THE DETERMINANTS OF CRYPTO CURRENCY PRICE: THE CASE OF BITCOIN

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APRIL 2019

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A final year project submitted in partial fulfillment of the requirement for the degree of

BACHELOR OF BUSINESS ADMINISTRATION (HONS)
BANKING AND FINANCE

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FACULTY OF BUSINESS AND FINANCE
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APRIL 2019

DECLARATION

We hereby declare that:

(1) This undergraduate FYP is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Equal contribution has been made by each group member in completing the FYP.

(4) The word count of this research report is 13,797 words.

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ACKNOWLEDGEMENT

Our research project has been successfully conducted with the assistance of various authorities. Hence, we would like to grasp this opportunity to express our sincere appreciation and acknowledge those who had been contributed towards our research project.

First of all, we would like to express our appreciation to Universiti Tunku Abdul Rahman (UTAR) for giving us this opportunity to participate in the research project. Throughout this research progress, we gain a lot of valuable experience and knowledge which cannot be directly absorbed from course structure.

Besides, we would also like to show our gratitude to our former supervisor, Dr Yii Kwang Jing who provided insight and expertise that greatly assisted the research. Not least than that, we give thank to our existing supervisor Mr Koh Chin Min who provide his advice and guidance throughout this project. We appreciate them for sharing their pearls of wisdom with us during the course of this research and it is our pleasure to be supervised by both of them, their opinions and guidance had assisted us to complete this project.

DEDICATION

We would like to express our sincere gratitude to our honour supervisor, Dr Yii Kwang Jing and Mr Koh Chin Min, for their valuable guidance, advice and motivation in assisting the completion of this research project.

Furthermore, we would like to dedicate this research project to our family members for the appreciation of their encouragement and financial support. Moreover, this research project is dedicated to all of our group members who have contributed most of the time, effort, energy, knowledge and cooperation in conducting this research. Our collaboration, understanding, respect and enthusiasm towards this research highly lead to the completion of this research project.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
ARDL	Autoregressive Distributed Lag
BDD	Bitcoin days destroyed
BIT	Price Formation of Bitcoin
BQR	Bayesian quantile regression
CUSUM	Cumulative Sum
DS	Velocity in Bitcoin Circulation
ETH	Price of Ethereum
GP	Gold Price
HR	Computational Power of Bitcoin Miners
IoT	Internet of Thing
PP	Philips Perron
RESET	Ramsey Regression Equation Specification Error Term
SD	Standard Deviation
SVM	Support Vector Machines
TOL	Tolerance
VAR	Vector Autoregressive
VDC	Variance Decomposition Analysis
VECM	Vector Error Correction Model
VIF	Variance Inflation Factor
VSM	Vector Space Model

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PREFACE

The determinants of Bitcoin price have been a significant issue that concern many researchers to examine the types of determinants that affecting the price of Bitcoin. One of the main questions in the emerging blockchain ecosystem related to the investment decision making is how a crypto currency to be priced. Debates and problems about the usage of crypto currencies as a transaction medium are the impact from the price fluctuations in Bitcoin exchange markets. Apart from the studies undertaken by previous researchers, we found that substitution coin (Ethereum) has left to be carried out that that could explain the price formation of Bitcoin.

In this study, the relationship between the price formations of Bitcoin with the determinants such as computational power of Bitcoin miners (hash rate), gold prices, velocity of Bitcoin in circulation (demand-supply fundamentals) and the price of Ethereum as a substitution coin will be examine and discuss.

This study provides substantial insight to the fields of finance and economics, information systems, applied cryptography and crypto currency investors or miners while also contributes an improved research model that incorporated a important variable which is the price of Ethereum as a substitution coin which can influence the price of Bitcoin as Ethereum is the largest and most well-established, open-ended decentralized software platform that enables smart contracts and distributed applications to be built and run without any downtime, fraud, control or interference from a third party.

ABSTRACT

This study examines the relationship between the determinants that will affect on the price formation of Bitcoin from period year 2016 Aug 2 to 2018 May 30, which consist of daily data of 239 observations. A theoretical framework is constructed to test on the relationship between the Bitcoin Price determinants with the independent variables which are computational power of Bitcoin miners (hash rate), gold prices, velocity of Bitcoin in circulation (demand-supply fundamentals) and the price of Ethereum as a substitution coin. Autoregressive Distributed Lag (ARDL) is adapted to test on the long run relationship between the determinants. Besides, causality direction, dynamic stability and shocks of the empirical model are examined in this study.

CHAPTER 1 : RESEARCH OVERVIEW

1.0 Introduction

The emergence of crypto currency or digital currency as a new revolutionary type of currency gives a significant impact to recent economic and financial market. Meanwhile, it also successfully attracts public's attention to discover the background and price formation of crypto currency particularly Bitcoin. In this chapter, there are seven sections to be discussed which are research background, problem statement, research objectives, research questions, significant of study, chapter layouts and a short conclusion. The research background will be conferred to propose our research topic at first. Follow by the problem statement which will be present to highlight the issue occurred. In order to deliver the purpose of this study, research arguments and research objectives will be guided by the research questions. Next, the hypothesis and significance of this research will be defined. Moreover, chapter layouts will briefly discuss the outline of this whole research which included five chapters. Lastly, a summary of chapter 1 will be written in conclusion.

1.1 Research Background

A decentralized, low transaction fees and even the issuance and ownership are not from government instead it is digitally hold by peer-to-peer network community. This new form of currency emerging in current network circulations is known as digital currency or crypto currency. Crypto currency derive from the word 'crypto' which mean it requires a strong cryptography to ensure that the transactions are safe and confirmed while it also authorize the formation of an additional unit of the currency (Kristoufek, 2015). Bitcoin as one of the dominant in the crypto currency market had largely attracted the investor's attention to find out what is the factor that drives up the Bitcoin value. In recent crypto currency market, Bitcoin owns 42.6% of dominance with an estimated market capitalisation of $253 billion in the market which roughly occupied 1/3 of the crypto currency (CoinMarketCap, 2018).

According to Gil (2018), Bitcoin traded from one personal wallet to another. The private key in Bitcoin wallet is used to sign the transactions while also acts as a mathematical proof that arises from the owner's wallet. Bitcoin transaction is non reversible however it can only be refunded by the person who had received the funds. After getting through the mining process, the entire transactions will be broadcast to the network and it takes 10-20 minutes to arrive at confirmation. This neutrality of the network is protected by setting in a chronological way. Moreover, all transactions must be contained in a block that equips with strict cryptographic rules that will be verified by the network. These rules aim to prevent the modification of the previous blocks where it will cause all the following blocks to become invalid. Mining also creates an aggressive lottery that restricts any individual from adding new blocks to the block chain easily. The entire Bitcoin network relies on a shared public ledger which known as block chain (Bitcoin, 2018).

Bitcoin can be use in everywhere and anytime as individual can transact easily using the Bitcoin address. In addition, there are no involvements of banks which take at least three working days for processing as well as no extra fees charged for making any international transfer. Bitcoin also gives control over individual's money and provides a stable and steady protection against fraud. This is because Bitcoin transactions are highly protected by military-grade cryptography where no one can withdraw money or make a payment on their behalf (Scheck, 2017).

1.2 Problem Statement

The increasing popularity and acceptance level of Bitcoin has largely attracted not only investors but also public's interest to find out the factors that drive the Bitcoin price. The value of Bitcoin has strike up to $1000 again in the first day of February 2017 which brings a great milestone for the crypto currency history since the highest price performance on year 2013 was $1150 per BTC (CoinMarketCap, 2018). An argument arises to the maturity increment on Bitcoin although the price volatility is declining. The reason behind is the rising acceptance level for being a method of payment in distinct businesses transaction. The issues in the adoption of Bitcoin such as hacking, immoral reputation and being ban by government do not stop Bitcoin from expanding and successfully become the most developed crypto currency in the market.

There is still a limitation for people who desire to use crypto currency in daily transaction as they are still immature and not largely known in the market where it has not been adopt by most of the companies and businesses as a means of payment or transaction. Furthermore, the transactions made earlier are irreversible. In other words, once the funds are being transact, the anonymity of users makes funds nearly inaccessible for tracking, this make the users to be very alert on typing addresses and sending their funds. The anonymous has made crypto currency vulnerable to criminal activities. It allows criminals to trade illegal assets such as weapons and drugs without getting caught. Bitcoin is considered being a high risk investment, the investors or miners will need to bear the risk and have pre-awareness to lose their investment if everything goes wrong.

In the digital currency world, fraud is a very real thing and it is easy to lose the investment to dishonest actors. While there is a large potential to realize high return, there will be a high potential that the speculation bubble may pop, the investment may be defrauded, and the Bitcoin and other altcoins may be ruled illegal in local jurisdiction. Bitcoin was proved to be the most attractive attempt for criminals (Marr, 2017). The world’s largest Bitcoin exchange Mt.Gox went off in January 2014 as the Bitcoin in it was dishonestly got into someone hands on a haul which was valued at $450 million dollars. The emergence of Bitcoin and other digital currencies is urging both consumers and merchants to be more tech-savvy. While investing in Bitcoin could be an option for the investors to do their portfolio diversification, the security and cost will be as tough as the market it is traded in. By not mentioning fraud, Bitcoin have been subjected to large fluctuation in price over the years. There is an unclear future for Bitcoin, but the business community will surely be riding on a roller-coaster (Barlin, 2017).

According to Hayes (2015), Bitcoin becomes the dominant in crypto currency market not only in listed and over-the-counter, however it is also included in the derivatives market. Due to the rapid emergence of Bitcoin, there are important question arises by most of the public: What are the determinants that affect the price of Bitcoin? Why do Bitcoin have value? Is Bitcoin appeared as a speculative bubble?

The determinants of price for Bitcoin range from economic, transaction and technical driver. Kristoufek (2015) adopt trading usage, circulation of money in the market and the level of price to be the determinants of Bitcoin prices in long term. Arising from technical views point, the main factor for user to become miners is motivated by the high Bitcoin price which gives them the opportunity to gain profit. However, there will be a diminishing effect in profit in longer time period because the unique mining hardware components will drive up the hash rates and the difficulty level. The discussion on Bitcoin has commonly post on various financial websites, blogs and media relating to the currency's methodological, assurance and juridical issues. In the similar manner, Yelowitz and Wilson (2015) examine the interest's determination in Bitcoin by collecting Google Trends data. They find that undiscovered illegal activities and users who interested in computer programming increase the interest toward Bitcoin.

In this study, we will focus on the key factors affecting the price of Bitcoin which are computational power of Bitcoin's miners (hash rate), the market price of gold, velocity of Bitcoin in circulation (demand-supply fundamentals) and the price of Ethereum as a substitution to Bitcoin.

1.3 Research Questions

General Research Question

What are the determinants of crypto currency price in the case of Bitcoin?

Specific Research Question

i. What is the relationship between velocity of Bitcoin in circulation (demand-supply fundamentals) and the price formation of Bitcoin?
ii. What is the relationship between computational power of Bitcoin miners (hash rate) and the price formation of Bitcoin?
iii. What is the relationship between gold prices and the price formation of Bitcoin?
iv. What is the relationship between and the price of Ethereum as a substitution coin and the price formation of Bitcoin?

1.4 Research Objectives

General Research Objectives

To examine the determinants of crypto currency price in the case of Bitcoin.

Specific Research Objectives

i. To examine the relationship between velocity of Bitcoin in circulation (demand-supply fundamentals) and the price formation of Bitcoin.
ii. To examine the relationship between computational power of Bitcoin miners (hash rate) and the price formation of Bitcoin.
iii. To examine the relationship between gold prices and the price formation of Bitcoin.
iv. To examine the relationship between and the price of Ethereum as a substitution coin and the price formation of Bitcoin.

1.5 Significance of Study

A variety of research have done on the determinants of price formation for Bitcoin which focus on independent variables such as velocity of Bitcoin in circulation (demand-supply fundamentals), computational power of Bitcoin miners (hash rate), gold price, crude oil price, interest rate, exchange rate and others macroeconomic factors. However, limited studies were accomplished to examine the relationship between price of Ethereum and Bitcoin. Taking into consideration of the significant implication of the price of substitution goods, this study aims to examine the existence of trade-off relationship between the price of Ethereum and Bitcoin. Ethereum refers to Ether which is also defined as hypothetical material, filling all the space but impalpable, in which the light waves were supposed to propagate (Madani, 2017). Based on the Coin Market, the market cap of Ether (ETH) is higher than Ripple and Litecoin which is the second largest market capitalization among crypto currency, after Bitcoin. This led us to choose Ethereum to compare with Bitcoin. Furthermore, the additional Ether is created via the mining process which is similar to Bitcoin (Harm, Obregon & Stubbendick, 2016). Bitcoin and Ethereum are two highly disruptive crypto currencies looking to influence block chain technology to drive innovation across several industries. The great breakthrough and volatility of both Bitcoin and Ethereum are affected by the result of news, hype and speculation (D'Alfonso, Langer & Vandelis, 2016). Recently, financial players distinguish that Ethereum has more benefits and holds a greater value due to their extensive implementation and reduction of restrictions with the smart contract application. As a result, there is an increasing demand for Ethereum while this gives effect to the demand and price of Bitcoin. A change in the price of Ethereum can directly affect the demand for Bitcoin (Sovbetov, 2018). For example, when the price of Ethereum decreases, the demand on Ethereum will increase, it then leads to a decline on the demand for Bitcoin. Therefore, this study will mainly focus on which determinants will affect the price of Bitcoin.

This study provides a substantial insight to the fields of finance and economics, information systems, applied cryptography and crypto currency investors or miners. The information enable the businessman and investor to have precise preparation for their activities and investments as more businesses are starting to accept Bitcoin and other crypto currency as a medium of exchange instead for an investment or commodity. Other than that, the information is also useful for government and policy makers by suggesting them the explanatory variables in designing the policy. Government may impose some of the restriction on coin ownership or increase regulation on the type of crypto currency.

By conducting this study, government is able to be aware of more about the factors that affect the price of Bitcoin. Hence, it provides a more robust result to government and investors on impact of velocity of Bitcoin in circulation, computational power of Bitcoin miners, gold price and price of Ethereum since maintaining a low and stable in Bitcoin price has always become the core objectives targeted by the government and financial players.

1.6 Chapter layouts

The remaining chapters of this paper are organized consequently. Chapter 2 focuses on framework of the study, literature review of previous studies on determinants of crypto currency price in the case of Bitcoin. Chapter 3 will be discussing on research methodology of the current study by using secondary data. Chapter 4 presents the result and discussion and Chapter 5 conclude and provide some recommendation.

1.7 Conclusion

Bitcoin uses peer-to-peer technology to function with no government or central banks to control the transactions and the issuance of Bitcoin. It is collectively hold by peer-to-peer network community. Bitcoin is an open source which everyone can play a part in. Bitcoin has many distinctive characteristics which change the idea that people think about money. In conclusion, concerns on the determinants of Bitcoin price become increasingly significant in the recent years and maintaining a low and constant Bitcoin price is one of the challenges. This study contributes an important variable which is the price of Ethereum as it acts as a substitution coin which can influence the price formation of Bitcoin. Ethereum that enables smart contracts is the second largest while also standing on a great and firm position. It is also an open-ended decentralized software platform that delivers applications to be built and ran without any downtime, fraud, control or interference from a third party. This chapter presents as a brief outline and a groundwork that allow readers to have an exceptional comprehension in the following chapters.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

Chapter 2 starts with the analysis of theoretical framework in order to support our study. Next, in depth review of previous empirical studies on each variable will be carried out. Furthermore, proposed conceptual framework will be identified. At last, this chapter will end with the hypotheses established for this study.

2.1 Theoretical Foundation

2.1.1 Quantity theory of Money

By following the standard economic theory, in specific the quantity theory of money, assuming Bitcoin as a medium of exchange, its price should be determined by standard supply and demand interactions (Ciaian, Rajcaniova & Kancs, 2016; Buchholz, Delaney, Warren & Parker, 2012). Fisher's equation of exchange connected with the quantity theory of money stipulates MV=PT (Fisher, 1922).

Where,
M : nominal supply of money,
V : velocity of money circulation,
P : general price level
T : size of the underlying economy

Quantity Theory of Money explains that the velocity of Bitcoin in circulation (V) is positively correlated to the Bitcoin price (P) (Kristoufek, 2013). In the equation, the nominal supply of Bitcoin is assumed to be constant and thus any changes in the velocity of Bitcoin circulation will cause the Bitcoin price level or size of the underlying economy to change. Moreover, there is an assumption saying that the size of the Bitcoin market is fixed since the availability of Bitcoin that can be mined in the market is constant at 21 million. Once all the Bitcoin have been mined, the supply will be tapped out. Therefore, it can be said that any changes in the velocity of Bitcoin circulation will only cause price of Bitcoin to alter.

2.1.2 Cost of production model

Mining process involves a competition among the miners since the rate of new unit formation is constant and thus the supply of Bitcoin is fixed and unable to manifest it even demand keeps on increasing. Therefore, this elasticity is manifested through increasing the system wide marginal cost of production.

When demand on Bitcoin increases, it represents that the number of miners that join the Bitcoin network increase. When the input increases, the quantity of products produced will also rise. Thus, marginal products tend to increase in the initial stage. When the number of product reaches the maximum level, the marginal product will drop since supply of Bitcoin is constant. The difficulty of solving the mathematical operations and hash rate will become higher. Consequently, the cost of hardware required and electricity usage in mining process rise substantially and force majority miners to leave the mining pool. These miners will become Bitcoin purchasers when they employ the coins as a substitution to the direct investment, which will give an upward pressure to the demand and price of Bitcoin.

2.2 Review of the Literature

2.2.1 Price Formation of Bitcoin

In the theory of economy, price of a currency is determined by the market forces which are demand and supply and also by the price level in a transaction. If the demand on the currency increases more than the supply level, the value of the currency will increase as there is an insufficient supply to fulfil the required demand. On the other hand, when the supply of the currency increases more than the required demand, that particular currency value will drop. According to Ciaian et al. (2016), the market force of supply-demand fundamentals play a significant role on the fluctuation of Bitcoin price and it is a key determinant for the price of Bitcoin. The impact from the demand side is stronger as compared to the supply side of Bitcoin whether in present or in the future. The reason behind is, the supply of Bitcoin is fixed and pre-determined based on the method of calculation which is known publicly while the unfixed demand is affected by the favor level and behavior of the investor to trade the Bitcoin (Kristoufek, 2013). In other words, it can be explained that when the fixed supply of Bitcoin cannot meet the demand on the currency, it will automatically drive up the Bitcoin price.

In order to keep the fixed supply, the mining process requires an algorithm to mine the Bitcoin. Miners are required to solve the rewarding problem where its difficulty level rises subsequently to the computational power of the miners. Based on the study of Li and Wang (2017), they include mining difficulty as one of the determinants to the exchange rate per Bitcoin (USD per Bitcoin) since they propose that Bitcoin price will be affected by two general categories of factors, they are technological factors and economic factors. Under technology factors, they expect that mining difficulty, mining technology and public recognition have a positive impact on Bitcoin price. Hayes (2015) states that the greater the amount of computational power devoted in mining process, the higher the price of Bitcoin. It is because the more the mining power, the more the acceptance for Bitcoin can be inferred.

Bitcoin price formation is affected by the whole commodity market which include the gold market in spite of Bitcoin is part of an alternative economy. Gold price has a statistically major impact on Bitcoin price. Higher gold price tends to encourage the holding of virtual currencies in order to avoid the risk of losses from the potential price reduction of holding other financial assets (Ciaian, Rajcaniova & Kancs, 2018).

2.2.2 Velocity of Bitcoin in Circulation (Demand Supply Fundamentals)

Velocity of Bitcoin in circulation is one of the factors that affects the Bitcoin price. Velocity measures the speed of Bitcoin circulates in the economy and it is determined by the spending amount in each transaction (Michael & William, 2014). In other words, velocity can be measured by the supply-demand fundamentals because the more the transaction incurred using Bitcoin, the quicker the velocity.

According to Ciaian et al. (2016) and Buchholz et al. (2012), the key determinant of Bitcoin price and the price fluctuation are affected by the market forces which are the supply and demand of the Bitcoin. Whether it is in present or future, the impact from the demand side is always stronger as compared to the supply side of Bitcoin. The underlying reason is because the supply of Bitcoin is fixed and pre-determined based on the method of calculation known publicly while the unfixed demand on Bitcoin effect from the favorability and investor's behavior to trade the Bitcoin (Kristoufek, 2013).

However, there is also researcher argues that supply-demand fundamentals should not be a determinant of Bitcoin price. For instance, Kristoufek (2013) argues that Bitcoin price cannot be explained by the Standard Economic Theory due to the issuance of Bitcoin is not by legal entity, central bank or government and it is disengaged from real economy although it is as a type of currency which is defined as alternative currency and is accepted to be used as medium of exchange by companies and people.

Bouoiyour and Selmi (2017) use Bayesian quantile regression (BQR) to examine the influence level of the independent variables on affecting the Bitcoin price. The result of their study shows that the constantly increasing demand of Bitcoin for a controlled supply of Bitcoin causes the Bitcoin price to be raised while the supply is negatively correlated with Bitcoin price. This result is supported by Ciaian et al. (2016), Michael and William (2014), Kristoufek (2015) and Kristoufek (2013) which state that the result is same with their theoretical prediction. They agree that the Bitcoin price is able to be explained by the Standard Economic Theory, in specific the Quantity Theory of Money at which the velocity of Bitcoin in circulation is positively correlated to the Bitcoin price while there is negative relationship between Bitcoin price and amount of Bitcoin stock.

In the study of Ciaian et al. (2016), the augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test are applied to examine the stationary of time series while Johansen's co-integration method is used to determine the long-term relationship between the price series. Multiple-regression analysis is used by Michael and William (2014), the variables involved in this model to control the demand are gold price, transaction number, inflation rate of US, Google trends metric, and Bitcoin days destroyed (BDD).

While in the research study of Kristoufek (2015), the trade-exchange ratio is used as a measurement to determine the relationship between velocity and

Bitcoin price. Lower ratio indicates there is a high usage of Bitcoin as medium of exchange for transactions which in turn give a rise in Bitcoin price. Besides, the study conducted by Kristoufek (2013) to study the relationship between the search queries on Google Trends, Wikipedia, and Bitcoin price finds out that the price of Bitcoin is strongly positively correlated to the search queries on both Google Trends and Wikipedia. In other words, when the people's interest on Bitcoin rises, the Bitcoin price will also increase.

2.2.3 Computational Power of Bitcoin Miners (Hash Rate)

Mining difficulty is always one of the popular factors that investors and miners concern about. There are a lot of existing studies that examine the relationship between the difficulty of mining and Bitcoin price. In the study of Bouoiyour and Selmi (2015), the impact of a set of factors such as ratio of exchange-trade volume, hash rate which indicate the difficulty of mining, stock market, investors' attractiveness, gold price and estimated output volume on Bitcoin price are being carried out. They apply several methods including Autoregressive Distributed Lag (ARDL) Bounds Testing Method, Innovative Accounting approach and VEC Granger causality. According to Bouoiyour and Selmi (2015), hash rate is measuring the Bitcoin network's processing power. In the process of mining, the latter is required to make intensive mathematical operations to fulfill the purpose of security. It causes a rise in the hash rate. Consequently, the Bitcoin purchasers may be affected and increases substantially the demand of Bitcoin, then lead the Bitcoin price grows. The result confirms that the greater the number of miners joining the Bitcoin network, the greater the network hash rate. However, Meland and Øyen (2017) who apply the same method conclude that there is no significant relationship between both of these variables. The finding fails to prove technical factors as mining difficulty exert any impact on the price of Bitcoin.

The researchers suggest that this finding should be taken into account in future research on Bitcoin by other researchers.

Kristoufek (2015) utilizes wavelets methodology to examine the potential determinants for the price of Bitcoin, range from fundamental source to speculative and technical one. The outcome indicates that when the number of miners that join the Bitcoin network increases, this will cause the cost of hardware required and electricity usage in mining process rise substantially and force majority miners to leave the mining pool. These miners will become Bitcoin purchasers if they employ the coins as a substitute to the direct investment, then will increase the demand and price of Bitcoin. This result is supported by Hayes (2015) who also proves that the potential of Bitcoin mining leads the development and enhancement of hardware. This also affects the formation of mining pools where miners combine their computational power. Hence, it exerts positive pressure on Bitcoin price.

Researchers like Li and Wang (2017) obtain the result as mining difficulty and Bitcoin price have positive relationship by employing different method. First, they examine the stationary of the time-series data by using Augmented Dickey-Fuller (ADF) test, while also support their choice of lags on the Akaike Information Criterion (AIC). Apart from that, in order to assess the extent of co-integration in their data, they employ Vector Error Correction Model (VECM) approach and Johansen's test on the variables. They include mining difficulty as one of the determinants to the exchange rate per Bitcoin (USD per Bitcoin) since they propose that Bitcoin price will be affected by two general categories of factors, technological factors and economic factors. They find out that mining difficulty exerts a positive pressure on Bitcoin price. Moreover, the result also implies that the effect of mining difficulty on Bitcoin price weakens over the time. It is due to the progression in mining technology decrease the cost of mining and thus the positive impact on Bitcoin price.

Georgoula, Pournarakis, Bilanakos, Sotiropoulos and Giaglis (2015) attempt to detect the determinants of Bitcoin price by using several methods such as Vector Space Model (VSM), Support Vector Machines (SVMs), Dickey-Fuller (ADF) test, Phillips-Perron (PP) unit root test, KPSS test and VECM model. They claim that the mining difficulty is positively associated with Bitcoin price. This is because when the mining difficulty rises, the marginal production cost will increase and in turn lead to a growth in Bitcoin price. Kristoufek (2015) conclude that any determinants that tend to lower the cost of Bitcoin production will have a negative impact on Bitcoin price. For instance, lower mining difficulty, lower worldwide electricity price and higher mining efficiency, all of these factors will reduce the cost of production and lead Bitcoin price drop also. Therefore, the relationship between mining difficulty and Bitcoin price is positive. At the same time, if there is more hashing power joining the global mining network, the mining difficulty will become higher and thus rise the price of Bitcoin.

On the other hand, Huhtinen (2014) takes market sizing calculation, regression analysis and Granger causality test to analyze the price drivers for Bitcoin as an investment instrument. Hash rate which represents the amount of computing power that is utilized by the Bitcoin network is included as a new variable to be studied. The findings show that hash rate is used to predict the future Bitcoin price. The following month's Bitcoin price can be forecast by using this month's change in network hash rate. Furthermore, the changes in hash rate in short run will not affect the Bitcoin price since there are computers constantly joining and quitting the Bitcoin network.

2.2.4 Gold Price

Gold price is one of the main drivers that affects the price formation of Bitcoin. According to Ciaian et al. (2018), gold price has a statistically great impact on

Bitcoin price in the short run and long run using Autoregressive distributed lag (ARDL) bound testing approach. When the price of gold decreases, it can also explain the reasons of why the Bitcoin price decreases. Higher gold price tends to encourage the holding of virtual currencies in order to avoid the risk of losses from the potential price reduction of holding other financial assets. The positive long run relationship may be an outcome of the arbitrage return among other investment opportunities, if only the virtual currencies are recognized as investment assets. In addition, by using the ARDL model, the significant relationship between Bitcoin price and gold price is also supported by Bouri, Gupta, Lahiani and Shahbaz (2018).

The past changes in Bitcoin prices had affect their own present variations in a contributable positive manner at the medium to high quantiles at dissimilar lags in the short run, whereas, the past changes in gold price show a significant influence together with the changes in Bitcoin price. In the short run, past changes in Bitcoin price have a positive cumulative impact on current changes in Bitcoin price. The finding suggests that gold price is one of the main drivers of Bitcoin price where Bitcoin price is affected by the whole commodity market although Bitcoin is part of a substitute economy.

Moreover, virtual currencies are highly affected by macro financial sign in the short run than in the long run. Bitcoin price and gold price have various tendencies which indicate that they have the same trend in the short run and different trend in the long run. Even though Bitcoin price does not affect gold price in the long run, it shows short run causality between each other. Thus, Bitcoin is treated as a hedge asset to gold in the short run which shows that the Bitcoin acts similar to gold. Zhu, Dickinson and Li (2017) apply the Augmented Dickey–Fuller (ADF) unit root test to build Vector Autoregressive (VAR) model followed to examine the cointegration relationship using Johansen test as well as building Vector Error Correction (VEC) model and employ Granger causality test to examine causal relationship. In addition, Dyhberg (2016) also states that the features of Bitcoin are almost similar to gold as they contain identical hedging capabilities and react symmetrically to any favourable and unfavourable condition in order to reduce the possibility of sudden shocks using GARCH model.

On the other hand, by using ordinary least square and Bayesian quantile regression analysis, Bouoiyour and Selmi (2017) find that there is an insignificant relationship between Bitcoin price and gold price where Bitcoin and gold do not move in the same direction. This situation indicates that the decreases of gold price act as hedge and safe haven in turbulent time. Evidence shows that Bitcoin and the constant changes of gold are expected to be more or less interdependent in bearish regimes, thus both assets are not considered as safe haven. This is supported by Kristoufek (2015) who explains that the rapid increase of gold price in the first period and continues to have a stable decline of gold price during the certain extent of time. Thus, it shows that the Bitcoin is disconnect or unrelated to the constant changes of gold price as there is no evidence show that whether the gold is still acting as safe haven like previous days. It would be positively correlated if the Bitcoin is truly a safe haven. However, there is still an absent sign that the Bitcoin is a safe haven.

2.2.5 Alternative Crypto currency (Ethereum)

Some of the researchers have argued that there is a positive or negative relationship between price of Bitcoin and price of altcoin (Ethereum). Through the research done by Gandal and Halaburda (2014), they state that substitution effect has occurred between Bitcoin and altcoin. When the substitution effect takes place, the large increase in value of Bitcoin, those investors that interested in Bitcoin as financial assets might choose other crypto currency to invest. This is because the Bitcoin has become more popular and more people demand for it, the financial player in the market may fear that the value of Bitcoin might be overestimated and search for substitution crypto currency. Ethereum has become more important since more people are willing to invest in technology sector while Bitcoin was designed to be a currency.

However, Ethereum is created to be role more than a payment system. It had been used to facilitate the software processing by using a token system called Ether (Fattington, 2018). It uses the same underlying technology principles, but uses them to facilitate monetary transactions. Other than that, a lot of apps have been developed by using Ethereum and yet more financial sectors are getting involved in the space. The nature of network effects is different for currency competition than for competition between exchanges. Sellers will take advantages from a large amount of buyers and buyers will take advantage from a large amount of sellers. Conversely, sellers will choose a lower amount of other sellers, since they compete for buyers, while, buyers would prefer a lower amount of other buyers to prevent others from competing against them (Gandal & Halaburda, 2014). This is because the more popular the digital currency, the more attractive for new buyers and sellers to invest which might lead to an increase in amount of competitors that exists in the market.

Zhang and Song (2013) suggest that there might have a relationship between Bitcoin and alternative crypto currency. In the research done by Gandal and Halaburda (2014), they examine the competition among a few number of crypto currencies in the market and online exchange. Their study shows a positive relationship between the Bitcoin value and other crypto currencies value. As the virtual currency market does not truly explain a strong network effect, and with newer crypto currency like Ethereum or Litecoin, Bitcoin is facing a number of competitions from newer crypto currency for its main player position (Nguyen, de Bodisco & Thaver, 2018). Hayes (2017) proposes a positive relationship between altcoin that employ on the scrypt algorithm will be more valuable than SHA-256. This is due to the longer a crypto currency has been occurred and used, the more the value it has in a competitive market as the expected priori that scrypt altcoin are more valuable than SHA-256. Therefore, people are more willing to invest in altcoin rather than Bitcoin if there is a greater profitability in mining for an altcoin than mining to a Bitcoin. Thus, it will lead to a declining demand for Bitcoin which gives a downward pressure on Bitcoin price. Microsoft mentions it chooses Ethereum over Bitcoin because Ethereum offers the flexibility and extensibility that many customer are demanding for (Gray, 2015). Hence, by using Ethereum as part of Azure, Microsoft is developing the technology that is more available to future users (Harm, Obregon & Stubbendick, 2016). Since more devices are connected to Internet, the more technology is using Ethereum as an Internet of Thing (IoT), which make people able to work together with one another by using Ethereum' s smart contract (Christidis & Devetsikiotis, 2016). For this reason, Ethereum has a better technological foundation compared to Bitcoin and Ethereum will become more valuable. People will demand more for Ethereum compared to Bitcoin. There might also a negative relationship between value of Bitcoin and value of Ethereum (Harm, Obregon & Stubbendick, 2016).

2.3 Proposed Conceptual Framework

Diagram 1 implies the relationship between the independent variable and dependent variable. The dependent variable responded to the independent variable. Meanwhile, all the independent variables (Gold Price, Velocity of Bitcoin in circulation, Mining difficulty and Price of Ethereum) will affect the dependent variable (Price of Bitcoin). Thus, there are four independent variables that related to the dependent variable.

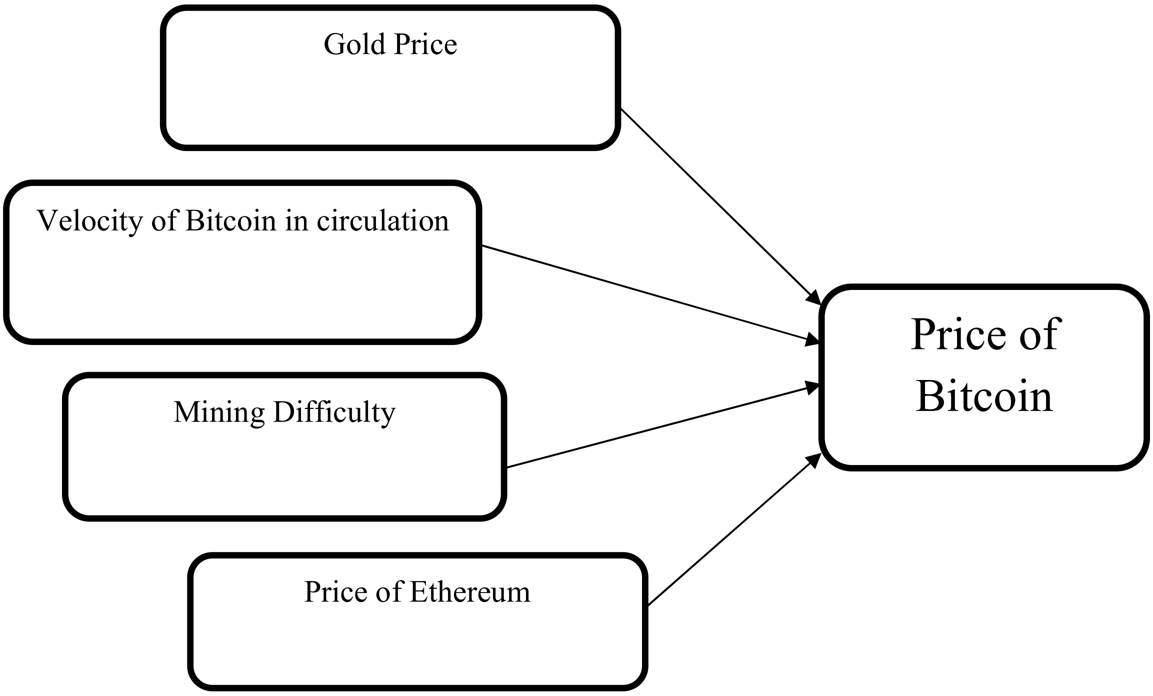


Figure 1: Conceptual Framework

2.4 Hypotheses Development

Based on this study, there are four hypotheses had been conducted to identify the factors that affecting the price formation of Bitcoin.

1. H_0: There is no significant relationship between velocity of Bitcoin in circulation and the price formation of Bitcoin.

   H_1: There is a significant relationship between velocity of Bitcoin in circulation and the price formation of Bitcoin.

2. H_0: There is no significant relationship between computational power of Bitcoin miners and the price formation of Bitcoin.

H_1: There is a significant relationship between computational power of Bitcoin miners and the price formation of Bitcoin.

3. H_0: There is no significant relationship between gold prices and the price formation of Bitcoin.

   H_1: There is a significant relationship between gold prices and the price formation of Bitcoin.

4. H_0: There is no significant relationship between the price of Ethereum as a substitution coin and the price formation of Bitcoin.

   H_1: There is a significant relationship between the price of Ethereum as a substitution coin and the price formation of Bitcoin.

2.5 Conclusion

In this chapter, the costs of production model and quantity theory of money are adapted in our study. It contains the review of previous literature for each and every identified dependent and independent variables. Based on the review, there is still a huge gap in the literature on the influence of price for Ethereum with price formation of Bitcoin. To fill the gap between previous researchers finding and our curiosity on how the price of Ethereum is going to affect the price formation of Bitcoin, we will further investigate this by using the theory or concept as guideline and support. After that, the proposed conceptual framework is developed proceed by four hypotheses based on previous study. In chapter 3, research methodology will be discussed in detail.

CHAPTER 3: METHODOLOGY

3.1 Research Design

This study aims to examine the determinants of crypto currency price in the case of Bitcoin. Quantitative method and time series analyses are included in this study. Quantitative research method seeks to confirm hypothesis about the phenomena and their relationships. It also helps to clarify on relationships between measurable variables with an objective to explain, forecast and control a phenomenon (Muijs, 2010). In this study, we decide to see the causal effect occurs between the variation in an independent variable, lead to or results, on average, in variation in another dependent variable. Causality study used to determine what impact a specific change will have on existing norms and assumptions and many social scientist look for causal explanation that reflect test of hypothesis (University of Southern California, 2018).
By using quantitative method, we able to draw a conclusion about the topic from a range of studies. Besides, time series analysis is adopted in our study as it is useful for creating a baseline measure, describing the changes over the time, and keeping track of trends (Campbell & Stanley, 2015). For the time series design, the data is easy to be collected and ease for interpretation (Campbell & Stanley, 2015).

3.2 Source of Data

In accordance to the objective, to study the determinants that affect the Bitcoin price which are velocity of Bitcoin in circulation, computational power, gold price and price of Ethereum. We employ secondary data for our study. Secondary data analysis is examination of data that was collected by someone else for another primary purpose (Johnston, 2017). The data of price of Bitcoin, velocity of Bitcoin in circulation and hash rate are obtained from Blockchain.com. Whereas the data of price of Ethereum is obtained from Etherscan.io. and gold price data is taken from Kitco.com. This analysis is based on time series daily data in range from 2016 Aug 2 to 2018 May 30 which consists of 239 observations. In addition, the sources of data are shown as below:

Table 3.1 Data Sources

Variables	Sources
Price of Bitcoin	Blockchain.com
Supply and Demand	Blockchain.com
Hash Rate	Blockchain.com
Gold Price	Kitco.com
Price of Ethereum	Etherscan.io

3.3 Definition of Variables

3.3.1 Price Formation of Bitcoin

Economist defines value as the amount of desirability towards an object or commodity will, or the amount that an individual would give up in exchange for some other desired commodity. A currency price is simply determined by the basic economic theory such as scarcity, utility and market forces of supply and demand. A useful but rare in amount commodity must contain with value and a specific demand price, with all other things being equal (Ciaian et al., 2016). For example, gold is expensive in terms of its availability and also to satisfy some customers who demand it. These two elements form the value of gold by which the price is determined from the market's supply and demand. Bitcoin is just like gold, it is scarce and useful as it is built on an open protocol where anyone can create on top of it and make the system works better. Bitcoin is scarce in terms of supply where the maximum existence or creation for Bitcoin is cap at 21 million. Price formation of Bitcoin is the continuous interaction of trading between the buyers and sellers that determines the specific price of Bitcoin. The price of Bitcoin is measured in terms of USD.

3.3.2 Velocity of Bitcoin in circulation (Supply and Demand Fundamentals)

Velocity of Bitcoin in circulation is the speed of the Bitcoin changes hand. It is a measurement of how rapidly Bitcoin is circulating in the economy and is determined by the amount of Bitcoin spent in each of the transaction (Michael & William, 2014). Velocity connects the relationship between supply and demand of Bitcoin and it is measured by the supply-demand fundamentals since it follows the standard economic theory which is Quantity Theory of Money. This theory implies the changes in Bitcoin price correspond to changes of Bitcoin supply and demand. Supply of Bitcoin is fixed and pre-determined according to the calculation whereas the Bitcoin demand is unfixed and it is obtained from the favorability of investor to use the Bitcoin as a medium of exchange in transaction (Kristoufek, 2013). Therefore the impact from the demand side is always stronger than the supply side of Bitcoin, and the higher velocity of Bitcoin in circulation is associated with higher demand of Bitcoin.

3.3.3 Computational Power of Bitcoin (Hash Rate)

Mining is a process whereby new Bitcoin is created as a reward for transaction processing work in which users offer their computing power to verify and record payments into the public ledger. Individuals or firms involve in mining activity to earn newly created blocks of Bitcoins. In the process of mining, the miners will require specialize hardware which has a certain amount of computational power, which measured in hashed per second. All the mining effort employed around the world will be accumulated to the Bitcoin network. For instant, every one Gigahash per second that any individual miners put online, the amount will be added to the overall network power. Mining is quite competitive since the probability for the miners who with more computational power and greater efficiency are higher (Hayes, 2015). Hash rate is an indicator of the processing power of the Bitcoin network. For security goal, the latter must make intensive mathematical operations, which representing that an increase in the hash rate and thus the mining difficulty (Bouoiyour & Selmi, 2015). Mining is the only method to obtain a new Bitcoin. By design, the number of Bitcoin generated per block starts at 50 and decreases by a half every 210,000 blocks. A block is generated approximately every ten minutes. The mining difficulty is adjusted every 2016 blocks in order to control over the block generation speed. Higher mining difficulty is associated with more computing power investment per Bitcoin (Li & Wang, 2017).

3.3.4 Gold price

Gold is a type of precious metals traded on the spot and futures market. Based on New York Mercantile Exchange (NYMEX), a contract unit of gold equals to 100 troy ounces where one tick is $0.10 per troy ounce (World Gold Council, 2018). International gold prices are set by the paper gold market where gold prices are derived from London Over-the-Counter (OTC) spot gold market trading and Commodity Exchange (COMEX) gold futures trading. On the other hand, alternative markets like Multi Commodity Exchange (MCX), Shanghai Gold Exchange (SGE) and physical gold markets are typically price takers who take in and use the gold prices established by the paper gold markets in London and New York. The London OTC market mainly involves trading of synthetic non-allocated gold which means that the trades are settle in cash. Whereas for the derivative market, COMEX, the gold is traded in futures and 99.95% of trades are settled in cash. There is only one out of 2500 gold futures contracts is settled in delivery. A very lower chance that the physical gold is delivered to COMEX warehouse and even less gold is withdrawn from it. Moreover, the seller can fulfill the obligation without delivering actual gold when the buyer in COMEX exercises his right to purchase physical gold (Hirani, 2018).The proxy of gold price used in this research is measured in USD, per troy ounce (World Gold Council, 2018).

3.3.5 Price of Ethereum

A decentralized virtual machine, which conducts programs called contract upon request of users is the feature of Ethereum. It is an application which conducted in a precise manner with the absent of the chances in any downtime, censorship, fraud or third-party interference. Custom built block chain was carrying out in these apps. It is an exceptionally dominant shared global infrastructure which allows the value to move around and signify the ownership of property. By using Ethereum, financial player is allowed to register a contract that will hold a contributor's money until the agreed date or goal is reached. Deciding from the outcome, either the funds will be released to the project owners or it will be refunded back to the contributors without any 3rd party such as centralized arbitrator or clearinghouse

(Ethereum Foundation, 2018). An outstanding characteristic of Ethereum's contract is transferring Ether to or for users and to other contract. Ether is the name of the currency used within Ethereum. The price of Ethereum is measured in terms of USD.

3.4 Empirical Model

3.4.1 Functional model:

Price Formation of Bitcoin = f (Velocity of Bitcoin in Circulation, Computational Power of Bitcoin, Gold Price, Price of Ethereum)

3.4.2 The empirical model of this study can be specified as below:

$lnBIT_t = \beta_0 + \beta_1 lnDS_t + \beta_2 lnHR_t - \beta_3 lnGP_t + \beta_4 lnETH_t + \mu_t$

where,

BIT_t= Price Formation of Bitcoin (USD)

DS_t = Velocity of Bitcoin in circulation (unit)

HR_t = Computational Power of Bitcoin (Gigahash/Second)

GP_t = Gold price (USD)

ETH_t= Price of Ethereum (USD)

μ_t = Error that obtained from the data that collected

The expected sign for price formation of Bitcoin and velocity of Bitcoin in circulation is positive which are supported by Bouoiyour and Selmi (2017); Ciaian et al. (2016); Michael and William (2014); Kristoufek (2015). Bitcoin price is able to be explained by the Standard Economic Theory, in specific the

Quantity Theory of Money at which the velocity of Bitcoin in circulation is positively correlated to the Bitcoin price. Whereas the expected sign for price formation of Bitcoin and computational power of Bitcoin is positive sign. This is because when mining difficulty rises, the marginal production cost increases and thus Bitcoin price rises. It is supported by Georgoula et al. (2015); Li and Wang (2017); Hayes (2015). They find out that mining difficulty exerts a positive pressure on Bitcoin price due to the progression in mining technology increases the cost of mining and thus exerts a positively impact on Bitcoin price.

The expected sign for price formation of Bitcoin and gold price is negative sign. According to Bouoiyour and Selmi (2017) and Kristoufek (2015), the rapid increase of gold price in the first period and continues to have a stable decline of gold price during the certain extent of time. Thus, it shows that the gold price negatively correlated with Bitcoin.

On the other hand, the expected sign for price formation of Bitcoin and price of Ethereum is positive sign. Zhang and Song (2013) suggest that there might have a positive relationship between Bitcoin and alternative crypto currency. Study shows a positive relationship between the Bitcoin value and other crypto currencies value competition among a few number of crypto currency in the market and online exchange. As the value of Bitcoin increasea in terms of the USD, the value of the other altcoin will also increase against the USD at a faster rate (Gandal & Halaburda, 2014).

3.5 Analysis Method

3.5.1 Descriptive Analysis

This method is used to summarize continuous data. Large volumes of data may be easily summarized in statistical tables of mean, counts standard deviation and others (NCCS Statistical Software, 2018). Descriptive analysis is succinct descriptive coefficients that sum up a given data set, it would be either a representation of the entire or a sample of a population. There are four types of descriptive analysis. The first type is Measures of Frequency. It includes count, percent and frequency. This category of descriptive analysis is used when we want to show often a response is given. The second type is Measures of Central Tendency. Mean, median, and mode are included in order to locate the distribution by various points. We apply this when we intend to present how an average or most commonly indicated response. Next, Measures of Dispersion or Variation is the third type of descriptive analysis. It consists of range, variance and standard deviation. It is used to show how the data are being "spread out". How the spreading out data affects the mean are very useful. The last category refer to Measures of Position, Percentile ranks and Quartile ranks which are used to examine scores fall in relation to each other.

3.5.2 Unit Root Test

Unit root test is used to test on the stationary of time series variables and to determine whether there is existence of any unit root. When the variable is stationary at a weak level, it is said to be I(0) or else it may be stationary after taking into account a certain degree of differentiation. A unit root of time series will not provide a simple and absolute understanding as it will bring statistical interpretation problems to the empirical economist. In Yule (1926), nonsense correlation can be categorized as the correlation between two unrelated I(1) series. It is either attributes to plus or minus one. Above that, a regression of one I(1) series on another I(1) series will create an R2 that closer to one (Newbold & Granger, 1974). Both the difference stationary and trend stationary are mainly two methods to model the unit root processes.

3.5.3 Autoregressive Distributed Lag (ARDL)

Autoregressive Distributed Lag co integration technique is more likely to be used in dealing variables that are integrated at different order which consist of I(0), I(1) or combination of both in the long run relationship. The model involves unrestricted lag of the regressor in a regression function. This ARDL approach provides realistic and efficient estimates where it helps us to know whether the underlying variables in the model are cointegrated. The advantage of this approach is it has multiple cointegrating vectors as well as lower endogeneity problem because it is free of residual correlation (Nkoro & Uko, 2016).

3.5.4 Granger Causality

Granger Causality is a popular method to examine the casual effect between measurable variables in a time series. Granger causality which being carried out in the time domain or the frequency domain, assumes linear interaction by virtue of the auto-regressive model structure (Oweiss, 2010). This will lead to incorrect conclusions when nonlinear relations occur, mainly in higher level association cortices. The advantage of Granger causality is to identify directional impact of part on another with no any priori hypothesis about which part are involved in particular sub networks (Hickok & Small, 2015).

3.5.5 Impulse Response Function

Impulse Response Function is useful to satisfy the interest of ones to know the interaction between one variable to another variable in a model that involved a few of other variables by investigating the response of the variable give an impulse in another variable (Rossi, n.d.).This method is often used after Granger Causality test since Granger Causality may only tell the direction of causal relationship without focusing on the complete story of the relationship. Impulse Response Function is able to indicate the sign of the relationship and effect in long run or short run within a specified time frame after a shock in a given moment (Alloza, n.d.).

3.5.6 Variance Decomposition Analysis

Variance Decomposition Analysis is a prominent tool to indicate the amount or percentage of the shock of each variable impacts the forecast error of the dependent variable. It is also a method to determine and quantify the importance of each shocks in explaining the variation in each of the variables in the model (Sims, 2011).The advantage of Variance Decomposition Analysis is it is able to measure the magnitude of the relevant effect which is limitation of Impulse Response Function (Lau, Yii, Lee, Chong & Lee, 2018).

3.5.7 Diagnostic test

Breusch-Godfrey Serial Correlation LM Test is a test to assess the validity of some of the modeling assumptions inherent in applying regression-like models to observed data series. The purpose of carrying the test is to identify the presence of serial correlation that has not been included in a proposed model structure. If serial correlation is found that present in the test, it implies that incorrect conclusions would be drawn from other tests.

Multicollinearity exists when there are two or more of the variables in a regression model are moderately or highly correlated. The coefficients become unstable and the standard errors can get wildly inflated when the degree of multicollinearity increases. Whenever a variable whose Variance Inflation Factor (VIF) value greater than 10 are subjected to further checking. Tolerance is used to check on the degree of collinearity.

Heteroscedasticity test is a test to figure out whether the variance of the errors from a regression is dependent on the values of the independent variables. Heteroscedasticity is a systematic change in the spread of the residuals over the range of measured values. Heteroscedasticity is a problem since ordinary least squares (OLS) regression has an assumption which is all residuals are drawn from a population that has a constant variance or known as homoscedasticity.

Ramsey's RESET test is designed to recognize if there are any neglected nonlinearities in the model. If there is any nonlinear combinations of the explanatory variables have effect in explaining the response variable, the model will be stated as a misspecified model. In this case, the data generating process might be better approximated by a polynomial or another non-linear functional form.

CHAPTER 4 : DATA ANALYSIS

4.0 Introduction

Chapter 4 provides a research finding analysis based on data that has been collected. EViews is used to analyze the data and generate the results which used to examine the hypotheses that have been constructed in this study. Several analyses have been presented in this chapter which consists of descriptive analysis, scale measurement and inferential analysis.

4.1 DESCRIPTIVE ANALYSIS

As mentioned in the third chapter, Auto regressive distributed lag model (ARDL) has been chosen as the primary approach in the study to examine the determinants that would affect the price formation of Bitcoin from 2016 Aug 2 to 2018 May 30. The analysis consists of 239 observations.

Table 4.1 Summary of Descriptive Statistic

	BIT	DS	HR	GP	ETH
Mean	4490.767	270751.2	9511783.0	1274.207	292.8347
Maximum	17771.90	425008.0	37253335.0	1363.750	1261.030
Minimum	515.0619	131875.0	1426365.0	1125.700	7.2100
Std Dev	4386.674	52774.21	9144097.0	51.76469	313.4155

Table 4.1 present the descriptive statistics of the variables applied in our study. The mean of Bitcoin price (BIT) is amounted to 4490.767 USD with standard deviation of 4386.674 over the period of 2016 Aug 2 to 2018 May 30. Bitcoin price can reach up to as high as 17771.90 USD or as low as 515.0619 USD throughout this period.

According to Coindesk, Bitcoin price increases by 15 times in year 2017 and fell dramatically in the first month of 2018. Bitcoin price has been very unstable as Bitcoin limit its supply.

Besides, the average of velocity of Bitcoin in circulation (DS) is reported as 270751.2 per unit with the maximum and minimum values of 425008 unit and 131875 unit respectively. The standard deviation is higher than the Bitcoin price which is 52774.21.

Moreover, the average of hash rate of Bitcoin (HR) is 9511783 Gigahash/Second. The hash rate of Bitcoin can achieve as high as 37253335 Gigahash/Second or as low as 1426365 Gigahash/Second. It shows the highest standard deviation which is 9144097 compared to other variables.

Gold price (GP) has a mean of 1274.207 USD. The maximum value is 1363.75 USD while the minimum value is 1125.70 USD. Gold price has the lowest standard deviation based on the observation which is 51.76469.

Lastly, the average of Ethereum price (ETH) is 292.8347 USD. The highest Ethereum price is 1261.030 USD while the lowest is 7.21 USD. According to coindesk, Ether prices have fallen 60 percent in the time and are now losing a 94 percent from the highest of 1,431 USD hit in January 2018. Hence, the standard deviation is 313.4155 which is less fluctuate than Bitcoin price.

4.2 Unit Root Test

Table 4.2 and 4.3 show the outcome of the Augmented Dickey Fuller (ADF) and Philips Perron (PP) unit root test for the five variables both at level and first difference of the natural log values.

Table 4.2 Augmented Dickey Fuller (ADF)

Augmented Dickey-Fuller Unit Root Test				
	At Level		First Difference	
Variables	Intercept	T&I	Intercept	T&I
Lgbit	-1.144062	-0.984352	-14.41027***	-14.40876***
Lgds	-3.130467**	-3.359339*	-11.66499***	-11.69163***
Lghr	0.742474	-2.867813	-11.39115***	-11.44120***
Lggp	-2.265409	-2.930572	-15.60466***	-15.63149***
lgeth	-1.077855	-0.774993	-14.38056***	-14.36224***

Notes: ***, ** and * denote significance at 1%, 5% and 10%, respectively

Table 4.3 Philips Perron (PP) unit root test

Phillips-Perron Unit Root Test				
	At Level		First Difference	
Variables	Intercept	T&I	Intercept	T&I
Lgbtc	-1.138069	-1.254692	-14.43122***	-14.42842***
Lgds	-4.757713***	-5.005435***	-42.03910***	-51.45227***
Lghr	0.193634	-8.785287***	-56.74243***	-101.8258***
Lggp	-2.321108	-2.925952	-15.60466***	-15.63120***
lgeth	-1.073656	-1.095839	-14.46650***	-14.45018***

Notes: ***, ** and * denote significance at 1%, 5% and 10%, respectively

Table 4.2 and 4.3 show the result generated from Augmented Dickey Fuller (ADF) and Philips Perron (PP) unit root test. The tables above show that all of the variables (Bitcoin price-lnbit, Demand velocity of Bitcoin in circulation-lnds, Hash rate of Bitcoin-lnhr, Gold price-lngp, Price of Ethereum- lnether). All of the variables in Augmented Dickey Fuller (ADF) unit root test conducted are unable to reject null hypotheses except for the demand and supply of Bitcoin in the level. The p-value of demand and supply of Bitcoin is less than 0.05 significant levels, which means that all variables are not stationary and contain of unit root test at the level except for DS.

Moreover, when progresses to Philips Perron (PP) unit root test, the variables that reject the null hypothesis as the p-value show are less than 0.05 significant level contain of velocity of Bitcoin in circulation(DS), hash rate of Bitcoin (HR) and Price of Ethereum (Ether). The reason is that these three variables are stationary and do not contain of unit root at level form.

Based on the result in Table 4.2 and Table 4.3, we know that at the first difference of Augmented Dickey Fuller (ADF) and Philips-Perron (PP) unit root test, all variables are able to reject null hypothesis as all the p-values are less than 0.05 significant levels. Hence, all the variables are stationary and do not contain of unit root test in the first difference when carry on to the first difference in the Augmented Dickey Fuller (ADF) and Philips Perron (PP) unit root test.

In view of the fact that this study has to ensure all the variables are able to reject the null hypothesis at the level form. However, the result only being rejected after the first difference and thus the results are unable to provide important long run information.

4.3 Auto Regressive Distributed Lag (ARDL)

Table 4.4 ARDL Bound Test

Model	**F-statistic**	
BIT=f (DS, HR, GP,ETH)	**2.384577**	
Optimal lag	**[1,0,0,0,4]**	
Critical value	**I(0)**	**I(1)**
1% significance level	**3.29**	**4.37**
5% significance level	**2.56**	**3.49**
10%significance level	**2.2**	**3.09**

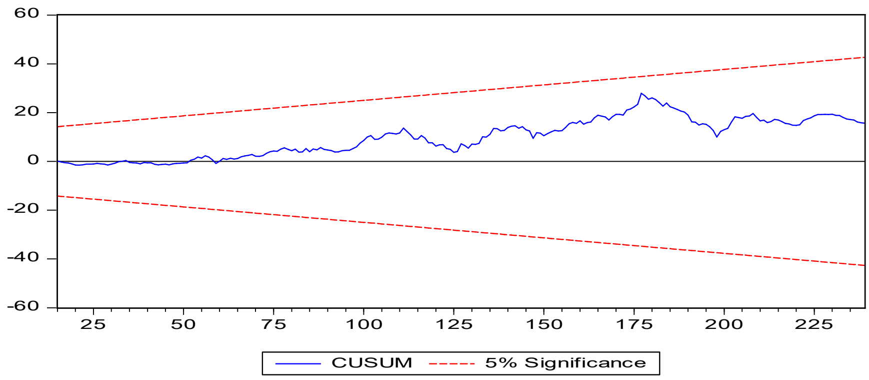
Diagnostic test	**F -Statistic**
Breusch-Godfrey Serial Correlation LM Test	0.544730 (0.5808)
Heteroscedasticity Test (ARCH)	0.403855 (0.5251)
Ramsey RESET Test	0.174096 (0.6769)

Notes: () refers to p-values.

Table 4.4 presents the results of the bounds test based on formation of Bitcoin price (BIT) and its determinants. The computed F-statistic of 2.3846 in ARDL bound test is lower than the upper critical bound value of 4.37 at 1, 5, and 10% significance level. This implies that the null hypothesis of no cointegration cannot be accepted at the 1%, 5% and 10% level. Hence, there is no cointegration relationship among the variables.

The optimal lag selected is one based on AIC test. The robustness of the model is confirmed by the diagnostic tests such as Breusch-Godfrey serial correlation Lagrange multiplier (LM) test, Heteroscedasticity (ARCH) Test and Ramsey RESET. Based on the results, our model is free from serial correlation problem and heteroscedasticity problem. Furthermore, Ramsey RESET test shows that there is no functional form misspecification. Other than that, plots of cumulative sum (CUSUM) in Figure 1 indicate that no misspecification and structural instability of long-run and short-run estimated parameters emerged in the sample period. Hence, this means that the estimated parameter of the model construct a reliable estimation.

Figure 2: Plot of cumulative sum (CUSUM) test for the model



Moreover, Multicollinearity Test is used to test whether between or among the exogenous variables have linear or non-linear relationship. High pair-wise correlation coefficients can be used to measure the degree of correlation among two or more variables which range from -1 to 1. Thus, if the correlation between 2 independent variables is more than 0.8, there could be a possible of serious multicollinearity occurred in the model.

Table 4.5 Correlation Analysis

	LNDS	LNHR	LNGP	LNETH
LNDS	1.000000	-0.261919	-0.417545	-0.151046
LNHR	-0.261919	1.000000	0.457112	0.912722
LNGP	-0.417545	0.457112	1.000000	0.506034
LNETH	-0.151046	0.912722	0.566034	1.000000

As shown in the correlation analysis in table 4.5, the highest pair-wise correlation between price of Ethereum and hash rate of Bitcoin is 0.912722. Therefore, this study will carry out regression analysis for the high pair wise correlation between the independent variables in order to get R^2 to conduct VIF and TOL.

Table 4.6 Results of VIF and TOL

	LNDS	**LNHR**	**LNGP**	**LNETH**
LNDS	1.0000 (1.0000)	1.0737 (0.9314)	1.2112 (0.8257)	1.0227 (0.9778)
LNHR	1.0737 (0.9314)	1.0000 (1.0000)	1.2642 (0.7910)	5.9902 (0.1669)
LNGP	1.2112 (0.8257)	1.2642 (0.7910)	1.0000 (1.0000)	1.3442 (0.7439)
LNETH	1.0227 (0.9778)	5.9902 (0.1669)	1.3442 (0.7439)	1.0000 (1.0000)

Notes: () refers to result of TOL

Based on the result above, all of the degree of VIF and TOL of the four independent variables is fall between 1 and 10 (no serious multicollinearity) and is more than zero. Thus, this model has no serious multicollinearity problem existed in the model. The estimated parameters are unbiased, efficient and consistent.

Table 4.7 Long-run coefficient of formation of Bitcoin price

Variable	Coefficient	Standard Error	T-satistic
C	**-19.860**	**28.029**	**1.565**
LNDS	**1.911****	**0.794**	**-0.203**
LNHR	**0.447**	**0.286**	**2.424**
LNGP	**-0.659**	**3.244**	**-0.709**
LNETH	**0.387****	**0.160**	**2.407**

Notes: ***, ** and * denote significance at 1%, 5% and 10%, respectively

The results of long run elasticity of independent variables on formation of Bitcoin price as shown in table 4.7. Based on the results, all the explanatory variables are found to be significant in affecting the formation of Bitcoin price except for HR and GP. It is proved that the velocity of Bitcoin in circulation (DS) shows a positive and significant coefficient all the way through the long run at 5% and 10% significance level. According to Ciaian et al. (2016) and Buchholz et al. (2012), the key factor that would affect the formation of Bitcoin price is always affected by the market force which is the supply and demand of the Bitcoin. Thus, when there is 1 % increase in velocity of Bitcoin in circulation, on average, the price of Bitcoin would increase by 1.911%, holding other variables constant. The result is supported in the VAR Granger Causality as the velocity of Bitcoin in circulation (DS) will significantly affect Bitcoin price in a short run relationship at 1% significance level.

Moreover, computational power of Bitcoin miners (HR) shows a positive but insignificant relationship towards the Bitcoin price in a long run relationship. When there is an increase in percentage of computational power of Bitcoin miners (HR), on average, it will increase the Bitcoin price by 0.447%, holding other variables constant. According to Li and Wang (2017), they obtain the result as mining difficulty and Bitcoin price have positive relationship by employing different method. This result implies that the effect of mining difficulty on Bitcoin price grows weaker over the time. This is because the development in mining technology will reduce the cost of mining and thus a positive impact on formation of Bitcoin price.

On the other hand, gold price (GP) surprisingly is barely a determinant to manipulate Bitcoin price. Based on our result, GP shows a negative but insignificant relationship toward the Bitcoin price which mean when 1% increase in gold price, on average, there will be a decrease of 0.659% in Bitcoin price, holding other variables constant. As virtual currency is more affected by macro financial indicators in the short run than in the long run, so gold price has no influence on Bitcoin price in the long run however the short run causality exists (Zhu, Dickinson & Li, 2017).

Besides, price of Ethereum shows a positive and significant relationship all the way through the long run at 5% and 10% significance level. The value 0.387 implies that when there is an additional percentage increase in Ethereum price (ETH), on average, the Bitcoin price will increase by 0.387%, holding other variables constant. This prove that there is a substitution effect occurred between Bitcoin and Ethereum. Our finding agrees with Ethereum may be a substitute for Bitcoin. This is because the crypto currency market does not truly show a strong network effect, and with new runners-up like Ethereum or Litecoin, Bitcoin is facing a quantity of serious competitions from newer crypto currency for its main player role (Nguyen, de Bodisco & Thaver, 2018). Bitcoin has grown to be more popular and more people demand for it, the financial player in the market may fear that the value of Bitcoin might be overestimated and hence look for substitution crypto currency (Gandal & Halaburda, 2014).

4.4 VAR Granger Causality

Table 4.8 VAR Granger Causality

Dependent Variable	Bit	DS	HR	GP	Ether
Bit	-	1.654552	1.326269	0.855375	2.278811
DS	14.33947***	-	15.28804***	3.999213	2.400673
HR	11.12308***	10.62047***	-	1.575881	1.151596
GP	1.045123	1.360851	0.588393	-	2.193380
ETH	1.108335	7.162368***	1.810436	0.494806	-

Notes: ***, ** and * denote significance at 1%, 5% and 10%, respectively

The results of granger causality as shown in table 4.8 pointed out that formation of Bitcoin price (BIT) does granger-cause velocity of Bitcoin in circulation (DS) in a unidirectional way at 1% significance level. This affirms the findings of Bouoiyour and Selmi (2017) where the results show that the constantly increasing demand of Bitcoin in a fixed supply causes the Bitcoin price to be raised while the supply is negatively correlated with Bitcoin price. However, our findings show contrast from the study done by Kristoufek (2013) who found no causality between supply-demand fundamentals and Bitcoin price.

Moreover, a bidirectional causal relationship is found from computational power of Bitcoin miners (HR) to velocity of Bitcoin in circulation (DS) at 1% significance level. This implies that the hash rate is influencing the Bitcoin price. Similar to findings obtained by Li and Wang (2017), they find out that mining difficulty exerts a positive pressure on Bitcoin price.

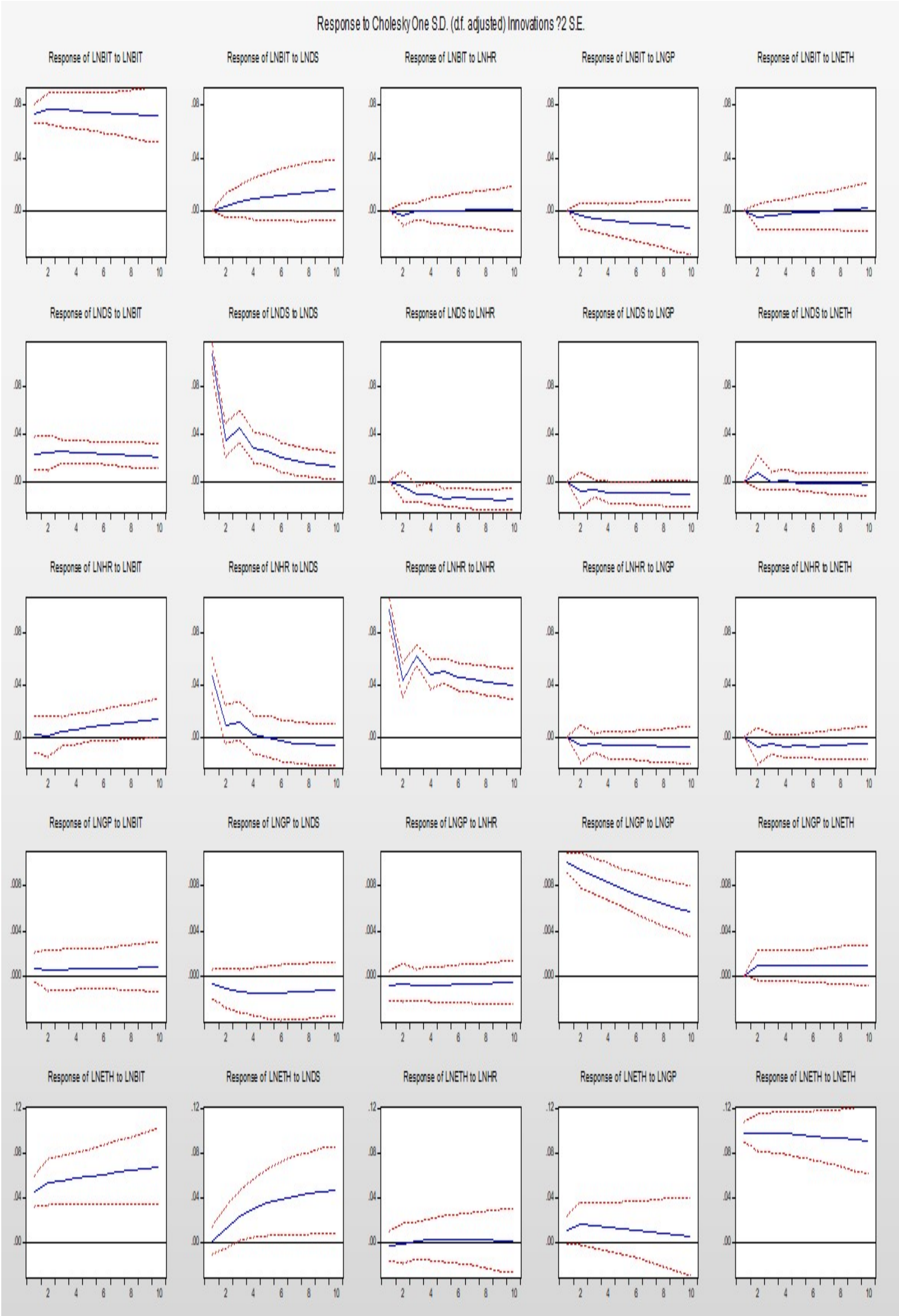
In a nutshell, the velocity of Bitcoin in circulation has significant causal effect with price of Ethereum at 1% significance level. Based on the results, the substitution effect has occurred between Ethereum and Bitcoin. Our result agrees on the research done by Gandal and Halaburda (2014) where they state that the occurrence of substitution effect between Bitcoin and altcoin had happened.

4.5 Impulse Response Function

Figure 2 shows the results of impulse response function that reflect the destabilization experienced by the endogenous variables (BIT-Price Formation of Bitcoin, DS-Velocity in Bitcoin Circulation, HR-Computational Power of Bitcoin Miners, GP-Gold Price and ETH-Price of Ethereum) in response to one external standard deviation (SD) shock within other variables. Bitcoin price is found to be quite passive to its own shock with the continuing slight negative effect. Besides, the response of BIT to one SD shock of DS indicates the steadily positive trend from the second year to tenth year. This supports the long-run positive relationship between the velocity of Bitcoin in circulation and the price formation of Bitcoin. Nevertheless, the BIT would remain unchanged from the fourth year until tenth year when there is one SD shock given to hash rate. Same goes to the impulsive response between BIT and ETH where BIT shows slight response in SD shock. Moreover, BIT shows negative response to gold price as the impact on BIT from the shock of GP continues to decline until tenth year.
In addition, DS and GP remain stable from the occurrence of a shock in BIT whereas HR and ETH went up gradually when there is one SD shock given to BIT.

Furthermore, the response of DS and HR to their own shock is found to be significantly impacted. It plunged till the second year, rose at the second year then continually decline till tenth year. However, the response of GP and ETH to their own shock is significant as it decline gently from first year until tenth year. On the other hand, GP response is found to be negative after the first year when there is an occurrence of shock in DS. It shows the same result of HR response to GP.

Figure 3 : Impulse Response Function



4.6 Variance decomposition analysis

Table 4.9 shows the results of variance decomposition analysis (VDC) for price formation of Bitcoin. The results show that 96.44% of Bitcoin price is explained by its own shocks. The price of Ethereum seems to be the major driver of Bitcoin price as it displays a percentage of 25.47%. However, the results indicate that gold price (GP) and computational power of Bitcoin miners (HR) play a minor role in determining the price of Bitcoin where show only 0.73% and 2.49%. The VDC for price formation of Bitcoin clearly imply that the velocity in Bitcoin circulation (DS) and price of Ethereum (ETH) are undoubtedly explaining the price formation of Bitcoin. The shocks to BIT in response to a one standard deviation innovation in DS and ETH highly range from 0% to 21.57% and 25.47%. This indicates that the velocity of Bitcoin in circulation and the price of Ethereum are significant in contributing the price formation for Bitcoin.

Furthermore, the VDC of DS reveals the most significant shocks effect of BIT (21.57%) towards the shocks of DS compared to HR (6%), GP (2.92%) and ETH (0.32%) respectively. Nonetheless, the VDC of HR implies that the shocks effect of DS highly responds to one standard deviation innovation in HR. This is in line with the study done by Ciaian et al. (2016) and Buchholz et al. (2012) where they mentioned that the key determinant of Bitcoin price and the price fluctuation are affected by the market force which is the supply and demand of the Bitcoin. Moreover, the contributions of BIT, DS, HR and ETH to GP are amounted to 0.73%, 2.58%, 0.77% and 1.19% respectively. In addition, the changes of ETH are clarify by one standard deviation shock in BIT, DS, HR and GP with the percentage of 25.47%, 8.94%, 0.05% and 1.05% respectively.

Table 4.9 Variance decomposition analysis for price formation of Bitcoin

Variance Decomposition of LNBIT						
Period	S.E	LNBIT	LNDS	LNHR	LNGP	LNETH
1	0.073332	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.106693	99.53504	0.107523	0.067389	0.110445	0.179607
3	0.131632	99.19794	0.343880	0.044305	0.224985	0.188890
4	0.152258	98.84564	0.609592	0.033437	0.341379	0.169851
5	0.170227	88.46867	0.896609	0.028153	0.463536	0.143032
6	0.186321	98.07703	1.183377	0.025216	0.594201	0.120174
7	0.201019	97.67346	1.465196	0.024773	0.732953	0.103617
8	0.214615	97.26432	1.737433	0.025058	0.879135	0.094056
9	0.227318	96.85192	1.999112	0.025983	1.031510	0.091477
10	0.239276	96.43881	2.249840	0.026998	1.188899	0.095453
Variance Decomposition of LNDS						
Period	S.E	LNBIT	LNDS	LNHR	LNGP	LNETH
1	0.110056	4.626924	95.37038	0.000000	0.000000	0.000000
2	0.118534	8.052309	90.98991	0.104753	0.416466	0.436557
3	0.130201	10.44050	87.80439	0.801100	0.592192	0.361821
4	0.136185	12.82057	84.56955	1.320415	0.950018	0.339449
5	0.141731	14.79611	81.42764	2.183180	1.275264	0.317810
6	0.146082	16.58130	78.54370	2.940207	1.631011	0.303780
7	0.150025	18.10481	75.84003	3.781867	1.972175	0.301112
8	0.153502	19.43617	73.40233	4.553552	2.305440	0.302499
9	0.156686	20.57806	71.18453	5.307703	2.620923	0.308780
10	0.159588	21.56539	69.19565	6.002727	2.919311	0.316929
Variance Decomposition of LNHR						
Period	S.E	LNBIT	LNDS	LNHR	LNGP	LNETH
1	0.108609	0.062939	18.96202	80.97504	0.000000	0.000000
2	0.117738	0.056520	16.83942	82.47208	0.213668	0.418314
3	0.133985	0.157783	13.81307	85.26448	0.291485	0.473181
4	0.142698	0.296245	12.20037	86.39562	0.433403	0.674361
5	0.151813	0.520378	10.77949	87.38363	0.543436	0.773065

6	0.159099	0.801037	9.850565	87.81187	0.657595	0.878928
7	0.166002	1.143958	9.112925	88.04423	0.757272	0.941615
8	0.172171	1.541425	8.562846	88.05811	0.850517	0.987104
9	0.177948	1.991706	8.113076	87.95179	0.934582	1.008847
10	0.183305	2.492030	7.740624	87.73996	1.012191	1.015199
Variance Decomposition of LNGP						
Period	S.E	LNBIT	LNDS	LNHR	LNGP	LNETH
1	0.010145	0.520320	0.475649	0.680569	98.32347	0.000000
2	0.013917	0.405879	0.904616	0.579771	97.64511	0.464622
3	0.016601	0.403544	1.293493	0.647716	97.02181	0.633436
4	0.018661	0.428890	1.616086	0.674615	96.53636	0.744050
5	0.020315	0.464919	1.885365	0.709917	96.11348	0.826316
6	0.021677	0.508072	2.101966	0.731893	95.75670	0.901364
7	0.022816	0.556208	2.273379	0.749593	95.44772	0.973097
8	0.023780	0.608813	2.405739	0.760709	95.17943	1.045314
9	0.024603	0.665529	2.505572	0.767779	94.94225	1.118873
10	0.025310	0.726328	2.578519	0.771180	94.72937	1.194604
Variance Decomposition of LNETH						
Period	S.E	LNBIT	LNDS	LNHR	LNGP	LNETH
1	0.108372	17.45706	0.030177	0.050638	1.175866	81.28626
2	0.157028	20.09409	0.755185	0.025201	1.700417	77.42511
3	0.195177	21.16700	1.965344	0.024140	1.752194	75.09132
4	0.227950	21.86860	3.232706	0.033237	1.695119	73.17034
5	0.257269	22.46481	4.461673	0.043828	1.598323	71.43136
6	0.284044	23.04075	5.581397	0.051523	1.486031	69.84030
7	0.308825	23.62440	6.583249	0.055526	1.370180	68.36664
8	0.331978	24.22398	7.469045	0.056217	1.256936	66.99382
9	0.353767	24.83966	8.250422	0.054464	1.149776	65.70568
10	0.374395	25.46864	8.940005	0.051189	1.050632	64.48954

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATION

5.0 Introduction

Chapter 5 provides a discussion of major research findings for the hypotheses testing, implications and limitations of the study as well as it provides a channel for future research.

5.1 Discussions of Major Findings

This research attempts to clarify on the Bitcoin price fluctuations. We intend to construct a clearer understanding of the fluctuations by looking for which variables that may influence the Bitcoin price by estimating an ARDL model.

Therefore, we have regressed Bitcoin price on demand and supply of Bitcoin, hash rate of Bitcoin, gold price and price of Ethereum using ARDL Bounds Testing method, Augmented Dickey Fuller (ADF), Philips Perron (PP) unit root test and VAR Granger Causality test for daily data covering the period from 2016 Aug 2 to 2018 May 30.

Results obtained from the long run elasticity of independent variables on formation of Bitcoin price reveal that demand and supply of Bitcoin and price of Ethereum are the main determinants that affecting the price of Bitcoin. The result shows that these both factors exert positive pressure on Bitcoin price. It is found that hash rate of Bitcoin and gold price are insignificantly affecting Bitcoin price.

On the other hand, from the result of VAR Granger Causality test, it implies an unidirectional causality relationship running from Bitcoin price to demand and supply of Bitcoin and also from demand and supply of Bitcoin to price of Ethereum. This explains that when Bitcoin price increases, the demand of Bitcoin will increase by assuming the supply is fixed since more people willing to invest in Bitcoin. As the demand of Bitcoin increases, the price of Ethereum rises also due to the substitution effect between Ethereum and Bitcoin. Therefore, there is an indirect impact of Bitcoin price on Ethereum price. Moreover, it is also proved that there is an unidirectional Granger causality is running from Bitcoin price to hash rate of Bitcoin, but not vice versa. It proves that when Bitcoin price increases, hash rate of Bitcoin also increases since more people are trying to mine Bitcoin thus causes the mining difficulty level increases. As an impact, higher hash rate is required in order to get the Bitcoin. Furthermore, it is confirmed that there is a bidirectional Granger causality exists between hash rate of Bitcoin and velocity of Bitcoin. When the demand of Bitcoin increases by assuming supply is constant, there is a positive effect on the hash rate of Bitcoin.

5.2 Implications of the Study

Our findings found several key implications for velocity of Bitcoin in circulation and Bitcoin price. There is a significant relationship between velocity of Bitcoin in circulation and Bitcoin price. When there is more transaction incurred using Bitcoin, the velocity of Bitcoin in circulation tends to be quicker. Bitcoin price formation and the role of a medium of exchange is heavily contributable in applying the monetary policy point of view and economic point of view. Above that allowing government and policy makers have a clear view in developing effective policies in order to safeguard Bitcoin price which will affect the supply and demand of Bitcoin.

Relevant authorities are calling for the implementation of proportionate regulation to improve standards and encourage the growth of crypto currency. Regulation may cause the demand for Bitcoin change. This is because consumers are exposed to the unregulated market that aid money laundering given the high price volatility and the hacking vulnerability of exchanges. The price of crypto-assets is also volatile where the potential gains are large as well as for the potential losses (Monaghan, 2018). Moreover, governments should take the option or completely block Bitcoin or other crypto currencies that do not follow the regulation. This would be difficult to impose the regulation as government had found it is difficult to be completely blocked access to websites (Kristjanpoller & Minutolo, 2018).

In addition, crypto currency providers should also act as regulators by ensuring that anti money laundering regulations are complied with. Some of the existing exchanges like Coinbase had enforced the regulations in order to control the supply and demand of Bitcoin in the market. In the event that Bitcoin is decentralized and not regulated, policy makers should understand how crypto currency fit into the national and global economic systems. They should continue to formulate methods for centralizing a decentralized asset. The U.S. Securities and Exchange Commission has initiated plans to regulate the crypto currencies. Generally, by implementing appropriate regulations and policy for crypto currencies tend to build up consumer's confidence towards crypto currency and thus, affect the supply and demand of Bitcoin in the market (Chu, Chan, Nadarajah & Osterrieder, 2017).

Over the past several years, the use of crypto currency has been increased drastically especially Bitcoin and Ethereum. Financial investors, central banks and government are concern and worry about crypto currency and its potential to interrupt currency markets and operational control to supervise against fraud, terrorist financing and money laundering (The Implication of Blockchain and cryptocurrency, 2018). On the other hand, the technology and equipment behind the crypto currency has the potential to transform the payment system supply chain and make available additional security for private and confidential information. Financial industries are heavily regulated internationally, the implementation of crypto currency within the investor will depend on government acceptance and action (Smith, 2018). Consequently, policy makers should change their perspective to be more collaborative with the industries versus reactive to adjust.

Besides, our model proves that price of Ethereum has a significant in explaining the price formation of Bitcoin in long run. Ethereum has a substitution effect on Bitcoin. It means when there is an increase in Bitcoin price; it will lead to an increase in Ethereum price. This is because Bitcoin is facing various severe competitions from newer crypto currency for its dominant player role. As a result, central banks are recommended to develop and launch their own crypto currency as an alternative or even a replacement for their current money base. This might help the central banks to develop a new crypto currency that come out with different function and purpose in order to maintain the price of Bitcoin and prevent in overestimating Bitcoin value. While Bitcoin's investors think about a decentralized payment system, Ethereum's investors will prefer a block chain system that can construct more application ahead. Hence, financial investor will prefer a less risky and less competitive crypto currency to invest. The governor of the Bank of England has widely uttered interest in the idea of a crypto currency backed by a central bank and Sweden's Riksbank is actively involved in launching an "e-krona" crypto currency within next decade (O'Sullivan, 2018).

Central banks are recommended to implement crypto currency technologies that might need to make decision on to the issuance of a digital currency whose monetary issue is centralized in hands of the bank. Crypto currency can provide a very similar purpose to currency which is a semi-anonymous medium of exchange available not only to banks but also the residents. The characteristics and functions of crypto currency are attractive as it may be cheaper and easier to control than a cash system. The block chain technology also allows for cross border payment, lower cost and able to settle payment in real time (Smith, 2018). Bank of Canada and Monetary Authority of Singapore are imitating real time gross settlement system using a block chain like structure and may acquire constructive tools for forward looking central banks (O'Sullivan, 2018).

5.3 Limitations of the Study

The existence of a number of limitations in this study may give chances for future research. Basically, the study is only paying attention on four factors as independent variables which may influence the Bitcoin price in spite of including other factors which have been mentioned by other researches. Thus, factors such as availability of currency exchange, government regulations and legal matters are not presenting in this study.

Moreover, the method of data collection in the study is purely relying on quantitative approaches where the results presented are more reliable and consistent. However, a comprehensive picture of the research findings cannot be provided in such way compared to the qualitative methodology. Consequently, the factors such as the digital behavioral traces of investors by means of social media use, search queries and user base may not be able to explain in this study.

5.4 Recommendations for Future Research

First of all, additional independent variables that have been proposed by previous studies are encouraged to be included by future researchers in order to enhance and extend the research model that is currently adopted in this study. The reasons above also bring in contributing the determination of Bitcoin price.

Besides, future research could extend current data collection method into other research methodology. Future researchers are recommended to apply other research methodologies such as questionnaires, survey, and case study in order to provide better insights of crypto currency and understanding about the determinants of Bitcoin price.

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APPENDICES

Appendix 4.1 Descriptive Statistic (*Source: Developed for research via EViews 10.0)*

	BITCOIN	DS	HR	GP	ETHER
Mean	4490.767	270751.2	9511783.	1274.207	292.8347
Median	2585.349	269280.0	5277829.	1275.600	227.0900
Maximum	17771.90	425008.0	37253335	1363.750	1261.030
Minimum	515.0619	131875.0	1426365.	1125.700	7.210000
Std. Dev.	4386.674	52774.21	9144097.	51.76469	313.4155

Appendix 4.2 Augmented Dickey-Fuller Unit Root Test (*Source: Developed for research via EViews 10.0)*

Null Hypothesis: LNBIT has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.144062	0.6985
Test critical values:	1% level	-3.457747	
	5% level	-2.873492	
	10% level	-2.573215	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNBIT has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.984352	0.9430
Test critical values:	1% level	-3.997083	
	5% level	-3.428819	
	10% level	-3.137851	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNBIT) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.41027	0.0000
Test critical values:	1% level	-3.457865	
	5% level	-2.873543	
	10% level	-2.573242	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNBIT) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.40876	0.0000
Test critical values:	1% level	-3.997250	
	5% level	-3.428900	
	10% level	-3.137898	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNDS has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.130467	0.0257
Test critical values:	1% level	-3.457865	
	5% level	-2.873543	
	10% level	-2.573242	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNDS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.359339	0.0595
Test critical values:	1% level	-3.997250	
	5% level	-3.428900	
	10% level	-3.137898	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNDS) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.66499	0.0000
Test critical values:	1% level	-3.458225	
	5% level	-2.873701	
	10% level	-2.573327	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNDS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.69163	0.0000
Test critical values:	1% level	-3.997758	
	5% level	-3.429146	
	10% level	-3.138043	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNHR has a unit root
Exogenous: Constant
Lag Length: 5 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.742474	0.9928
Test critical values:	1% level	-3.458347	
	5% level	-2.873755	
	10% level	-2.573355	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNHR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.867813	0.1750
Test critical values:	1% level	-3.997758	
	5% level	-3.429146	
	10% level	-3.138043	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNHR) has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.39115	0.0000
Test critical values:	1% level	-3.458347	
	5% level	-2.873755	
	10% level	-2.573355	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNHR) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.44120	0.0000
Test critical values:	1% level	-3.997930	
	5% level	-3.429229	
	10% level	-3.138092	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNGP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.265409	0.1842
Test critical values:	1% level	-3.457747	
	5% level	-2.873492	
	10% level	-2.573215	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNGP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.930572	0.1548
Test critical values:	1% level	-3.997083	
	5% level	-3.428819	
	10% level	-3.137851	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNGP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-15.60466	0.0000
Test critical values:	1% level	-3.457865	
	5% level	-2.873543	
	10% level	-2.573242	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNGP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-15.63149	0.0000
Test critical values:	1% level	-3.997250	
	5% level	-3.428900	
	10% level	-3.137898	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNETH has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.077855	0.7249
Test critical values:	1% level	-3.457747	
	5% level	-2.873492	
	10% level	-2.573215	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNETH has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.774993	0.9654
Test critical values:	1% level	-3.997083	
	5% level	-3.428819	
	10% level	-3.137851	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNETH) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.38056	0.0000
Test critical values:	1% level	-3.457865	
	5% level	-2.873543	
	10% level	-2.573242	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNETH) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.36224	0.0000
Test critical values:	1% level	-3.997250	
	5% level	-3.428900	
	10% level	-3.137898	

*MacKinnon (1996) one-sided p-values.

Appendix 4.3 Phillips-Perron Unit Root Test (*Source: Developed for research via EViews 10.0)*

Null Hypothesis: LNBIT has a unit root
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.138069	0.7010
Test critical values:	1% level	-3.457747	
	5% level	-2.873492	
	10% level	-2.573215	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNBIT has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.254692	0.8960
Test critical values:	1% level	-3.997083	
	5% level	-3.428819	
	10% level	-3.137851	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNBIT) has a unit root
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-14.43122	0.0000
Test critical values:	1% level	-3.457865	
	5% level	-2.873543	
	10% level	-2.573242	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNBIT) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-14.42842	0.0000
Test critical values:	1% level	-3.997250	
	5% level	-3.428900	
	10% level	-3.137898	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNDS has a unit root
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.757713	0.0001
Test critical values:	1% level	-3.457747	
	5% level	-2.873492	
	10% level	-2.573215	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNDS has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-5.005435	0.0003
Test critical values:	1% level	-3.997083	
	5% level	-3.428819	
	10% level	-3.137851	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNDS) has a unit root
Exogenous: Constant
Bandwidth: 53 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-42.03910	0.0001
Test critical values:	1% level	-3.457865	
	5% level	-2.873543	
	10% level	-2.573242	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNDS) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 57 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-51.45227	0.0001
Test critical values:	1% level	-3.997250	
	5% level	-3.428900	
	10% level	-3.137898	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNHR has a unit root
Exogenous: Constant
Bandwidth: 103 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		0.193634	0.9717
Test critical values:	1% level	-3.457747	
	5% level	-2.873492	
	10% level	-2.573215	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNHR has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.785287	0.0000
Test critical values:	1% level	-3.997083	
	5% level	-3.428819	
	10% level	-3.137851	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNHR) has a unit root
Exogenous: Constant
Bandwidth: 92 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-56.74243	0.0001
Test critical values:	1% level	-3.457865	
	5% level	-2.873543	
	10% level	-2.573242	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNHR) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 82 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-101.8258	0.0001
Test critical values:	1% level	-3.997250	
	5% level	-3.428900	
	10% level	-3.137898	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNGP has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.321108	0.1662
Test critical values:	1% level	-3.457747	
	5% level	-2.873492	
	10% level	-2.573215	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNGP has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.925952	0.1562
Test critical values:	1% level	-3.997083	
	5% level	-3.428819	
	10% level	-3.137851	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNGP) has a unit root
Exogenous: Constant
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-15.60466	0.0000
Test critical values:	1% level	-3.457865	
	5% level	-2.873543	
	10% level	-2.573242	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNGP) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-15.63120	0.0000
Test critical values:	1% level	-3.997250	
	5% level	-3.428900	
	10% level	-3.137898	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNETH has a unit root
Exogenous: Constant
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.073656	0.7265
Test critical values:	1% level	-3.457747	
	5% level	-2.873492	
	10% level	-2.573215	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LNETH has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.095839	0.9266
Test critical values:	1% level	-3.997083	
	5% level	-3.428819	
	10% level	-3.137851	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNETH) has a unit root
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-14.46650	0.0000
Test critical values:	1% level	-3.457865	
	5% level	-2.873543	
	10% level	-2.573242	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LNETH) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-14.45018	0.0000
Test critical values:	1% level	-3.997250	
	5% level	-3.428900	
	10% level	-3.137898	

*MacKinnon (1996) one-sided p-values.

Appendix 4.4 Auto Regressive Distributed Lag Model (*Source: Developed for research via EViews 10.0)*

ARDL Long Run Form and Bounds Test
Dependent Variable: D(LNBIT)
Selected Model: ARDL(1, 0, 0, 0, 4)
Case 2: Restricted Constant and No Trend
Date: 03/10/19 Time: 09:05
Sample: 1 239
Included observations: 235

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.855733	1.225499	-0.698273	0.4857
LNBIT(-1)*	-0.043089	0.018548	-2.323101	0.0211
LNDS**	0.082344	0.030643	2.687163	0.0077
LNHR**	0.019262	0.016616	1.159230	0.2476
LNGP**	-0.028380	0.139228	-0.203841	0.8387
LNETH(-1)	0.016667	0.008640	1.929142	0.0550
D(LNETH)	0.270307	0.040315	6.704859	0.0000
D(LNETH(-1))	-0.057392	0.040772	-1.407615	0.1606
D(LNETH(-2))	-0.043210	0.040883	-1.056932	0.2917
D(LNETH(-3))	-0.073801	0.040260	-1.833120	0.0681

* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation
Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNDS	1.911028	0.793968	2.406932	0.0169
LNHR	0.447032	0.285620	1.565131	0.1190
LNGP	-0.658647	3.243715	-0.203053	0.8393
LNETH	0.386817	0.159575	2.424040	0.0161
C	-19.85972	28.02922	-0.708536	0.4793

EC = LNBIT - (1.9110*LNDS + 0.4470*LNHR -0.6586*LNGP + 0.3868 *LNETH -19.8597)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	2.384577	10%	2.2	3.09
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37
Actual Sample Size	235		Finite Sample: n=80	
		10%	2.303	3.22
		5%	2.688	3.698
		1%	3.602	4.787

Appendix 4.5 Breusch-Godfrey Serial Correlation LM Test (*Source: Developed for research via EViews 10.0)*

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	0.544730	Prob. F(2,223)	0.5808
Obs*R-squared	1.142503	Prob. Chi-Square(2)	0.5648

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 01/19/19 Time: 15:56
Sample: 5 239
Included observations: 235
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNBIT(-1)	-0.002609	0.019323	-0.135022	0.8927
LNDS	0.001374	0.030738	0.044712	0.9644
LNHR	0.001474	0.016825	0.087636	0.9302
LNGP	-0.000795	0.139549	-0.005697	0.9955
LNETH	-0.001677	0.040429	-0.041489	0.9669
LNETH(-1)	0.003567	0.058435	0.061035	0.9514
LNETH(-2)	-0.001101	0.058385	-0.018859	0.9850
LNETH(-3)	-9.89E-05	0.057911	-0.001708	0.9986
LNETH(-4)	0.000160	0.040342	0.003974	0.9968
C	-0.017930	1.228187	-0.014599	0.9884
RESID(-1)	0.067028	0.068625	0.976735	0.3298
RESID(-2)	-0.026352	0.068498	-0.384715	0.7008

R-squared	0.004862	Mean dependent var	1.84E-15
Adjusted R-squared	-0.044226	S.D. dependent var	0.064453
S.E. of regression	0.065863	Akaike info criterion	-2.552767
Sum squared resid	0.967359	Schwarz criterion	-2.376107
Log likelihood	311.9501	Hannan-Quinn criter.	-2.481546
F-statistic	0.099042	Durbin-Watson stat	1.994680
Prob(F-statistic)	0.999915		

Appendix 4.6 Heteroskedasticity Test (ARCH) (*Source: Developed for research via EViews 10.0)*

Heteroskedasticity Test: ARCH

F-statistic	0.401095	Prob. F(1,232)	0.5271
Obs*R-squared	0.403855	Prob. Chi-Square(1)	0.5251

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/19/19 Time: 15:56
Sample (adjusted): 6 239
Included observations: 234 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003977	0.000688	5.780092	0.0000
RESID^2(-1)	0.041550	0.065606	0.633321	0.5271

R-squared	0.001726	Mean dependent var	0.004150
Adjusted R-squared	-0.002577	S.D. dependent var	0.009653
S.E. of regression	0.009665	Akaike info criterion	-6.431999
Sum squared resid	0.021674	Schwarz criterion	-6.402466
Log likelihood	754.5438	Hannan-Quinn criter.	-6.420091
F-statistic	0.401095	Durbin-Watson stat	2.002391
Prob(F-statistic)	0.527148		

Appendix 4.7 Ramsey RESET test (*Source: Developed for research via EViews 10.0)*

Ramsey RESET Test
Equation: UNTITLED
Specification: LNBIT LNBIT(-1) LNDS LNHR LNGP LNETH LNETH(-1) LNETH(-2) LNETH(-3) LNETH(-4) C
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	0.417248	224	0.6769
F-statistic	0.174096	(1, 224)	0.6769
Likelihood ratio	0.182574	1	0.6692

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.000755	1	0.000755
Restricted SSR	0.972085	225	0.004320
Unrestricted SSR	0.971330	224	0.004336

LR test summary:

	Value
Restricted LogL	311.3774
Unrestricted LogL	311.4687

Unrestricted Test Equation:
Dependent Variable: LNBIT
Method: Least Squares
Date: 01/20/19 Time: 16:18
Sample: 5 239
Included observations: 235

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNBIT(-1)	1.008767	0.125662	8.027598	0.0000
LNDS	0.085236	0.031472	2.708268	0.0073
LNHR	0.018423	0.016768	1.098710	0.2731
LNGP	0.002613	0.158030	0.016535	0.9868
LNETH	0.280712	0.047468	5.913686	0.0000
LNETH(-1)	-0.327047	0.069820	-4.684160	0.0000
LNETH(-2)	0.015463	0.058421	0.264680	0.7915
LNETH(-3)	-0.031305	0.057925	-0.540441	0.5894
LNETH(-4)	0.076127	0.040717	1.869652	0.0628
C	-1.305436	1.633708	-0.799063	0.4251
FITTED^2	-0.003009	0.007211	-0.417248	0.6769

R-squared	0.996484	Mean dependent var	7.892196
Adjusted R-squared	0.996327	S.D. dependent var	1.086581
S.E. of regression	0.065851	Akaike info criterion	-2.557181
Sum squared resid	0.971330	Schwarz criterion	-2.395243
Log likelihood	311.4687	Hannan-Quinn criter.	-2.491895
F-statistic	6348.806	Durbin-Watson stat	1.881110
Prob(F-statistic)	0.000000		

Appendix 4.8 VAR Granger Causality (*Source: Developed for research via EViews 10.0)*

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 01/19/19 Time: 16:02
Sample: 1 239
Included observations: 237

Dependent variable: LNBIT

Excluded	Chi-sq	df	Prob.
LNDS	1.654552	2	0.4372
LNHR	1.326269	2	0.5152
LNGP	0.855375	2	0.6520
LNETH	2.278811	2	0.3200
All	5.485596	8	0.7046

Dependent variable: LNDS

Excluded	Chi-sq	df	Prob.
LNBIT	14.33947	2	0.0008
LNHR	15.28804	2	0.0005
LNGP	3.999213	2	0.1354
LNETH	2.400673	2	0.3011
All	24.28309	8	0.0021

Dependent variable: LNHR

Excluded	Chi-sq	df	Prob.
LNBIT	11.12308	2	0.0038
LNDS	10.62047	2	0.0049
LNGP	1.575881	2	0.4548
LNETH	1.151596	2	0.5623
All	19.14959	8	0.0141

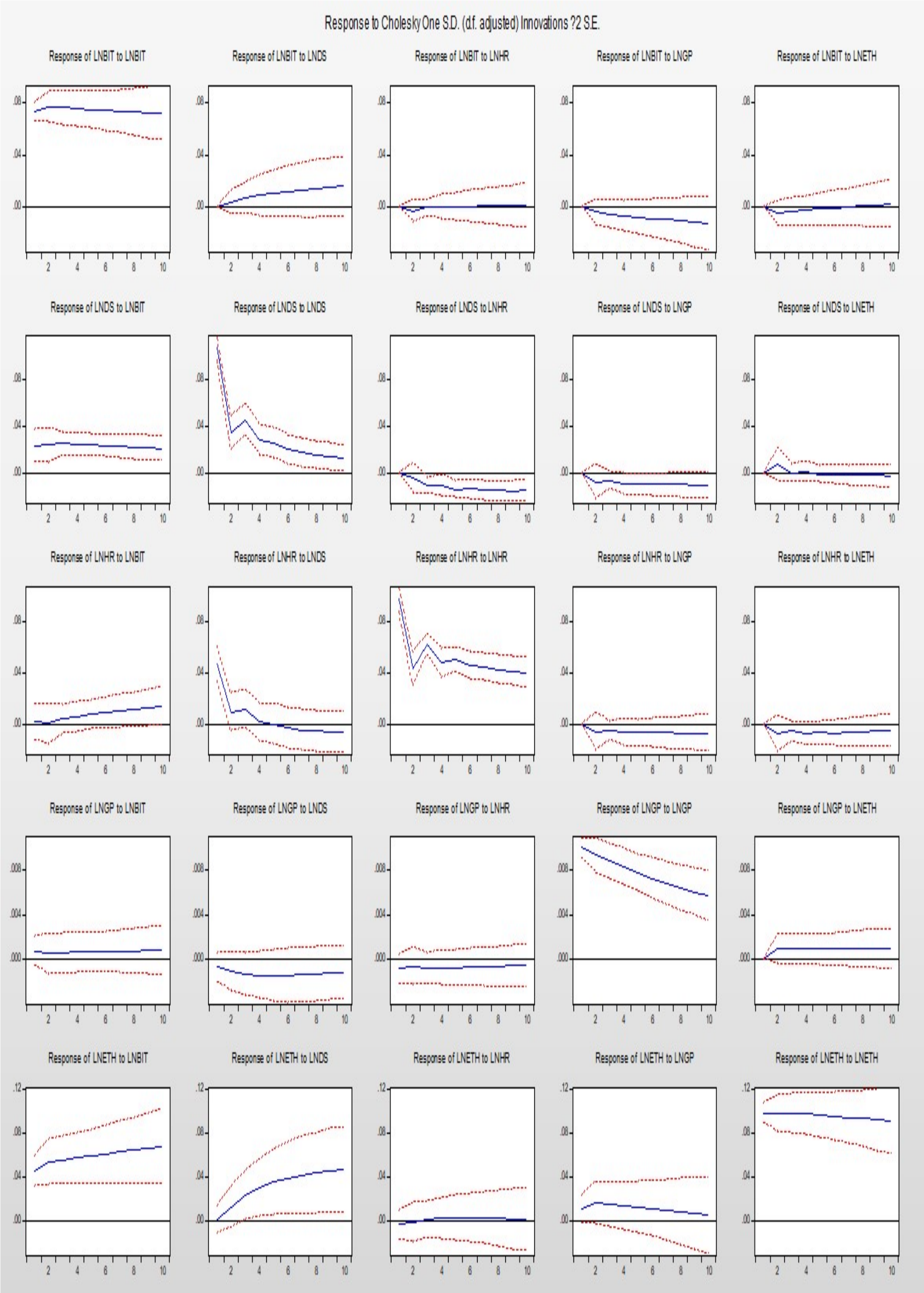
Dependent variable: LNGP

Excluded	Chi-sq	df	Prob.
LNBIT	1.045123	2	0.5930
LNDS	1.360851	2	0.5064
LNHR	0.588393	2	0.7451
LNETH	2.193380	2	0.3340
All	8.910115	8	0.3499

Dependent variable: LNETH

Excluded	Chi-sq	df	Prob.
LNBIT	1.108335	2	0.5746
LNDS	7.162368	2	0.0278
LNHR	1.810436	2	0.4045
LNGP	0.494806	2	0.7808
All	11.15692	8	0.1930

Appendix 4.9 Impulse Response Function (*Source: Developed for research via EViews 10.0)*



Appendix 4.10 Variance decomposition analysis (*Source: Developed for research via EViews 10.0)*

Variance Decomposition of LNBIT						
Period	S.E	LNBIT	LNDS	LNHR	LNGP	LNETH
1	0.073332	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.106693	99.53504	0.107523	0.067389	0.110445	0.179607
3	0.131632	99.19794	0.343880	0.044305	0.224985	0.188890
4	0.152258	98.84564	0.609592	0.033437	0.341379	0.169851
5	0.170227	88.46867	0.896609	0.028153	0.463536	0.143032
6	0.186321	98.07703	1.183377	0.025216	0.594201	0.120174
7	0.201019	97.67346	1.465196	0.024773	0.732953	0.103617
8	0.214615	97.26432	1.737433	0.025058	0.879135	0.094056
9	0.227318	96.85192	1.999112	0.025983	1.031510	0.091477
10	0.239276	96.43881	2.249840	0.026998	1.188899	0.095453
Variance Decomposition of LNDS						
Period	S.E	LNBIT	LNDS	LNHR	LNGP	LNETH
1	0.110056	4.626924	95.37038	0.000000	0.000000	0.000000
2	0.118534	8.052309	90.98991	0.104753	0.416466	0.436557
3	0.130201	10.44050	87.80439	0.801100	0.592192	0.361821
4	0.136185	12.82057	84.56955	1.320415	0.950018	0.339449
5	0.141731	14.79611	81.42764	2.183180	1.275264	0.317810
6	0.146082	16.58130	78.54370	2.940207	1.631011	0.303780
7	0.150025	18.10481	75.84003	3.781867	1.972175	0.301112
8	0.153502	19.43617	73.40233	4.553552	2.305440	0.302499
9	0.156686	20.57806	71.18453	5.307703	2.620923	0.308780
10	0.159588	21.56539	69.19565	6.002727	2.919311	0.316929
Variance Decomposition of LNHR						
Period	S.E	LNBIT	LNDS	LNHR	LNGP	LNETH
1	0.108609	0.062939	18.96202	80.97504	0.000000	0.000000
2	0.117738	0.056520	16.83942	82.47208	0.213668	0.418314
3	0.133985	0.157783	13.81307	85.26448	0.291485	0.473181
4	0.142698	0.296245	12.20037	86.39562	0.433403	0.674361

5	0.151813	0.520378	10.77949	87.38363	0.543436	0.773065
6	0.159099	0.801037	9.850565	87.81187	0.657595	0.878928
7	0.166002	1.143958	9.112925	88.04423	0.757272	0.941615
8	0.172171	1.541425	8.562846	88.05811	0.850517	0.987104
9	0.177948	1.991706	8.113076	87.95179	0.934582	1.008847
10	0.183305	2.492030	7.740624	87.73996	1.012191	1.015199
Variance Decomposition of LNGP						
Period	S.E	LNBIT	LNDS	LNHR	LNGP	LNETH
1	0.010145	0.520320	0.475649	0.680569	98.32347	0.000000
2	0.013917	0.405879	0.904616	0.579771	97.64511	0.464622
3	0.016601	0.403544	1.293493	0.647716	97.02181	0.633436
4	0.018661	0.428890	1.616086	0.674615	96.53636	0.744050
5	0.020315	0.464919	1.885365	0.709917	96.11348	0.826316
6	0.021677	0.508072	2.101966	0.731893	95.75670	0.901364
7	0.022816	0.556208	2.273379	0.749593	95.44772	0.973097
8	0.023780	0.608813	2.405739	0.760709	95.17943	1.045314
9	0.024603	0.665529	2.505572	0.767779	94.94225	1.118873
10	0.025310	0.726328	2.578519	0.771180	94.72937	1.194604
Variance Decomposition of LNETH						
Period	S.E	LNBIT	LNDS	LNHR	LNGP	LNETH
1	0.108372	17.45706	0.030177	0.050638	1.175866	81.28626
2	0.157028	20.09409	0.755185	0.025201	1.700417	77.42511
3	0.195177	21.16700	1.965344	0.024140	1.752194	75.09132
4	0.227950	21.86860	3.232706	0.033237	1.695119	73.17034
5	0.257269	22.46481	4.461673	0.043828	1.598323	71.43136
6	0.284044	23.04075	5.581397	0.051523	1.486031	69.84030
7	0.308825	23.62440	6.583249	0.055526	1.370180	68.36664
8	0.331978	24.22398	7.469045	0.056217	1.256936	66.99382
9	0.353767	24.83966	8.250422	0.054464	1.149776	65.70568
10	0.374395	25.46864	8.940005	0.051189	1.050632	64.48954