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Essays on Bitcoin and Cryptocurrencies

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ESSAYS ON BITCOIN AND CRYPTOCURRENCIES

by

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Bitcoin and cryptocurrencies, invented as potential digital international currencies, have gradually drawn more and more attention since their birth. The growing popularity of cryptocurrencies in the past decade and the recent acceptance of Bitcoin as legal tender in El Salvador suggests that there is growing acceptance of these instruments and that cryptocurrencies are here to stay. Among these cryptocurrencies, Bitcoin has a unique place being the first and most well-known cryptocurrency in terms of price, market capitalization, and trading volume. The first two essays of this dissertation focus on Bitcoin and the third essay focuses on the cryptocurrency market in general, through studies of their return time series.

The first essay explores whether Bitcoin is a speculative asset by studying its volatility. Based on generalized autoregressive conditional heteroskedasticity (GARCH) models with daily data, I compare the conditional volatility of Bitcoin with that of the U.S. dollar, the euro, the British pound sterling, gold, the S&P 500 Index, and the CBOE VIX, and find that, at this time, Bitcoin behaves closer to a speculative vehicle than an international currency due to its much higher volatility. This may explain why it has not yet been widely accepted in the world as a payment method.

The second essay examines the effect of U.S. monetary policy on Bitcoin during times of quantitative easing (QE). The Federal Reserve has launched large-scale asset purchases programs, referred to as quantitative easing, since the nominal interest rate reaches its zero lower bound. To capture the possible shocks from both conventional and unconventional monetary policy, GARCH models are used in this essay to ascertain its effect on Bitcoin. In addition, the shocks from the stock market, the gold market, and the oil market are also examined. The results of these inquiries show that Bitcoin is not directly impacted by monetary policy but appears to be impacted from the stock market suggesting possible indirect channels through which Bitcoin is impacted by monetary policy.

The third essay investigates the impact of the global COVID-19 pandemic on the cryptocurrency market following the event-study approach (ESA). Having shaped the world in many ways, the COVID-19 pandemic has profoundly influenced the world economy and financial markets in the short run. To study if the cryptocurrency market is also impacted by the COVID pandemic, I incorporate a three-factor model into the ESA along with a large data set, including 100 cryptocurrencies and over 150,000 daily observations. I first show that the three-factor model built on training data captures the common risk factors (i.e., market, size, and momentum) of the cryptocurrency market quite well. Then I use the ESA along with the three-factor model on the test dataset to test if there is a significant event effect. I find that though the daily impact of the COVID pandemic is not always significant, the accumulated effect on cryptocurrencies is significantly negative and does not disappear over time, at least in the short run.

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CHAPTER 1

INTRODUCTION

In 2009, Bitcoin was introduced as the first decentralized cryptocurrency,[1] by the anonymous Satoshi Nakamoto, in the aftermath of the Great Recession of 2007-08. It was initially conceived as a global digital currency, an alternative to government-backed fiat currencies. The idea behind Bitcoin is deeply rooted in the Austrian school of economics and especially lies in the work of Friedrich August von Hayek (1978) who advocated a free market of competitive private moneys to end the monopoly of central banks. It is well-known that central banks can control the supply of their moneys and in some cases print too much money in order to counteract short-term problems of their economy. The monopoly power of a country's central bank has led many to blame hyperinflation and even economic breakdowns during the last century on the central bank's monopoly power. Moreover, fiat currencies have their own sovereignty jurisdiction and there are borders between them which limit their use across the boundaries. People need foreign exchange to travel from one county to another so global currencies are widely desired. An optimal currency area (Mundell 1961) is one possible solution and the euro is its best-known application. Yet there is no sign that there will be a global currency built on the theories of

[1] In this dissertation, the term cryptocurrency refers to decentralized cryptocurrency. The terms "cryptocurrency" and "decentralized cryptocurrency" are used interchangeably. "Decentralized" is added before cryptocurrency in some cases in order to emphasize the feature of decentralization.

optimal currency areas (OCA). However, Bitcoin and many of its cryptocurrency counterparts, by adopting decentralized payment systems based on blockchain cryptography, can overcome potential shortcomings of centralized fiat money and provide potential alternatives to the fiat currencies.

1.1 Bitcoin: The First Decentralized Cryptocurrency

1.1.1 Bitcoin: Some Important Features

Bitcoin is the first decentralized digital currency based on blockchain cryptograph. In October 2008, the pseudonymous Satoshi Nakamoto introduced the concept of Bitcoin in a whitepaper titled "Bitcoin: A Peer-to-Peer Electronic Cash System" (Nakamoto 2008). The name Bitcoin is a compound of bit and coin. Before that, the domain name *bitcoin.org* was quietly registered in August 2008. In January 2009, Nakamoto launched the open-sourced Bitcoin software and created the Bitcoin network by mining the starting block of the Bitcoin blockchain, the so-called genesis block (Nakamoto 2009). The first Bitcoin transaction was executed on 12 January 2009, in which Hal Finney received 10 bitcoins[2] (BTC or XBT) from Nakamoto (Peterson 2014). The first commercial Bitcoin transaction

[2] Capitalization of Bitcoin: In this dissertation, the lowercase bitcoin is used only when bitcoin is a unit of account (e.g., one bitcoin, two bitcoins, etc.). In all other cases, the capitalized Bitcoin is used whether referring to the concept, the network, or the currency. This follows the guide of bitcoin.org: "Bitcoin - with capitalization, is used when describing the concept of Bitcoin, or the entire network itself. e.g. 'I was learning about the Bitcoin protocol today.' bitcoin - without capitalization, is used to describe bitcoins as a unit of account. e.g. 'I sent ten bitcoins today.'; it is also often abbreviated BTC or XBT."

is known to occur in 2010 when programmer Laszlo Hanyecz spent 10,000 BTC to buy two Papa John's pizzas (Kharpal 2018).

Decentralization is the key feature of Bitcoin. Contrary to fiat currencies which are monitored and managed by central banks, Bitcoin has no such central authority. Furthermore, in the Bitcoin system, there is no central server; there is no central storage; and there is no single administrator. That is, Bitcoin is purely peer-to-peer (P2P). A decentralized P2P system contrasts with the monopoly power that is held by central banks with traditional fiat currencies.

Pseudonymity is another important feature of Bitcoin. All users of Bitcoin are only identified by their public address and it is not possible to reveal the true identity of a user by her public address. Therefore, anyone can safely use Bitcoin to make transactions and make payments without exposing their identities. Thus, their privacy is very well protected and many people are interested to Bitcoin due to this feature.

Bitcoin is built on a new technology called blockchain cryptograph and Bitcoin is the first cryptocurrency employing blockchain technology. The Bitcoin blockchain is a public ledger recording Bitcoin transactions and consists of a chain of blocks. The blockchain technology (256 bit) securely solves the double-spending problem.[3]

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[3] Double-spending is a potential issue in a digital payment system that the same token is spent twice. Double-spending is impossible for physical currencies as the same physical coin cannot exist in more than one hand at the same time. For Bitcoin, once a new block is created, it will be added to the blockchain and broadcasted to all nodes on the network. Double-spending a bitcoin is possible if a single user controls over 50% of the computing power maintaining the Bitcoin network. It is theoretically possible but practically unlikely especially when the network grows.

The total supply of Bitcoin is limited to 21 million bitcoins, which is designed to be reached in 2140. After that, no more new bitcoins will be created. Furthermore, the growth rate of Bitcoin is pre-determined and decreasing. New bitcoins are created by a process called “mining”. The mining process is simply the validation[4] of transactions using the Proof-of-Work (PoW) algorithm. Bitcoin is designed in this way to avoid the potential problem of inflation or hyperinflation existing in traditional fiat currencies. As of 10 October 2021, there is a total of about 18.8 million bitcoins in circulation.[5]

Bitcoin software is free and open-sourced. This means Bitcoin software is free to download and open to use to anyone for any purpose. Bitcoin is traded 24 hours a day and 7 days a week (24/7) around the world. One unit of Bitcoin is called one bitcoin (BTC or XBT), and one BTC can be divided into 1,000 millibitcoins (mBTC) or 1,000,000 microbitcoins (µBTC) or 100,000,000 satoshis (sat). Satoshi is the smallest unit of Bitcoin.

1.1.2 The Bitcoin Network

Figure 1.1 shows the peer-to-peer (P2P) network of Bitcoin. It is a collection of all nodes within the network. All nodes in the Bitcoin network are peers to each other and are all equal. They connect to each other without a third party. There is no central server or storage or single administrator in the Bitcoin network.[6]

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[4] Validating, or mining, simply put is a computation process to obtain the solution of a mathematical puzzle (Proof-of-Work) in the Bitcoin protocol. Once the PoW is solved, it is very easy for the other nodes to verify the solution.

[5] Data Source: CoinMarketCap.com

[6] For more details, refer to Antonopoulos (2017).

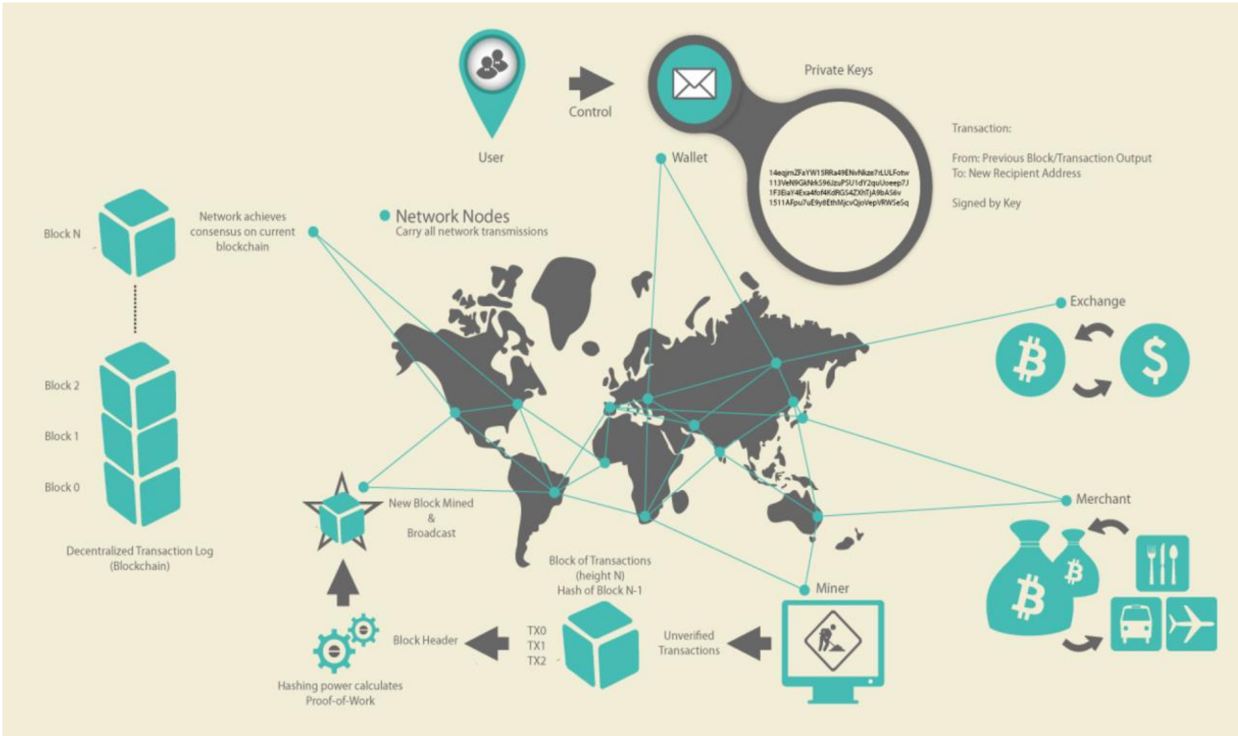

Figure 1.1 Bitcoin Network Overview (Source: Antonopoulos 2017)

There are four typical types of nodes within the network based on their functionality. One is called full node, which maintains a complete and up-to-date copy of the Bitcoin blockchain. Miners are usually full nodes and they create new blocks by the PoW algorithm validation with the complete history of the blockchain.

User wallet is another type of nodes and most of them are just a subset of the full nodes. Bitcoin wallet is a device or an application storing keys and transaction information. Bitcoin uses public-key cryptography invented in 1970s to generate the private-public key pair. Specifically, the owner of a wallet can pick any random 256-bit number between 1 and 2^{256} as the private key. The private key is only known to its owner and can be stored physically or digitally. The public key can be calculated from the private key using elliptic curve multiplication (see Figure 1.2). Mathematically, elliptic curve multiplication is a one-way function and guarantees the safety of the private key since it is easy to calculate the public key from the private key but practically impossible to reveal the private key from the public key. The wallet address can be further generated from the public key using hashing functions (SHA256) in a similar fashion as the public-key cryptography. The address can be known to the public and it is the address, not the public key, that is used for sending and receiving bitcoins.

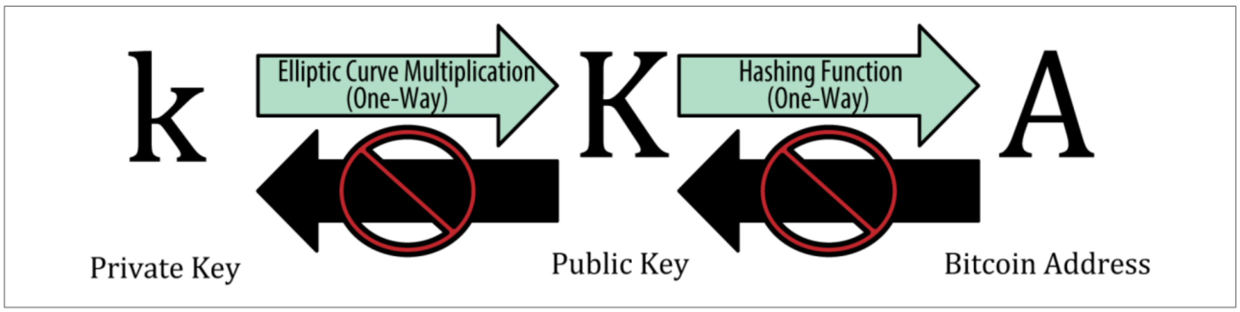

Figure 1.2 Private Key, Public Key, and Bitcoin Address (Source: Antonopoulos 2017)

1.1.3 Bitcoin Transactions

To understand how a transaction in Bitcoin works, a simple example will help. Suppose Alice buys a used laptop from Bob worth 0.015 BTC. First, Alice obtains the Bitcoin address of Bob's wallet. Then Alice broadcasts a transaction of 0.015 BTC from her Bitcoin wallet (address) to Bob on the Bitcoin network, namely, all nodes. Every node can independently verify this transaction based on a long list of criteria. Once this transaction is verified and it will be put in a pool along with other transactions waiting for miners to validate. Now the miners step in and compete to validate these transactions by solving the PoW of a new block. Suppose miner C finishes the PoW of this block first so he broadcasts this block to the Bitcoin network. Once his block is confirmed and accepted by the Bitcoin network, his block becomes an official part of the Bitcoin blockchain and the transaction between Alice and Bob is complete. The result looks like Figure 1.3, and it is shared to all nodes in the network. On average it takes about 10 minutes to create a new block on the Bitcoin blockchain. As a result, miner C gets the transaction fee of 0.0005 BTC and a reward from the Bitcoin network. As an incentive to miners, the Bitcoin network rewards 50 BTC for mining one new block in 2009 when Bitcoin was invented but this reward halves every 210,000 blocks or in roughly four years. The reward for mining a new block is 6.25 BTC as of October 2021.

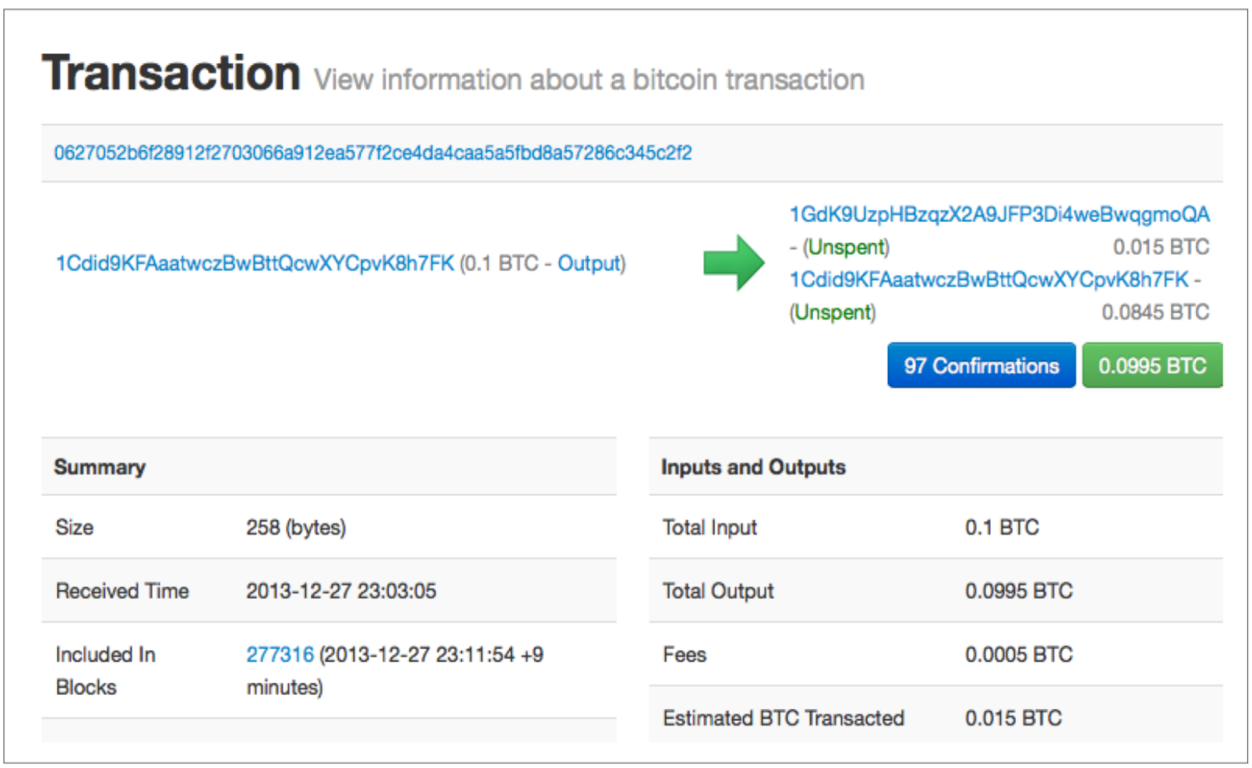

Figure 1.3 Bitcoin Transaction between Alice and Bob (Source: Antonopoulos 2017)

Though this transaction is included in some other miners' blocks, they will not get the reward or the transaction fee because their block does not become part of the blockchain. Furthermore, they have to remove all the transactions they have validated but are already included in this new block mined by miner C. One thing to notice is that there is 0.1 BTC in Alice's wallet but she only needs to pay Bob 0.015 BTC so the Bitcoin network will take the transaction of 0.015 BTC and the transaction fee of 0.0005 BTC and makes a change of 0.0845 BTC back to Alice's wallet. It is Alice who decides how much transaction fee she wants to include for completing her transaction.[7]

1.2 Bitcoin and Alternative Cryptocurrencies

1.2.1 Alternative Cryptocurrencies

Alternative cryptocurrencies (i.e., altcoins) are generally referred to as cryptocurrencies other than Bitcoin. Since Bitcoin's introduction as the first decentralized cryptocurrency in 2009, more and more alternative cryptocurrencies followed its step and have developed to be a market worth multi-trillion U.S. dollars today. Most of the altcoins developed their network based on Bitcoin with some differences. For instance, Litcoin, the

[7] Transaction fees are a reflection of the speed the user wants her transaction to be validated. Transaction fees are optional and the miners can choose which transactions they will validate first. Since one block of the blockchain contains a maximum size of data, the number of the transactions is limited in this block. Transaction fees are generally based on the data space a transaction takes but not necessarily the number of bitcoins included in this transaction. Transaction fees are measured in satoshi per byte (sat/b). Usually a wallet provides some options for the user before she sends her bitcoins. A high rate of transaction fees can make the transaction as fast as seconds and a low fee might takes several days to complete the transaction (Antonopoulos 2017).

first altcoin which was launched in 2011 by Charlie Lee, modifies the Bitcoin network by decreasing block generation time from 10 minutes to 2.5 minutes and adopts the hashing algorithm *scrypt* instead of Bitcoin's SHA256. Some other altcoins add features such as smart contract[8] into their network to allow broader applications. A good example is Ethereum, secondary only to Bitcoin in terms of market capitalization. Introduced in 2015, Ethereum has developed into a system on which ERC-20 (Ethereum Request for Comments 20) tokens and decentralized finance (DeFi) platforms such as stablecoin Dai are built. Stablecoins are a special subcategory of cryptocurrencies. A stablecoin is a coin or a token aiming to be pegged to a fiat currency, a cryptocurrency, or exchange-traded commodities. For instance, Tether (USDT) and USD Coin (USDC) are USD-backed; Dai is anchored on Ethereum; and Digix Gold Tokens (DGX) and petro gold are linked to gold.

Cryptocurrencies can be further divided into cryptocurrency coins and cryptocurrency tokens. Cryptocurrency coins are cryptocurrencies that have their own blockchain and cryptocurrency tokens are usually based on top of the blockchain of some coin so they do not have to run their own blockchain. A cryptocurrency coin is usually invented to be a payment system whilst a cryptocurrency token is often used by some company for raising funds for their projects or further development through the initial coin offering (ICO) process. Bitcoin has been the most popular coin and stablecoins such Tether and USD Coin are among the most famous tokens.

[8] A smart contract is a protocol that automatically executes code according to the terms of a contract or an agreement and is a "collection of code and data (sometimes referred to as functions and state) that is deployed using cryptographically signed transactions on the blockchain network" (Yaga et al. 2018).

1.2.2 The Dominance of Bitcoin

Among thousands of cryptocurrencies, Bitcoin has been in a unique position since its birth so it is worth special attention. Figure 1.4 shows the largest ten cryptocurrencies as percentage of the cryptocurrency market in terms of market capitalization from 28 April 2013 to 10 October 2021. From 2013 to early 2017, Bitcoin's share of the cryptocurrency market rarely falls below 80% and goes as high as of over 95%. Dropping from 80% to below 40% in around three months (from March to June 2017), that share then fluctuates between 40% and 60% from mid-2017 to mid-2019. After that, Bitcoin maintains its status representing over 60% of the cryptocurrency market in the next 21 months or so most of the time. Then it falls sharply to 40% in about two months and stands above this level until

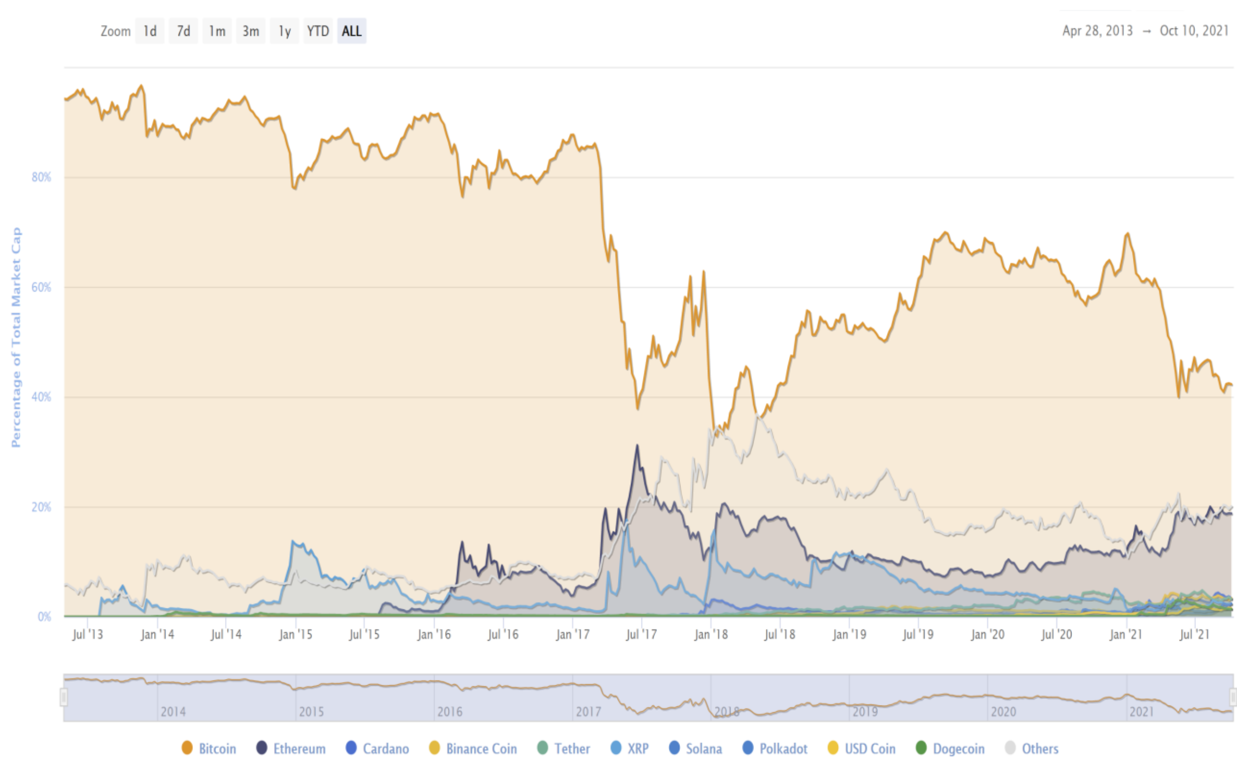

Figure 1.4 Major Cryptocurrencies by Percentage of Total Market Capitalization (Source: CoinMarketCap.com)

today. Though Bitcoin’s market share among thousands of cryptocurrencies today is not as high as it was before 2017 when there was just a handful of altcoins, it is still higher than the sum of the next largest nine cryptocurrencies.

1.2.3 Legal Status and Recent Development

After over one decade of development, the legal status of Bitcoin has varied substantially from state to state. Table 1.1 displays the legality of Bitcoin in some major

Table 1.1
Legal Status of Bitcoin

Region	Country		Region	Country	
	Legal	Illegal		Legal	Illegal
Africa	Nigeria	Algeria	Asia	India	China
	South Africa	Egypt		Iran	
	Tanzania	Morocco		Japan	
	Zimbabwe			Pakistan	
Americas	Argentina	Bolivia		Russia	
	Brazil			Taiwan	
	Canada			Turkey	
	Chile		Europe	EU	
	Cuba			Norway	
	El Salvador			Switzerland	
	Mexico			UK	
	United States		Oceania	Australia	
				New Zealand	
Source: Global Legal Research Directorate (2018, 2019)					

developed and developing economies across the globe as of October 2021 based on the reports conducted by the Global Legal Research Directorate of the Law Library of Congress (2018, 2019).

China is the only major economy which completely bans trading and mining cryptocurrencies. But in most developed economies, it is perfectly legal to trade and mine Bitcoin and use Bitcoin as a means of payment. In the meanwhile, some countries partially legalize Bitcoin: they either ban Bitcoin and cryptocurrencies from the banking system or allow holding, trading, and mining Bitcoin while not allowing payment with Bitcoin.

The milestone of Bitcoin's legislation is that Bitcoin has become the second legal tender of El Salvador. The "Bitcoin Law" was passed by the Legislative Assembly of El Salvador in June 2021 and took in effect on 7 September 2021. Thereafter, Salvadorans can receive remittances directly with Bitcoin as with USD. Before that, an experiment has been conducted since 2019 in a small coastal Salvadoran town of El Zonte where people receive salaries, pay bills, and buy food from local shops with Bitcoin (Fieser 2021). Tourism is an important sector of El Salvador and accounts for over 10% of its GDP. International tourists from now on can visit El Salvador even without carrying USD and only need to bring their smartphone installed with a Bitcoin wallet. Over 50% of its roughly 7 million's Salvadoran people owns a Bitcoin wallet about one month after the adoption of Bitcoin as a legal tender and this number is growing. The Bitcoinization[9] of El Salvador,

[9] Bitcoinization, imitating dollarization, is widely used in the cryptocurrency community and it refers to when an economy such as El Salvador adopts Bitcoin as its official currency instead of introducing its own.

the first case of its kind, is a game changer and is a big step forward to fulfill the initial intent of Bitcoin as an alternative global currency and international payment system. Shortly after El Salvador, Cuba announced in its Official Gazette on 26 August 2021 that it would recognize and regulate cryptocurrencies for payments, in part because of the difficulty of obtaining remittances due to U.S. sanctions (Sigalos 2021).

1.3 Dissertation Summary

This dissertation studies the price behavior of Bitcoin and cryptocurrencies in different scenarios through their return series. All return series in this dissertation are compiled from daily price time series and are referred to as log returns. All major estimations use log returns as the dependent variables. Considering the special role and position Bitcoin maintains among the cryptocurrencies, the first two essays focus on Bitcoin and the third essay studies the whole cryptocurrency market.

The first essay (chapter 2) explores whether Bitcoin is a speculative vehicle or a borderless international currency by studying its price volatility. There is a wide belief that Bitcoin is a highly speculative asset rather than a real global currency due to its unusual high volatility. I check for this through the study of conditional volatility (conditional standard deviation) of Bitcoin returns. Specifically, I build generalized autoregressive conditional heteroskedasticity (GARCH) models to compare the conditional volatility of Bitcoin returns with that of a broad class of assets, including three fiat currencies (the U.S.

dollar, the euro, and the British pound sterling), one worldwide-traded commodity (gold), and two widely used market indices (the S&P 500 Index and the Chicago Board Options Exchange Volatility Index). For each of them, I only include its own return to build the GARCH model and exclude any exogenous variables so the conditional volatility obtained reflects purely the time-evolving price behavior of its own. I use Bitcoin returns compiled from its prices in both U.S. dollar and euro. I find that the conditional volatility of Bitcoin is at least several times higher than that of the assets included above, that Bitcoin clearly is a much riskier asset than the others, and that Bitcoin behaves highly speculatively in this introductory life-cycle stage. The findings confirm the widely held belief that Bitcoin is a speculative asset.

Among the assets considered, two pairs are of special interest. The first pair is Bitcoin and the U.S. dollar (USD). The USD has been widely accepted across the globe to be the "world reserve currency" and is the closest thing we have to a global currency. Comparing Bitcoin with the USD can reveal certain features of Bitcoin as a currency. The second pair is Bitcoin and gold. Bitcoin shares several similarities with gold. Their supplies are both limited, they are both traded 24/7 globally, and neither of them is government controlled or backed. For these reasons, some refer to Bitcoin as "virtual gold" (Dyhrberg 2016b). Results show Bitcoin return is much more persistent than that of the USD and gold and suggest that Bitcoin is not a currency yet and that it is too early to say Bitcoin is virtual gold.

The second essay (chapter 3) further studies the price behavior of Bitcoin but is more focused on the impact of monetary policy of the U.S. central bank during times of quantitative easing (QE). Bitcoin was invented in the aftermath of the financial crisis of 2007-08 and it is non-inflationary since its supply is designed to be limited to 21 million BTC and to grow in a pre-determined and decreasing rate. In contrast, the central banks control the monetary supply of the traditional fiat currencies and can print as much money as they want. The U.S. central bank (the Federal Reserve or the Fed), who could not lower the federal funds rate (FFR, the major conventional monetary policy tool) any further, chose to pursue unconventional monetary policies and launched four rounds of quantitative easing (QE), amounting to trillions of USD large-scale asset purchases (LSAP) that injected enormous amounts of liquidity into the economy. The QE programs stimulated economic growth, employment, and the asset markets but also risked initiating inflation in the long run. Bitcoin represents a new class of assets and it is interesting and important to test the effective of monetary policies on it for it might be helpful for monetary authorities to closely monitor and deal with Bitcoin and the broader cryptocurrency market in conducting monetary policies in the future. Bitcoin holders and investors might wish to understand impact of monetary policy changes on Bitcoin behavior. With daily data from 4 August 2010 to 31 July 2019 I build a GARCH model using total asset of the Fed as a measure of its monetary policy stance. The results show that Bitcoin returns are completely unresponsive to monetary policy of the Federal Reserve.

I also check for the potential impact on Bitcoin returns from the stock market, the gold market, and the oil market and find that the stock market has some positive effect on Bitcoin returns but the gold market has no such impact and the oil market has a smaller but negative impact. These findings suggest the Bitcoin market is not directly impacted by monetary policy but it might be indirectly impacted by monetary policy through the stock market and the oil market.

The third essay (chapter 4) extends the study of Bitcoin to the cryptocurrency market and investigates the short-term impact of the COVID-19 pandemic on the price behavior of cryptocurrencies. In additional to the sever health consequences, the COVID-19 pandemic shocked the world economy and the financial markets in both scale and depth, at least in the short run. In the United States alone, following the outbreak of the pandemic both real GDP and consumption shrank by over 30% in the second quarter of 2020 and the unemployment rate reached a record-high of 14.8%, levels not seen since the Great Depression. From February to March 2020, the stock markets experienced a dramatic decrease in free-fall fashion and both S&P 500 and NASDAQ Composite dropped by over 30%. The U.S. oil market collapsed and the West Texas Intermediate (WTI) index experienced a negative price for the first time on record in April 2020. It is natural to test if there exits some similar impact on the cryptocurrency market and if the cryptocurrency market can be used as safe haven. Methodologically, I follow the event-study approach (ESA) and incorporate a three-factor model as the benchmark (training) model along with a two-factor sorting process into the ESA. Employing a large data set with 100 representative cryptocurrencies and over 150,000 daily observations (running from 2 April 2018 to 30 April 2020), I first train a three-factor model analogous to the Fama-French three-factor model and Carhart four-factor model in the estimation window (2 April 2018 to 22 January 2020) using three factors: market, size, and momentum. I find the three factors fit the model very well indicating the three factors capture the common risks of the cryptocurrency market quite well. Then I test the trained three-factor model in the event window (11 February 2020 to 30 April 2020) with adjusted Patell test and adjusted BMP test. Results first show, during the event window, the impact from the COVID-19 pandemic on the cryptocurrency market is not significant on a day-to-day basis. Nonetheless, the accumulated overall effect on the cryptocurrency market from the COVID-19 pandemic is significant and does not disappear, at least in the short run.

CHAPTER 2

BITCOIN VOLATILITY: A GARCH ANALYSIS

2.1 Introduction

The concept of Bitcoin was introduced under the alias of Satoshi Nakamoto in 2008 (Nakamoto 2008) and shortly thereafter the network of Bitcoin was launched in January 2009. Bitcoin has emerged as the first and best-known decentralized (peer-to-peer) cryptocurrency and a worldwide payment system. Bitcoin is created on the basis of a new technology called blockchain cryptography.

Bitcoin has drawn so much attention from economic scholars, practitioners, the media, and the public mainly due to its philosophy and some unique features. First and foremost, Bitcoin is decentralized, meaning there is no central authority managing the Bitcoin network and it is not government-backed and there is no “central bank” or clearing house for Bitcoin. This decentralization is the key feature of Bitcoin. Second, there is a limited total supply of 21 million bitcoins which is expected to be reached in 2140 with a fixed decreasing growth rate of supply over time. This supply process is closely related to “mining”, which is a process using computation power to verify transactions and record them in a public ledger (the so-called blockchain). Third, all Bitcoin transactions are irreversible. Once a transaction is confirmed and recorded in a ledger, it cannot be reversed. This is not the same as payments using checking accounts, credit cards, or other bank notes, in which a refund is processed if a transaction is cancelled or reversed. Fourth, Bitcoin is traded globally 24 hours a day and 7 days a week (24/7).

Bitcoin has caught the eye of many also due to its potential role as a borderless global currency. Bitcoin does not have any intrinsic value just like fiat currencies. There are no “savings accounts” for Bitcoin and holding Bitcoin does not earn interest or dividends. Therefore, it is natural to compare Bitcoin with fiat currencies especially the U.S. dollar (USD) to see if they have similar behavior since the USD has been seen as the “world reserve” currency and Bitcoin intends to function as a global currency and an alternative to fiat currencies like the USD so their comparison might reveal certain features of Bitcoin as a currency.

Another interesting point to note is that Bitcoin shares several similarities with gold, a worldwide-traded commodity. Bitcoin and gold are both in limited supply and therefore scarce in some way. They both are “mined” to add new units to their supply. Both Bitcoin and gold are traded globally 24/7. More importantly, neither Bitcoin nor gold is government backed or controlled. These are reasons some refer to Bitcoin as “virtual gold” (Dyhrberg 2016b).

Despite its increasing acceptance by worldwide merchants, many consider it more a speculation vehicle rather than a medium of exchange (Baur, Hong, and Lee 2018). This raises a fundamental question of Bitcoin: is Bitcoin a real currency, or rather a speculative asset?

This paper adopts the standard generalized autoregressive conditional heteroskedasticity (GARCH) model to compare the conditional volatility of Bitcoin returns with that of a wide range of assets: three major fiat currencies (the USD, the euro, and the British pound sterling), a worldwide-traded commodity namely gold, and two widely adopted market indices (the S&P 500 and the Chicago Board Options Exchange Volatility Index). By comparing their conditional volatilities, I ask the following questions: Is Bitcoin a speculative asset? Dose Bitcoin behave like the USD? Is Bitcoin virtual gold?

2.2 Literature Review

Speculators hold an asset to seek opportunities for higher returns. But there is no free lunch. Higher returns are generally accompanied by higher risks. Return and risk are two sides of a coin. This study intends to build a bridge between speculation and risk measured as conditional volatility in the Bitcoin market.

The economic examination of whether Bitcoin is a speculative asset is currently in the early stage of the economics literature. Yermack (2015), Glaser et al. (2014), Baek and Elbeck (2015), and Baur, Hong, and Lee (2018) all support the idea that Bitcoin is more like a speculative asset than a currency. Yermack (2014) did not directly test the speculative aspect of Bitcoin but rather did a basic analysis on Bitcoin seeking to answer to what degree it fulfills the three roles of a standard fiat currency: as a medium of exchange, as a unit of account, and as a store of value. Yermack found that Bitcoin failed to fulfill those three roles. He therefore concluded Bitcoin was more a speculative investment than a currency. Glaser et al. (2014) also investigated this topic by examining users' intentions when changing domestic currency into Bitcoin. They found little evidence that the users intended to keep Bitcoin as a means for paying goods and services. Instead, users treated Bitcoin as a speculative asset. They found Bitcoin's use for payment did not increase along with the supply of Bitcoin and the introduction of new Bitcoin users. Therefore, they argue that Bitcoin is being used mainly as a speculative asset. Baek and Elbeck (2015) compared the detrended ratio of Bitcoin return and that of the S&P 500 return. They argued that Bitcoin was a speculative vehicle relative to the stock market as the standard deviation of the detrended ratio of Bitcoin (1.1552) was 26 times of that of S&P 500 (0.0447). Baur, Hong, and Lee (2018) studied this topic by analyzing survey responses from users of Bitcoin and found that very few users held Bitcoin purely as a medium of exchange and a dominant group of users treated Bitcoin as a speculative investment asset.

All the studies mentioned above used data only up to June 2015 and none of them used GARCH-type models to explore conditional volatility of Bitcoin returns. While a set of studies exists that investigate the volatility of Bitcoin returns, they do not explicitly investigate the topic of this chapter, whether Bitcoin is a speculative asset or a medium of exchange. Some of the literature does explicitly compare Bitcoin with the USD and gold, another focus of this paper.

There are generally two branches of literature that focus on Bitcoin return series. The first group of papers relies entirely on the information existing in Bitcoin such as prices and trading volumes and does not take exogenous variables into consideration directly. My paper fits into this class and only takes into account the information contained in Bitcoin prices. Katsiampa (2017) compared six different members of the family of GARCH models and selected component GARCH (CGARCH) model specifically AR(1)-CGARCH(1,1) as the best-fitting one, based on Akaike information criterion (AIC), Bayesian information criterion (BIC), and Hannan-Quinn criterion (HQ). Chu et al. (2017) considered 12 types of GARCH-based models and extend the analysis to 7 cryptocurrencies (Bitcoin, Dash, LiteCoin, MaidSafeCoin, Monero, DogeCoin, and Ripple). The authors argued the best two models are integrated GARCH (IGARCH) and GJR-GARCH models, based on AIC, AICc (corrected AIC), CAIC (consistent AIC), BIC, and HQ.

The other group of papers studies the return volatility of Bitcoin including other explanatory variables other than Bitcoin price, return, or trading volume. Some examples of those variables are gold prices, currency exchange rates, and indices of markets such as the S&P 500 and the VIX. Dyhrberg (2016a) adopted GARCH and exponential GARCH (EGARCH) models to compare Bitcoin, gold, and the USD using gold futures and claimed that Bitcoin behaves somewhere between gold and USD because it contains properties of a medium of exchange but also of a hedging tool. Dyhrberg (2016b) also found that the hedging capabilities of Bitcoin against stocks in the Financial Times Stock Exchange Index (FTSE) and USD with a threshold GARCH (TGARCH) model shared high similarity with gold. However, a replication and extension study by Baur, Dimpfl, and Kuck (2018) argued that Bitcoin is not similar to either the USD or gold. Kasper (2017) compared 39 least developed countries' currencies with Bitcoin and found that Bitcoin is much more volatile and does not qualify as an alternative to the currencies analyzed.

This paper is the first one to use GARCH-type models to explicitly examine whether Bitcoin is a speculative asset by comparing the conditional volatility of Bitcoin returns with that of major fiat currencies (USD, EUR, and GPB), gold, and market indices (S&P 500 and VIX). This paper is also the first one to directly compare Bitcoin with the USD by using Bitcoin and USD prices in EUR. Furthermore, this paper tests if trading in the weekends would reveal more information and different aspects of Bitcoin. Last but not least, this study extends the data to May 2018, which doubles the number of observations of those that examines the speculative aspect of Bitcoin.

2.3 Data

2.3.1 Data Source

All return series used in this paper are weekly time series compiled from daily data from 26 July 2010 to 21 May 2018, which includes a total of 408 observations.

The Bitcoin prices in both USD and EUR used in this paper are from CoinDesk.[10] CoinDesk publishes Bitcoin Price Index (XBX)[11] in USD, EUR, and GBP, calculated every

[10] CoinDesk: www.coindesk.com

[11] CoinDesk Bitcoin Price Index (XBX): https://www.coindesk.com/indexes/xbx/

minute based on trading prices from leading global exchanges. For example, CoinDesk BPI in USD is the non-weighted average of closing prices in USD from four leading exchanges, namely Bitstamp, Coinbase, itBit, and Bitfinex. Bitcoin is traded 24 hours a day and 7 days a week globally. The closing price is defined as the average price of the last minute of each day, which spans from 11:59pm to 12:00am Coordinated Universal Time (UTC).

The Bitcoin prices contain trading information during the weekends therefore it is interesting to test whether trading during weekends reveals more information of Bitcoin. To do this, I compare Bitcoin returns with and without Bitcoin trading days during the weekends.

The exchange rate of a currency against the base currency is indicated as its price in the base currency. In this paper, the GBP price in USD and the EUR price in USD are retrieved from Federal Reserve Economic Data (FRED). The USD price in euro and the GBP price in euro are both from European Central Bank (ECB). The gold price in USD is from London Bullion Market Association (LBMA). The data for the S&P 500 and the VIX are both from their official websites.[12]

In this paper, the log return of an asset, y_t, is defined as the first difference of the logged price:

[12] S&P 500: https://us.spindices.com/indices/equity/sp-500
VIX: http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data

(2.1) $y_t = logP_t - logP_{t-1} = p_t - p_{t-1}$,

where y_t is the weekly return at week t, P_t is the weekly price at week t, and $p_t = logP_t$ is the logged weekly price at week t.

To obtain the weekly return series I get the weekly price series first. In this chapter, each weekly price series is compiled as the non-weighted average of daily price from Tuesday through the following Monday. CoinDesk XBX provides daily price of Bitcoin against USD and EUR dating back to 18 July 2010. The data used in this paper start from 20 July 2010 the first Tuesday following 18 July 2010. There are 409 observations in the weekly price series of Bitcoin.

2.3.2 A First Look at Bitcoin Data

Before getting into the technical analysis of Bitcoin, let us take a look at a graphical representation of Bitcoin prices and returns. Figure 2.1 shows the weekly Bitcoin prices in USD and EUR. The first thing to notice is that Bitcoin prices in USD and EUR show strong co-movement with each other. Bitcoin prices in USD should serve as a good indicator of its behavior.

We zoom-in on part of Figure 2.1 when the price of Bitcoin was relatively low (26 July 2010 to 6 February 2017) as reproduced in Figure 2.2. Before 14 February 2011, Bitcoin price was less than $1. Its price stayed stable until 1 February 2013. Then it started to climb, breaking $100 on 8 April 2013. It reached a high of over $1,000 on 2 December 2013. After that, it gradually dropped and fluctuated between approximate $200 and $1,000 over the following three years. It touched $1,000 again on 6 January 2017. In less than one year, the price rocketed to a peak of about $18,000 in December 2017. However, it did not stay at that price for long. It rapidly decreased to below $10,000 in 7 weeks, on 5 February 2018.

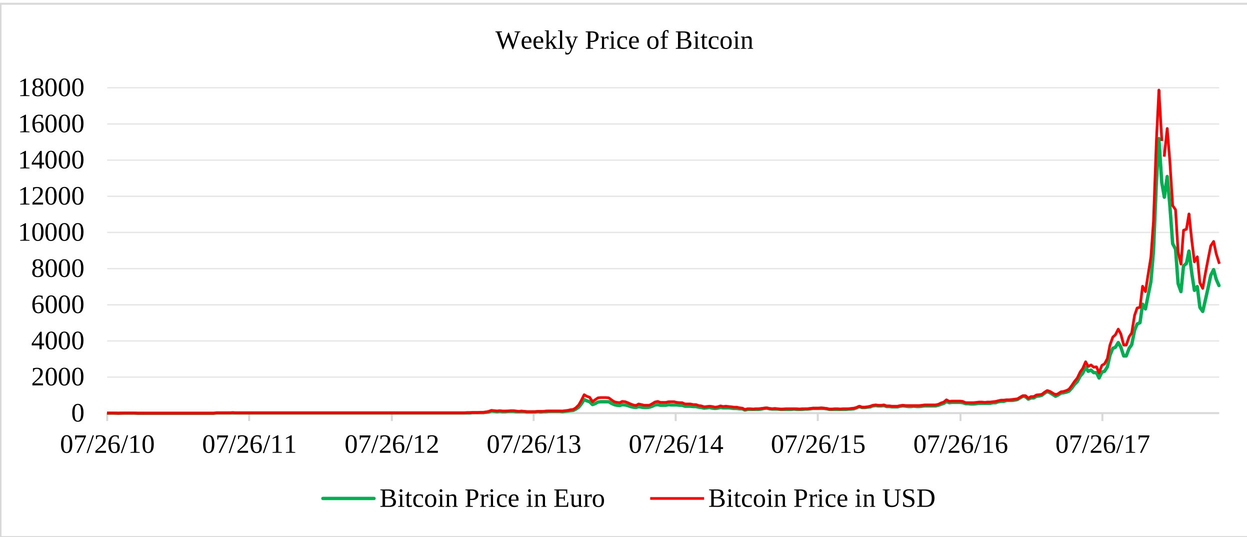

Figure 2.1 Weekly Prices of Bitcoin in USD and EUR (Data Source: CoinDesk)

Figure 2.2 Weekly Prices of Bitcoin in USD (Data Source: CoinDesk)

The Bitcoin returns provide us with its behavior from a different perspective. For a financial asset, people focus on returns more than prices because the return of the asset provides a complete summary of the investment opportunity and return series are more attractive than prices with respect to understanding their statistical properties (Campbell et al. 1997). Figure 2.3, depicting Bitcoin returns in USD and EUR seem to overlap with each other most of the time. The highest gains are close to 70% and the biggest losses are close to 40%. The total range of the return is over 100%, which is huge. It is easy to see that most of the time, the returns fall between negative 20% and positive 20%. Furthermore, there are times of high volatility as well as periods of tranquility. The volatility is not constant over time, suggesting heteroscedasticity in the return series. Another important feature displayed in the plot is that high volatility is likely to be followed by high volatility. In other words, the volatility tends to be highly persistent and clustered.

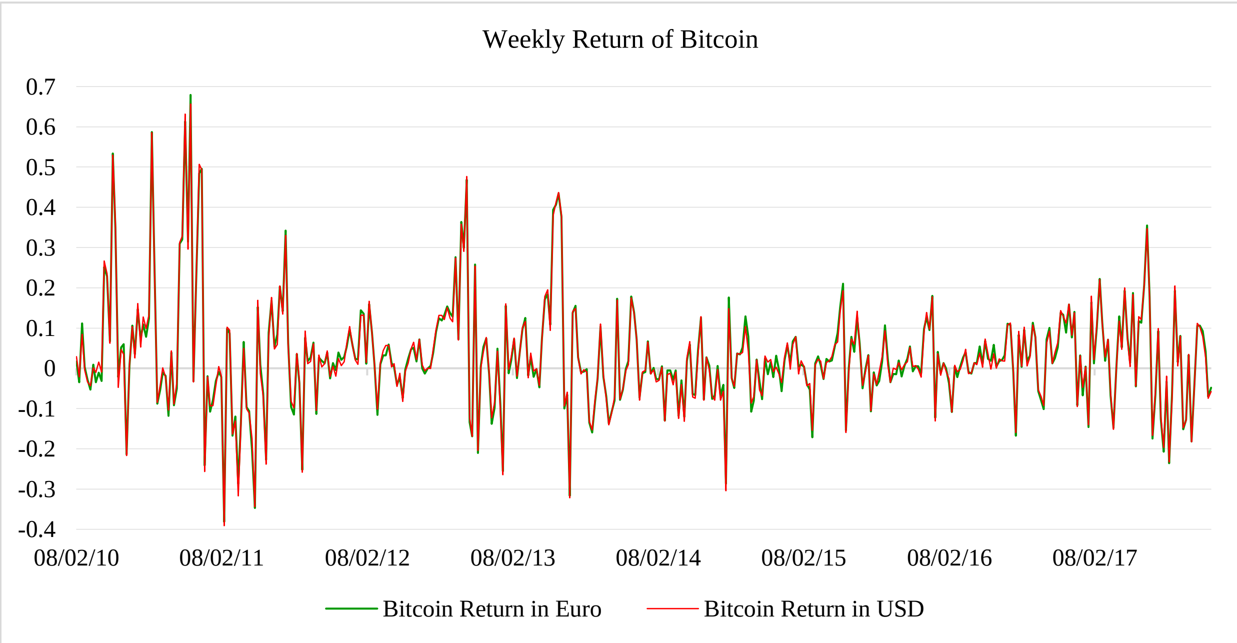

Figure 2.3 Weekly Return of Bitcoin in USD and EUR (Data Source: CoinDesk)

2.4 Methodology

The primary method used in this paper is the generalized autoregressive conditional heteroskedasticity (GARCH) model. To capture the heteroskedasticities existing in the data, one common approach, the GARCH approach, has been well developed since the introduction of the autoregressive conditional heteroskedasticity (ARCH) model by Engle (1982). The ARCH model was later extended to generalized autoregressive conditional heteroskedasticity (GARCH) model by Bollerslev (1986). Some commonly used variates of the GARCH model have been further developed, such as the integrated GARCH (IGARCH) model of Engle and Bollerslev (1986), the exponential GARCH (EGARCH) model of Nelson (1991), the GJR-GARCH (GJR refers to the initials of the authors' last names) model of Glosten, Jagannathan, and Runkle (1993). An important feature of GARCH-based models is that volatility persistency can be explicitly explored. That is why it is so widely used.

Consider the standard GARCH(1, 1) model with AR specification, denoted as AR (p)-GARCH(1, 1).

(2.2) $y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t$

(2.3) ${\sigma_t}^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$

(2.4) $\varepsilon_t = \upsilon_t \cdot \sigma_t, \upsilon_t \sim WN(0,1)$

where y_t is the variable of interest, p is the lag of the AR process, ε_t is the error term, ${\sigma_t}^2$ is the conditional variance of ε_t, and υ_t is a white noise.

Here α and β indicate the ARCH effect and the GARCH effect respectively. The ARCH effect reflects the short-run shocks from last period. The GARCH effect measures the effect of volatility of today on tomorrow's volatility. It can also be shown that the unconditional variance of ε_t is proportional to $1/(1-\alpha-\beta)$ (Bollerslev 1986). Therefore, with the constraint that $\alpha+\beta<1$, a bigger value of $\alpha+\beta$ increases the volatility in the long run.

To build the GARCH model for return series, the following procedure is followed. First, I use the ADF (augmented Dickey–Fuller) and KPSS (Kwiatkowski et al. 1992) tests to test stationary in the return series. Next, I fit an AR (p) model for the return series based on the autocorrelation function (ACF) and partial autocorrelation function (PACF). Third, I use Jarque-Bera test (Jarque and Bera 1980) to test for presence of skewness and kurtosis. Fourth, I employ McLeod-Li test (McLeod and Li 1983) to find the ARCH effects. Finally, I simultaneously estimate the mean equation and the variance equation. To fit the residuals from the mean equation, I consider eight distributions, namely, skewed Normal distribution, Student's *t* distribution, skewed Student's *t* distribution, generalized error distribution (GED), skewed generalized error distribution (SGED), Normal inverse Gaussian distribution (NIGD), generalized hyperbolic distribution (GHD), and Johnson's SU distribution (JSUD). The selection of the optimal distribution is based on the three information criteria: AIC, BIC, and HQ (see Appendix A).

2.5 Empirical Analysis

2.5.1 Descriptive Statistics

Table 2.1 shows the descriptive statistics for all the return series. There are three panels in this table. I begin with panel A, with return series in USD. Recall that I average daily Bitcoin prices to obtain weekly prices, in the first case including the weekend prices

Table 2.1

Descriptive Statistics of Return Series

	N	Mean	Median	Min	Max	St.D.	Skewness	Kurtosis
Panel A: Return Series Priced in USD								
Bitcoin	408	0.0290	0.0131	-0.3910	0.6566	0.1339	1.0873	4.0462
Bitcoin w/o Weekend	408	0.0289	0.0138	-0.4301	0.7150	0.1344	1.1179	4.8461
EUR	408	-0.0002	-0.0007	-0.0370	0.0291	0.0101	-0.0513	0.3870
GBP	408	-0.0003	-0.0006	-0.0632	0.0252	0.0098	-0.7474	3.7116
Gold	408	0.0002	0.0004	-0.0891	0.0523	0.0180	-0.5508	1.6242
Panel B: Return Series Priced in EUR								
Bitcoin	408	0.0292	0.0158	-0.3815	0.6792	0.1337	1.1075	4.0346
Bitcoin w/o Weekend	408	0.0291	0.0171	-0.4330	0.7142	0.1347	1.1413	4.8669
USD	408	0.0002	0.0002	-0.0277	0.0392	0.0100	0.0750	0.2693
GBP	408	-0.0001	0.0006	-0.0539	0.0246	0.0090	-0.6000	2.6411
Panel C: Market Indices								
S&P500	408	0.0022	0.0041	-0.0771	0.0517	0.0145	-0.6953	2.4713
VIX	408	-0.0014	-0.0123	-0.3427	0.5621	0.1153	0.5463	2.5294

and in the second case without weekend quotes. For comparison purposes, I collect time series of the EUR against the USD, the GBP against the USD, and gold prices in USD. These are also converted to return series and they are displayed in rows 3-5 of panel A. Panel B of the table displays comparable series priced in euros and panel C a comparable return series for two market indices, the S&P 500, and the VIX.

For Bitcoin, all of the four return series, namely Bitcoin returns priced in USD and Euro with and without weekend data, shows that the average weekly return of Bitcoin is about 2.9%. That makes the compounded annual return over 150%. By examining the extremes of the return series, we see the highest gains are all over 65% and the biggest losses are over 39%, which indicate a range of over 100% in the return series. Furthermore, there exist significant excess skewness and kurtosis.

One can also notice, by comparing with Bitcoin return both in USD and EUR, that the mean of the Bitcoin return without weekends is slightly lower, that the maximum is higher and the minimum is lower, and that the skewness and the kurtosis are bigger. Those facts do suggest that trading in the weekend has some impact on the Bitcoin returns.

One fact we cannot ignore is that the mean of Bitcoin return is about 100 times of that of USD, EUR, GBP, and gold. In terms of excess skewness and kurtosis, if we forget the sign of them for now, we can see that the GBP, gold, the S&P 500, and the VIX also show some similar behavior. However, it is not the case for the Euro and the USD because the skewness and the kurtosis are only slightly different from zero.

Despite of the unusual excess returns and huge range of returns, it is not enough to justify that Bitcoin is a speculative asset. One needs to look into the volatility further. That is the job of the next two subsections where I estimate each return series independently using a GARCH process.

2.5.2 Results from Bitcoin Returns Priced in USD

Table 2.2 shows the estimation results of the employed GARCH(1, 1) model of Bitcoin returns priced in USD. An AR(1) process is specified in the mean. Here, the ARCH effect (α), the GARCH effect (β), and their sum ($\alpha + \beta$) are the focus of analysis.

Table 2.2
Results from GARCH(1, 1) with AR Specification in the Mean (USD)

	Bitcoin	Bitcoin w/o Weekend	EUR	GBP	Gold	S&P 500	VIX
μ	0.0150*** (0.0038)	0.0105*** (0.0021)	-0.0003 (0.0005)	-0.0001 (0.0006)	0.0004 (0.0011)	0.0031*** (0.0006)	-0.0025 (0.0031)
ϕ_1	0.2937*** (0.0718)	0.3115*** (0.0365)	0.2644*** (0.0509)	0.2542*** (0.0506)	0.2914*** (0.0491)	0.1315*** (0.0465)	-0.0806* (0.0452)
ϕ_2	-	-	-	-	-	-	-0.1751*** (0.0374)
ω	0.0005** (0.0003)	0.0007* (0.0004)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.00002)	0.00001*** (0.0000)	0.0025*** (0.0008)
α	0.2770*** (0.0735)	0.3413*** (0.0889)	0.0764 (0.1590)	0.0678** (0.0289)	0.1127** (0.0518)	0.1780*** (0.0366)	0.1479*** (0.0536)
β	0.7220*** (0.0566)	0.6577*** (0.0693)	0.9061*** (0.1807)	0.9071*** (0.0340)	0.7858*** (0.1034)	0.7672*** (0.0415)	0.6593*** (0.0743)
Note: Standard errors are in parentheses. ***, *p*-value <0.01; **, *p*-value <0.05; *, *p*-value <0.1.							

The first thing to notice is that the GARCH effect dominates the ARCH effect because β is much larger than α ($\beta \gg \alpha$) for all return series. It is the case for all the assets included. The second thing one cannot ignore is that the ARCH effect of Bitcoin is much higher than that of the other assets. The ARCH term only exists for one period, which indicates a larger value of α indicates a larger value of current conditional variance from the shocks of the last period. Therefore, Bitcoin is more responsive to new shocks than other assets. Moreover, the ARCH effect increases and the GARCH effect decreases when the weekends are excluded from the data.

We also want to compare the values of $\alpha + \beta$. Recall $1/(1 - \alpha - \beta)$ represents unconditional (long-run) variance of ε_t. As the value of $\alpha + \beta$ increases (as long as it is less than one), the unconditional volatility is higher. From Table 2.2, we can see that this $\alpha + \beta$ value for Bitcoin is the highest indicating Bitcoin is the most volatile with respect to long-term forecast.[13]

The β estimates of the EUR and the GBP are quite close to each other but quite different from those of Bitcoin. This suggests Bitcoin does not behave like the EUR or the GBP.

As an example, I also compare the conditional standard deviation (volatility) of Bitcoin and gold over time from a graphical perspective (see Figure 2.4). The left panel displays conditional standard deviation of Bitcoin over time along with its returns and the

[13] The estimates of $\alpha + \beta$ (see Table 2.2) are 0.9990 for Bitcoin and 0.8985 for gold. The values of $1/(1 - \alpha - \beta)$ for Bitcoin and gold are 1000 and 9.85 respectively, which show the huge difference of their unconditional volatility.

right for gold. One can see that the conditional volatility goes up and down along the returns for both Bitcoin and gold. This confirms the point that an asset with higher risks do require higher returns for compensation. We need to pay attention that the scales of those two panels are different. One grid of volatility for Bitcoin is 0.1 and 0.02 for gold. Most of the time, gold volatility stays below 0.02 and does not bypass 0.04 all the time. This is not the case for Bitcoin. The conditional volatility of Bitcoin minimizes at approximate 0.06, which is almost twice the maximum of that for gold. Bitcoin volatility goes beyond 0.2 several times and reaches at a maximum of approximate 0.38. These suggest that Bitcoin is always a much riskier asset with higher returns comparing with gold and it is too early to say it is virtual gold.

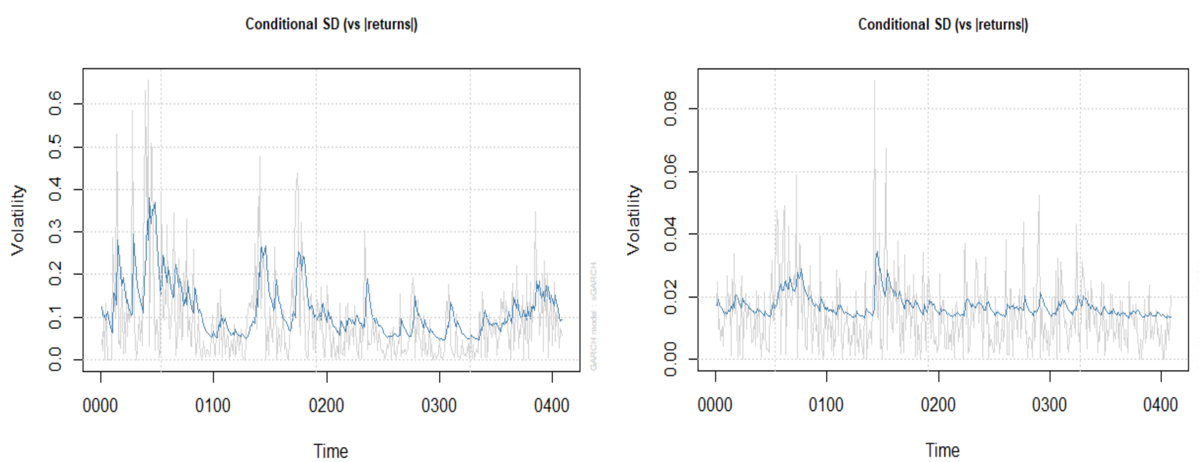

Figure 2.4 Conditional Volatility of Bitcoin and Gold (Left, Bitcoin; Right, Gold)

Based on the analysis above, Bitcoin is more likely a speculative asset in this introductory life-cycle stage because Bitcoin displays opportunities for speculators who favor high returns regardless of high risks.

2.5.3 Robustness Check

In this subsection, I obtain the results from the GARCH(1, 1) model of Bitcoin returns priced in euro. This can be used as a robustness check and also allows us to compare Bitcoin with USD directly in the meantime because both Bitcoin and the USD are priced in Euro. Table 2.3 shows the results, which are similar to those in Table 2.2. All the conclusions drawn in section 2.5.2 are confirmed.

Table 2.3

Results from GARCH(1, 1) with AR Specification in the Mean (EUR)

	Bitcoin	Bitcoin w/o Weekend	USD	GBP	Gold	S&P 500	VIX
μ	0.0163*** (0.0048)	0.0145*** (0.0046)	0.0003 (0.0006)	0.0004 (0.0007)	0.0004 (0.0011)	0.0031*** (0.0006)	-0.0025 (0.0031)
ϕ_1	0.2834*** (0.0418)	0.3096*** (0.0419)	0.2690*** (0.0488)	0.2028*** (0.05604)	0.2914*** (0.0491)	0.1315*** (0.0465)	-0.0806* (0.0452)
ϕ_2	-	-	-	-	-	-	-0.1751*** (0.0374)
ω	0.0006** (0.0003)	0.0008* (0.0004)	0.0000 (0.000006)	0.0000 (0.00002)	0.0000 (0.00002)	0.00001*** (0.0000)	0.0025*** (0.0008)
α	0.2814*** (0.0786)	0.3552*** (0.0945)	0.0760 (0.0760)	0.0721 (0.3202)	0.1127** (0.0518)	0.1780*** (0.0366)	0.1479*** (0.0536)
β	0.7176*** (0.0613)	0.6438*** (0.0716)	0.9074*** (0.0798)	0.9117*** (0.3504)	0.7858*** (0.1034)	0.7672*** (0.0415)	0.6593*** (0.0743)

Note: Standard errors are in parentheses. ***, *p*-value <0.01; **, *p*-value <0.05; *, *p*-value <0.1.
Gold, S&P 500, and VIX are reproduced here from Table 2.2 for comparison.

In terms of conditional volatility, Bitcoin, whether the weekends are excluded or not, does not behave similarly to the USD. α and β characterize the persistence of the conditional volatility and this persistence is essential to learn the behavior of the assets. All of USD, EUR, and GBP have similar estimates so they show similar behavior regarding conditional volatility persistence. But Bitcoin's conditional volatility persistence is quite different from the three currencies. Therefore, Bitcoin is not anything like the USD.

Comparing with gold, the ARCH effect of Bitcoin is higher but the GARCH effect is lower. In contrast to Dyhrberg (2016a), here we can see that Bitcoin is not something between gold and the USD either.

2.6 Concluding Remarks

In this chapter, I use a standard GARCH model to explore the conditional variance processes of Bitcoin returns and returns of other assets, namely, three major fiat currencies (USD, EUR, GBP), a worldwide traded commodity (gold), and two market indices (S&P 500 and VIX). By doing this, I investigate the following topics: Whether Bitcoin is a speculative asset; Whether Bitcoin is virtual gold; Whether Bitcoin is currency similar to the USD. In terms of both excess return and risk measured as conditional volatility in this paper, Bitcoin is found to be more a speculative asset than a currency comparing with other assets tested because Bitcoin shows huge speculation opportunities providing very high returns along with very high risks. There is little evidence showing that Bitcoin is virtual gold. Furthermore, Bitcoin does not behave like the USD, the EUR, or the GBP. Besides, Bitcoin is not something between the USD and gold. Last but not least, the trading information contained during the weekends does impact the volatility of Bitcoin returns but mainly in the short run. Specifically speaking, excluding weekends makes Bitcoin returns more volatile in the short term but less volatile in the long run.

CHAPTER 3

THE IMPACT OF U.S. MONETARY POLICY ON THE BITCOIN MARKET

3.1 Introduction

This chapter examines the impact of U.S. monetary policy on the Bitcoin market. Monetary policy, as one of two major policies implemented by government authorities, has been among the hottest debating subjects. Either targeting inflation or interest rates, monetary policy is widely believed to be essential to maintain price stability and sustained economic growth. More and more evidence since 1980s has emerged to support that monetary policy has wide-spread influences on different markets. To reflect these influences on markets, studies have been widely conducted on short-term and longer-term interest rates (Fuhrer 1996; Ellingsen and Söderström 2001), asset prices (Bernanke, Boivin, and Eliasz 2005), stock markets (Rigobon and Sack 2003), foreign exchange market (Galí and Monacelli 2005), and commodity markets (Frankel 2006), to name a few. Monetary policy has become a key factor and cannot be ignored in understanding the behavior of many markets. As a representative of a new asset class, cryptocurrencies, it is natural and interesting to consider the influence of monetary policy on the Bitcoin market. For monetary authorities, this helps them understand how their policy affect this market. For Bitcoin holders, traders, and investors, this also help them to effectively respond to policy changes and avoid potential losses.

The U.S. central bank, the Federal Reserve or the Fed, typically conducts monetary policy through targeting the federal funds rate (FFR), the interest rate at which depository institutions borrow and lend to each other overnight for fulfilling reserve requirements set by the Fed. The FFR is the central interest rate in the U.S. market, and it is important to differentiate two FFRs, the federal funds target rate (FFTR) and the effective federal funds rate (EFFR). The FFTR is determined by the Federal Open Market Committee (FOMC) who usually meets eight times a year. The EFFR is the volume-weighted average rate of all the funds traded between depository institutions. The EFFR is essentially determined by the market, but the FOMC can use open market operations to influence the EFFR to follow the FFTR. In practice, the EFFR is usually used as a representation of the FFR (see Figure 3.1).

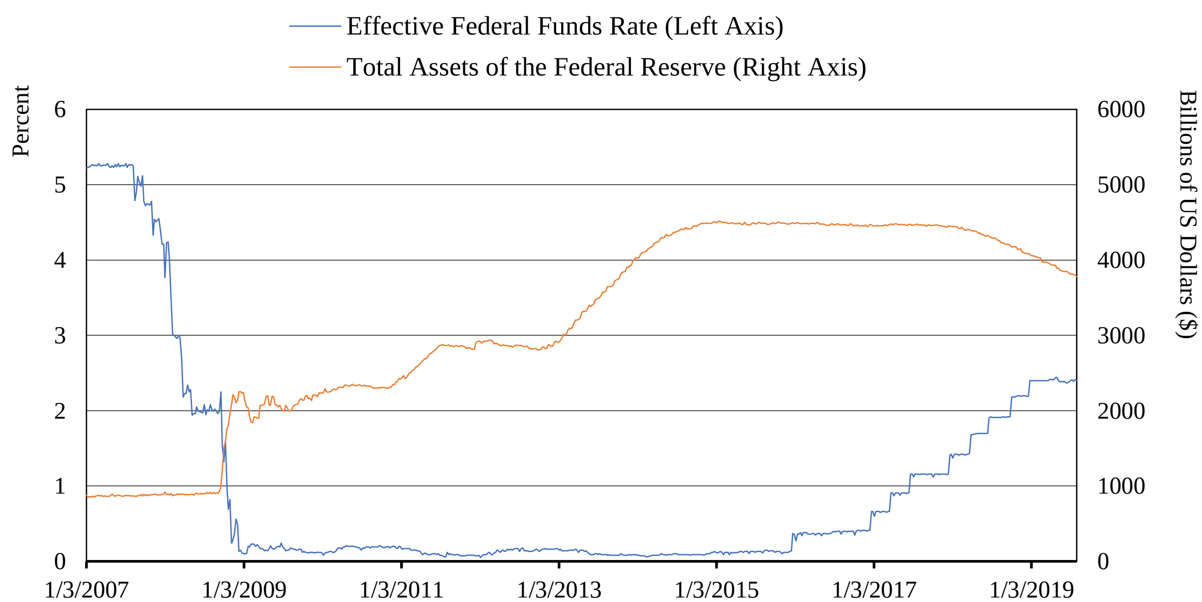

Figure 3.1 Effective Federal Funds Rate and Total Assets of the Fed (2007-2019)

(Data Source: Board of Governors of the Federal Reserve)

During the Great Recession of 2007-08, the EFFR dramatically decreased from over 5% in July 2007 to almost 0% in December 2008. Starting January 2009, the EFFR entered into a period of zero lower bound (ZLB), in which the lower limit of the FFTR is zero and the EFFR was between 0% and 0.25%. During ZLB, the Fed could not lower the interest rate further. Therefore, conventional monetary policy became ineffective. This ZLB situation lasted about 7 years until December 2015, and then the EFFR increased above ZLB in January 2016 and went up gradually to about 2.4% in July 2019. This conventional monetary policy, EFFR, aims to affect short-term interest rates and to maintain a stable and low inflation. This direct channel of monetary policy was well documented especially in Woodford (2003).

After entering the ZLB period, the Fed launched its quantitative easing (QE) programs as a form of unconventional expansionary monetary policy to fight against the financial crisis and to stimulate the economy. These QE programs, namely large-scale asset purchases (LSAP), included purchases of Treasury securities, agency securities, and agency mortgage-backed securities (MBS) released enormous amount of liquidity to the economy. The Fed's QE programs were rolled out in four stages, known as QE1, QE2, QE3, and QE4. QE1 officially started in November 2008 when the Fed announced its intent to buy $600 billion in mortgage-backed securities. But even before the announcement, the Fed began purchasing assets starting September 2008. After 3 months, the total assets of the Fed increased to $2.2 trillion in November 2008 and maintained around that level until June 2010. The second round of quantitative easing (QE2) began in November 2010 and lasted until June 2011, though the Fed continued to buy more assets to maintain its asset level after that. In this period, the total assets of the Fed went up by about $600 billion. To maintain robust economic growth, the Fed launched QE3 in September 2012 and ended it in December 2012. Right after QE3, in January 2013, Ben Bernanke, the then-chair of the Fed, announced that the Fed would continue quantitative easing until either unemployment fell below 6.5% or inflation rose above 2.5%. QE4 officially ended in October 2014. The Fed's total assets reached its historical high of $4.5 trillion in January 2015 and had accumulated a huge amount, $3.6 trillion of assets from what it held before the Great Recession. Between 2015 and 2018, the Fed maintained its asset level within the range of $4.4 trillion to $4.5 trillion. After January 2018, the Fed kept selling its asset and gradually reduced it to $3.8 trillion in July 2019.

The implementation of unconventional monetary policy's intent to influence the medium- and long-term interest rates and wider economy are well explored (Gagnon et al. 2011; Chen, Cúrdia, and Ferrero 2012; Christensen and Rudebusch 2012; Swanson and Williams 2014), but the channels and transmission mechanisms of such are less clear. Krishnamurthy and Vissing-Jorgensen (2011) suggest several channels and three of them are of particular interest. The signaling channel, via the expectation hypothesis that future FFR would be low, lowers yield on all bond rates, but may have a larger impact on intermediate-maturity rates than on long-maturity rates. The liquidity channel increases yield on more liquid assets by reducing the liquidity premium to hold Treasury bonds, since QE injects liquidity by large purchases of Treasury securities. The inflation channel tends to raise nominal interest rates by increasing inflation expectation because QE is expansionary. D'Amico et al. (2012) introduce a fourth channel, the preferred-habitat/scarcity channel, in addition to the signaling channel. Christensen and Krogstrup (2019) investigate the reserve-induced portfolio balance transmission channel of QE to long-term interest rates. They distinguish reserve-induced portfolio balance effect from supply-induced portfolio balance effect of QE using a unique dataset from the Swiss National Bank.

From the descriptions above, either FFR or QE alone does not stand for the Fed's monetary policy during this period. Instead, both FFR and QE are part of and should be considered as the stance of the Fed's monetary policy. Therefore, to examine the effect of the Fed's monetary policy on Bitcoin, neither FFR nor QE should be ignored. This chapter will consider both factors and their interaction to explore how monetary policy affect the Bitcoin market. I include three different categories of variables. The first category are monetary policy variables, proxied by total assets of the Federal Reserve, change of EFFR, and their interaction. The second category consists of three market indices, the S&P 500 index, gold price, and West Texas Intermediate (WTI) index. The third one contains some key internal driving forces of the Bitcoin system, the total supply, the transaction volume, the mining difficulty, and the transaction cost of bitcoins.

3.2 Literature Review

Two prevalent strands of literature on the study of the impact of unconventional monetary policies on interest rates, asset prices, and the wider economy are the event-study approach and the counterfactual approach. The event-study approach focuses on the effects of the announcements of the central banks on the market rates (Gagnon et al. 2011; Krishnamurthy and Vissing-Jorgensen 2011; Christensen and Rudebusch 2012; Wright 2012; Christensen and Krogstrup 2019). A major drawback of the event-study approach is that it is only informative about interest rates within a very narrow time window. Thus, some others conduct counterfactual analysis on this subject (Gagnon et al. 2011; Kapetanios et al. 2012; Dahlhaus, Hess, and Reza 2018). The counterfactual approach normally studies the period prior to the implementation of a policy and then compares with the change after the implementation of the policy assuming the fundamental economic relationships remain unchanged. However, this assumption is easily challenged during financial crisis and economic turmoil because there could be some structural change and the fundamental economic relationships do not hold any more.

The economic literature on the Bitcoin market has grown enormously in recently years but not with respect to monetary policy. Applying traditional methods to study the effect of monetary policy on these assets is still in its early stage. The event-study approach is heavily emphasized probably because the counterfactual approach is not applicable because there is no way to study the impact of monetary policy on the Bitcoin market before the implementation of QE.

Corbet, McHugh, and Meegan (2017) use an event-study approach to investigate the influence of four central banks' (the Fed, the Bank of Japan, the Bank of England, and European Central Bank) monetary policy on the Bitcoin market and find that all the QE announcements of these central banks have significant positive impact on the return volatility of Bitcoin. Corbet et al. (2020) also study the reaction of cryptocurrencies to Federal Open Market Committee (FOMC) announcements. They classify cryptocurrencies of their sample into three different categories based on their primary use, namely currencies, protocols, and decentralized applications. Currencies are for financial payment (Bitcoin is the most famous case), protocols are a set of rules for data transferring across networks similar to HTTP, and decentralized applications are decentralized user interfaces built on existing blockchain platforms. They find that currencies respond to FOMC announcements but both protocols and decentralized applications do not. In their article, Bitcoin lies within the category of currencies. On the opposite, Vidal-Tomás and Ibañez (2018) find that monetary policy news does not affect the Bitcoin market by studying the semi-strong efficiency of Bitcoin through the event-study approach. Although all three papers use GARCH-based models, the model specifications are different and may result in quite different conclusions. Specifically, Corbet, McHugh, and Meegan (2017) uses an exponential GARCH (EGARCH) model, Corbet et al. (2020) uses a standard GARCH model, but Vidal-Tomás and Ibañez (2018) employs a component GARCH-in-mean (CGARCH-M) model.

As mentioned above, for studies on Bitcoin and cryptocurrencies, counterfactual analysis is not an option simply because they do not exist before the QE era. The ESA also suffers from some serious limitations. First the ESA focuses only on the short window around the announcement. Second, it is difficult to quantify the announcements as a stance of the monetary policy. Third, it is sometimes very difficult to differentiate the announcements from other events during the same period unless a training model is well-built. Therefore, instead of using ESA and counterfactual analysis, I build a generalized autoregressive conditional heteroskedasticity (GARCH) model and use total asset of the Federal Reserve as the stance of its monetary policy.

3.3 Data and Methodology

3.3.1 Data

All the raw data used in this chapter are weekly time series from 4 August 2010 to 31 July 2019, a total of 470 observations. There are 9 time series included in this raw dataset: Bitcoin price, total assets of the Fed, total supply of Bitcoin, Bitcoin mining difficulty, transaction volume of Bitcoin, average transaction cost of Bitcoin, S&P500 index, gold price, and West Texas Intermediate (WTI) index.

The Bitcoin price in USD is from CoinDesk. CoinDesk is a global leader of cryptocurrency news and market data. CoinDesk publishes Bitcoin price index (BPI) in USD, calculated every minute, based on trading prices from leading global exchanges, namely Bitstamp, Coinbase, itBit, and Bitfinex. The data for the total supply of bitcoins, the Bitcoin mining difficulty, the transaction volume of Bitcoin, and the average transaction cost of Bitcoin are from Blockchain.com.

The data for total assets of the Fed and the EFFR are from the Board of Governors of the Federal Reserve. The gold prices are retrieved from the London Bullion Market Association (LBMA). Gold is traded primarily via over-the-counter (OTC) transactions internationally and London is the largest OTC market. The LBMA publishes the gold price in USD twice a day, at 10:30 AM and 3 PM respectively. The gold price used in the paper is the average of these two prices.

The data for the S&P 500 index are from S&P Dow Jones Indices LLC. The S&P 500 is a capitalization-weighted stock market index representing the stock performance of 500 large companies listed on U.S. stock exchanges including the New York Stock Exchange (NYSE), the NASDAQ, and the Chicago Board Options Exchange (CBOE). The S&P 500 index is widely regarded as the best single gauge of large-cap U.S. equities.

The data for the WTI price are from U.S. Energy Information Administration. WTI crude oil is one of the two main benchmarks in oil pricing worldwide and is the underlying commodity of the oil futures contracts of the New York Mercantile Exchange.

3.3.2 GARCH Model

The GARCH model is a two-equation system, including a mean equation and a variance equation. The AR (1)-GARCH(1, 1) model considered in this chapter is as follows:

(3.1) $\Delta y_t = \phi \cdot \Delta y_{t-1} + \beta_1 \cdot \Delta B_t + \beta_2 \cdot \Delta SP500_t + \beta_3 \cdot \Delta Gold_t + \beta_4 \cdot \Delta WTI_t + \beta_5 \cdot \Delta M_t + \beta_6 \cdot \Delta Diff_t + \beta_7 \cdot \Delta Tran_t + \beta_8 \cdot \Delta Cost_t + \varepsilon_t + \varepsilon_{t-1}$,

(3.2) $\varepsilon_t = \upsilon_t \cdot \sigma_t$, $\upsilon_t \sim WN(0,1)$

(3.3) $\sigma_t{}^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$

$\Delta y_t = lnP_t - lnP_{t-1}$ is the log return of Bitcoin at *t*,

$\Delta B_t = B_t - B_{t-1}$ is the change of total assets of the Fed (QE) at *t*,

$\Delta SP500_t = lnSP500_t - lnSP500_{t-1}$ is the log return of S&P 500 index at *t*,

$\Delta Gold_t = lnGold_t - lnGold_{t-1}$ is the log return of gold at *t*,

$\Delta WTI_t = lnWTI_t - lnWTI_{t-1}$ is the log return of WTI at *t*,

$\Delta M_t = M_t - M_{t-1}$ is the change of the total supply of bitcoins at *t*,

$\Delta Diff_t = lnDiff_t - lnDiff_{t-1}$ is the change rate of the mining difficulty of the Bitcoin network at *t*,

$\Delta Tran_t = Tran_t - Tran_{t-1}$ is the change of the transaction volume of Bitcoin at *t*,

$\Delta Cost_t = Cost_t - Cost_{t-1}$ is the change of the average transaction cost of Bitcoin at *t*,

ε_t is the error term, υ_t is a white noise, and $\sigma_t{}^2$ is the conditional variance of ε_t.

We can see that the error terms ε_t are not correlated but dependent since the first moment is not correlated (equation (3.2)) but the second moments are correlated (equation (3.3)).

3.4 Empirical Analysis

3.4.1 A First Look at Bitcoin Data

Figure 3.2 shows the weekly Bitcoin price in USD. Notice that, in 2017, Bitcoin price climbed to a record high of $17,491 in a very short time period and then dropped sharply below $10,000 in less than 2 months. Prior to 2017, Bitcoin prices rose and fell but remained within the interval of $0 and $1,000.

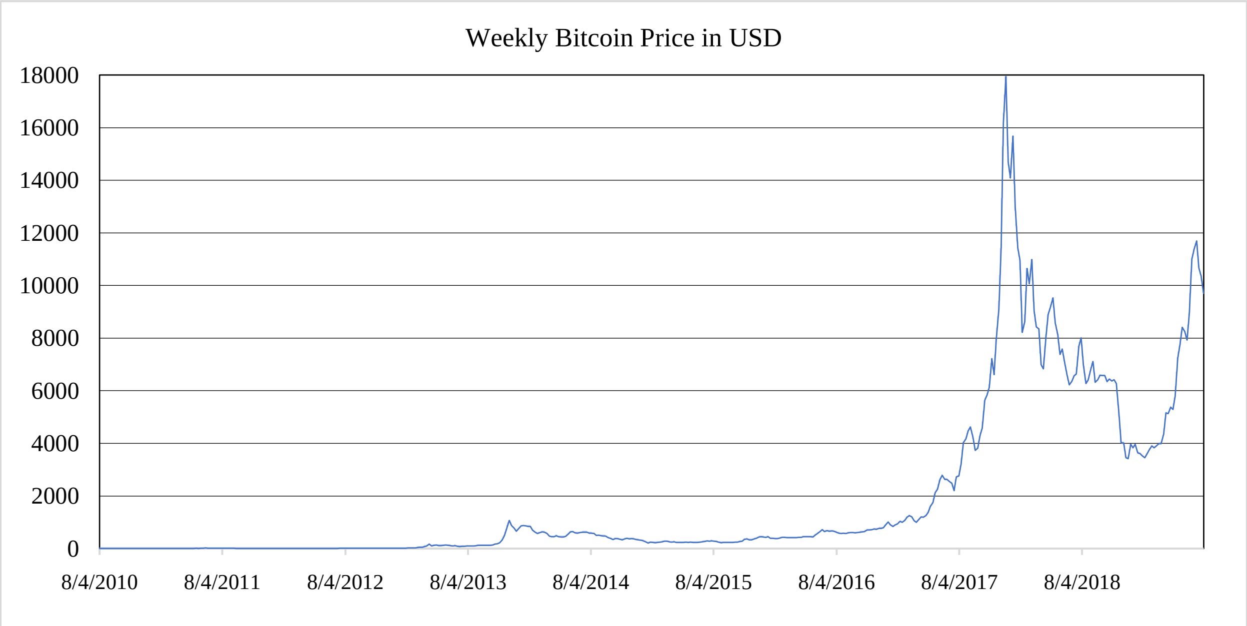

Figure 3.2 Weekly Bitcoin Price (08/04/2010—07/31/2019) (Data Source: CoinDesk)

Looking at the data from another perspective, the Bitcoin returns, provide quite a different view, as shown in Figure 3.3. One should first notice that the so-called volatility clustering is in place in the data. That is, volatility tends to be persistent over time. Therefore, there are periods of high volatility following with high volatility. Besides, the values of the peaks and troughs of the Bitcoin returns are noticeable. The highest return is almost 80% and the biggest loss is close to 60%, with a range of nearly 140%. Nonetheless, Bitcoin returns remain between -20% and 20% most of the time.

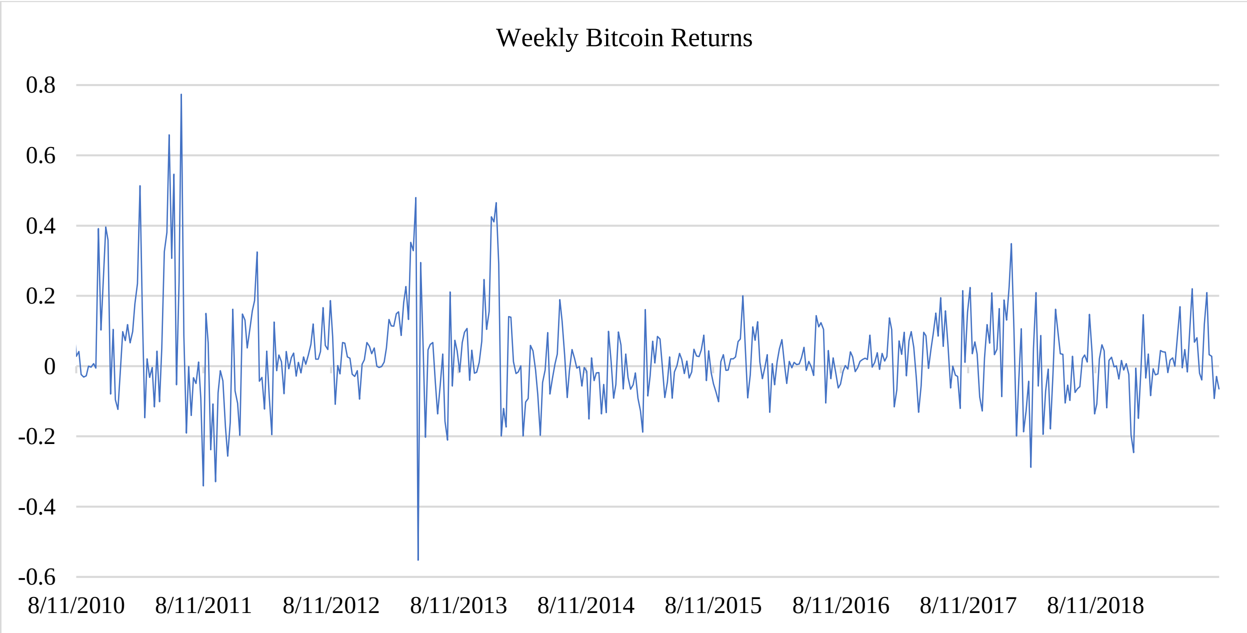

Figure 3.3 Weekly Bitcoin Returns (08/11/2010—07/31/2019) (Data Source: CoinDesk)

3.4.2 Descriptive Statistics

Table 3.1 and table 3.2 show the descriptive statistics respectively for the original time series and the series differentiated into first differences.

Table 3.1

Descriptive Statistics for Original Time Series

Variable	Unit	N	Mean	Median	Min	Max	St.D.
y_t	USD	470	1853	387	0.056	17941	3183.3
B_t	USD, Billion	470	3819	4208	2295	4516	751035
$SP500_t$	Index	470	1964	1996	1058	3009	536.38
$Gold_t$	USD per Troy Ounce	470	1352	1296	1064	1860	179.2
WTI_t	USD per Barrel	470	72.82	71.16	28.81	111.86	22.77
M_t	BTC, Million	470	12.85	13.77	3.51	17.84	3.984
$Diff_t$	Million	470	1104.08	42.64	0.000	9060	2213.98
$Tran_t$	BTC, Million	470	1.410	1.250	0.113	25.68	1.479
$Cost_t$	USD	470	21.82	9.405	0.000	138.54	25.82

Table 3.2

Descriptive Statistics for Differenced Time Series

	N	Mean	Median	Min	Max	St.D.
Δy_t	469	0.0257	0. 0144	-0.5524	0.7738	0.1303
ΔB_t	469	3093	1831	-47011	81797	16448
$\Delta SP500_t$	469	0.0021	0.0032	-0.0954	0.0448	0.0154
$\Delta Gold_t$	469	0.0004	0.0010	-0.0765	0.0475	0.0173
ΔWTI_t	469	-0.0007	0.0009	-0.1270	0.1475	0.0366
ΔM_t	469	30490	26736	10293	83429	17741
$\Delta Diff_t$	469	0.0522	0.0273	-0.1459	0.5127	0.0819
$\Delta Tran_t$	469	1699	-9518	-19398214	14611532	1305927
$\Delta Cost_t$	469	0.1334	0.0333	-21.3650	35.5359	4.3093

In Table 3.1, let us focus on the minimum and maximum values of some key variables. First, Bitcoin price ranges from \$0.056 to \$17,941. That is, the maximum is over 300,000 times of the minimum. Though, from the minimum to the maximus, the S&P 500 index triples, the gold price almost doubles, the oil price increases by about three times, they are far from comparable with Bitcoin. In the sample, the total assets of the Fed nearly doubled, from \$2.295 trillion to \$4.516 trillion.

In Table 3.2, the Bitcoin return goes from -55% to 77%, with a range of over 130%. This shows Bitcoin is an anomaly among all assets including S&P 500, oil, and gold. The second row of Table 3.2 tells us that weekly sales of the Fed's assets goes down to \$47 billion and weekly buy reaches \$81.8 billion. Overall, the Fed purchased \$3.09 billion of assets on average, indicating the expansionary nature of its monetary policy.

3.4.3 GARCH Results

The estimates from the GARCH model are shown in Table 3.3. Equations (3.1) and (3.3) are rewritten here for reading easiness.

(3.1) $\Delta y_t = \phi \cdot \Delta y_{t-1} + \beta_1 \cdot \Delta B_t + \beta_2 \cdot \Delta SP500_t + \beta_3 \cdot \Delta Gold_t + \beta_4 \cdot \Delta WTI_t + \beta_5 \cdot \Delta M_t + \beta_6 \cdot \Delta Diff_t + \beta_7 \cdot \Delta Tran_t + \beta_8 \cdot \Delta Cost_t + \varepsilon_t + \varepsilon_{t-1}$,

(3.3) $\sigma_t{}^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$.

The first and foremost result to be noticed is that there exists no effect from U.S. monetary policy on Bitcoin returns. It should not be too surprising considering that Bitcoin is quite new to the world and the nature of Bitcoin remains to be discovered. The findings are close to Vidal-Tomás and Ibañez (2018) that there is no impact of monetary policy announcements do not impact the Bitcoin market but contrary to Corbet et al. (2020) that such an impact is positive. Therefore, Bitcoin returns are not driven by monetary policy.

Table 3.3

Results from GARCH Estimation

	Parameter Estimate		Parameter Estimate
Mean Equation (3.2)			
ΔB_t	0.0000 (0.0000)	ΔM_t	0.0000 (0.0000)
$\Delta SP500_t$	0.7244* (0.3265)	$\Delta Diff_t$	0.2080* (0.0936)
$\Delta Gold_t$	0.4839 (0.2148)	$\Delta Tran_t$	0.0000 (0.0000)
ΔWTI_t	-0.1790* (0.0984)	$\Delta Cost_t$	0.0131*** (0.0170)
Variance Equation (3.4)			
ω	0.0000** (0.0000)		
α	0.0500*** (0.0029)		
β	0.9000*** (0.0170)		
Note: Standard errors are in parentheses. ***, p-value <0.001; **, p-value <0.01; *, p-value <0.05.			

For the stock market, it has a positive effect on the Bitcoin market: every 1% increase in the S&P 500 will cause a 0.72% increase in the Bitcoin return. This makes sense because the rise of the return from the stock market would also require an increase of return from the investment on the Bitcoin market. The gold market and the oil market also impact Bitcoin returns. The gold market positively impacts Bitcoin return but the oil market's effect is negative. 1% increase in gold return causes 0.48% increase in Bitcoin return but 1% increase in oil return decreases Bitcoin return by 0.18%. We can safely say that the stock market, gold market, and oil market are all drivers of Bitcoin returns.

For the internal driving forces, both the mining difficulty and the transaction cost both have a positive impact on the Bitcoin market. As mining difficulty increases by 1%, the return of Bitcoin would also increase, by 0.20%. As the Bitcoin network grows, every additional transaction and block need more computation power to confirm and validate and thus the mining difficulty grows. And it is going to more and more difficult to mine a new bitcoin. More work comes with more payment compensation and the Bitcoin return maybe go up due to this reason. But the supply of bitcoins does not affect the Bitcoin return. This is possibly because the growth rate of supply of bitcoins is pre-determined by the design and protocols of the Bitcoin network, in which the total amount of bitcoins is set to be 21 million and the growth rate of the supply follows the protocols introduced in the White Paper of Bitcoin (Nakamoto 2008). Finally, the transaction volume of Bitcoin does not affect the Bitcoin return either. This is unusual as we know from many markets that transaction volume plays an important role in trading, such as in stock market (Gebka and Wohar 2013). Moreover, Balcilar, Gupta, and Roubaud (2017) do find that volume can predict Bitcoin returns. Here I find not all internal elements matter and only mining difficulty and transaction cost are drivers of Bitcoin returns.

3.4.4 Robustness Check

Instead of using total asset of the Fed as a measure of the stance of monetary policy, I use the Wu-Xia shadow federal funds rate (Wu and Xia 2016) to do a robustness check. The shadow rate derives from the idea of Fischer Black (Black 1995) that currency is an option. The shadow rate translates unconventional monetary policy such as quantitative easing to an interest rate. The shadow rate can be negative and cannot be observed directly on the market. Wu and Xia (2016) further developed Black's shadow rate term structure model by building a more trackable approximation and showed their constructed shadow federal funds rate was a good measure of the monetary policy stance when the nominal interest rate was at the zero lower bound. Since the Wu-Xia shadow federal funds rate is only available in monthly frequency and I have obtained the data from their website directly[14], I use monthly data (from July 2010 to July 2019) instead of weekly data for the other variables in this robustness check and each data point used in the estimation is identified as the value of that variable on the last trading date of each month. The model setting is similar but the mean equation is different:

(3.4) $$\Delta y_t = \phi \cdot \Delta y_{t-1} + \beta_1 \cdot i_t + \beta_2 \cdot \Delta SP500_t + \beta_3 \cdot \Delta Gold_t + \beta_4 \cdot \Delta WTI_t + \beta_5 \cdot \Delta M_t + \beta_6 \cdot \Delta Diff_t + \beta_7 \cdot \Delta Tran_t + \beta_8 \cdot \Delta Cost_t + \varepsilon_t + \varepsilon_{t-1}$$

[14] Wu-Xia Shadow Federal Funds Rate: https://www.atlantafed.org/cqer/research/wu-xia-shadow-federal-funds-rate

$$(3.5)\ \varepsilon_t = \upsilon_t \cdot \sigma_t,\ \upsilon_t \sim WN(0,1)$$

$$(3.6)\ {\sigma_t}^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

where i_t is the Wu-Xia shadow federal funds rate in month t; the other variables are defined the same as in section 3.4.3.

Tables 3.4 shows the results of this robustness check. First and foremost, the result

Table 3.4

Robustness Check for GARCH Estimation

	Parameter Estimate		Parameter Estimate
Mean Equation (3.4)			
i_t	0.0381 (0.0142)	ΔM_t	0.0000 (0.0000)
$\Delta SP500_t$	1.6108* (0.7738)	$\Delta Diff_t$	0.3602* (0.1474)
$\Delta Gold_t$	-0.2378 (0.5397)	$\Delta Tran_t$	0.0000 (0.0000)
ΔWTI_t	-0.3084 (0.2502)	$\Delta Cost_t$	0.0185*** (0.0020)
Variance Equation (3.6)			
ω	0.0001 (0.0003)		
α	0.0500*** (0.0029)		
β	0.9000*** (0.0170)		
Note: Standard errors are in parentheses. ***, p-value <0.001; **, p-value <0.01; *, p-value <0.05.			

found earlier in this chapter is confirmed: there is no impact from the monetary policy of the Fed Reserve on Bitcoin returns. There is no impact from the gold market either. The same two internal driving forces of Bitcoin returns, mining difficulty and transaction cost, are found and confirmed. There are some differences though. No shocks from the oil market are detected. Moreover, the impact from the stock market is significantly higher. Specifically, 1% increase in the S&P 500 induces a 1.61% rise in Bitcoin return, which is more than twice the result (0.72%) found in section 3.4.3.

3.5 Concluding Remarks

In the aftermath of the financial crisis of 2007-08, the main instrument of the Federal Reserve's conventional monetary policy, the federal funds rate (FFR), reached its zero lower bound (ZLB) and ceased to be effective. Therefore, the Federal Reserve sought alternative tools to implement its monetary policy. Unconventional monetary policies such as quantitative easing (QE) programs were introduced, including large-scale purchase of assets—Treasury securities, agency securities, and agency mortgage-backed securities (MBS). To measure the stance of the monetary policy of the Federal Reserve, I use total asset of the Fed to incorporate both FFR and QE and then use the Wu-Xia shadow federal funds rate to do the robustness check.

Other than using event-study approach or counterfactual analysis, in this chapter I construct a GARCH model to examine the impact of the Federal Reserve's monetary policy on the Bitcoin market. The first finding is that the Federal Reserve's monetary policy does not significantly affect Bitcoin returns. That is, despite of tremendous liquidity injected into the economy through QE programs by the Fed, Bitcoin, as a representative of a new and highly speculative market of cryptocurrencies, does not seem to be impacted.

The Bitcoin market was affected by the stock market. Specifically, 1% increase in the S&P 500 would raise 0.72% in Bitcoin return. This fact indicates that the stock market is a positive stimulator of the Bitcoin market. A smaller negative effect is detected for the oil market but no effect is found for the gold market.

Furthermore, one technological internal factor, the mining difficult of the Bitcoin network, significantly impacted Bitcoin returns. As the mining difficult went up by 1%, Bitcoin return would go up by 0.21%. Lastly, one economic factor, the transaction cost of bitcoins, increases Bitcoin return by about 0.01% from one dollar's increase. Nonetheless, another economic factor, the transaction volume of Bitcoin, does not cause any change of Bitcoin return.

Overall, I find among the three categories of potential drivers of Bitcoin returns (i.e., exogeneous policy variable, exogeneous market variables, and internal variables), monetary policy does not impact the Bitcoin market but the stock market does. I also find two internal drivers of the Bitcoin market, mining difficulty and transaction cost. That is, Bitcoin return is not driven by monetary policy but by markets such as stock market and also by internal forces within the Bitcoin system, mining difficulty and transaction cost.

CHAPTER 4

CRYPTOCURRENCIES IN THE CORONAVIRUS ERA

4.1 Introduction

People could not imagine in 2019 that a pandemic ahead would sweep across the world and wipe out millions of souls in less than two years. It all started from a central Chinese city of Wuhan, where this novel coronavirus disease (COVID-19) was first detected in December 2019. The situation went down quickly there and the Chinese officials soon locked down the city to avoid further spreading of COVID-19. In the first few weeks, COVID-19 was primarily a concern of the Chinese government though some cases were found in other counties from time to time. Yet it did not draw enough attention globally possibly because people back then did not realize the severity and the human-to-human transmission of COVID-19. After that more and more cases were found around the globe and more and more countries started to ban international travels. The World Health Organization (WHO) had to officially announce COVID-19 as a global pandemic in March 2020.

Since then, COVID-19 has been a global health crisis and a constant dominant factor in people's life. Public gatherings were forbidden, curfews were deployed, and hygiene and sanitation measures were mandated. More and more non-essential stores and businesses were shut down and essential sectors' operational hours were greatly shortened.

Virtual meetings have grown to be a prevalent form of communications. COVID-19 has shaped the global landscape of how people live and do business. Though economically the long-term impact of COVID-19 is yet to be known, the severe short-term effects are outstanding and catastrophic. The following narrative focuses on the United States but similar situation can be found globally. In the United States alone, the real GDP in the second quarter of 2020 shrunk by over 31% comparing with the previous quarter, which was already on a downward road, and this is the biggest drop in any single quarter since World War II (U.S. Bureau of Economic Analysis). It is the same case with consumption which declined by over 33% during the same period (U.S. Bureau of Economic Analysis). U.S. unemployment rate has fluctuated mainly between 2.5% and 10% from 1948 to 2019 but in April 2020, it raised dramatically, setting a record high of 14.8% since the Great Depression (U.S. Bureau of Labor Statistics). The financial markets such as the stock markets responded with: both S&P 500 and NASDAQ Composite dropping by about 30% in a month from February to March 2020. As a representative of the energy markets, the U.S. oil market totally collapsed and the West Texas Intermediate (WTI) index experienced a negative price for the first time on record in April 2020. All these facts suggest a short-run significant effect on markets from COVID-19.

Considering the magnificent impact of COVID-19 on global markets, a natural question could be raised: as a new class of assets and potential moneys, how does the cryptocurrency market react to the COVID-19 pandemic? That is, is there also a significant negative impact from the pandemic, or is the cryptocurrency market immune from it? In this chapter, I employ the event-study approach (ESA) to examine the impact of the COVID-19 pandemic on the cryptocurrency market in the short term. The ESA has been proved to very effective in capturing short-term impact when events occur to the concerning party. As the biggest event in recent history, it is important to explore if and how this event has impacted the cryptocurrency market. I incorporate a three-factor model analogous to the Fama-French three-factor model (Fama and French 1993) and Carhart four-factor model (Carhart 1997) to capture the common risks in the cryptocurrency market. To the best of my knowledge, this is the first paper to investigate the impact of COVID-19 on the cryptocurrency market using the ESA framework based on the three-factor model.

4.2 Literature Review

This section consists of two parts, the literature reviews of the event study approach (ESA) and its underlying benchmark model, the multi-factor model. The ESA is widely considered one of the major building blocks of modern corporate finance and may originate from as early as Dolley (1933) when he investigated the price reaction to stock splits. In the following decades, the ESA was further developed and revised. In the 1960s, Ball and Brown (1968) and Fama et al. (1969) introduced what is essentially regarded as the ESA we use today. Their success partly attributed to the then-new market model of Sharpe (1964), the capital asset pricing model (CAPM). Since then, the ESA has been further developed and improved. Though originally applied in accounting and finance studies, the

ESA has been adapted to be widely used in economics especially in studying the effect of the announcements on interest rates or the wider economy (e.g., Krishnamurthy and Vissing-Jorgensen 2011; Christensen and Rudebusch 2012; Wright 2012; Christensen and Krogstrup 2018). Basically, the ESA first splits the sample under investigation into the training part and the test part based on the event of interest, then builds a model based on the training data and tests its effectiveness on the test data. The model built on the training sample is called the benchmark model of ESA and multi-factor models are among the most popular category.

In CAPM, Sharpe (1964) introduced the first factor, the market excess return or simply market, to the family of factor models. Then Fama and French (1993) added two factors, size and value, in their renown three-factor model. Carhart (1997) proposed a four-factor model adding the momentum factor. Most recently, Fama and French (2015) constructed a five-factor model replacing Carhart's (1997) momentum with profitability and investment factors. Though many more factors could be added (Harvey, Liu, and Zhu 2015), these six factors are good enough to capture the common features in many cases and adding more factors only generates similar results (Fama and French 2018). To construct a multi-factor model for cryptocurrencies, one key fundamental difference one needs to recognize from conventional financial assets: cryptocurrencies do not earn interest or dividend thus they do not generate cash flows as do financial assets like stocks or bonds. Therefore, not all the factors used to build the multi-factor model can be used as in the previous literature mentioned above. To be more specific, in this chapter the three-factor model is built in a similar manner as Shen, Urguhart, and Wang (2020) and Liu, Liang, and Gui (2020) based on both Fama and French (1993) and Carhart (1997). The selected three factors are market factor, size factor, and momentum factor. More details about how to construct these factors are provided in the next section.

Many studies have been conducted to study the cryptocurrency market and a few are worth emphasizing as they also examine possible impacts of the COVID-19 pandemic on the cryptocurrency market. Mnif, Jarboui, and Mouakhar (2020) adopted the multifractal detrended fluctuation analysis (MFDFA) of Kantelhardt et al. (2002) to study the efficiency levels of the cryptocurrency market before and after the COVID-19 pandemic and found that COVID-19 improved the cryptocurrency market efficiency. But their study only included five cryptocurrencies thus suffered from under-sampling. Lahmiri and Bekiros (2020) also examined the evolution of the efficiency of the cryptocurrency market comparing with equities by using Largest Lyapunov Exponent (LLE) and the Approximate Entropy and they found that the cryptocurrency market became more unstable and higher irregular after the pandemic thus showed the pandemic decreased efficiency of the cryptocurrency market. They had a larger sample including 45 cryptocurrencies. Both of these two papers identified December 2019 as the time of outbreak of COVID-19. But back then COVID-19 was just a reginal health crisis in China and was far too early to be recognized as a global pandemic. This misidentification of the event might significantly impact their results. Neither of them used the ESA.

4.3 Methodology

4.3.1 The Event-Study Approach

The central concept in the event-study approach (ESA) is the abnormal return (AR), which is defined as the deviation of the actual return from the normal return. The normal return (NR), assuming the event does not occur, is estimated by the underlying benchmark model prior to the event.

The general working procedure of the ESA adopted in this article is as follows. Firstly, divide the whole sample into three periods, the estimation window, the event window, and the gap between them. The estimation window is the period prior to the event of interest. In many cases, the exact date of the event is unknown and one good guess should be put in place before doing any empirical tests. Therefore, to prevent missing any information, the event window usually contains some period before the approximate date of the event. Nonetheless, to eliminate the interactive effects of the two, the event window should not overlap with the estimation window. The period between the two windows is called the gap. Secondly, construct the so-called benchmark model in the ESA, using observations in the estimation window, namely the training dataset. This training model is essential to calculate the normal returns in the event window, thus is essential to obtain the abnormal returns. Thirdly, use the benchmark model to obtain the normal returns within the event window. Fourthly, calculate abnormal returns in the event window. Finally, test the significance of the abnormal returns from the previous step.

Mathematically the abnormal return in the event window is defined as follows

(4.1) $AR_t^i = r_t^i - R_t^i = r_t^i - E(r_t^i | I_{t-1})$

where AR_t^i is the abnormal return of cryptocurrency i at t, r_t^i is its actual log return at t, I_{t-1} indicates the information set at $t-1$, thus $R_t^i = E(r_t^i | I_{t-1})$ represents its normal return at t, which is estimated using the benchmark model.

The cumulative abnormal return (CAR) for cryptocurrency i at time T is defined accordingly as

(4.2) $CAR_T^i = \sum_{t=1}^{T} AR_t^i = \sum_{t=1}^{T} (r_t^i - R_t^i)$

For the cryptocurrency market, the average abnormal return (AAR) at time t and the cumulative average abnormal return (CAAR) at time T are respectively

(4.3) $AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_t^i$

(4.4) $CAAR_T = \sum_{t=1}^{T} AAR_t = \frac{1}{N} \sum_{i=1}^{N} CAR_T^i$

where N is the number of cryptocurrencies in the sample.

From equation (4.4), we can see there are two approaches to calculate $CAAR_T$. In the first approach, we calculate AAR for the cryptocurrency market at each individual time point t then sum them up from $t = 1$ to $t = T$. In the second one, we first obtain the CAR for each cryptocurrency then average them across the cryptocurrency market. There is not much difference if there are no strong cross-sectional correlations between the cryptocurrencies but it could be an issue if the correlations are significant. Therefore, I adopt the second approach to avoid possible cross-correlation between the cryptocurrencies.

Since abnormal return reflects the deviation of the actual return from the normal return, we want to see if AR and CAR are significant for a single cryptocurrency i and if AAR and CAAR are significant for the cryptocurrency market. For this chapter, AAR and CAAR are of much more interest as they reflect the impact on the whole market instead of individual cryptocurrencies. Furthermore, CAAR is also more important than AAR since the accumulated effects can be significant regardless of the significance of AAR. Therefore, AAR and CAAR are the focus of the empirical report.

4.3.2 The Three-Factor Model

The three-factor model functions as the benchmark model for calculating the normal return in this chapter. It is estimated based on the data in the estimation window. Specifically, the model is constructed as follows

$$(4.5)\ r_t^i - r_t^f = \alpha_i + \beta_i\left(r_t^m - r_t^f\right) + \gamma_i SMB_t + \delta_i WML_t + \varepsilon_t^i$$

where r_t^i is the return of cryptocurrency i at t, r_t^f the risk-free return, r_t^m the average return of the cryptocurrency market, SMB_t (Small minus Big)[15] size premium,

[15] Small and Big are related to the size factor and measured by capitalization for any portfolio, so if the market capitalization of a portfolio is larger than it is a Big portfolio, otherwise, it is a Small portfolio. Small minus Big means the difference between the average return of a Small portfolio and a Big portfolio.

WML_t (Winner minus Loser)[16] momentum premium, and ε_t^i the error term. The exact definition of SMB_t and WML_t will be given below.

From the equation above, we can derive r_t^i as

(4.6) $r_t^i = \alpha_i + (1 - \beta_i)r_t^f + \beta_i r_t^m + \gamma_i SMB_t + \delta_i WML_t + \varepsilon_t^i$

By time series regression, we can obtain the normal return

(4.7) $R_t^i = E(r_t^i | I_{t-1}) = \widehat{\alpha_\iota} + \left(1 - \widehat{\beta_\iota}\right)r_t^f + \widehat{\beta_\iota} r_t^m + \widehat{\gamma_\iota} SMB_t + \widehat{\delta_\iota} WML_t$

The three factors in a standard three-factor model are usually referred to market, size, and momentum. The market factor represents the market excess return. For size, it is also straightforward. The size of cryptocurrency i is defined as its market capitalization. The momentum of cryptocurrency i at time t is defined as the cumulative log return of cryptocurrency i during the previous 60 days and is calculated in a rolling-window fashion. That is, at time t, the momentum is the cumulative return from $t - 60$ to $t - 1$; at time $t + 1$, the momentum is the cumulative return from $t - 59$ to t; and so on. Since log return is used in this chapter, the momentum at t is the sum of log returns from $t - 60$ to $t - 1$. In contrary to a one-year period, which is widely used in the literature, 60 days is chosen because of data availability and also because the cryptocurrency market is much more

[16] Winner and Loser are related to the factor momentum and measured by accumulated returns for any portfolio, so if a portfolio has a higher accumulated return in the chosen previous period then it is called a Winner and similarly a Loser if its return is lower in the same period. Winner minus Loser means the difference between the average return of a Winner portfolio and a Loser portfolio.

volatile and including longer data might not reflect its volatility. Momentum of cryptocurrency i at t can be mathematically expressed as

(4.8) $MOM_t^i = \sum_{j=1}^{60} r_{t-j}^i$.

But in the three-factor model (4.7), I do not use all these factors directly. The market factor is incorporated directly in the equation, but size and momentum are incorporated via the inclusion of SMB_t and WML_t.

The factor sorting process is essential to obtain these two factors and needs to be demonstrated. At time t, one can sort the cryptocurrencies based on only a single factor or two factors. If one sorts the cryptocurrencies by two factors and divides them into n groups for each factor, then we say she uses an $n \times n$ strategy and induces n^2 portfolios. At time t, if one would like to sort the cryptocurrencies by size, he bases them on capitalization at time $t-1$; if one wants to sort them by momentum, he uses the momentum defined above. For each factor, one sorts the cryptocurrencies into deciles and choses two break points, the third decile and the seventh decile, to classify the cryptocurrencies into three groups. That is, for size, the lower 30% of the cryptocurrencies is Small, the intermediate 40% is Medium, and the higher 30% is Big. Similarly, for momentum, the lower 30% is Loser, the middle 40% Medium, and the higher 30% Winner.

For the two-factor soring process, it is important to distinguish between conditional sorting and unconditional sorting. Conditional sorting means that one first sorts the cryptocurrencies based on one factor to classify them, then further sorts within each group based on the second factor. Unconditional sorting does the sorting using two factors simultaneously. Therefore, it matters for conditional sorting to choose the sorting order of the factors but it does not for unconditional sorting.

For conditional sorting, say, if one sorts the cryptocurrencies by size first, then she has three groups[17], Small, Medium, and Big. Then within each group, she further sorts them by momentum to get three portfolios, Loser, Medium, and Winner. Thus, in group Small, for instance, she will have three portfolios, SL, SM, and SW. However, if she sorts the cryptocurrencies by momentum first and by size second, then she will have different portfolios. This time in group Winner, she has WS, WM, and WB. Note SW and WS are not the same portfolio! Nonetheless, this sorting process produces a fixed number of cryptocurrencies in each portfolio regardless of the sorting order.

In this chapter, I use a two-factor sorting process and apply 3×3 strategy to construct 9 portfolios using all the 100 cryptocurrencies in the sample based on two factors, size and momentum. Tables 4.1 and 4.2 show the results from two different conditional two-factor sorting processes. The order of the soring process is size first and momentum second in Table 4.1 but momentum first and size second in Table 4.2. It is clear that the sorting processes generate the same number of cryptocurrencies in each portfolio switching

[17] I distinguish group from portfolio even though they both are essentially a bundle of cryptocurrencies. Group means it is the result of a single-factor sorting and it is not final and a further sorting process needs to be done; portfolio means it is the final product of the two-factor sorting process. I use one capital letter to indicate a group after sorting with one single factor, e.g., B for group Big after sorting by size and W for group after sorting by momentum. I use two ordered capital letters to indicate a portfolio after the two-factor sorting process is completed, e.g., SW for portfolio Small Winner after sorting by size first and by momentum second and WS for portfolio Winner Small after sorting by momentum first and by size second. The numbers next to the letter(s) in the tables indicates the number of cryptocurrencies included within the group (portfolio). Portfolio MM is of little importance.

the order of the soring factors but the portfolios in the same position of the tables do not include the same cryptocurrencies anymore.

Table 4.1

Portfolios for Conditional Sorting on Size First and Momentum Second

	L30	**M40**	**W30**
S30	SL9	SM12	SW9
M40	ML12	MM16	MW12
B30	BL9	BM12	BW9
Note: The number on the right of the letter(s) represents the number of cryptocurrencies in that portfolio.			

Table 4.2

Portfolios for Conditional Sorting on Momentum First and Size Second

	S30	**M40**	**B30**
L30	LS9	MS12	LB9
M40	MS12	MM16	MB12
W30	WS9	WM12	WB9
Note: The number on the right of the letter(s) represents the number of cryptocurrencies in that portfolio.			

However, for the unconditional sorting process, this order does not matter. That is, we sort the cryptocurrencies by size and momentum simultaneously. Thus, each cryptocurrency falls into one of the nine portfolios in this way: based on its ranking of capitalization in all 100 cryptocurrencies, it is either S, M, or B; based on its momentum, it is either L, M, or W. Thus, the sorting order of the factors does not matter and switching the order does not change its place in the portfolios. In contrast to the conditional sorting, the number of cryptocurrencies in each portfolio is not fixed.

After obtaining the portfolios using the two-factor sorting process we can now exactly define SMB_t and WML_t. SMB_t is the average return of the three Small portfolios minus that of the three Big portfolios; WML_t is the average return of the three Winner portfolios minus that of the three Loser portfolios. That is,

(4.9) $SMB_t = \frac{1}{3}(SL_t + SM_t + SW_t) - \frac{1}{3}(BL_t + BM_t + BW_t)$

(4.10) $WML_t = \frac{1}{3}(WS_t + WM_t + WB_t) - \frac{1}{3}(LS_t + LM_t + LB_t)$

SL_t indicates the equal-weighted average return of cryptocurrencies in portfolio SL at time t; the rest are defined in the same manner.

4.4 Data

The daily prices and market capitalizations of the selected 100 cryptocurrencies, retrieved from coinpaprika.com, spans from 2 April 2018 to 30 April 2020. For each variable, I have 100 time series, in which each has 760 data points. The total observations of the whole sample of cryptocurrencies are 152,000. The sample domain is divided into three periods, the estimation window, the event window, and the gap between them. Specifically, the estimation window starts on 2 April 2018 and ends on 22 January 2020, the day before Wuhan was officially locked down. The event window starts from 11 February 2020, when WHO unified different names people referred to this coronavirus disease as COVID-19. This date is chosen as an indicator of global attention drawn to the coronavirus disease. In this chapter, the event date is identified as 11 March 2020, the day WHO officially announced COVID-19 as a global pandemic. The event window goes until 30 April 2020, the most recent data available when this chapter was firstly drafted. And the gap between these two windows consists of 19 days, from 23 January 2020 to 10 February 2020. Thus 600 observations are obtained for the three-factor model for each cryptocurrency in the estimation window whilst there are a total 80 data points for each time series within the event window. The one-month Treasury Bill rate is used as the risk-free return and is obtained from U.S. Department of Treasury.

The final sample, including 100 cryptocurrencies (see Appendix B), is selected by the following criteria:

1. **Market Capitalization**: Each candidate cryptocurrency falls within the top 300 cryptocurrencies by market capitalization as of 30 April 2020;

2. **Data Availability**: Each candidate cryptocurrency has at least 661 original data points for both price and market capitalization in the estimation window, which guarantees 600 observations to be used in the benchmark model;

3. **Non-Dollar Anchored**: Cryptocurrencies targeting to maintain their price equal to one U.S. dollar are excluded since they do not efficiently reflect market fluctuations;

4. **Length of Trading Data**: For cryptocurrencies fulfilling the three conditions above, they are ranked based on the length of their available trading data, sorted from longest to shortest. The first 100 cryptocurrencies are selected as the final sample. The ranking is based on trading data length instead of market capitalization. The rationale is that the length of active trading indicates the durability and the value of a cryptocurrency but its market capitalization may be volatile in the short-run; therefore once it meets the market capitalization criterion, the length of its trading data matters more.

4.5 Empirical Analysis

4.5.1 Results from the Three-Factor Model

Table 4.3 shows the estimates from the three-factor model with conditional two-factor sorting process during the estimation window for the cryptocurrency market and the top three cryptocurrencies, which is measured by market capitalization as of 30 April 2020. All the constants (α) are not significant from zero (see Appendix C). This result tells us that the factors capture the common risks in the market quite well.

Table 4.3

The Three-Factor Model Estimates

		β	γ	δ
Cryptocurrency Market	Min	-0.0054	-0.9173	-0.9716
	Max	1.2847	2.1159	0.4536
	Mean	1.0000	0.0000	0.0000
	Median	1.0084	-0.0552	-0.0064
Top 3 Cryptocurrencies	BTC	0.7440***	-0.2904***	0.2556***
	ETH	1.0019***	-0.5120***	0.0794
	XRP	0.8430***	-0.6478***	-0.1338*
Note: ***, p-value <0.001; **, p-value <0.01; *, p-value <0.05.				

The market β reflects the sensitivity of a cryptocurrency to the market factor. That is, 1% change of market excess return (i.e., market return minus free interest rate) would induce $\beta\%$ change of excess return in that cryptocurrency. If $\beta > 1$, then 1% of change of market excess return would induce more than 1% of excess return change in that cryptocurrency in the same direction; If $0 < \beta < 1$, then 1% of change of the market excess return would induce less than 1% of excess return change in that cryptocurrency in the same direction; If $\beta = 1$, then the change of the market excess return would induce the same amount of excess return change in that cryptocurrency; If $\beta < 0$, then the excess return in that cryptocurrency would change in the opposite direction of the change of the market excess return. For the cryptocurrency market, the minimum, -0.0054, is negative but not significant from zero. This is the only negative number in the β estimates (see Appendix C) and means only one cryptocurrency negatively responds to market change of excess return. The maximum, 1.2847, says that the most responsive cryptocurrency would increase by 1.28% if the cryptocurrency market goes up by 1%. The mean, not surprisingly, is equal to one by definition. There are 45 estimates below one and 55 ones above one (see Appendix C). Both the β estimates of Bitcoin (BTC) and Ripple (XRP) are less than one and that of Ethereum (ETH) is slightly more than one. Therefore, both Bitcoin and Ripple are less responsive and Ethereum respond almost accordingly to the market change.

The effect of size factor, γ, is the response to the size-related long-short strategy, longing the Small portfolios and shorting the Big portfolios. It ranges from -0.9173 to 2.1159, indicating that the size premium has a much more diversification across cryptocurrencies comparing with the market premium. Interestingly, all the top three cryptocurrencies negatively react to this strategy but as market capitalization increases, this effect decreases. This is probably because they all belong to the Big portfolios but the bigger (by market capitalization) the cryptocurrency the smaller is the response. Therefore, Bitcoin is the least responsive among the top three.

The effect of momentum factor, δ, is the response to the momentum-related long-short strategy, longing the Winner portfolios and shorting the Loser portfolios. It spans from -0.9716 to 0.4356, a much narrower range than the size factor. The momentum factor accounts for both Bitcoin (positive) and Ripple (negative) but not for Ethereum.

Overall, the three-factor model works very well to capture the common risks of the cryptocurrency market. Therefore, it can serve as the benchmark model for the ESA.

4.5.2 Results from the Event-Study Approach

Based on the three-factor model, we can calculate the normal return for each cryptocurrency and the cryptocurrency market in the event window. We first construct the factors in the event window based on conditional sorting procedure as in the estimation window. Then we calculate the abnormal returns using equation (4.7). From equation (4.1) and (4.2), we can obtain the abnormal return and CAR for each cryptocurrency. In this section, I will focus on AAR and CAAR for the entire cryptocurrency market. Figure 4.1 displays the abnormal returns for the cryptocurrency market. Similar to the residuals of the estimation the estimation window, the AARs and CAARs are in a very small scale, 10^{-6}, which is reasonable. And we need to do further tests to see whether they are significant or not based on the training dataset. This is a task of the next subsection.

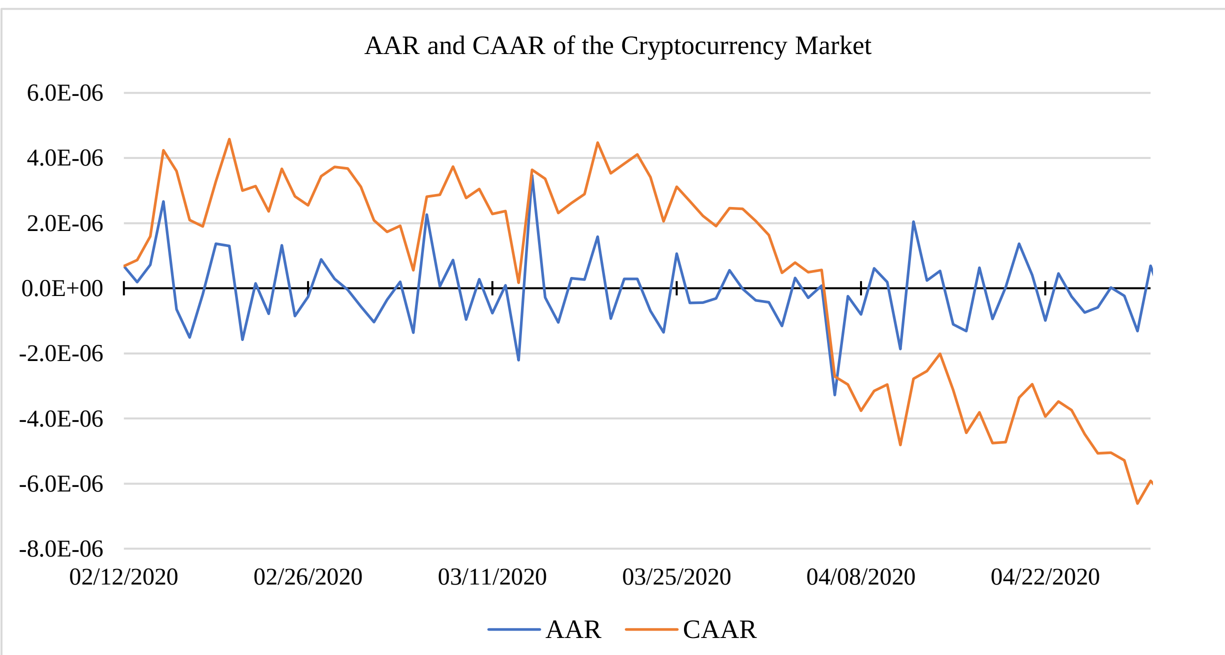

Figure 4.1 AAR and CAAR of the Cryptocurrency Market

4.5.3 Significance Tests

There are generally two types of significance tests for ESA: parametric and non-parametric. Among the most widely used parametric tests, two are the Patell (1976) test and the BMP (Boehmer, Musumeci, and Poulsen 1991) test. They are later refined and improved by accounting for cross-sectional correlation in Kolari and Pynnönen (2010). These two are named as adjusted Patell test and the adjusted BMP test. For non-parametric tests, the sign test of Cowan (1992), the rank test of Corrado (1989), and the generalized rank test of Kolari and Pynnönen (2011) are widely used in the literature. In this section, I will report mainly on the significance results from the adjusted Patell test and the adjusted BMP test.

Figure 4.2 shows the two significance tests for AAR and only those significant are displayed ($p < 0.05$). Note any dot present does not indicate the exact p value of the test

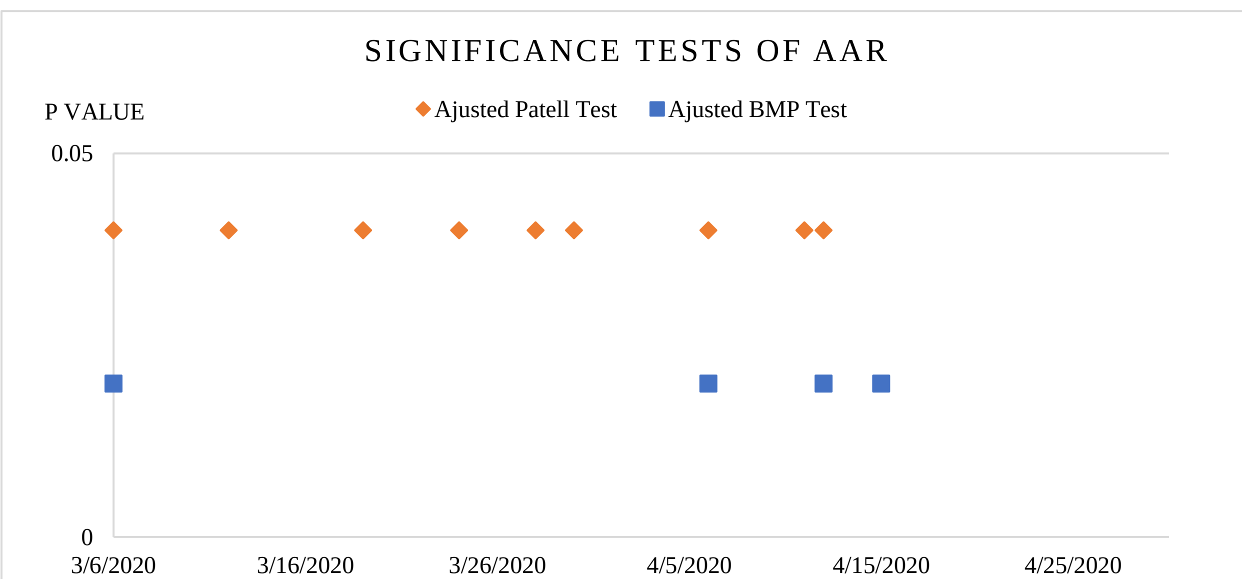

Figure 4.2 Significance Tests of Cryptocurrency Market AAR

on a specific date from one of the two tests. Instead, it only shows that its p value falls below the chosen level of 0.05, namely, it is significant at level 5%. Both the adjusted Patell test and the adjusted BMP test detect multiple significant data points, though they are just a small portion of the sample. Besides, both the adjusted Patell test and the adjusted BMP test shows that only one day prior to 11 March 2020, meaning this day is a good capture of the actual date the event occurs. Moreover, much more significant results, especially for the adjusted Patell test, are detected after the event date indicating that there exists an impact on the event on the cryptocurrency market. Though this effect is not significant every day, the tests show in the near future, within 50 days of the occurrence of the event, the impact does not disappear. Since it is more important whether there is accumulated effect of the event on the cryptocurrency market, we should look further to test the significance of the CAARs.

Based on the results from AARs above, I only show the significance results of the adjusted Patell and BMP tests from 11 March 2020 forward. As showed in Figure 4.3, both the adjusted Patell test and the adjusted BMP test clearly show that there exist significant accumulated overall effects for the majority of the sample at 5% level and the accumulated effect do not decay or disappear over time, though in some minor days these effects are not detected. It is a fact that the adjusted Patell test and the adjusted BMP test do not agree on all days when the accumulated effects are significant, but they do have many days in common indicating significant effects especially in the later part of the sample. It is obvious to us, during this part of the sample, the accumulated effects remain significant until the end of the sample, 30 April 2020.

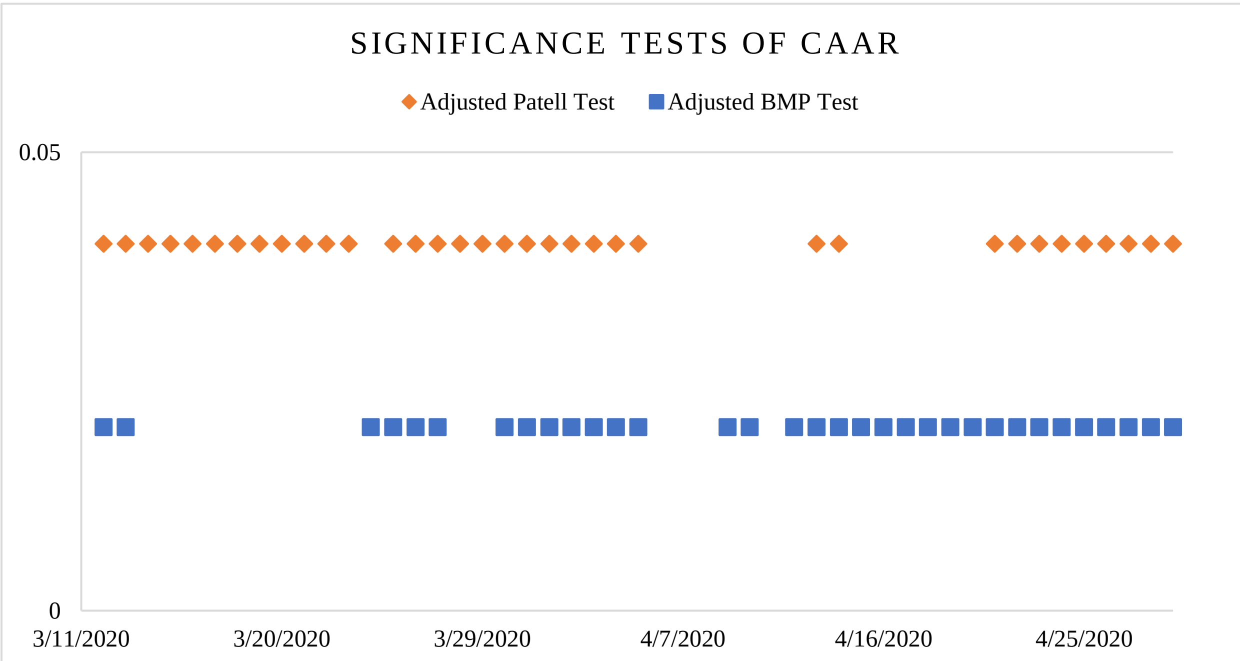

Figure 4.3 Significance Tests of Cryptocurrency Market CAAR

The significance results of the adjusted Patell test and the adjusted BMP test strongly suggest the accumulated effects of the COVID-19 pandemic on the cryptocurrency market are significant and do not disappear over time, at least in the short run, even the daily effects are not always significant. More interestingly, though the cryptocurrency market seems to absorb a positive effect when COVID-19 started to spread, the downward trend of CAAR (see Figure 4.1) in the later part suggests there exists a continuous significant negative impact of COVID-19 on the cryptocurrency market.

4.6 Concluding Remarks

The coronavirus disease 2019 (COVID-19) has change our world permanently. People around the globe have not seen such a devastating pandemic at this scale since the Spanish flu of 1918-19. No one can deny that COVID-19 has been at the center of our lives since its outbreak and no other single event impacted our life so dramatically as COVID-19 in recent years. It is not just a global health crisis, but also a source for great economic uncertainty. In the long-run, the impact of COVI-19 on global economy and markets remains to be understood, yet in the short term, its effect can be investigated and tested. Therefore, it is of interest to examine if there exist any significant effects on the cryptocurrency market from COVID-19 in the short-run. Methodologically, I employ the event-study approach incorporating a three-factor model based on the Fama-French three-factor model and Carhart four-factor model as the benchmark. The empirical results shows that the three-factor model used in the chapter fits the data very well and the three factors, market, size, and momentum, accurately reflects the common risks in the cryptocurrency market. Results further suggest that prior to the event of interest, little effect is detected. However, when the event occurs, there is a notable effect. To be more specific, the accumulated effects are significant based on the significance tests and remain significant throughout the sample. Moreover, the effects seem to have a downward trend after a period of absorption of the impact of COVID-19. That is, there is strong evidence suggesting an overall significant negative effect of COVID-19 on the cryptocurrency market, at least in the short run.

CHAPTER 5

CONCLUSIONS

Bitcoin and other decentralized cryptocurrencies were created in the aftermath of the global financial crisis of 2007-08 as alternative currencies. As the first and most famous decentralized cryptocurrency, Bitcoin represents some of the best features found in cryptocurrencies. It is decentralized so that no central authority or single party can manipulate the system. Its limited supply, embedded in its algorithm, avoids the potential over-issuing problem that can surface with fiat currencies. Its blockchain-based network securely solves the double-spending problem. It has no jurisdiction boundaries and can be used in any corner of the world where it is accepted. These advantages over traditional fiat currencies make Bitcoin a potential candidate as a global currency. More and more merchants around the world have started to accept Bitcoin as a payment method in the past decade. The groundbreaking development of Bitcoin as a payment system lies in El Salvador's adoption of Bitcoin as the second legal tender after the USD in September 2021. The adoption of Bitcoin as legal tender was soon followed by Cuba.

It has been over 12 years since the birth of Bitcoin in January 2009 and the popularity of Bitcoin and alternative cryptocurrencies has grown steadily over time. The number of cryptocurrencies has risen from a handful a decade ago to thousands today. The market for Bitcoin and cryptocurrencies has grown to be one that many governments cannot ignore. Though evolving over a decade, Bitcoin and the cryptocurrency market are still young and in their early stage of the life-cycle in comparison with their fiat currency counterparts. This dissertation intends to get a better understanding of Bitcoin and the cryptocurrency market by exploring their price behavior, specifically by examining the price volatility of Bitcoin, the response of Bitcoin to monetary policies, and the impact of a worldwide event on the cryptocurrency market. The first two of the three essays focus on Bitcoin and the third one extends the study to the cryptocurrency market.

The first essay finds that Bitcoin behaves more like a speculative asset than a world currency in its early stage, confirming this widely held public opinion. The conditional volatility of Bitcoin is far higher than that of most-traded fiat currencies, the USD, the euro, and the British pound sterling while all of these three currencies show some similar behavior. Similar findings lie among the comparisons between Bitcoin with gold, the S&P 500, and the VIX. Though higher volatility alone does not justify if an asset is speculative in nature, the unusual higher volatility found in Bitcoin does suggest evidence concerning the speculative feature of Bitcoin. Considering that Bitcoin belongs to a total new class of asset generating no interest or dividends, standard economic theory does not provide any foundation for Bitcoin evaluation. What we have is just the prices of Bitcoin and this essay only takes into consideration Bitcoin prices and exclude any exogenous variables for now.

The second finding in essay one is that Bitcoin and the USD are not much alike. The USD is the "world reserve" currency and comparing Bitcoin price in euro and the exchange rate of USD against euro allows us to directly compare the USD with Bitcoin as a potential candidate as a global currency. Another interesting finding is that Bitcoin is not virtual gold. While Bitcoin and gold share several similarities, the analogy between gold and digital asset Bitcoin might justify the scarcity and value preservation of Bitcoin in the world of digital assets as gold's place in the commodities. Yet no evidence is found to support this statement.

The second essay continues to study Bitcoin but focuses on its response to U.S. monetary policies. The first finding of essay two is that Bitcoin returns are unresponsive to monetary policy of the Federal Reserve from 2010 to 2019. This finding suggests there is no direct channel for monetary policy to influence the Bitcoin market. Instead of studying the short-time effect around the announcements of QE such as those using event-study approach, this finding is found based on detecting longer-term effects of both the announcements and the actual actions of the Fed. The approach adopted in this essay thus does not have the limitation of the event-study approach. Another fining in this essay is that the stock market has a major impact on Bitcoin with 1% increase of the S&P 500 inducing about 0.72% increase of Bitcoin return. As an asset, Bitcoin requires return compensation if the stock market is in its bull market phase. But if the stock market is in its bear phase, Bitcoin return falls but on a smaller scale, suggesting that Bitcoin is not so responsive to stock market fluctuation. The third finding in essay two is that the increase of mining difficulty and transaction cost of Bitcoin network requires a compensating differential return.

The first two findings of essay two show that monetary policy does not directly affect the Bitcoin market but instead influence Bitcoin returns indirectly through the stock market. For the Federal Reserve, the first finding helps it to assess the effectiveness of its monetary policies on the Bitcoin market and may help direct future policies related to Bitcoin and cryptocurrencies. For Bitcoin holders and investors, it seems that it is important to closely monitor the stock market and oil market as Bitcoin is more responsive to them than monetary policy.

The third essay concludes that the cryptocurrency market is negatively impacted by the COVID-19 pandemic, at least in the short run. This effect is accumulated over time after the occurrence of the pandemic and does not disappear. This essay expands the sample used I this dissertation from Bitcoin to incorporating 100 cryptocurrencies as representative of the cryptocurrency market and investigates the short-term impact of the COVID-19 pandemic. The event-study approach (ESA) has been proven to be an effective tool in the literature to ascertain the short-run effects from a shock when an event is identified and the COVID-19 pandemic is such an event. As the first paper to apply event-study analysis to cryptocurrency market, this essay methodologically contributes to the cryptocurrency literature and adds one unique example to the literature of the ESA.

In the three-factor model trained in this essay, the three factors, market, size, and momentum are showed to capture the common risks of the cryptocurrency market very well. Using 100 cryptocurrencies with over 150,000 observations, this essay also extends previous cryptocurrency literature to an appropriate sample neither overrepresenting nor underrepresenting the cryptocurrency market.

Overall, the prices of Bitcoin are quite volatile compared with the wide range of assets considered in the dissertation and show some speculative features in its first decade of existence; the Bitcoin returns are not responsive to the monetary policy of the Federal Reserve during times of quantitative easing; in the short term, the cryptocurrency market is negatively impacted by the global COVID-19 pandemic. Future studies related to this dissertation can be conducted at least in the following ways. First, the Bitcoinization of El Salvador sets a milestone for Bitcoin to become a potential international currency and using data starting from the recent period might reveal further development of Bitcoin as a currency rather than a speculative asset. It is possible for Bitcoin to evolve to be an international currency when more and more countries join El Salvador and the prices of Bitcoin become more stable. We can also examine the short-term effect of the Bitcoinization of El Salvador using the event-study approach. Second, during times of quantitative easing, the Bitcoin market does detect some effect from the stock market, so if we can find a way to quantify the effect of the U.S. monetary policy on the stock market and estimate these two effects, then we can more accurately assess the effectiveness of monetary policy of the Fed. Third, the event-study approach has been proved to be most efficient detecting short-run effects and applying it to assess the longer-term effects becomes much more complicated. By extending the length of the event window, we can test if the effects detected by the ESA will decay or disappear over time.

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Appendix A

Information Criteria

		Skewed Normal	Student's *t*	Skewed Student's *t*	GED	Skewed GED	NIG	GH	Johnson's SU
Bitcoin Returns in USD	AIC	-1.6398	-1.7262	-1.7233	-1.7356	-1.7367	-1.7293	-1.7300	-1.7266
	BIC	-1.5808	-1.6672	-1.6545	-1.6766	-1.6679	-1.6605	-1.6514	-1.6578
	HQ	-1.6165	-1.7029	-1.6961	-1.7122	-1.7095	-1.7021	-1.6989	-1.6994
Bitcoin Returns in USD w/o Weekends	AIC	-1.6856	-1.7587	-1.7576	-1.7887	-1.7892	-1.7702	-1.7809	-1.7640
	BIC	-1.6266	-1.6997	-1.6888	-1.7297	-1.7204	-1.7014	-1.7023	-1.6952
	HQ	-1.6622	-1.7353	-1.7303	-1.7653	-1.7620	-1.7430	-1.7498	-1.7368
Bitcoin Returns in Euro	AIC	-1.6256	-1.7182	-1.7144	-1.7195	-1.7176	-1.7180	-1.7140	-1.7167
	BIC	-1.5666	-1.6592	-1.6456	-1.6605	-1.6488	-1.6491	-1.6353	-1.6479
	HQ	-1.6023	-1.6949	-1.6872	-1.6962	-1.6904	-1.6907	-1.6828	-1.6895
Bitcoin Returns in Euro w/o Weekends	AIC	-1.6649	-1.7397	-1.7373	-1.7612	-1.7583	-1.7477	-1.7513	-1.7429
	BIC	-1.6059	-1.6807	-1.6685	-1.7023	-1.6895	-1.6789	-1.6727	-1.6741
	HQ	-1.6416	-1.7164	-1.7101	-1.7379	-1.7311	-1.7205	-1.7202	-1.7157
Euro Returns in USD	AIC	-6.4715	-6.4715	-6.4666	-6.4715	-6.4666	-6.4666	-6.4617	-6.4667
	BIC	-6.4125	-6.4125	-6.3977	-6.4125	-6.3978	-6.3978	-6.3830	-6.3979
	HQ	-6.4481	-6.4482	-6.4393	-6.4482	-6.4394	-6.4393	-6.4306	-6.4395
GBP Returns in USD	AIC	-6.5149	-6.5458	-6.5424	-6.5203	-6.5208	-6.5370	-6.5383	-6.5400
	BIC	-6.4461	-6.4769	-6.4638	-6.4515	-6.4422	-6.4583	-6.4498	-6.4614
	HQ	-6.4877	-6.5185	-6.5113	-6.4931	-6.5216	-6.5059	-6.5033	-6.5089

Gold Returns in USD	AIC	-5.3358	-5.3327	-5.3373	-5.3237	-5.3326	-5.3391	-5.3347	-5.3396
	BIC	-5.2768	-5.2737	-5.2685	-5.2647	-5.2638	-5.2703	-5.2561	-5.2708
	HQ	-5.3125	-5.3093	-5.3101	-5.3004	-5.3053	-5.3119	-5.3036	-5.3124
S&P 500 Returns	AIC	-5.7899	-5.7787	-5.7950	-5.7798	-5.7979	-5.7965	-5.7920	-5.7961
	BIC	-5.7309	-5.7197	-5.7262	-5.7208	-5.7290	-5.7277	-5.7134	-5.7273
	HQ	-5.7666	-5.7553	-5.7678	-5.7564	-5.7706	-5.7693	-5.7609	-5.7689
VIX Returns	AIC	-1.5713	-1.5926	-1.6155	-1.5703	-1.6058	-1.6117	-1.6085	-1.6131
	BIC	-1.5024	-1.5238	-1.5369	-1.5015	-1.5272	-1.5331	-1.5200	-1.5344
	HQ	-1.5440	-1.5654	-1.5844	-1.5430	-1.5747	-1.5806	-1.5735	-1.5820
USD Returns in Euro	AIC	-6.4944	-6.4929	-6.4882	-6.4941	-6.4902	-6.4882	-6.4833	-6.4892
	BIC	-6.4354	-6.4339	-6.4194	-6.4351	-6.4213	-6.4194	-6.4047	-6.4204
	HQ	-6.4711	-6.4696	-6.4610	-6.4708	-6.4629	-6.4610	-6.4522	-6.4620
GBP Returns in Euro	AIC	-6.7083	-6.7185	-6.7148	-6.5155	-6.5147	-6.7135	-6.7096	-6.7141
	BIC	-6.6395	-6.6595	-6.6460	-6.4565	-6.4458	-6.6447	-6.6309	-6.6453
	HQ	-6.6810	-6.6952	-6.6876	-6.5159	-6.5152	-6.6863	-6.6785	-6.6869

Note: GED: Generalized Error Distribution; NIG: Normal Inverse Gaussian; GH: Generalized Hyperbolic.

Appendix B

Alphabetical Listing of Cryptocurrencies in the Sample

NO.	Name	Symbol	Type
1	0x	ZRX	token
2	Aave	LEND	token
3	aelf	ELF	token
4	Aeternity	AE	coin
5	Aion	AION	coin
6	Aragon	ANT	token
7	Ardor	ARDR	coin
8	Ark	ARK	coin
9	Augur	REP	token
10	Bancor	BNT	token
11	Basic Attention Token	BAT	token
12	Binance Coin	BNB	coin
13	Bitcoin	BTC	coin
14	Bitcoin Cash	BCH	coin
15	Bitcoin Gold	BTG	coin
16	BitShares	BTS	coin
17	Bytom	BTM	coin
18	Cardano	ADA	coin
19	CasinoCoin	CSC	coin
20	Chainlink	LINK	token
21	Cindicator	CND	token
22	Civic	CVC	token
23	Dai	DAI	token
24	Dash	DASH	coin

25	Decentraland	MANA	token
26	Decred	DCR	coin
27	Dent	DENT	token
28	DigiByte	DGB	coin
29	Dogecoin	DOGE	coin
30	Dragonchain	DRGN	token
31	Dynamic Trading Rights	DTR	token
32	Eidoo	EDO	token
33	Electroneum	ETN	coin
34	Enjin Coin	ENJ	token
35	EOS	EOS	coin
36	Ethereum	ETH	coin
37	Ethereum Classic	ETC	coin
38	Factom	FCT	coin
39	FunFair	FUN	token
40	Gas	GAS	token
41	Gnosis	GNO	token
42	Golem	GNT	token
43	Groestlcoin	GRS	coin
44	GXChain	GXC	coin
45	Horizen	ZEN	coin
46	HyperCash	HC	coin
47	ICON	ICX	coin
48	iExec RLC	RLC	token
49	Ignis	IGNIS	token
50	IOST	IOST	coin
51	IOTA	MIOTA	coin
52	Komodo	KMD	coin
53	Kyber Network	KNC	token

54	Lisk	LSK	coin
55	Litecoin	LTC	coin
56	Loopring	LRC	token
57	MaidSafeCoin	MAID	token
58	Maker	MKR	token
59	MCO	MCO	token
60	Metal	MTL	token
61	MonaCoin	MONA	coin
62	Monero	XMR	coin
63	Nano	NANO	coin
64	Nebulas	NAS	coin
65	NEM	XEM	coin
66	NEO	NEO	coin
67	Nexus	NXS	coin
68	NULS	NULS	coin
69	Numeraire	NMR	token
70	Obyte	GBYTE	coin
71	OmiseGO	OMG	token
72	PIVX	PIVX	coin
73	Populous	PPT	token
74	Power Ledger	POWR	token
75	PRIZM	PZM	coin
76	Qtum	QTUM	coin
77	ReddCoin	RDD	coin
78	Ripio Credit Network	RCN	token
79	Ripple	XRP	coin
80	Siacoin	SC	coin
81	Status	SNT	token
82	Steem	STEEM	coin

83	Stellar	XLM	coin
84	Storj	STORJ	token
85	Storm	STORM	token
86	Stratis	STRAT	coin
87	Streamr DATAcoin	DATA	token
88	Syscoin	SYS	coin
89	Telcoin	TEL	token
90	THETA	THETA	coin
91	Tierion	TNT	token
92	TRON	TRX	coin
93	Verge	XVG	coin
94	Vertcoin	VTC	coin
95	Waltonchain	WTC	coin
96	Waves	WAVES	coin
97	WAX	WAXP	coin
98	WhiteCoin	XWC	coin
99	Zcash	ZEC	coin
100	Zcoin	XZC	coin

Appendix C

Coefficient Estimates for the Three-Factor Model

NO.	Symbol	α	β	γ	δ
1	ADA	0.0020	1.0786	-0.4909	-0.0790
2	AE	-0.0006	1.0954	-0.1770	-0.2975
3	AION	0.0034	1.2847	0.0487	-0.1711
4	ANT	-0.0032	0.8540	0.3053	0.0642
5	ARDR	0.0013	1.0440	0.2782	0.1218
6	ARK	0.0006	1.0963	0.3569	-0.1370
7	BAT	0.0038	1.0473	-0.0494	0.0568
8	BCH	0.0059	1.1852	-0.9173	0.0122
9	BNB	-0.0003	0.8328	-0.3177	0.0796
10	BNT	-0.0018	0.9830	-0.0754	0.1699
11	BTC	-0.0020	0.7440	-0.2904	0.2556
12	BTG	-0.0002	0.9270	-0.7608	0.2076
13	BTM	0.0021	1.1439	-0.5831	-0.2913
14	BTS	-0.0008	1.0079	-0.3377	-0.0303
15	CND	0.0012	1.1191	0.3268	-0.1376
16	CSC	0.0026	0.9732	2.1159	0.2479
17	CVC	0.0007	1.1039	0.2664	-0.0652
18	DAI	-0.0206	-0.0054	0.0903	0.1139
19	DASH	0.0011	0.9835	-0.5668	0.0478
20	DATA	0.0010	1.0422	0.3585	0.0229
21	DCR	-0.0023	0.8940	-0.2624	-0.0148
22	DENT	-0.0007	1.0991	0.1065	0.0192
23	DGB	0.0013	1.0473	-0.1013	-0.0070
24	DOGE	-0.0051	0.6626	-0.3523	0.1753

25	DRGN	-0.0001	1.0610	0.0154	0.0571
26	DTR	-0.0069	0.6523	0.0389	0.0022
27	EDO	-0.0038	0.8737	0.0659	-0.0601
28	ELF	0.0017	1.1734	-0.0912	-0.1585
29	ENJ	0.0047	1.0637	0.6851	0.3652
30	EOS	0.0045	1.1441	-0.7076	-0.0236
31	ETC	0.0010	0.9375	-0.5578	0.0913
32	ETH	0.0013	1.0019	-0.5120	0.0794
33	ETN	-0.0014	0.9212	-0.3289	0.0848
34	FCT	-0.0037	0.8635	0.0756	0.0650
35	FUN	0.0000	1.0668	0.2086	-0.0656
36	GAS	0.0005	1.1357	-0.0861	-0.2480
37	GBYTE	-0.0039	0.8404	-0.0492	0.1415
38	GNO	-0.0052	0.7645	-0.0563	0.1146
39	GNT	-0.0008	1.0595	0.2743	-0.1270
40	GRS	-0.0011	0.9878	0.9511	-0.1170
41	GXC	-0.0013	0.9781	-0.0372	-0.0542
42	HC	0.0040	1.1461	-0.5322	0.1075
43	ICX	0.0010	1.1565	-0.1440	-0.2897
44	IGNIS	0.0019	1.0012	1.2059	0.4429
45	IOST	0.0051	1.2653	-0.4112	-0.2375
46	KMD	0.0007	1.0040	-0.0178	-0.0160
47	KNC	0.0025	1.1153	0.2793	-0.0075
48	LEND	0.0086	1.2825	0.4912	0.1164
49	LINK	0.0070	0.9983	-0.3389	0.2230
50	LRC	0.0009	1.1516	-0.1078	-0.2043
51	LSK	-0.0031	0.9213	-0.1428	-0.0214
52	LTC	0.0020	0.9907	-0.6313	0.0887
53	MAID	-0.0017	0.9062	-0.1140	0.1099

54	MANA	-0.0001	0.9392	0.0907	0.1207
55	MCO	0.0026	0.9954	0.0817	0.1257
56	MIOTA	-0.0006	1.0053	-0.5740	-0.1564
57	MKR	0.0010	0.9158	-0.3130	0.2582
58	MONA	-0.0041	0.7614	-0.3943	0.0733
59	MTL	0.0035	1.1906	0.6000	0.1466
60	NANO	0.0023	1.1181	-0.2903	-0.1725
61	NAS	-0.0004	1.1102	-0.3229	-0.4295
62	NEO	0.0033	1.1328	-0.5997	-0.0989
63	NMR	0.0000	0.8624	0.3673	0.4365
64	NULS	0.0010	1.1363	0.1328	-0.1838
65	NXS	0.0020	1.1294	0.3344	0.1651
66	OMG	0.0017	1.1350	-0.5421	-0.0787
67	PIVX	-0.0001	1.0812	0.1568	-0.1209
68	POWR	0.0016	1.0921	0.2801	-0.0057
69	PPT	-0.0019	1.0801	0.2769	-0.1960
70	PZM	-0.0182	0.2028	1.1985	0.1456
71	QTUM	0.0030	1.1264	-0.5522	0.0854
72	RCN	0.0079	1.2109	0.6976	0.4536
73	RDD	-0.0007	0.9862	-0.2796	0.1276
74	REP	0.0000	0.9488	-0.2365	-0.0129
75	RLC	0.0035	1.1116	0.4006	0.0408
76	SC	-0.0002	1.0392	-0.0773	-0.0812
77	SNT	-0.0010	0.9990	-0.0930	-0.0525
78	STEEM	-0.0008	1.0396	0.0119	-0.0565
79	STORJ	-0.0008	1.0198	0.5526	-0.2108
80	STORM	-0.0025	1.0266	0.2604	-0.2152
81	STRAT	0.0034	1.2123	0.0250	-0.1242
82	SYS	-0.0020	0.9855	0.1964	0.0135

83	TEL	-0.0036	0.8316	0.1775	0.3607
84	THETA	0.0010	0.9767	-0.0924	-0.0197
85	TNT	0.0071	1.1960	0.7881	0.2427
86	TRX	0.0023	1.0657	-0.3973	-0.0789
87	VTC	0.0004	0.9615	0.7426	0.2935
88	WAVES	-0.0020	0.8843	-0.0541	0.1230
89	WAXP	-0.0014	1.0089	0.1378	-0.2310
90	WTC	-0.0002	1.1321	0.0559	-0.2415
91	XEM	-0.0017	0.9293	-0.3852	-0.0466
92	XLM	-0.0016	0.9297	-0.4480	-0.1487
93	XMR	0.0006	0.9545	-0.4720	0.0155
94	XRP	-0.0026	0.8430	-0.6477	-0.1338
95	XVG	0.0019	1.1413	-0.0886	-0.1515
96	XWC	-0.0061	0.9881	1.6824	-0.9716
97	XZC	0.0000	0.9754	-0.0799	0.1948
98	ZEC	-0.0005	0.9566	-0.5764	-0.0247
99	ZEN	-0.0015	0.8752	0.0880	0.1393
100	ZRX	0.0009	1.0484	-0.2153	-0.1417