-505.774	1.3448	1	0.246	.978784	2.81643	2.83353	2.85943
4	-505.766	.01709	1	0.896	.984161	2.82191	2.84328	2.87566

```
   * optimal lag
   Endogenous: NewsMentions
    Exogenous: _cons
```

```
. varsoc BitcoinReturns
```

Lag-order selection criteria

Sample: 3/12/2022 thru 3/8/2023 Number of obs = 362

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-927.507				9.89467*	5.12987*	5.13415*	5.14062*
1	-927.447	.12109	1	0.728	9.94616	5.13506	5.14361	5.15656
2	-926.671	1.5518	1	0.213	9.95849	5.1363	5.14912	5.16855
3	-926.113	1.1157	1	0.291	9.98285	5.13874	5.15584	5.18175
4	-925.943	.34015	1	0.560	10.0287	5.14333	5.1647	5.19708

* optimal lag
Endogenous: BitcoinReturns
Exogenous: _cons

```
. varsoc Ethereum
```

Lag-order selection criteria

Sample: 3/12/2022 thru 3/8/2023 Number of obs = 362

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1041.53				18.5776*	5.75983*	5.76411*	5.77058*
1	-1041.41	.24407	1	0.621	18.6679	5.76468	5.77323	5.78618
2	-1041.2	.425	1	0.514	18.7493	5.76903	5.78186	5.80129
3	-1039.91	2.5669	1	0.109	18.72	5.76747	5.78456	5.81047
4	-1039.61	.61264	1	0.434	18.7919	5.7713	5.79267	5.82505

* optimal lag
Endogenous: Ethereum
Exogenous: _cons

```
. varsoc SP500
```

Lag-order selection criteria

Sample: 3/12/2022 thru 3/8/2023 Number of obs = 362

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2470.51				49855.5	13.6548	13.659	13.6655
1	-1917.53	1106*	1	0.000	2362.04*	10.6052*	10.6137*	10.6267*
2	-1917.43	.21234	1	0.645	2373.74	10.6101	10.6229	10.6423
3	-1917.28	.29402	1	0.588	2384.95	10.6148	10.6319	10.6578
4	-1916.44	1.6754	1	0.196	2387.09	10.6157	10.6371	10.6695

* optimal lag
Endogenous: SP500
Exogenous: _cons

```
. varsoc MinerRevenue
```

Lag-order selection criteria

Sample: 3/12/2022 thru 3/8/2023 Number of obs = 362

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-6269.37				6.5e+13	34.6429	34.6472	34.6537
1	-5900.47	737.8	1	0.000	8.5e+12	32.6103	32.6189	32.6318
2	-5862.44	76.07	1	0.000	6.9e+12	32.4057	32.4185	32.438
3	-5837.27	50.335*	1	0.000	6.1e+12	32.2722	32.2893*	32.3152*
4	-5836.24	2.0558	1	0.152	6.1e+12*	32.2721*	32.2934	32.3258

* optimal lag
Endogenous: MinerRevenue
Exogenous: _cons

```
. varsoc Gold

Lag-order selection criteria

Sample: 3/12/2022 thru 3/8/2023                    Number of obs = 362
```

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2145.73				8287.34	11.8604	11.8646	11.8711
1	-1626.44	1038.6	1	0.000	472.974	8.99692	9.00547	9.01842*
2	-1624.2	4.4826	1	0.034	469.742	8.99006	9.00288*	9.02231
3	-1623.06	2.2735	1	0.132	469.387	8.9893	9.0064	9.03231
4	-1620.81	4.5111*	1	0.034	466.143*	8.98237*	9.00374	9.03612

```
* optimal lag
Endogenous: Gold
 Exogenous: _cons
. varsoc Monero

Lag-order selection criteria

Sample: 3/12/2022 thru 3/8/2023                    Number of obs = 362
```

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1031.42				17.5687	5.704	5.70827	5.71475*
1	-1029.99	2.8735	1	0.090	17.5264	5.70158	5.71013	5.72308
2	-1027.01	5.9581*	1	0.015	17.3358*	5.69065*	5.70347*	5.7229
3	-1026.96	.09057	1	0.763	17.4275	5.69592	5.71302	5.73893
4	-1026.83	.26485	1	0.607	17.5112	5.70072	5.72209	5.75447

```
* optimal lag
Endogenous: Monero
 Exogenous: _cons
```

FIGURE V
GRANGER GRADUALITY WALD TEST

Granger causality Wald tests

Equation	Excluded	F	df	df_r	Prob > F
BitcoinReturns	NewsMentions	.17025	1	361	0.6801
BitcoinReturns	ALL	.17025	1	361	0.6801
NewsMentions	BitcoinReturns	.00065	1	361	0.9796
NewsMentions	ALL	.00065	1	361	0.9796

Granger causality Wald tests

Equation	Excluded	F	df	df_r	Prob > F
BitcoinReturns	MinerRevenue	.74989	4	352	0.5586
BitcoinReturns	ALL	.74989	4	352	0.5586
MinerRevenue	BitcoinReturns	18.52	4	352	0.0000
MinerRevenue	ALL	18.52	4	352	0.0000

Granger causality Wald tests

Equation	Excluded	F	df	df_r	Prob > F
NewsMentions	Monero	1.447	2	304	0.0991
NewsMentions	ALL	1.447	2	304	0.0991
Monero	NewsMentions	.71136	2	304	0.8143
Monero	ALL	.71136	2	304	0.8143