Lisbon School of Economics & Management
Universidade de Lisboa

MASTER

MATHEMATICAL FINANCE

MASTER´S FINAL WORK

DISSERTATION

AN ANALYSIS OF BITCOIN AS AN ASSET

CATARINA SOARES PEREIRA

OCTOBER-2021

MASTER

MATHEMATICAL FINANCE

MASTER´S FINAL WORK

DISSERTATION

AN ANALYSIS OF BITCOIN AS AN ASSET

CATARINA SOARES PEREIRA

SUPERVISION:

MARGARIDA ABREU

NUNO CRATO

OCTOBER-2021

GLOSSARY

EBA – European Banking Authority

CFTC – Commodity Futures Trading Commission

CME – Chicago Mercantile Exchange

CBOE – Chicago Board Options Exchange

ARCH – Autoregressive Conditional Heteroskedasticity

GARCH – Generalized Autoregressive Conditional Heteroskedasticity

E-GARCH – Exponential Generalized Autoregressive Conditional Heteroskedasticity

ACF – Autocorrelation Function

PACF – Partial Autocorrelation Function

ABSTRACT

Bitcoin is nowadays one of the most popular topics among the public and academia. The increased popularity and market capitalization of Bitcoin have generated much controversy among the scientific community about whether this cryptocurrency can be used as an asset or as a new form of a medium of exchange.

With these questions in mind, I decided first to assess if Bitcoin can be incorporated into one singular category, asset, or medium of exchange; or if it is a mix of these two. Second, enquire how its variance shifts according to shocks in the market and if this reaction can be compared with Gold. Third, infer if there is an asymmetry effect in volatility, i.e., if bad news generate less volatility than good news.

The conclusions drawn from this study are that Bitcoin does not fit entirely into one category. There is no clear indication as to whether Bitcoin is a medium of exchange or an asset. Regarding its behavior in the market, it is possible to conclude that Bitcoin does not have management capabilities, and concerning the comparison with Gold, I concluded that Gold is still superior in terms of being a good asset to hedge market risk. The asymmetry effect is not significant in Bitcoin, whereas in Gold, several studies proved that this effect is one of the main properties that make Gold a safe haven.

Keywords: Bitcoin, Asset, Medium of exchange, Market, Gold

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

I would like to give a special thank you to Professor Margarida Abreu for all the support and comprehension in doing this dissertation. To Professor Nuno Crato, a heartfelt thank you for his patience, attention, and help during this period.

This dissertation is dedicated to all my friends and family, especially my mother, sister, boyfriend, borrowed cousins, and aunt. Without their support and persistence, it would be impossible to conclude this work.

1. INTRODUCTION

Bitcoin was introduced to society in 2009 by an anonymous author who used the alias Satoshi Nakamoto and wrote a paper about a peer-to-peer electronic cash system. This novelty brought a whole new dimension to the world: up to this point, online money was only used in video games and never brought into financial markets or even into the real world. Commerce on the internet mostly depends on financial institutions serving as intermediaries to process electronic payments. The cost of having a third-party mediating increases transaction costs, limits the size of transactions, and reduces the possibility for small and casual transactions – this is where Bitcoin enters (Nakamoto, 2008).

One of the original goals of this author was to eliminate the third party required for a standard transaction between fiat currencies; the intention was to introduce the concept of a decentralized currency. The differentiating factor revolving around this subject is the creation of the blockchain technology, which introduced a decentralized distributed ledger that records the origin of a digital asset and every transaction made. Blockchain also involves elements such as cryptography, consensus mechanisms[1] , and smart contracts[2].

There were 21 million Bitcoins created in total. They are discovered through mining, which consists of solving pre-specified cryptography problems that other miners posteriorly verify. Up to this day, 18.6 million Bitcoins have been mined, and the last Bitcoin is predicted to be mined in 2140. To enforce this calendarization, protect the Bitcoin exchange rate from the inflationary pressures, and strengthen the concept of digital scarcity[3], the miner's rewards are split in half every 210000 blocks mined. This process happens approximately every four years, which brings the reward for each block mined to 6.25 Bitcoins up to now.

In recent years, and now due to the COVID-19 pandemic, investors have been searching for potential sources of return that are not correlated to the traditional financial

---

[1] Fault tolerant mechanism that is useful for keeping records.

[2] Smart contracts are blockchain technology-based and self-executing, since they run in the blockchain they are free from the control of any entity (Forum, World Economic, 2021).

[3] Limiting resources through a software, it is possible to control the number of coins and how they are exchanged in the online world (Citi GPS: Global Perspectives and Solutions, 2021).

markets. These new policies have been driving attention to cryptocurrencies. All the speculation around this topic has created a generalized interest in the public and academia, with diverging opinions arising, some in favor and some against Bitcoin being used as an asset or as a means of payment. The prospect of having international transfers with low transaction costs and the autonomy and discretion factors involving these actions has been most desired by economic agents.

The answer to the research questions will be essential to explain the meaning of Bitcoin and its role in financial markets. Bitcoin has lately been called “the new Digital Gold.” If this comparison holds, there is a possibility that the market capitalization of Bitcoin may start to move towards the market capitalization of Gold in the future, introducing a valuable trade (Citi GPS: Global Perspectives and Solutions, 2021).

In this dissertation, I will study Bitcoin by examining its evolution in the financial markets. I will contrast the results with those obtained by previous papers, which analyzed the first of the cryptocurrency data.

Research Questions:

- What are the user’s intentions when acquiring Bitcoin? Does Glaser et al., (2014) approach still make sense today?
- How does Bitcoin react to market indexes, a commodity such as Gold, and interest rates? Is Bitcoin more sensitive to disturbances in the European or American market?
- Is Bitcoin influenced by the same variables as Gold? Is the asymmetry effect significant in Bitcoin? Is this a good indicator for Bitcoin to be used as a hedging instrument?

In order to investigate these research questions, I will proceed as follows.

For the first question, I will be following the approach of Glaser et al., (2014) and see if the conclusions maintain, which are that new users are likely to stay with the exchange trading, holding Bitcoin as an alternative investment asset, instead of using Bitcoin as a medium of exchange for purchasing goods and services.

To evaluate this, I am going to use Google trend searches on the word “Bitcoin”, the network volume, and the exchange volume, i.e., the volume that records the transactions that occur due to acquiring goods and services and the volume that records the buying and selling of Bitcoins in exchange markets, respectively.

In this model, the objective is to infer if the authors' results in the early ages of Bitcoin still apply to more recent data. By analyzing the impact that Google trend, network volume, and exchange volume have on each other, it will be possible to conclude if, as the number of Bitcoin searches increases, the exchange and the network volume follow the same path. If the Google trend searches impact the exchange volume or the network volume, this would mean that people searching the word Bitcoin on Google may positively or negatively impact the volumes.

Before executing this model, it is already expected to encounter some limitations due to using the Google trend as a proxy for new users. Nowadays, because the world is familiarized with Bitcoin, there is no need to search the web for more information about this cryptocurrency before investing.

For the second question, I will analyze how certain market indexes, interest rates, and commodities influence Bitcoin's variance by using an ARCH/GARCH model and the variables S&P500, Eurostoxx50, Gold price, German bonds, and Federal Funds with 3-month maturity, and the EUR_USD exchange rate. In this section, I will follow the work of Dyhrberg (2016). This approach helps investors estimate the volatility of the variables and use this information to determine risk and which assets may offer greater returns. It can also be perceived if Bitcoin is more susceptible to European or American markets by using the market indexes and interest rate proxies for the larger two economies in the western world.

I will also fit an ARCH/GARCH model for Gold to test if the same variables influence it. Since the 20th century, Gold has been a good hedging instrument during an economic crisis due to its properties. Nowadays, Bitcoin and Gold have been compared as safe haven[4] due to some similarities in their properties.

This model will assess the price volatility and infer similarities in how they react to financial markets.

For the third and last question, I will estimate an exponential GARCH model or E-GARCH. This model will assess whether there is an asymmetry effect, i.e., if negative

[4] A strong / weak safe haven is defined as, an asset that is negatively correlated / uncorrelated with another asset or portfolio in certain periods only.

shocks have a more significant influence on future volatility than positive shocks, which will allow evaluating if it is possible to use Bitcoin to hedge market risk.

When there is a negative shock in the market (for example, bad news), the returns on Bitcoin decrease less than they increase when there is a positive shock (for example, good news); this does show an asymmetry.

In the paper, Dyhrberg (2016) concluded that positive and negative shocks do not affect Bitcoin returns asymmetrically and assumed from previous studies that Gold behaves in the same way. So, it is possible to use them to hedge market risks that affect other assets asymmetrically. According to Dyhrberg (2016), when there is a time of financial stress, Bitcoin and Gold are good assets to escape the stress the market is suffering.

This work will be divided into five chapters starting with the introduction. The second chapter will analyze several papers discussing themes of interest for this dissertation, such as the use of Bitcoin in financial markets and the comparison made with Gold. In the third chapter, I have the data methodology that will englobe, the data context - where it will be explained the models used and the data collection - where it will be described how the data was collected and treated. The fourth chapter will be the empirical strategy; this will be composed by the data modeling - in this part, I will estimate several models to find the best fit for our dataset, by the estimation problems, and by the results - where I will evaluate the models chosen as the best fit and weigh the significance of the variables. The fifth and final chapter will be the conclusion.

2. LITERATURE REVIEW

2.1. FROM THE FUNCTIONS OF MONEY TO THE EVOLUTION OF THE PAYMENT SYSTEM

Theoretically, money is defined in terms of the function it performs; the specifications money must meet are of a medium of exchange/means of payment, a unit of account, and a store of value. Out of these three, the medium of exchange and unit of account functions are considered the most important. The means of payment function implies that money must act as a medium to buy and sell goods and services. The unit of account function is used to measure economic value; this indicates that money must provide standardized terms in which prices are quoted. The store of value function means that the purchasing power is transferred from the present to the future. An economic agent must be able to save his money in the present to spend in the future (Mishkin, 1986).

Money is not the only one that can function as a store of value; for example, assets like stocks and bonds can also perform this function, and most of the time, they pay a higher interest rate than money. However, these assets face a problem money does not: liquidity, i.e., how fast and easy can an asset be converted into a medium of exchange. Since money is already a medium of exchange, it is the most liquid asset, so it is a superior store of value.

In a more specific definition, money is anything accepted directly as a medium of exchange. In consumer economies, the currency held by the public and decreed by the government as legal tender [5] performs this role.

Acquiring goods and services has been necessary since the early ages. Since humans started to produce more than they required, the need for commerce started, and so did the need for money as a means of payment. First, the Barter economy appeared; people traded goods and services according to their needs, this was an economy without money. This was not especially efficient; the trades possible to execute were very restricted and with very high transaction costs. The next phase was to use precious metals or any other commodity to serve as money; since money must be universally accepted, a natural

[5] Anything recognized by law that is accepted as payment.

candidate was precious metals such as silver and Gold that had value to everyone, was easily divided, and did not quickly deteriorate. This was known as Commodity money, and it had drawbacks like the difficulty in transporting.

These days, we have paper money. Money represents purchasing power, but in itself has no value; it is just symbolic. As it is called, fiat money is not backed by any physical commodity, and it is paper currency decreed by the government that legally it must be taken as payment. This allows it to perform as a medium of exchange (Mishkin, 1986).

In the 21st century a new asset emerged, cryptocurrencies, they are a subsection of virtual currencies that use cryptography to create a secure peer-to-peer decentralized network to handle electronic transactions. Bitcoin is the first cryptocurrency that reached this level of curiosity and acceptance worldwide and with the biggest market share.

2.2. ARGUMENTS AGAINST BITCOIN AS A MEANS OF PAYMENT

To meet the standards of a currency, Bitcoin must convene the three functions stated above; it must function as a medium of exchange, a unit of account, and a store of value. Yermack (2015) explains why there are problems with considering Bitcoin a currency. The first function of money is to act as a means of payment, regarding Bitcoin performing this function, the problem lies in the fact that its value as a means of payment depends on its widespread acceptance, which requires its widespread use in the economy.

To function as a unit of account, consumers must treat it as a numeraire when comparing prices, the problem here lies in the extreme volatility presented by Bitcoin; the prices would have to be frequently recalculated, which would prove costly and confusing.

"The volatile price moves can wipe out any profit margin of a merchant within a matter of hours." (Roubini, 2021).

The store of value functions is questioned due to the system's threats and the fact that Bitcoin has no intrinsic value, and it can instantly lose its value.

Besides these, there are other characteristics Bitcoin does not possess, for example, it is not possible to deposit it in a bank it must be kept through a system of "digital wallets" that is expensive to preserve and vulnerable to attacks, so it does not guarantee the same safety as a financial institution.

Since its launch, there were always divergent opinions about whether it serves best as a currency or speculative investment. One of the main problems associated with Bitcoin is the high price volatility, which makes it challenging to consider this cryptocurrency a medium of exchange; and its lower liquidity, it takes too long to migrate from the electronic to the physical system.

The lack of liquidity can impact the transaction volume. The Bid-Ask Spread, the difference between the bid and the ask price – the bid is the price the seller offers, and the ask is the price the buyer demands – has a negative relation with the transaction volume. This means that if a high bid-ask spread makes it more difficult to buy and sell Bitcoin in the cryptocurrency market, it will also be more difficult to acquire it for purchases and other non-financial transactions (Pagano and Sedunov, 2020).

The awareness and generalized virality are critical factors in Bitcoin's demand and interest surge. News, positive or negative, can influence investors to buy, sell, or bring new investors to the market. The introduction of cryptocurrencies in the market has drawn attention from regulators concerned about the lack of legislation worldwide to address these decentralized coins legally.

The fact that Bitcoin is not legally regulated brings out some uneasiness concerning the possible illegal activities achievable by using this as a means of payment. The Silk Road is an example of the use of Bitcoin for illegal activities; this online black market was launched in 2011 and named after the historical trade route that connected Europe and east Asia. There, it was possible to acquire illegal goods and services, such as drugs, sex workers, and hitmen. When the US Department of Justice seized this website, it was found that approximately 9.5 million Bitcoins changed hands between sellers and consumers, and it had 1.2 billion dollars' worth of illegal goods and services (Coindesk, n.d.). This event brought uncertainty and lack of confidence in the Bitcoin market because the primary argument used in favor of cryptocurrencies was anonymity and freedom from any government.

Gandal et al., (2018) discovered that suspicious trading was related to increased prices. The Mt. Gox hack was an event that proved the system lacked security: a once thought secure Bitcoin exchange, based in Japan, that controlled approximately 80% of Bitcoin transactions worldwide. In the days preceding this event, exchange rates and trading volume both increased significantly; on the other hand, in the days where no suspicious trading occurred, the exchange rate was flat or decreasing. As the Bitcoin ecosystem becomes more united with international finance and payment systems, regulators are on high notice to take active oversight roles.

Regulatory and risk agencies such as the European Banking Authority (EBA) warned about the risks deriving from buying, holding, or trading virtual currencies, namely Bitcoin. The EBA stated that consumers were exposed to a high level of risk since there was no regulation to protect them and recommended prudence due to the unpredictability around its value (European Banking Authority, 2014).

2.3. THE ROLE OF BITCOIN IN FINANCIAL MARKETS AND ITS PERFORMANCE DURING A CRISIS

There is some interest in understanding why and if Bitcoin transactions influence the market and give some indicators to traders. The openness of the Bitcoin network and the transparency about the information distribution of the transfers allow market participants to identify, classify and incorporate relevant events in their trading strategies. According to Ante and Fiedler (2021), large Bitcoin transfers make the market react; this is an important feature of Bitcoin's market structure and informational efficiency[6]; specific transactions can predict short-term returns. However, this strategy is only sustainable for high-frequency traders[7].

To comprehend Bitcoin, it is first valuable to know how newly introduced economic agents perceive it. Glaser et al., (2014) researched whether the demand for exchanging the local currency into Bitcoin and using Bitcoin to buy and sell goods and services increases with the initial attention on Bitcoin. The conclusion was that newly attracted users seemed to prefer to use it as an asset and trade it on exchanges for its speculative purpose, as an alternative investment vehicle. This study was made with very early data on Bitcoin.

[6] Informational efficiency is a natural consequence of competition, few barriers to entry, and low costs of obtaining and publishing information. Investors have access to the same amount of information.

[7] High-frequency trading (HFT) is a system of trading that uses computer programs to transact large numbers of orders in fractions of seconds.

In theory, if Bitcoin is mainly used as a medium of exchange to pay for goods and services, it will compete with fiat currencies, such as the American dollar or the Euro, and influence the value of the fiat currency. Eventually, this will affect monetary policies implemented by the central bank. However, if it is mainly used as a speculative asset, it will compete with other assets, such as government bonds, stocks, and commodities (Baur et al., 2018).

Bitcoin has a fixed supply; as mentioned, only 21 million were created. However, the demand is not fixed. This disequilibrium in supply and demand could lead to deflationary effects - demand growth may continually exceed supply growth in the future (Baur et al., 2018).

In September 2015, Bitcoin was considered a commodity by the Commodity Futures Trading Commission (CFTC). Furthermore, in December 2017, it joined the league of the legitimate asset classes when Bitcoin-based futures contracts were introduced in the Chicago Mercantile Exchange (CME) and the Chicago's Board Options Exchange (CBOE). In January 2020, the CME launched Bitcoin futures Option. These advancements brought new possibilities on how Bitcoin can be used and how it affects financial markets (Li et al., 2021).

Baur et al., (2018) analyzed whether Bitcoin was a medium of exchange or a speculative asset by comparing it with several assets, market indexes, and commodities such as Gold and silver. They observed that Bitcoin's returns display the highest returns and volatility compared with the other assets and that it presents very negative skewness, which indicates an asymmetric Bitcoin return distribution – this may represent the periods with high market volatility. They also concluded that Bitcoin was uncorrelated with any asset return and showed a low positive correlation with the S&P500; this did not happen with any other asset studied.

Bouri et al., (2020) studied the relationship between Bitcoin, Gold, and commodities against global and country stock market indexes through a wavelet analysis. This allows for a better understanding of the interdependence between markets and determines the best time-frequency for these three assets to act as a hedge or a safe haven. This method offers a more complete view of the correlation between the assets. The results show that the dependence between the assets and the stock market is weak, with Bitcoin being the least dependent. In terms of diversification benefits, Bitcoin showed superiority compared to the other variables.

Due to its easy transaction system and decentralization, Bitcoin is often seen as an escape from the country’s policies and weaknesses in the financial system. Previous studies (Luther and Salter, 2017) revealed that the price of Bitcoin increased dramatically during the European debt crisis of 2010-2013 and the Cypriot banking crisis of 2012-2013 as investors saw the opportunity to protect themselves against political risk.

Since Bitcoin is apart from the fiat money system and at this time does not play a significant role in the financial system, it may be possible to consider it a safe haven against financial stress despite its excess volatility when compared to other assets in the financial system. The uncorrelated relation between Bitcoin and market indexes such as the S&P500 provides a weak safe haven in times of financial turmoil or economic collapse (Baur et al., 2018).

To understand Bitcoin’s use during periods of economic stress, Pagano and Sedunov (2020) analyzed Venezuela's crisis. This country is one example of an unstable nation with political, social, and economic distress. Therefore, this serves as a test to understand whether economic agents prefer to transition to an alternative currency when their own is under extreme pressure. These authors assumed that if Bitcoin has value as a hedging instrument during stress periods, there would be an increase in its transactions as a way to escape the devaluation in the nation’s currency. This analysis supported the use of Bitcoin as a potential hedging instrument, as an interest in Bitcoin appeared and the transaction volume increased.

2.4. BITCOIN AND GOLD

Recently Bitcoin has been compared to Gold as a way to protect investments since they share some characteristics. Gold is a precious metal that belongs to the commodity family and is a well-known diversifier[8] against stock market returns, mainly due to its safe-haven properties that allow it to hedge stock movements in times of economic

[8] A diversifier is defined as an asset that is positively, but not perfectly correlated with another asset or portfolio on average (Baur and Lucey, 2009).

recessions (Baur and Lucey, 2009). I.e., Gold is uncorrelated or negatively correlated to other assets in periods where there exists market tension.

Gold is used in industrial components, jewelry, investment assets, and reserve assets. It is highly liquid, as it can be bought or sold 24h a day. Central banks hold a large proportion of Gold stocks for several reasons, such as diversification and economic security - Gold mitigates the impact of a crisis and maintains its value against the market crisis. Furthermore, the demand for Gold is prone to increase as the dollar depreciates since the mean value of Gold returns is negatively influenced by the dollar (Tully and Lucey, 2007).

The similarities between Bitcoin and Gold are important to understand since Bitcoin is being called “the new Digital Gold”. Both are mined, which means that there is a limited supply and a specific creation process (there are only 21 million units created for Bitcoin, and the amount of Gold left in the world is unknown). Moreover, as previously said, Bitcoin is now regulated as a commodity by the CFTC, like Gold (Bouri et al., 2020).

As to the differences, Gold and Bitcoin differ in history, tangibility, intrinsic value, volatility, and consumption (Bouri et al., 2020).

Bouri et al., (2016) showed evidence of the asymmetric impact of news on Bitcoin, specifically in the period before the crash of 2013, it is observed an inverse relation between past shocks and volatility, i.e., positive shocks increase the volatility more than negative shocks, this is considered the safe-haven property by the authors. In the post-crash period, this property ceased, which indicates that Bitcoin lost its ability to compensate investors for losses during periods of turmoil. Baur (2012) showed that Gold has the safe-haven property; the volatility of Gold returns reacts inversely to negative shocks. When there is an increase in the Gold price, investors understand this sign as a signal of future adverse conditions and uncertainty in other assets.

Due to the frequent comparison between Bitcoin and Gold, Al-Khazali et al., (2018) decided to analyze the impact of positive and negative macroeconomic news in Gold and Bitcoin volatility and returns by using macroeconomic news surprises indexes. The study confirmed an impact on the returns and volatility of both and that the impact of news surprises, both good and bad, is more substantial for Gold. However, Bitcoin is different from Gold, with returns and volatility reacting to macroeconomic news inconsistent with a safe haven. This finding is essential for investors since it implies predictability for Gold returns and volatility based on positive and negative news surprises, which do not happen for Bitcoin. The markets for Bitcoin and Gold do not share the same principles.

3. DATA AND METHODOLOGY

3.1. DATA COLLECTION

The data consists of 334 weekly observations dated from October 2014 until February 2021, of Bitcoin price, Bitcoin exchange volume (Yahoo Finance, n.d.), Bitcoin network volume (Blockchain, n.d.), Gold price (Yahoo Finance, n.d.), German bonds with 3 months maturity (Investing, n.d.), Federal Funds with 3 months maturity (Federal Reserve Economic Data, n.d.), S&P500 index (Investing, n.d.), Eurostoxx50 index (Investing, n.d.), EUR_USD exchange rate (Yahoo Finance, n.d.), and Google trend search on the word "Bitcoin" (Google Trend, n.d.)The prices variables used are of the "Close price".

Bitcoin price, exchange volume, Gold price, and EUR_USD exchange rate data are sourced from Yahoo Finance, posteriorly the Bitcoin price, the Gold price, and the EUR_USD exchange rate are annualized for the comparison with the interest rates proxies be more accurate since interest rates are annual. The network volume is sourced from Blockchain.com. To use these two distinct volumes, we take on the assumption done by the authors Glaser et al., (2014) that when economic agents want to buy and sell Bitcoin usually stay in the exchange, so the transaction is not recorded in the blockchain. As for the network volume, the transaction occurs and is verified in the blockchain to trade Bitcoin for goods and services.

The EUR_USD exchange rate measures how many US dollars are needed to buy one Euro; this exchange rate represents the world's two largest and most influential economies.

The German bonds with 3 months maturity, the S&P500 index, and the Eurostoxx50 index are obtained from Investing.com, and the Federal Funds with 3 months maturity are obtained from the Federal Reserve Economic Data (FRED of St. Louis). The German bonds and the Federal Funds act as proxies for interest rates for the American and European markets, respectively. The S&P500 index is considered the best single gauge of large-cap U.S equities, and it includes the 500 leading companies capturing roughly 80% coverage of available market capitalization. The Eurostoxx50 is Europe's leading Blue-chip index, and it tracks shares of recognized and financially stable publicly traded companies. The S&P500 and the Euroxtoxx50 are also annualized for the same reason enunciated above.

The Google Trend searches on the word "Bitcoin" are in percentage and will serve as a proxy for new Bitcoin users, people who are interested in acquiring the cryptocurrency, and in doing so, search the web for more information.

3.2. DATA CONTEXT

To start the models' estimations, it is necessary to check the stationarity of the time series. We need to perform unit root tests: the augmented Dickey-Fuller test (ADF) and the Philips-Perron test (PP). These tests have as a null hypothesis the existence of a unit root, so if we do not reject H0, the series has a unit root. So, it is necessary to do a proper transformation; most likely, it is required to take the first differences.

After checking and making our time series stationary, it is time to estimate models and assess the results.

In econometrics. it is necessary to do more than just checking whether one variable impacts another. Specifically, in financial applications, it is helpful to model the attitude of investors towards expected returns and, also, risk (uncertainty). These models need to be able to deal with the volatility associated with these series. Due to this fact, a heteroscedasticity model is introduced; this model can deal with the non-constant variance typically found in financial time series.

Engle developed the ARCH (Autoregressive Conditional Heteroskedasticity) model in 1982, where he states that the variance of the residuals at time *t* depends on the squared error terms from past periods. This model allows to analyze and forecast the variance of financial and economic time series over time.

It starts by allowing the variance of the residuals to depend on history or to have heteroskedasticity because the variance will change over time. This is possible by permitting the variance to depend on *lagged* periods of the squared error terms. If we only have one *lagged* term, we have the simplest form of the model, as in equation (3).

(1) $$Y_t = \alpha + \beta X_t + u_t$$

(2) $$u_t = \sigma_t \ \varepsilon_t \ , \varepsilon_t \sim \text{idd } (0,1)$$

(3) $$\sigma^2{}_t = \gamma_0 + \gamma_1 u_{t-1}^2$$

In this complete model described by these three equations, X_t is the explanatory variable, β is the coefficient, and ε_t is independently distributed (Asteriou and Hall, 2011).

If the conditional variance depends on more than one *lagged* period. Then ARCH(*q*) may be appropriate:

(4) $$\sigma^2{}_t = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + \ldots + \gamma_q u_{t-q}^2 \\ = \gamma_0 + \sum_{j=1}^{q} \gamma_j u_{t-j}^2$$

One of the major drawbacks of the ARCH specification was that it looked more like a moving average model than an autoregression. To correct this, Tim Bollerslev introduced a new model in 1986, the GARCH (Generalized Autoregressive Conditional Heteroskedasticity). This model included the *lagged* conditional variance terms as autoregressive terms (Asteriou and Hall, 2011). The simplest case is the following equation:

(5) $$\sigma^2{}_t = \gamma_0 + \delta_1 \sigma^2{}_{t-1} + \gamma_1 u_{t-1}^2$$

In the more general case, the GARCH (*p,q*) is represented as follows:

(6) $$\sigma^2{}_t = \gamma_0 + \sum_{i=1}^{p} \delta_i \sigma^2{}_{t-i} + \sum_{j=1}^{q} \gamma_j u_{t-j}^2$$

ARCH and GARCH models have become standard tools; these models provide a volatility measure that can be used in portfolio selection, risk analysis, and derivative pricing (Tully and Lucey, 2007).

Besides these two models, we also have the exponential GARCH or E-GARCH, a model first developed by Nelson in 1991. The GARCH and E-GARCH models differ in two main aspects. First, the E-GARCH model allows good and bad news to have a different impact on volatility, while the standard GARCH model does not. Second, the E-GARCH model allows big news to impact volatility more than the standard GARCH model significantly.

The E-GARCH model allows testing for whether the returns are asymmetrically affected by good and bad news, i.e., volatility falls under positive news and rises under negative news.

$$(7) \qquad log(\sigma^2{}_t) = \gamma + \sum_{j=1}^{q}\left|\frac{u_{t-j}}{\sqrt{h_{t-j}}}\right|\zeta_j + \sum_{j=1}^{q}\frac{u_{t-j}}{\sqrt{h_{t-j}}}\xi_j + \sum_{i=1}^{p}\delta_i log(h_{t-i})$$

On the equation above, we model the log of the variance series. If we have $\boldsymbol{\xi}_1 = \boldsymbol{\xi}_2 = \ldots = \boldsymbol{\xi}_q = 0$, then the model is symmetric; if $\varepsilon_j < 0$ for some j, then positive shocks (good news) generate less volatility than negative socks (bad news) (Asteriou and Hall, 2011).

3.3. EXPLORING DATA

Before initiating the estimation of the models, it is necessary to determine if all of the variables are stationary. To do this, we rely on the unit root tests, the Augmented Dickey-Fuller (ADF), and the Philip Perron (PP) tests.

The first model tests the Bitcoin network and exchange volume, the google trend searches on the word “Bitcoin”, and the returns of Bitcoin - which consists of the difference between two consecutive week prices; this difference represents an investor's profit when investing. After performing the two tests on all the variables, the empirical evidence suggests that the series are difference stationary.

The second model, the ARCH/GARCH estimation of Bitcoin and Gold price, tests the variables, Bitcoin price, Gold price, Eurostoxx50 index, S&P500 index, EUR_USD exchange rate, German bonds, and Federal Funds. After the stationarity tests, it is concluded that only the German bonds and the Federal Funds need to be transformed in their first differences, and all the other variables are already stationary. As in Dyhrberg (2016), the Bitcoin and the Gold prices are taken in logarithms form.

For the third model, the E-GARCH estimation, the dependent variable is Bitcoin, and it is transformed in the logarithm following the approach of the previous model and Dyhrberg (2016), the other variables used are all already proved to be stationary from the second model.

4. EMPIRICAL STRATEGY

4.1. DATA MODELING

According to the two hypotheses stated by the authors Glaser et al., (2014), an increase in Bitcoin participants is associated with an increase in the Bitcoin network and exchange volume. In this case, the variable is Google trend searches on the word "Bitcoin". By observing the graphs, it is perceptible that an increase in Google searches is not followed by equivalent Bitcoin volumes changes.

Figure 1: Bitcoin exchange and network volume

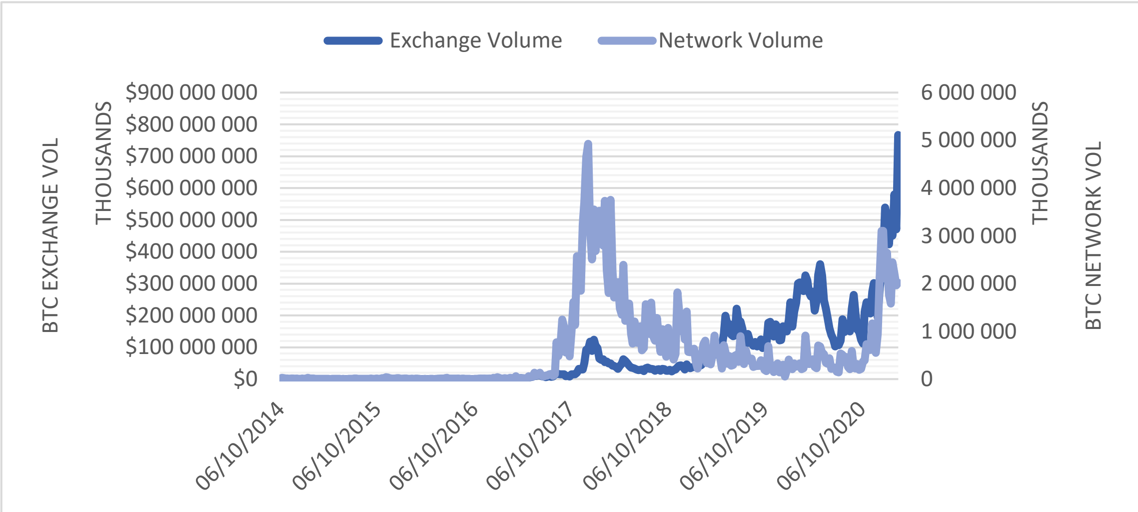


Figure 2: Google trend searches on the word "Bitcoin", as a fraction of the historical maximum (= 1)

Regarding the exchange and the network volume graphs, we can see that both volumes do not evolve in the same way; this seems to indicate that separate mechanisms propel their growth. An economic agent that uses Bitcoin as a means of payment will first increase the number of Bitcoins by exchanging its local currency, and this operation is only recorded in the exchange. The network volume will only be affected when he decides to withdraw the money from the exchange and apply to purchase goods and services. Based on this assumption, it is possible to evaluate both volumes separately and analyze whether they grow individually or are influenced by new users.

To analyze the relationship between both volumes and Google trend Glaser et al., (2014) performed a model described as bellow:

$$\Delta Y = \alpha + \sum_{i=1}^{3} \beta_1 \Delta NetworkVol_{t-1} + \sum_{i=1}^{3} \beta_2 \Delta ExchangeVol_{t-1} + \beta_3 \Delta Google_{t-1} + \beta_4 \Delta Returns_{t-1} + \beta_5 D_{week} + u_t \tag{8}$$

Where Δ represents the first differences, *Y* represents the *Network/Exchange* volume, *Google* represents the Google trend searches on the word "Bitcoin", *Returns* represents the raw difference between Bitcoin prices in consecutive weeks, and *D* represents the dummy variable for the first Monday of the year.

The hypothesis I stipulated for this model follow the assumptions made by Glaser et al., (2014):

1) If the Google trend variable has a positive and significant impact on the exchange volume, it is possible to conclude that new users tend to employ Bitcoin as a speculative investment.
2) If the Google trend variable has a positive and significant impact on the network volume, it is possible to conclude that new users may employ Bitcoin as a medium of exchange.
3) If none of the two previous conclusions holds, this suggests Bitcoin has evolved, so this cryptocurrency may not fit entirely into one of the previous categories.

To add controls for the week, month, and year effects, I introduced four dummy variables. A dummy variable is a binary variable that indicates the absence or presence of some categorical effect that may be expected to shift the outcome. I created a dummy for the first week of the month, a dummy for the first Monday of the year (which is equivalent to the first week of the year since the data is weekly), and a dummy for the last week of the year. For the exchange volume model, only the dummy for the first Monday of the year was significant. For the network volume model, no dummy was significant.

The first model analyses the exchange and the network volume to evaluate users' intentions when acquiring Bitcoin. For each volume, I performed three regressions. First, a parsimonious model with *lagged* Google trend searches and a one-order autoregressive term. Second, the same variables plus the Bitcoin *lagged* returns, the *lagged* network/exchange volume term, and a dummy variable for the first Monday of the year (in the case of the exchange volume model). Third, all these variables plus the autoregressive terms of orders two and three (since the data is weekly, it is enough to extend the term up to three weeks before, and with this, the robustness of the results increases).

The results are presented in Table I, including the significant and non-significant variables and the GARCH (1,1) model as in the paper followed.

Table I: Regression Results on Exchange and Network Volumes (*p*-values in parentheses)

	ΔBitcoin Exchange Volume			*ΔBitcoin Network Volume*		
Explanatory Variables	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
$\Delta \boldsymbol{Google_{t-1}}$	1.23E+10 (0.42)	146.E+10 (0.31)	1.28E+10 (0.37)	76012445 (0.66)	1.18E+08 (0.52)	2.78E+08 (0.11)
$\Delta \boldsymbol{ExchangeVol_{t-1}}$	-0.279 (0.00)	-0.299 (0.00)	-0.31 (0.00)		-0.0006 (0.44)	-0.0001 (0.85)
$\Delta \boldsymbol{ExchangeVol_{t-2}}$			-0.0224 (0.73)			
$\Delta \boldsymbol{ExchangeVol_{t-3}}$			-0.181 (0.01)			
$\Delta \boldsymbol{NetworkVol_{t-1}}$		11.188 (0.01)	10.27 (0.02)	-0.275 (0.00)	-0.265 (0.00)	-0.3106 (0.00)
$\Delta \boldsymbol{NetworkVol_{t-2}}$						-0.306 (0.00)
$\Delta \boldsymbol{NetworkVol_{t-3}}$						0.193 (0.00)
$\Delta \boldsymbol{Returns_{t-1}}$		-4.666 (0.00)	-4.695 (0.00)		0.0141 (0.21)	0.025 (0.02)
Constant	2.68E+09 (0.10)	1.78E+09 (0.25)	2.01E+09 (0.19)	7493809 (0.70)	8802371 (0.65)	9077635 (0.62)
Time Dummies	NO	YES	YES	NO	NO	NO
GARCH (1,1) coefficients						
ARCH	0.241 (0.00)	0.269 (0.00)	0.265 (0.00)	0.483 (0.00)	0.459 (0.00)	0.496 (0.00)
GARCH	0.508 (0.00)	0.534 (0.00)	0.533 (0.00)	0.677 (0.00)	0.650 (0.00)	0.662 (0.00)

For the second model, it is necessary to examine the behavior of Bitcoin´s price. The logarithm is performed to follow Dyhrberg’s (2016) structure. Bitcoin’s price exhibits some evidence of volatility clustering.

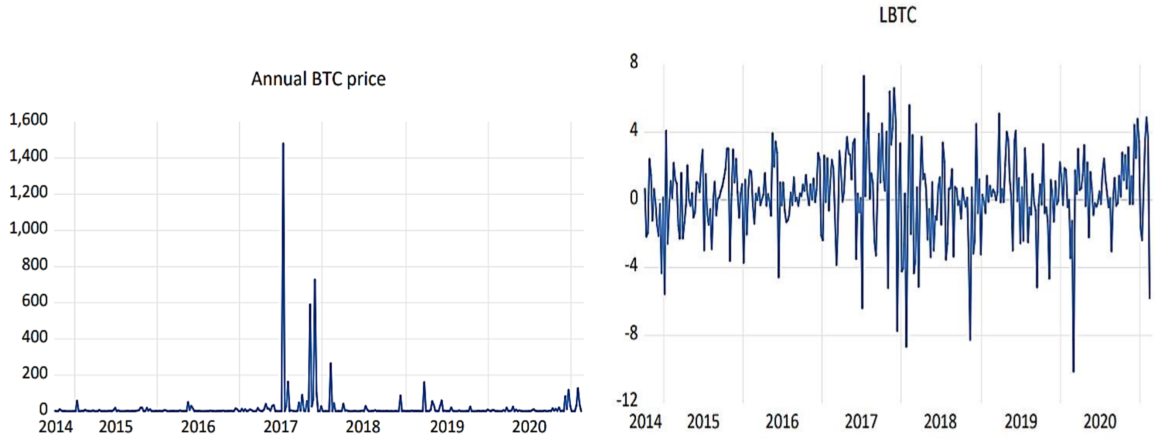


Figure 3: The levels of Bitcoin price and logarithm of Bitcoin price

From the graphs, it is noticeable that there are clusters of different volatility levels. There are periods in which large changes are followed by large changes and periods in which small changes follow small changes. This further suggests the usefulness of the ARCH/GARCH approach.

After performing the same model as Dyhrberg (2016), it was not possible to conclude how the variables affect Bitcoin. Because of this problem, I computed the correlation matrix of the observations and *lagged* observations to understand how the variables interact among themselves and then estimated a GARCH (1,1) model without explanatory variables.

	BTC	EUR_USD	EUROSTOX	FED_FUNDS	GERMAN_B	GOLD	S_P500
BTC	1.000000	0.050019	-0.022869	0.036130	-0.129298	0.038839	-0.001951
EUR_USD	0.050019	1.000000	-0.007590	-0.056241	0.023826	-0.017109	0.006857
EUROSTOXX50	-0.022869	-0.007590	1.000000	-0.137496	0.021587	0.073444	0.649507
FED_FUNDS	0.036130	-0.056241	-0.137496	1.000000	-0.327111	-0.036021	-0.079056
GERMAN_BONDS	-0.129298	0.023826	0.021587	-0.327111	1.000000	-0.013349	-0.028923
GOLD	0.038839	-0.017109	0.073444	-0.036021	-0.013349	1.000000	0.390058
S_P500	-0.001951	0.006857	0.649507	-0.079056	-0.028923	0.390058	1.000000
BTC(-1)	0.023205	0.059043	-0.018631	0.038020	-0.137976	-0.013048	-0.007807
EUR_USD(-1)	0.049697	0.730139	-0.002900	-0.049201	0.027711	-0.015899	0.018227
EUROSTOXX50(-1)	-0.009983	0.023514	0.013586	-0.135901	0.034583	-0.084526	-0.077604
FED_FUNDS(-1)	0.033305	-0.061254	-0.133474	0.997818	-0.323989	-0.030178	-0.073311
GERMAN_BONDS(-1)	-0.138127	0.027893	0.056711	-0.336346	0.961140	-0.005174	-0.019488
GOLD(-1)	-0.009431	0.005226	0.023947	-0.048077	0.013192	-0.038815	-0.020298
S_P500(-1)	0.004421	0.032474	-0.032948	-0.079645	-0.020307	-0.123497	-0.076724

	BTC(-1)	EUR_USD(-1)	EUROSTOX	FED_FUNDS(	GERMAN_B	GOLD(-1)	S_P500(-1)
BTC	0.023205	0.049697	-0.009983	0.033305	-0.138127	-0.009431	0.004421
EUR_USD	0.059043	0.730139	0.023514	-0.061254	0.027893	0.005226	0.032474
EUROSTOXX50	-0.018631	-0.002900	0.013586	-0.133474	0.056711	0.023947	-0.032948
FED_FUNDS	0.038020	-0.049201	-0.135901	0.997818	-0.336346	-0.048077	-0.079645
GERMAN_BONDS	-0.137976	0.027711	0.034583	-0.323989	0.961140	0.013192	-0.020307
GOLD	-0.013048	-0.015899	-0.084526	-0.030178	-0.005174	-0.038815	-0.123497
S_P500	-0.007807	0.018227	-0.077604	-0.073311	-0.019488	-0.020298	-0.076724
BTC(-1)	1.000000	0.049785	-0.023011	0.036084	-0.129187	0.038218	-0.002111
EUR_USD(-1)	0.049785	1.000000	-0.007791	-0.057628	0.032264	-0.013857	0.006765
EUROSTOXX50(-1)	-0.023011	-0.007791	1.000000	-0.138082	0.017954	0.071154	0.649235
FED_FUNDS(-1)	0.036084	-0.057628	-0.138082	1.000000	-0.331500	-0.039975	-0.079783
GERMAN_BONDS(-1)	-0.129187	0.032264	0.017954	-0.331500	1.000000	-0.010246	-0.031976
GOLD(-1)	0.038218	-0.013857	0.071154	-0.039975	-0.010246	1.000000	0.388181
S_P500(-1)	-0.002111	0.006765	0.649235	-0.079783	-0.031976	0.388181	1.000000

Figure 4: Correlation matrix

After fitting several models with all these explanatory variables and testing for the significance of each *F* statistic I was led to consider the following models with significant *F* statistic results:

(9) $$LBTC_t = \alpha + \beta_1 EUR\_USD_t + \beta_2 Gold_{t-1} + \beta_3 EUR\_USD_{t-1} + u_t$$

(10) $$\sigma^2{}_t = \gamma_0 + \delta_1 \sigma^2{}_{t-1} + \gamma_1 u_{t-1}^2$$

(11) $$LBTC_t = \alpha + \beta_1 EUR\_USD_t + \beta_2 EUR\_USD_{t-1} + u_t$$

(12) $$\sigma^2{}_t = \gamma_0 + \delta_1 \sigma^2{}_{t-1} + \gamma_1 u_{t-1}^2$$

(13) $$LBTC_t = \alpha + \beta_1 Gold_{t-1} + u_t$$

(14) $$\sigma^2{}_t = \gamma_0 + \delta_1 \sigma^2{}_{t-1} + \gamma_1 u_{t-1}^2$$

(15) $$LBTC_t = \alpha + \beta_1 S\&P500_t + u_t$$

(16) $$\sigma^2{}_t = \gamma_0 + \delta_1 \sigma^2{}_{t-1} + \gamma_1 u_{t-1}^2$$

(17) $$LBTC_t = \alpha + \beta_1 S\&P500_{t-1} + u_t$$

(18) $$\sigma^2{}_t = \gamma_0 + \delta_1 \sigma^2{}_{t-1} + \gamma_1 u_{t-1}^2$$

(19) $$LBTC_t = \alpha + \beta_1 Eurostoxx_t + u_t$$

(20) $$\sigma^2{}_t = \gamma_0 + \delta_1 \sigma^2{}_{t-1} + \gamma_1 u_{t-1}^2$$

(21) $$LBTC_t = \alpha + \beta_1 Eurostoxx_{t-1} + u_t$$

(22) $$\sigma^2{}_t = \gamma_0 + \delta_1 \sigma^2{}_{t-1} + \gamma_1 u_{t-1}^2$$

The same problem occurred regarding Gold; the variables were not significant, so I estimated and tested other models inspired by the correlation matrix above. The models that presented the best results, in terms of eliminating heteroskedasticity and in terms of significant *F statistic*, were the GARCH (1,2) models with equations as follows:

(23) $$LGold_t = \alpha + \beta_1 FederalFunds_t + \beta_2 FederalFunds_{t-1} + \beta_1 BTC_t + u_t$$

(24) $$\sigma^2{}_t = \gamma_0 + \delta_1\sigma^2{}_{t-1} + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2$$

(25) $$LGold_t = \alpha + \beta_1 EUR\_UDS_t + \beta_2 EUR\_USD_{t-1} + u_t$$

(26) $$\sigma^2{}_t = \gamma_0 + \delta_1\sigma^2{}_{t-1} + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2$$

(27) $$LGold_t = \alpha + \beta_1 S\&P500_t + \beta_2 S\&P500_{t-1} + u_t$$

(28) $$\sigma^2{}_t = \gamma_0 + \delta_1\sigma^2{}_{t-1} + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2$$

Table II exhibits the results of the GARCH models for Bitcoin and Gold, displayed in the equations above.

Table II: GARCH outputs for Bitcoin and Gold (*p*-values in parentheses)

	LBitcoin						***LGold***		
Explanatory Variables									
$\boldsymbol{Eurostoxx50_t}$			0.193 (0.04)						
$\boldsymbol{Eurostoxx50_{t-1}}$		0.168 (0.04)							
$\boldsymbol{S\&P500_t}$						0.199 (0.05)			0.067 (0.00)
$\boldsymbol{S\&P500_{t-1}}$					0.194 (0.05)				-0.059 (0.01)
$\boldsymbol{\Delta FederalFunds_t}$								1.193 (0.00)	
$\boldsymbol{\Delta FederalFunds_{t-1}}$								-2.053 (0.08)	
$\boldsymbol{EUR\_USD_t}$	2.723 (0.00)						2.522 (0.00)		
$\boldsymbol{EUR\_USD_{t-1}}$	-2.154 (0.00)						-2.281 (0.00)		
$\boldsymbol{Gold_t}$				0.226 (0.01)					
$\boldsymbol{Gold_{t-1}}$	-0.333 (0.02)								
$\boldsymbol{Bitcoin_t}$								0.000 (0.09)	
	GARCH (1,1) coefficients							**GARCH (1,2) coefficients**	
ARCH	0.31 (0.00)	0.26 (0.00)	0.27 (0.00)	0.27 (0.00)	0.27 (0.00)	0.26 (0.00)	0.30 (0.00)	0.16 (0.00)	0.16 (0.00)
GARCH	0.58 (0.00)	0.61 (0.00)	0.61 (0.00)	0.60 (0.00)	0.60 (0.00)	0.61 (0.00)	0.58 (0.00)	-0.00 (0.96) 0.79 (0.00)	-0.01 (0.89) 0.79 (0.00)

For the third and last model, I estimated an E-GARCH model in order to evaluate the asymmetry effect of Bitcoin. The equations of the model are as follows:

(29) $$LBTC_t = \alpha + \beta_1 EUR\_USD_t + \beta_2 Gold_{t-1} + \beta_3 EUR\_USD_{t-1} + u_t$$

(30) $$log(\sigma^2{}_t) = \gamma + \sum_{j=1}^{q} \left| \frac{u_{t-j}}{\sqrt{h_{t-j}}} \right| \zeta_j + \sum_{j=1}^{q} \frac{u_{t-j}}{\sqrt{h_{t-j}}} \boldsymbol{\xi}_j + \sum_{i=1}^{p} \delta_i log(h_{t-i})$$

I estimated an E-GARCH model for every model of the logarithm of Bitcoin previously presented in Table II, and all models presented similar results. The only difference was in the constant term, which varied between positive and negative values. Since this variable is not important for the estimation, I will only present the model results from equation (29) represented below in Table III and make conclusions from it.

Table III: E-GARCH output for Bitcoin (p-values in parentheses)

	LBitcoin
Explanatory Variables	
EUR_USD_t	2.604 (0.00)
EUR_USD_{t-1}	-2.024 (0.04)
$Gold_{t-1}$	-0.299 (0.01)
Variance Equation	
C4 (γ)	-0.019 (0.75)
C5 (ζ)	0.479 (0.00)
C6 (ξ)	-0.018 (0.74)
C7 (δ)	0.794 (0.00)

In the estimation output, C4 represents the constant (γ), C5 is the ARCH term (ζ), and it refers to the extent that the magnitude of a shock to the variance affects future volatility, C6 is the leverage effect term (ξ), and it gives insight into how the sign of the shock influences future volatility, C7 is the GARCH term (δ), and it helps to assess the persistence of past volatility and how it helps to predict future volatility.

4.2 ESTIMATION PROBLEMS

After estimating the models, it is necessary to see if there are problems with the estimations related to the residuals' heteroskedasticity, autocorrelation, and normality.

Financial time series are prone to conditional heteroskedasticity, i.e., periods of structural volatility changes and autoregressive dependencies. The ARCH estimation incorporates such changes within the errors.

For the first model, I performed an ARCH test in all regressions. This test should reveal whether there is any heteroskedasticity in the model's residuals. The results of the test confirm that there are indeed ARCH effects in all estimations. So, it is necessary to introduce a GARCH model for all regressions. Following Glaser et al., (2014), I estimated a GARCH (1,1): with this model, the residual heteroskedasticity is eliminated (APPENDIX A).

For the second model, after estimating the GARCH model, I executed the same test to confirm that there are no ARCH effects. For Bitcoin, the GARCH (1,1) can eradicate residual heteroskedasticity, for Gold it cannot. After testing several models, I concluded that the GARCH (1,2) is the most suitable (APPENDIX B).

Autocorrelation is often discussed in the context of time series; it refers to the degree of correlation between values of the same variables across different observations in the data. To verify if this problem exists in the regressions, a correlogram is an appropriate tool. The correlogram displays the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function); these functions exhibit how the present values are related to past values at different lags.

From the correlogram of the first model (APPENDIX C), I observed that the residuals are autocorrelated. The null hypothesis of the portmanteau *Q* test is that there is no autocorrelation in the residuals. As most of the *p*-values of the *Q* statistic are near 0, we reject the null hypothesis. So, the residuals of the six regressions performed present autocorrelation. This is a problem I could not eliminate. The standardized residuals could not be computed for this model.

From the correlogram of the second model, we can confirm that the standardized residuals – the values of each residual, divided by an estimate of its standard deviation- are not autocorrelated, as the *Q* statistics *p*-values are larger than the conventional critical probabilities (APPENDIX D). The standardized residuals appear not to be correlated.

From the histogram of both models, one can suspect that the residuals are not normally distributed. From Jarque-Bera tests, I correctly conclude that both residuals and standardized residuals are not normally distributed (APPENDIX E). The exception is the case of the Gold models from Table II: here, it may be accepted that the residuals are normally distributed (APPENDIX F).

4.3. RESULTS

From the results of Table I, I concluded that, in the exchange volume models, the autoregressive terms are all significant and negative, which means that an increase in the exchange volume tends to drive the future exchange volume down. The Bitcoin *lagged* returns, and the *lagged* network volume are also significant. Returns have a negative impact, suggesting that a Bitcoin valuation causes fewer exchanges. The network volume has a positive impact, suggesting that users increase their Bitcoin for exchanges after applying Bitcoin to acquire goods and services.

In the network volume models, the exchange volume has no significance in any of the estimations – this suggests that the trading on the exchange has no impact on Bitcoin's network. The autoregressive terms are all significant and negative, except for the third one in the third estimation, which is significant and slightly positive – one can thus assume that past network volume increases are essentially reversed in the coming weeks. Interestingly, the *lagged* Bitcoin returns have a positive impact on the network volume – which suggests that an increase in Bitcoin returns causes an increase in Bitcoin use as a medium of exchange.

These models show that a changing volatility structure exists both in Bitcoin prices and in transactions. From the graphs, it is visible that there is no clear trend in both the exchange and the network volume.

With the data from 2014 until early 2021, I could not detect any relationship between the variation of Google searches and the exchange and network volumes.

For either of the models, the Google trend searches have no significance, and this may indicate that people are now very acquainted with Bitcoin and investing in Bitcoin does not require previous Google searches. The approach made by the authors Glaser et al., (2014) in an early stage of Bitcoin release may no longer be adequate currently, as cryptocurrencies are now well known.

The results of Table II are also interesting. In the case of Bitcoin (9)**,** when there is a positive shock[9] in the *lagged* Gold and the *lagged* EUR_USD exchange rate, the variance of Bitcoin's price decreases. However, a positive shock in the *contemporaneous* EUR_USD makes the variance increase. As for the rest of the equations, a positive shock in the explanatory variables makes the variance of Bitcoin's price increase.

Except for the *lagged* EUR_USD and the *lagged* Gold, a positive volatility shock to the explanatory variables makes the volatility of the Bitcoin price increase. These findings are the opposite of those in Dyhrberg (2016).

The German bonds were not significant explanatory variables in any model and thus were not included; this suggests that Bitcoin's price is more susceptible to shocks in the American market. As Bitcoin is mostly traded in dollars, this is not surprising.

For the GARCH model, the estimates consistently point to a significant and positive ARCH coefficient with value steadily around 0.3 and to a positive and significant GARCH coefficient set steadily around 0.6.

Concerning Gold (23), we can see that a positive shock to the *lagged* federal funds makes the variance of Gold's price decrease, while a positive shock in the *contemporaneous* Federal Funds and Bitcoin price makes the variance increase (however, the effect is very mild for the Bitcoin variable). For the other equations with the Gold logarithm as the dependent variable, a *contemporaneous* positive shock in the S&P500 makes the variance increase, while the same shock in the *lagged* S&P500 makes the variance for the Gold price decrease.

The results indicate that Gold may have some hedging capabilities against stocks on the S&P500 and against the Federal Funds.

The GARCH models estimates consistently point to significant and positive ARCH coefficients and GARCH coefficient values around 0.2 and 0.8, respectively. The non-significant GARCH coefficients are not important for the estimation and have no impact on the model.

From the results of Table III, one can see that C5 (ζ) is positive and significant, so the shock size significantly impacts volatility. It shows a positive relationship between the past variance and the current variance in absolute value. This means that the bigger the

[9] A positive shock is an increase in volatility that translates in an increase in the standard deviation.

magnitude of the shock to the variance, the higher the volatility. The estimate for C6 (ξ) is negative, which could indicate a leverage effect. However, C6 (ξ) is not statistically significant, so it is not detected an asymmetry effect - good and bad news do not affect Bitcoin's price variance in a significantly different magnitude. Finally, C7 (δ) is positive and significant, which means that past volatility helps predict future volatility.

5. CONCLUSION

Estimating the first model, which consisted of analyzing the impact that Google searches for Bitcoin had on its network and exchange volume, I reached different conclusions from Glaser et al., (2014). Data used in this paper (Glaser et al., 2014) span from 2011 to 2013, where data used in this dissertation is more recent, from 2015 to 2021. As said in the beginning, new users no longer need to search the web for information about Bitcoin; this topic is now well disseminated in society and financial markets. The difference in the data frames could explain the distinct results.

One interesting question for future works would be to assess if the results would change if the variable was Google searches on the words “Bitcoin price”. Since nowadays, there is no interest in understanding what Bitcoin is, but there is in knowing how its price shifts according to time and financial shocks.

From the first model, I concluded that it is no longer possible to evaluate new users’ intentions when acquiring Bitcoin, as the variable google searches is not significant in any of the models’ estimations. The methodology is no longer applicable for these data and time.

Contrary to the expectations, Bitcoin did not have similar behavior to Gold for the second model. Gold exhibited some management capabilities since the *lagged* variables decreased the variance of the Gold price. Dyhrberg (2016) concluded that Bitcoin's returns' volatility mostly decreases when positive shocks occur in certain market indexes, commodities, and interest rates. My conclusions were not in accordance with these findings; even though the time frame, the variables, and the model are different, the conclusions were not expected to be this distinct.

The conclusions were that Bitcoin's variance would decrease when a positive shock in the Gold and EUR_USD exchange rate market exists. Nevertheless, this only happens for these two *lagged* variables, which means that the other variables increase the variance. An increase in variance makes investment returns riskier; this hints that Bitcoin does not have management capabilities, as Dyhrberg (2016) stated.

From the third model estimates, I concluded that Bitcoin does not display an asymmetry effect. So, Bitcoin is not fit to be a safe haven. When there is a crisis in the market, investors can turn to Gold to protect their funds, whereas Bitcoin would not perform this role.

These results are compatible with the idea that Bitcoin is not a medium of exchange but a financial asset with characteristics different from Gold.

6. REFERENCES

Al-Khazali, O., Bouri, E. and Roubaud, D. (2018). The impact of positive and negative macroeconomic news surprises: Gold versus Bitcoin. *Economics Bulletin*, 38(1), pp.373-382.

Ante, L. and Fiedler, I. (2021). Market reaction to large transfers on the Bitcoin blockchain - Do size and motive matter? *Finance Research Letters*, 39, pp.1-10.

Asteriou, D. and Hall, S.G. (2011). Applied econometrics. New York, NY: Palgrave Macmillan, p. 521.

Baur, D.G. (2012). Asymmetric Volatility in the Gold Market. *The Journal of Alternative Investments*, 14 (4), pp. 26-38.

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

Baur, Dirk G., and Lucey, Brian M. (2009). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds, and Gold. *SSRN Electronic Journal*, pp.217-229.

Bouri, E., Azzi, G. and Dyhrberg, A. H. (2016). On the Return-Volatility Relationship in the Bitcoin Market around the Price Crash of 2013 (November 15, 2016). Available at SSRN: https://ssrn.com/abstract=2869855 or http://dx.doi.org/10.2139/ssrn.2869855.

Bouri, E., Shahzad, S.J.H., Roubaud, D., Kristoufek, L. and Lucey, B. (2020). Bitcoin, gold, and commodities as safe havens for stocks: New insights through wavelet analysis. *The Quarterly Review of Economics and Finance*, 77, pp.156–164.

Coindesk. (n.d.). Retrieved from Silk Road: https://www.coindesk.com/company/silk-road.

Dyhrberg, A.H. (2016). Bitcoin, gold and the dollar – A GARCH volatility analysis. *Finance Research Letters*, 16, pp.85–92.

European Banking Authority. (2014). *EBA warns consumers on virtual currencies*. [online] Available at: https://www.eba.europa.eu/eba-warns-consumers-on-virtual-currencies.

Gandal, N., Hamrick, J., Moore, T. and Oberman, T. (2018). Price manipulation in the Bitcoin ecosystem. *Journal of Monetary Economics*, 95, pp.86–96.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M.C. and Siering, M. (2014). Bitcoin -Asset or currency? Revealing users' hidden intentions. *ECIS* 2014 (Tel Aviv), Available at SSRN: https://ssrn.com/abstract=2425247.

Citi GPS: Global Perspectives and Solutions (2021). *BITCOIN At the Tipping Point*. Available at: https://www.3bit-lab.com/documents/citi-bitcoin-at-the-tipping-point_202103.pdf.

Li, J.-P., Naqvi, B., Rizvi, S.K.A. and Chang, H.-L. (2021). Bitcoin: The biggest financial innovation of fourth industrial revolution and a portfolio's efficiency booster. *Technological Forecasting and Social Change*, 162, pp.1-10.

Luther, W.J. and Salter, A.W. (2017). Bitcoin and the bailout. *The Quarterly Review of Economics and Finance*, 66, pp.50–56.

Mishkin, F.S. (1986). Introduction. In: *The Economics of Money, Banking, and Financial Markets*, 4th Canadian ed. Pearson Canada, p.784.

Nakamoto, S. (2008). *Bitcoin: A Peer-to-Peer Electronic Cash System.* Available at: www.bitcoin.org.

Pagano, M.S. and Sedunov, J. (2020). Bitcoin and the Demand for Money: Is Bitcoin More Than Just a Speculative Asset? (June 11, 2020). Available at SSRN: https://ssrn.com/abstract=3293998 or http://dx.doi.org/10.2139/ssrn.3293998.

Roubini, N. (2021). Nouriel Roubini: Bitcoin is not a hedge against tail risk. *Financial Times* (February 10, 2021). Available at: https://www.ft.com/content/9be5ad05-b17a-4449-807b-5dbcb5ef8170.

Tully, E. and Lucey, B.M. (2007). A power GARCH examination of the gold market. *Research in International Business and Finance*, 21(2), pp.316–325.

World Economic Forum (2021) *Blockchain Dynamic Briefing*. Available at: https://theblockchaintest.com/uploads/resources/WEF%20-%20Blockchain%20Dynamic%20Briefing%20-%202021%20-%20Jan.pdf.

Yermack, D. (2015). Chapter 2 - Is Bitcoin a Real Currency? An Economic Appraisal. In: *Handbook of Digital Currency Bitcoin, Innovation, Financial Instruments, and Big Data*. Elsevier Inc, pp.31–43.

7. DATA SOURCES

Google (n.d.). *Google Trend* [online dataset]. Retrieved from Bitcoin: https://trends.google.com/trends/explore?date=today%205-y&q=bitcoin.

Investing. (n.d.). *Investing indices historical data* [online dataset]. Retrieved from: https://www.investing.com/indices.

Investing. (n.d.). *Investing rates-bonds historical data* [online dataset]. Retrieved from: https://www.investing.com/rates-bonds/germany-3-month-bond-yield-historical-data.

Yahoo Finance. (n.d.). *Yahoo Finance historical data* [online dataset] Retrieved from: https://finance.yahoo.com/quote.

APPENDIX

APPENDIX A – ARCH effects tests for Table I

Heteroskedasticity Test: ARCH

F-statistic	0.174855	Prob. F(1,329)	0.6761
Obs*R-squared	0.175825	Prob. Chi-Square(1)	0.6750

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/16/21 Time: 21:15
Sample (adjusted): 10/27/2014 2/22/2021
Included observations: 331 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.167473	0.954298	4.367056	0.0000
WGT_RESID^2(-1)	-0.023070	0.055170	-0.418157	0.6761

R-squared	0.000531	Mean dependent var	4.074723
Adjusted R-squared	-0.002507	S.D. dependent var	16.86532
S.E. of regression	16.88645	Akaike info criterion	8.496924
Sum squared resid	93815.02	Schwarz criterion	8.519897
Log likelihood	-1404.241	Hannan-Quinn criter.	8.506086
F-statistic	0.174855	Durbin-Watson stat	1.999902
Prob(F-statistic)	0.676105		

Heteroskedasticity Test: ARCH

F-statistic	0.040149	Prob. F(1,329)	0.8413
Obs*R-squared	0.040388	Prob. Chi-Square(1)	0.8407

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/16/21 Time: 21:16
Sample (adjusted): 10/27/2014 2/22/2021
Included observations: 331 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.321061	0.601535	2.196152	0.0288
WGT_RESID^2(-1)	-0.011046	0.055129	-0.200372	0.8413

R-squared	0.000122	Mean dependent var	1.306605
Adjusted R-squared	-0.002917	S.D. dependent var	10.84914
S.E. of regression	10.86496	Akaike info criterion	7.614986
Sum squared resid	38837.56	Schwarz criterion	7.637960
Log likelihood	-1258.280	Hannan-Quinn criter.	7.624149
F-statistic	0.040149	Durbin-Watson stat	2.000052
Prob(F-statistic)	0.841313		

ARCH effects test of model 1 for Exchange and Network volume

Heteroskedasticity Test: ARCH

F-statistic	0.219941	Prob. F(1,329)	0.6394
Obs*R-squared	0.221130	Prob. Chi-Square(1)	0.6382

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/16/21 Time: 21:16
Sample (adjusted): 10/27/2014 2/22/2021
Included observations: 331 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.261831	0.742915	4.390585	0.0000
WGT_RESID^2(-1)	-0.025857	0.055134	-0.468979	0.6394

R-squared	0.000668	Mean dependent var	3.180309
Adjusted R-squared	-0.002369	S.D. dependent var	13.12542
S.E. of regression	13.14096	Akaike info criterion	7.995369
Sum squared resid	56813.28	Schwarz criterion	8.018342
Log likelihood	-1321.233	Hannan-Quinn criter.	8.004531
F-statistic	0.219941	Durbin-Watson stat	2.000920
Prob(F-statistic)	0.639396		

Heteroskedasticity Test: ARCH

F-statistic	0.029629	Prob. F(1,329)	0.8634
Obs*R-squared	0.029807	Prob. Chi-Square(1)	0.8629

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/16/21 Time: 21:17
Sample (adjusted): 10/27/2014 2/22/2021
Included observations: 331 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.374165	1.228705	1.932249	0.0542
WGT_RESID^2(-1)	-0.009490	0.055130	-0.172131	0.8634

R-squared	0.000090	Mean dependent var	2.351828
Adjusted R-squared	-0.002949	S.D. dependent var	22.19661
S.E. of regression	22.22932	Akaike info criterion	9.046725
Sum squared resid	162572.9	Schwarz criterion	9.069699
Log likelihood	-1495.233	Hannan-Quinn criter.	9.055888
F-statistic	0.029629	Durbin-Watson stat	1.999981
Prob(F-statistic)	0.863440		

ARCH effects test of model 2 for Exchange and Network volume

Heteroskedasticity Test: ARCH

F-statistic	0.551068	Prob. F(1,327)	0.4584
Obs*R-squared	0.553505	Prob. Chi-Square(1)	0.4569

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/16/21 Time: 21:18
Sample (adjusted): 11/10/2014 2/22/2021
Included observations: 329 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.125280	0.575436	5.431151	0.0000
WGT_RESID^2(-1)	-0.041053	0.055302	-0.742339	0.4584

R-squared	0.001682	Mean dependent var	3.003347
Adjusted R-squared	-0.001371	S.D. dependent var	9.996368
S.E. of regression	10.00322	Akaike info criterion	7.449751
Sum squared resid	32721.04	Schwarz criterion	7.472827
Log likelihood	-1223.484	Hannan-Quinn criter.	7.458957
F-statistic	0.551068	Durbin-Watson stat	2.001492
Prob(F-statistic)	0.458415		

Heteroskedasticity Test: ARCH

F-statistic	0.028195	Prob. F(1,327)	0.8668
Obs*R-squared	0.028365	Prob. Chi-Square(1)	0.8663

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/16/21 Time: 21:18
Sample (adjusted): 11/10/2014 2/22/2021
Included observations: 329 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.861850	0.923716	2.015610	0.0447
WGT_RESID^2(-1)	-0.009285	0.055298	-0.167914	0.8668

R-squared	0.000086	Mean dependent var	1.844709
Adjusted R-squared	-0.002972	S.D. dependent var	16.62737
S.E. of regression	16.65206	Akaike info criterion	8.469005
Sum squared resid	90674.17	Schwarz criterion	8.492082
Log likelihood	-1391.151	Hannan-Quinn criter.	8.478211
F-statistic	0.028195	Durbin-Watson stat	2.000024
Prob(F-statistic)	0.866755		

ARCH effects test of model 3 for Exchange and Network volume

APPENDIX B – ARCH effects tests for Table II

Heteroskedasticity Test: ARCH

F-statistic	0.054649	Prob. F(1,329)	0.8153
Obs*R-squared	0.054972	Prob. Chi-Square(1)	0.8146

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 07/01/21 Time: 16:22
Sample (adjusted): 10/20/2014 2/15/2021
Included observations: 331 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.011834	0.115313	8.774701	0.0000
WGT_RESID^2(-1)	-0.012931	0.055314	-0.233772	0.8153

R-squared	0.000166	Mean dependent var	0.999009
Adjusted R-squared	-0.002873	S.D. dependent var	1.842648
S.E. of regression	1.845293	Akaike info criterion	4.069177
Sum squared resid	1120.280	Schwarz criterion	4.092150
Log likelihood	-671.4488	Hannan-Quinn criter.	4.078340
F-statistic	0.054649	Durbin-Watson stat	1.992298
Prob(F-statistic)	0.815307		

Heteroskedasticity Test: ARCH

F-statistic	0.205821	Prob. F(1,329)	0.6504
Obs*R-squared	0.206942	Prob. Chi-Square(1)	0.6492

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/20/21 Time: 14:53
Sample (adjusted): 10/20/2014 2/15/2021
Included observations: 331 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.024086	0.120460	8.501452	0.0000
WGT_RESID^2(-1)	-0.025061	0.055239	-0.453674	0.6504

R-squared	0.000625	Mean dependent var	0.999199
Adjusted R-squared	-0.002412	S.D. dependent var	1.948786
S.E. of regression	1.951136	Akaike info criterion	4.180724
Sum squared resid	1252.480	Schwarz criterion	4.203698
Log likelihood	-689.9099	Hannan-Quinn criter.	4.189887
F-statistic	0.205821	Durbin-Watson stat	1.992575
Prob(F-statistic)	0.650362		

ARCH effects test of equations 10 and 12

Heteroskedasticity Test: ARCH

F-statistic	0.274662	Prob. F(1,329)	0.6006
Obs*R-squared	0.276101	Prob. Chi-Square(1)	0.5993

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/20/21 Time: 14:55
Sample (adjusted): 10/20/2014 2/15/2021
Included observations: 331 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.028155	0.123384	8.332967	0.0000
WGT_RESID^2(-1)	-0.028930	0.055201	-0.524082	0.6006

R-squared	0.000834	Mean dependent var	0.999404
Adjusted R-squared	-0.002203	S.D. dependent var	2.008465
S.E. of regression	2.010676	Akaike info criterion	4.240843
Sum squared resid	1330.087	Schwarz criterion	4.263816
Log likelihood	-699.8595	Hannan-Quinn criter.	4.250006
F-statistic	0.274662	Durbin-Watson stat	1.993670
Prob(F-statistic)	0.600574		

Heteroskedasticity Test: ARCH

F-statistic	0.218429	Prob. F(1,330)	0.6405
Obs*R-squared	0.219608	Prob. Chi-Square(1)	0.6393

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/20/21 Time: 14:57
Sample (adjusted): 10/13/2014 2/15/2021
Included observations: 332 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.028786	0.121267	8.483641	0.0000
WGT_RESID^2(-1)	-0.025766	0.055131	-0.467364	0.6405

R-squared	0.000661	Mean dependent var	1.003193
Adjusted R-squared	-0.002367	S.D. dependent var	1.969143
S.E. of regression	1.971472	Akaike info criterion	4.201443
Sum squared resid	1282.611	Schwarz criterion	4.224366
Log likelihood	-695.4396	Hannan-Quinn criter.	4.210585
F-statistic	0.218429	Durbin-Watson stat	1.990406
Prob(F-statistic)	0.640548		

ARCH effects test of equations 14 and 16

Heteroskedasticity Test: ARCH

F-statistic	0.238598	Prob. F(1,329)	0.6255
Obs*R-squared	0.239875	Prob. Chi-Square(1)	0.6243

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/20/21 Time: 15:01
Sample (adjusted): 10/20/2014 2/15/2021
Included observations: 331 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.026310	0.122248	8.395331	0.0000
WGT_RESID^2(-1)	-0.026985	0.055244	-0.488465	0.6255

R-squared	0.000725	Mean dependent var	0.999523
Adjusted R-squared	-0.002313	S.D. dependent var	1.985458
S.E. of regression	1.987752	Akaike info criterion	4.217910
Sum squared resid	1299.931	Schwarz criterion	4.240884
Log likelihood	-696.0641	Hannan-Quinn criter.	4.227073
F-statistic	0.238598	Durbin-Watson stat	1.992622
Prob(F-statistic)	0.625546		

Heteroskedasticity Test: ARCH

F-statistic	0.237203	Prob. F(1,330)	0.6266
Obs*R-squared	0.238469	Prob. Chi-Square(1)	0.6253

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/20/21 Time: 15:02
Sample (adjusted): 10/13/2014 2/15/2021
Included observations: 332 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.029658	0.122086	8.433888	0.0000
WGT_RESID^2(-1)	-0.026851	0.055132	-0.487035	0.6266

R-squared	0.000718	Mean dependent var	1.002995
Adjusted R-squared	-0.002310	S.D. dependent var	1.986035
S.E. of regression	1.988327	Akaike info criterion	4.218470
Sum squared resid	1304.637	Schwarz criterion	4.241393
Log likelihood	-698.2661	Hannan-Quinn criter.	4.227612
F-statistic	0.237203	Durbin-Watson stat	1.990910
Prob(F-statistic)	0.626557		

ARCH effects test of equations 18 and 20

Heteroskedasticity Test: ARCH

F-statistic	0.235408	Prob. F(1,329)	0.6279
Obs*R-squared	0.236670	Prob. Chi-Square(1)	0.6266

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/20/21 Time: 15:03
Sample (adjusted): 10/20/2014 2/15/2021
Included observations: 331 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.026009	0.121679	8.432102	0.0000
WGT_RESID^2(-1)	-0.026805	0.055246	-0.485189	0.6279

R-squared	0.000715	Mean dependent var	0.999401
Adjusted R-squared	-0.002322	S.D. dependent var	1.973872
S.E. of regression	1.976163	Akaike info criterion	4.206215
Sum squared resid	1284.817	Schwarz criterion	4.229189
Log likelihood	-694.1286	Hannan-Quinn criter.	4.215378
F-statistic	0.235408	Durbin-Watson stat	1.992612
Prob(F-statistic)	0.627866		

Heteroskedasticity Test: ARCH

F-statistic	2.393528	Prob. F(1,328)	0.1228
Obs*R-squared	2.390677	Prob. Chi-Square(1)	0.1221

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 07/01/21 Time: 16:56
Sample (adjusted): 10/27/2014 2/15/2021
Included observations: 330 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.907059	0.102111	8.883099	0.0000
WGT_RESID^2(-1)	0.084949	0.054908	1.547103	0.1228

R-squared	0.007244	Mean dependent var	0.991615
Adjusted R-squared	0.004218	S.D. dependent var	1.570174
S.E. of regression	1.566859	Akaike info criterion	3.742065
Sum squared resid	805.2557	Schwarz criterion	3.765090
Log likelihood	-615.4408	Hannan-Quinn criter.	3.751250
F-statistic	2.393528	Durbin-Watson stat	1.993064
Prob(F-statistic)	0.122803		

ARCH effects test of equations 22 and 24

Heteroskedasticity Test: ARCH

F-statistic	0.481822	Prob. F(1,329)	0.4881
Obs*R-squared	0.484042	Prob. Chi-Square(1)	0.4866

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/20/21 Time: 15:07
Sample (adjusted): 10/20/2014 2/15/2021
Included observations: 331 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.965961	0.102419	9.431480	0.0000
WGT_RESID^2(-1)	0.038225	0.055069	0.694134	0.4881

R-squared	0.001462	Mean dependent var	1.004184
Adjusted R-squared	-0.001573	S.D. dependent var	1.569874
S.E. of regression	1.571108	Akaike info criterion	3.747464
Sum squared resid	812.0974	Schwarz criterion	3.770437
Log likelihood	-618.2052	Hannan-Quinn criter.	3.756626
F-statistic	0.481822	Durbin-Watson stat	1.988234
Prob(F-statistic)	0.488088		

Heteroskedasticity Test: ARCH

F-statistic	1.485129	Prob. F(1,329)	0.2238
Obs*R-squared	1.487442	Prob. Chi-Square(1)	0.2226

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/20/21 Time: 15:09
Sample (adjusted): 10/20/2014 2/15/2021
Included observations: 331 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.936105	0.101959	9.181204	0.0000
WGT_RESID^2(-1)	0.067012	0.054988	1.218659	0.2238

R-squared	0.004494	Mean dependent var	1.003098
Adjusted R-squared	0.001468	S.D. dependent var	1.563408
S.E. of regression	1.562260	Akaike info criterion	3.736169
Sum squared resid	802.9764	Schwarz criterion	3.759142
Log likelihood	-616.3359	Hannan-Quinn criter.	3.745331
F-statistic	1.485129	Durbin-Watson stat	1.987762
Prob(F-statistic)	0.223847		

ARCH effects test of equations 26 and 28

APPENDIX C – ACF and PACF for Table I

Correlogram of Residuals

Date: 05/20/21 Time: 12:06
Sample (adjusted): 10/20/2014 2/22/2021
Q-statistic probabilities adjusted for 1 dynamic regressor

Lag	AC	PAC	Q-Stat	Prob*
1	0.011	0.011	0.0413	0.839
2	0.026	0.026	0.2770	0.871
3	-0.095	-0.095	3.2927	0.349
4	0.049	0.051	4.1158	0.391
5	-0.111	-0.109	8.3069	0.140
6	0.040	0.033	8.8388	0.183
7	0.218	0.237	25.117	0.001
8	0.069	0.037	26.724	0.001
9	-0.027	-0.026	26.983	0.001
10	0.070	0.103	28.657	0.001
11	0.044	0.037	29.327	0.002
12	0.047	0.085	30.106	0.003
13	-0.105	-0.101	33.929	0.001
14	-0.024	-0.099	34.123	0.002
15	-0.059	-0.051	35.336	0.002
16	0.065	0.061	36.801	0.002
17	0.094	0.082	39.888	0.001
18	0.145	0.090	47.301	0.000
19	-0.037	-0.072	47.776	0.000
20	-0.099	-0.082	51.276	0.000
21	-0.089	-0.023	54.092	0.000
22	-0.114	-0.112	58.774	0.000
23	-0.028	-0.037	59.048	0.000
24	0.042	-0.009	59.678	0.000

*Probabilities may not be valid for this equation specification.

Correlogram of Residuals

Date: 05/20/21 Time: 12:08
Sample (adjusted): 10/20/2014 2/22/2021
Q-statistic probabilities adjusted for 1 dynamic regressor

Lag	AC	PAC	Q-Stat	Prob*
1	-0.099	-0.099	3.2518	0.071
2	-0.268	-0.281	27.468	0.000
3	0.250	0.206	48.513	0.000
4	-0.190	-0.253	60.744	0.000
5	-0.088	0.018	63.364	0.000
6	0.246	0.084	83.984	0.000
7	-0.033	0.059	84.348	0.000
8	-0.082	-0.021	86.661	0.000
9	0.174	0.119	97.111	0.000
10	-0.119	-0.095	101.99	0.000
11	-0.155	-0.068	110.31	0.000
12	0.180	0.037	121.56	0.000
13	0.049	0.092	122.39	0.000
14	-0.033	0.053	122.77	0.000
15	0.066	-0.013	124.28	0.000
16	-0.052	-0.012	125.23	0.000
17	-0.075	-0.009	127.23	0.000
18	-0.042	-0.132	127.86	0.000
19	0.024	0.015	128.07	0.000
20	0.013	-0.024	128.13	0.000
21	-0.056	-0.087	129.25	0.000
22	0.120	0.110	134.37	0.000
23	-0.102	-0.122	138.11	0.000
24	-0.109	0.003	142.41	0.000

*Probabilities may not be valid for this equation specification.

Correlogram of Residuals of model 1 for Exchange and Network volume

Correlogram of Residuals

Date: 05/20/21 Time: 12:09
Sample (adjusted): 10/20/2014 2/22/2021
Q-statistic probabilities adjusted for 1 dynamic regressor

Lag	AC	PAC	Q-Stat	Prob*
1	-0.005	-0.005	0.0074	0.931
2	-0.008	-0.008	0.0302	0.985
3	-0.099	-0.099	3.3295	0.344
4	0.054	0.053	4.3131	0.365
5	-0.089	-0.092	6.9994	0.221
6	0.073	0.066	8.8189	0.184
7	0.148	0.159	16.246	0.023
8	0.068	0.050	17.816	0.023
9	-0.095	-0.071	20.885	0.013
10	0.089	0.110	23.627	0.009
11	0.038	0.046	24.133	0.012
12	0.072	0.076	25.915	0.011
13	-0.148	-0.139	33.535	0.001
14	0.008	-0.041	33.560	0.002
15	-0.040	-0.025	34.127	0.003
16	0.069	0.057	35.798	0.003
17	0.074	0.075	37.742	0.003
18	0.091	0.026	40.644	0.002
19	-0.040	-0.026	41.215	0.002
20	-0.087	-0.051	43.898	0.002
21	-0.063	-0.023	45.319	0.002
22	-0.098	-0.143	48.746	0.001
23	0.016	0.004	48.833	0.001
24	0.009	-0.038	48.861	0.002

*Probabilities may not be valid for this equation specification.

Correlogram of Residuals

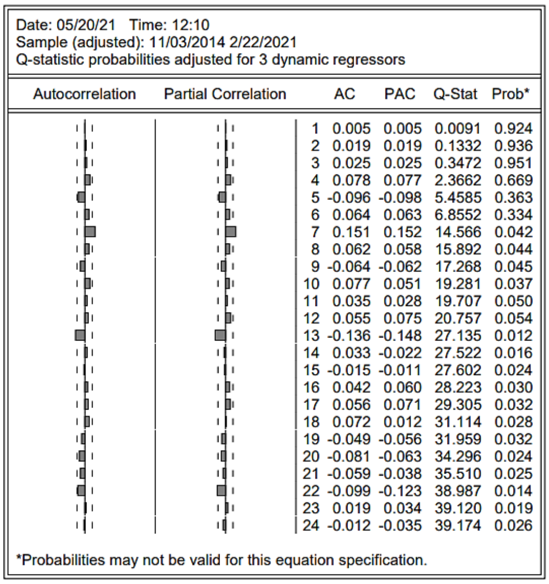
Date: 05/20/21 Time: 12:09
Sample (adjusted): 10/20/2014 2/22/2021
Q-statistic probabilities adjusted for 1 dynamic regressor

Lag	AC	PAC	Q-Stat	Prob*
1	-0.115	-0.115	4.4275	0.035
2	-0.262	-0.279	27.564	0.000
3	0.271	0.220	52.329	0.000
4	-0.193	-0.242	64.908	0.000
5	-0.088	0.016	67.555	0.000
6	0.241	0.076	87.312	0.000
7	-0.039	0.064	87.819	0.000
8	-0.075	-0.017	89.723	0.000
9	0.183	0.127	101.20	0.000
10	-0.121	-0.092	106.23	0.000
11	-0.154	-0.071	114.45	0.000
12	0.180	0.034	125.68	0.000
13	0.045	0.099	126.38	0.000
14	-0.031	0.057	126.71	0.000
15	0.077	-0.000	128.80	0.000
16	-0.059	-0.026	130.04	0.000
17	-0.081	-0.015	132.34	0.000
18	-0.028	-0.122	132.60	0.000
19	0.018	0.016	132.72	0.000
20	0.010	-0.019	132.76	0.000
21	-0.046	-0.086	133.52	0.000
22	0.113	0.103	138.10	0.000
23	-0.114	-0.129	142.73	0.000
24	-0.101	-0.002	146.37	0.000

*Probabilities may not be valid for this equation specification.

Correlogram of Residuals of model 2 for Exchange and Network volume

Correlogram of Residuals

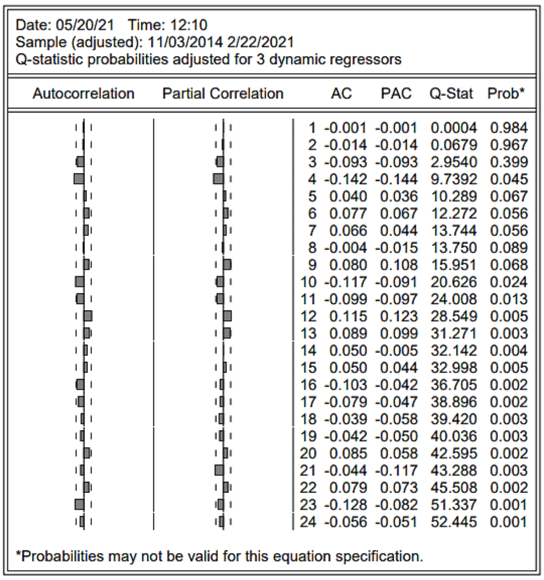


Date: 05/20/21 Time: 12:10
Sample (adjusted): 11/03/2014 2/22/2021
Q-statistic probabilities adjusted for 3 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.005	0.005	0.0091	0.924
		2	0.019	0.019	0.1332	0.936
		3	0.025	0.025	0.3472	0.951
		4	0.078	0.077	2.3662	0.669
		5	-0.096	-0.098	5.4585	0.363
		6	0.064	0.063	6.8552	0.334
		7	0.151	0.152	14.566	0.042
		8	0.062	0.058	15.892	0.044
		9	-0.064	-0.062	17.268	0.045
		10	0.077	0.051	19.281	0.037
		11	0.035	0.028	19.707	0.050
		12	0.055	0.075	20.757	0.054
		13	-0.136	-0.148	27.135	0.012
		14	0.033	-0.022	27.522	0.016
		15	-0.015	-0.011	27.602	0.024
		16	0.042	0.060	28.223	0.030
		17	0.056	0.071	29.305	0.032
		18	0.072	0.012	31.114	0.028
		19	-0.049	-0.056	31.959	0.032
		20	-0.081	-0.063	34.296	0.024
		21	-0.059	-0.038	35.510	0.025
		22	-0.099	-0.123	38.987	0.014
		23	0.019	0.034	39.120	0.019
		24	-0.012	-0.035	39.174	0.026

*Probabilities may not be valid for this equation specification.

Correlogram of Residuals



Date: 05/20/21 Time: 12:10
Sample (adjusted): 11/03/2014 2/22/2021
Q-statistic probabilities adjusted for 3 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.001	-0.001	0.0004	0.984
		2	-0.014	-0.014	0.0679	0.967
		3	-0.093	-0.093	2.9540	0.399
		4	-0.142	-0.144	9.7392	0.045
		5	0.040	0.036	10.289	0.067
		6	0.077	0.067	12.272	0.056
		7	0.066	0.044	13.744	0.056
		8	-0.004	-0.015	13.750	0.089
		9	0.080	0.108	15.951	0.068
		10	-0.117	-0.091	20.626	0.024
		11	-0.099	-0.097	24.008	0.013
		12	0.115	0.123	28.549	0.005
		13	0.089	0.099	31.271	0.003
		14	0.050	-0.005	32.142	0.004
		15	0.050	0.044	32.998	0.005
		16	-0.103	-0.042	36.705	0.002
		17	-0.079	-0.047	38.896	0.002
		18	-0.039	-0.058	39.420	0.003
		19	-0.042	-0.050	40.036	0.003
		20	0.085	0.058	42.595	0.002
		21	-0.044	-0.117	43.288	0.003
		22	0.079	0.073	45.508	0.002
		23	-0.128	-0.082	51.337	0.001
		24	-0.056	-0.051	52.445	0.001

*Probabilities may not be valid for this equation specification.

Correlogram of Residuals of model 3 for Exchange and Network volume

APPENDIX D – ACF and PACF for Table II

Correlogram of Standardized Residuals

Date: 09/20/21 Time: 15:35
Sample (adjusted): 10/13/2014 2/15/2021
Included observations: 332 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.079	0.079	2.1005	0.147
		2	0.102	0.097	5.6131	0.060
		3	0.019	0.005	5.7408	0.125
		4	-0.057	-0.070	6.8379	0.145
		5	0.045	0.053	7.5283	0.184
		6	0.017	0.023	7.6258	0.267
		7	-0.035	-0.048	8.0492	0.328
		8	0.022	0.019	8.2146	0.413
		9	0.029	0.041	8.4960	0.485
		10	0.024	0.016	8.6972	0.561
		11	-0.014	-0.033	8.7614	0.644
		12	0.027	0.033	9.0162	0.702
		13	-0.001	0.004	9.0164	0.772
		14	0.038	0.029	9.5175	0.797
		15	0.071	0.062	11.280	0.733
		16	-0.013	-0.022	11.338	0.788
		17	0.093	0.082	14.372	0.641
		18	0.034	0.025	14.791	0.676
		19	-0.100	-0.119	18.306	0.502
		20	-0.051	-0.056	19.232	0.507
		21	0.040	0.090	19.806	0.534
		22	-0.071	-0.074	21.626	0.482
		23	0.029	-0.002	21.929	0.525
		24	-0.020	0.000	22.080	0.575

*Probabilities may not be valid for this equation specification.

Correlogram of Standardized Residuals

Date: 09/20/21 Time: 14:54
Sample (adjusted): 10/13/2014 2/15/2021
Included observations: 332 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.070	0.070	1.6450	0.200
		2	0.107	0.102	5.4761	0.065
		3	0.030	0.016	5.7719	0.123
		4	-0.056	-0.071	6.8295	0.145
		5	0.058	0.063	7.9850	0.157
		6	0.013	0.019	8.0459	0.235
		7	-0.035	-0.048	8.4576	0.294
		8	0.017	0.012	8.5509	0.382
		9	0.021	0.036	8.6976	0.466
		10	0.026	0.020	8.9280	0.539
		11	-0.016	-0.034	9.0111	0.621
		12	0.021	0.026	9.1693	0.688
		13	-0.011	-0.006	9.2094	0.757
		14	0.037	0.032	9.6835	0.785
		15	0.057	0.049	10.804	0.766
		16	-0.021	-0.029	10.964	0.812
		17	0.075	0.066	12.970	0.738
		18	0.029	0.027	13.272	0.775
		19	-0.099	-0.117	16.730	0.608
		20	-0.043	-0.051	17.384	0.628
		21	0.044	0.094	18.075	0.644
		22	-0.063	-0.063	19.501	0.614
		23	0.027	-0.006	19.756	0.657
		24	-0.013	0.009	19.815	0.707

*Probabilities may not be valid for this equation specification.

Correlogram of Standardized Residuals of equations 10 and 12

Correlogram of Standardized Residuals

Date: 09/20/21 Time: 14:56
Sample (adjusted): 10/13/2014 2/15/2021
Included observations: 332 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.076	0.076	1.9106	0.167
		2	0.105	0.099	5.5861	0.061
		3	0.024	0.010	5.7828	0.123
		4	-0.067	-0.081	7.3183	0.120
		5	0.051	0.059	8.2100	0.145
		6	0.028	0.037	8.4846	0.205
		7	-0.029	-0.044	8.7678	0.270
		8	0.015	0.006	8.8494	0.355
		9	0.019	0.034	8.9724	0.440
		10	0.026	0.023	9.1975	0.513
		11	0.003	-0.016	9.2007	0.603
		12	0.019	0.019	9.3318	0.674
		13	-0.007	-0.003	9.3482	0.746
		14	0.024	0.021	9.5541	0.794
		15	0.047	0.041	10.318	0.799
		16	-0.017	-0.025	10.425	0.844
		17	0.073	0.067	12.319	0.780
		18	0.024	0.021	12.530	0.819
		19	-0.121	-0.139	17.722	0.541
		20	-0.050	-0.052	18.605	0.548
		21	0.025	0.079	18.830	0.596
		22	-0.040	-0.035	19.399	0.621
		23	0.034	-0.004	19.823	0.653
		24	0.024	0.041	20.028	0.695

*Probabilities may not be valid for this equation specification.

Correlogram of Standardized Residuals

Date: 09/20/21 Time: 14:58
Sample (adjusted): 10/06/2014 2/15/2021
Included observations: 333 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.072	0.072	1.7624	0.184
		2	0.100	0.096	5.1664	0.076
		3	0.014	0.000	5.2316	0.156
		4	-0.055	-0.067	6.2632	0.180
		5	0.048	0.055	7.0321	0.218
		6	0.037	0.044	7.5086	0.276
		7	-0.034	-0.050	7.9134	0.340
		8	0.020	0.012	8.0442	0.429
		9	0.027	0.041	8.2953	0.505
		10	0.022	0.018	8.4692	0.583
		11	0.003	-0.017	8.4729	0.670
		12	0.024	0.026	8.6728	0.731
		13	-0.014	-0.010	8.7391	0.792
		14	0.026	0.019	8.9778	0.832
		15	0.045	0.041	9.6726	0.840
		16	-0.013	-0.019	9.7305	0.880
		17	0.082	0.074	12.082	0.795
		18	0.023	0.017	12.269	0.833
		19	-0.123	-0.142	17.601	0.549
		20	-0.044	-0.043	18.297	0.568
		21	0.030	0.081	18.628	0.609
		22	-0.046	-0.048	19.386	0.621
		23	0.037	0.000	19.885	0.649
		24	0.017	0.040	19.993	0.697

*Probabilities may not be valid for this equation specification.

Correlogram of Standardized Residuals of equations 14 and 16

Correlogram of Standardized Residuals

Date: 09/20/21 Time: 15:00
Sample (adjusted): 10/13/2014 2/15/2021
Included observations: 332 after adjustments

	AC	PAC	Q-Stat	Prob*
1	0.072	0.072	1.7360	0.188
2	0.095	0.091	4.7861	0.091
3	0.025	0.013	5.0003	0.172
4	-0.073	-0.085	6.7999	0.147
5	0.057	0.065	7.8966	0.162
6	0.027	0.035	8.1510	0.227
7	-0.024	-0.037	8.3409	0.303
8	0.020	0.010	8.4802	0.388
9	0.027	0.041	8.7301	0.463
10	0.025	0.020	8.9405	0.538
11	-0.002	-0.022	8.9420	0.627
12	0.018	0.020	9.0538	0.698
13	-0.000	0.005	9.0538	0.769
14	0.018	0.012	9.1664	0.820
15	0.051	0.043	10.063	0.816
16	-0.020	-0.025	10.197	0.856
17	0.077	0.071	12.278	0.783
18	0.025	0.018	12.502	0.820
19	-0.117	-0.134	17.386	0.564
20	-0.046	-0.048	18.153	0.577
21	0.031	0.081	18.497	0.617
22	-0.042	-0.041	19.135	0.637
23	0.032	-0.008	19.496	0.672
24	0.020	0.038	19.644	0.717

*Probabilities may not be valid for this equation specification.

Correlogram of Standardized Residuals

Date: 09/20/21 Time: 15:02
Sample (adjusted): 10/06/2014 2/15/2021
Included observations: 333 after adjustments

	AC	PAC	Q-Stat	Prob*
1	0.069	0.069	1.5981	0.206
2	0.100	0.095	4.9522	0.084
3	0.018	0.005	5.0584	0.168
4	-0.057	-0.069	6.1576	0.188
5	0.042	0.048	6.7456	0.240
6	0.033	0.041	7.1213	0.310
7	-0.039	-0.052	7.6387	0.366
8	0.013	0.006	7.6946	0.464
9	0.024	0.038	7.8859	0.546
10	0.028	0.027	8.1577	0.613
11	0.009	-0.012	8.1829	0.697
12	0.036	0.035	8.6373	0.734
13	-0.006	-0.004	8.6500	0.799
14	0.030	0.021	8.9546	0.834
15	0.042	0.036	9.5596	0.846
16	-0.012	-0.018	9.6136	0.886
17	0.077	0.071	11.729	0.816
18	0.021	0.015	11.882	0.853
19	-0.122	-0.139	17.153	0.580
20	-0.055	-0.055	18.247	0.571
21	0.022	0.072	18.421	0.622
22	-0.050	-0.046	19.311	0.626
23	0.036	0.003	19.782	0.655
24	0.012	0.029	19.831	0.706

*Probabilities may not be valid for this equation specification.

Correlogram of Standardized Residuals of equations 18 and 20

Correlogram of Standardized Residuals

Date: 09/20/21 Time: 15:03
Sample (adjusted): 10/13/2014 2/15/2021
Included observations: 332 after adjustments

	AC	PAC	Q-Stat	Prob*
1	0.069	0.069	1.5805	0.209
2	0.101	0.097	5.0238	0.081
3	0.026	0.014	5.2601	0.154
4	-0.074	-0.087	7.0880	0.131
5	0.047	0.054	7.8400	0.165
6	0.018	0.028	7.9513	0.242
7	-0.028	-0.039	8.2280	0.313
8	0.019	0.010	8.3496	0.400
9	0.027	0.041	8.5975	0.475
10	0.027	0.023	8.8521	0.546
11	0.003	-0.017	8.8543	0.635
12	0.024	0.024	9.0505	0.699
13	0.010	0.014	9.0830	0.767
14	0.026	0.019	9.3181	0.810
15	0.055	0.046	10.388	0.795
16	-0.024	-0.031	10.587	0.834
17	0.080	0.075	12.819	0.748
18	0.020	0.014	12.958	0.794
19	-0.123	-0.140	18.303	0.502
20	-0.050	-0.053	19.203	0.509
21	0.018	0.072	19.322	0.565
22	-0.046	-0.041	20.075	0.578
23	0.029	-0.009	20.381	0.619
24	0.023	0.040	20.570	0.664

*Probabilities may not be valid for this equation specification.

Correlogram of Standardized Residuals

Date: 09/20/21 Time: 15:55
Sample (adjusted): 10/20/2014 2/15/2021
Included observations: 331 after adjustments

	AC	PAC	Q-Stat	Prob*
1	-0.037	-0.037	0.4503	0.502
2	0.029	0.027	0.7238	0.696
3	-0.041	-0.039	1.2893	0.732
4	-0.055	-0.059	2.3189	0.677
5	0.060	0.058	3.5340	0.618
6	-0.032	-0.027	3.8853	0.692
7	0.032	0.022	4.2348	0.752
8	0.002	0.007	4.2356	0.835
9	0.014	0.017	4.3024	0.890
10	-0.018	-0.022	4.4163	0.927
11	-0.011	-0.007	4.4615	0.954
12	-0.057	-0.059	5.5691	0.936
13	-0.048	-0.051	6.3720	0.932
14	-0.049	-0.056	7.2233	0.926
15	-0.054	-0.059	8.2339	0.914
16	0.026	0.013	8.4681	0.934
17	-0.083	-0.084	10.881	0.863
18	0.052	0.039	11.849	0.855
19	-0.017	-0.008	11.951	0.888
20	0.040	0.040	12.521	0.897
21	0.112	0.114	16.998	0.711
22	0.001	0.027	16.998	0.763
23	-0.068	-0.084	18.665	0.720
24	-0.044	-0.035	19.370	0.732

*Probabilities may not be valid for this equation specification.

Correlogram of Standardized Residuals of equations 22 and 24

Correlogram of Standardized Residuals

Date: 09/20/21 Time: 15:08
Sample (adjusted): 10/13/2014 2/15/2021
Included observations: 332 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.022	-0.022	0.1556	0.693
		2	-0.007	-0.007	0.1720	0.918
		3	-0.011	-0.011	0.2101	0.976
		4	-0.069	-0.070	1.8397	0.765
		5	0.079	0.076	3.9564	0.556
		6	0.003	0.005	3.9592	0.682
		7	0.011	0.011	3.9989	0.780
		8	0.020	0.018	4.1347	0.845
		9	0.014	0.026	4.2033	0.898
		10	-0.015	-0.020	4.2842	0.934
		11	-0.025	-0.024	4.4957	0.953
		12	-0.049	-0.050	5.3303	0.946
		13	-0.020	-0.023	5.4661	0.963
		14	-0.036	-0.045	5.9167	0.969
		15	-0.018	-0.023	6.0310	0.979
		16	0.022	0.017	6.1978	0.986
		17	-0.029	-0.025	6.4956	0.989
		18	0.040	0.039	7.0718	0.990
		19	-0.014	-0.006	7.1423	0.993
		20	-0.012	-0.002	7.1898	0.996
		21	0.121	0.121	12.442	0.927
		22	0.025	0.041	12.672	0.942
		23	-0.091	-0.100	15.663	0.869
		24	-0.018	-0.023	15.777	0.896

*Probabilities may not be valid for this equation specification.

Correlogram of Standardized Residuals

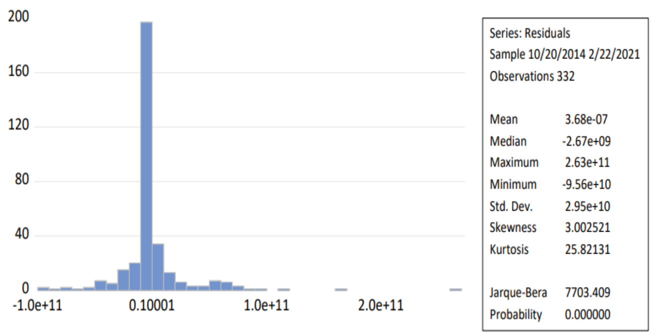
Date: 09/20/21 Time: 15:09
Sample (adjusted): 10/13/2014 2/15/2021
Included observations: 332 after adjustments

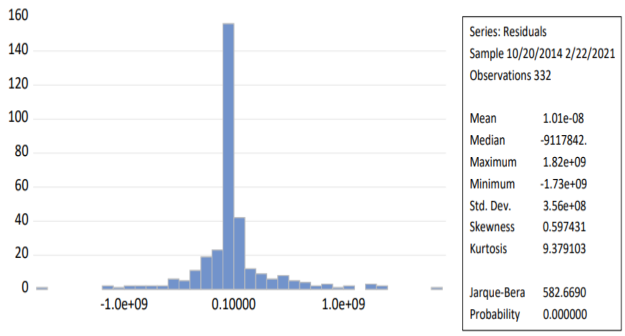
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.028	-0.028	0.2543	0.614
		2	-0.006	-0.006	0.2649	0.876
		3	-0.018	-0.019	0.3769	0.945
		4	-0.043	-0.044	1.0128	0.908
		5	0.054	0.051	1.9858	0.851
		6	0.015	0.017	2.0633	0.914
		7	0.005	0.005	2.0707	0.956
		8	0.009	0.010	2.1011	0.978
		9	0.018	0.024	2.2107	0.988
		10	-0.001	-0.001	2.2112	0.994
		11	-0.034	-0.035	2.6084	0.995
		12	-0.049	-0.051	3.4480	0.991
		13	-0.025	-0.028	3.6667	0.994
		14	-0.038	-0.044	4.1609	0.994
		15	-0.034	-0.043	4.5739	0.995
		16	0.032	0.028	4.9422	0.996
		17	-0.039	-0.035	5.4682	0.996
		18	0.043	0.042	6.1271	0.996
		19	-0.020	-0.014	6.2715	0.997
		20	0.003	0.012	6.2740	0.998
		21	0.110	0.112	10.559	0.971
		22	0.032	0.047	10.935	0.976
		23	-0.100	-0.104	14.516	0.911
		24	-0.001	-0.004	14.516	0.934

*Probabilities may not be valid for this equation specification.

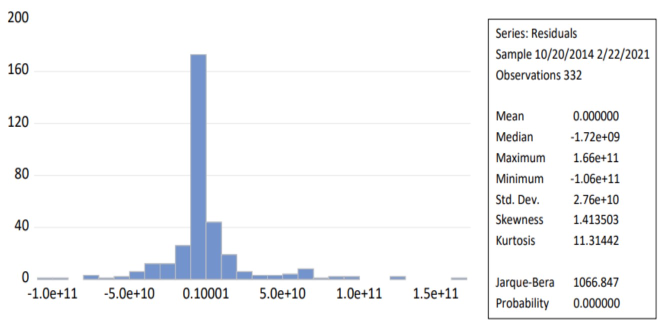
Correlogram of Standardized Residuals of equations 26 and 28

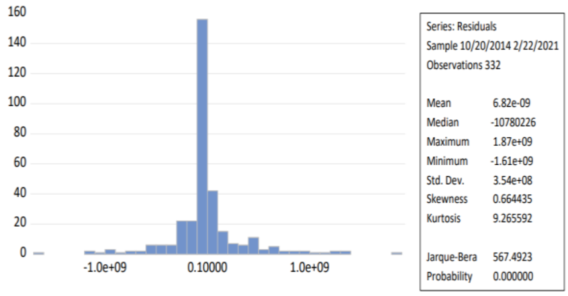
APPENDIX E – Histogram of TABLE I



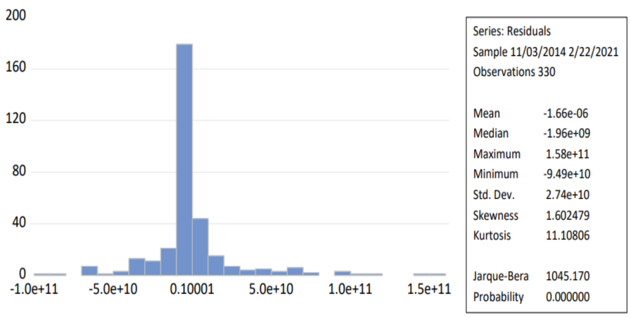


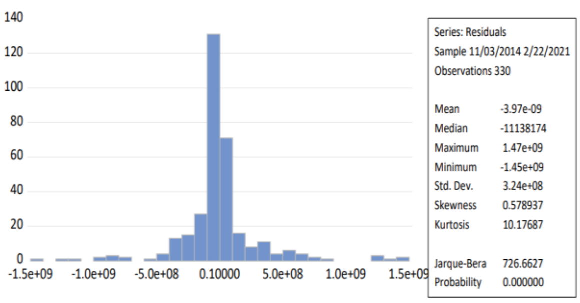
Histogram of model 1 for Exchange and Network volume





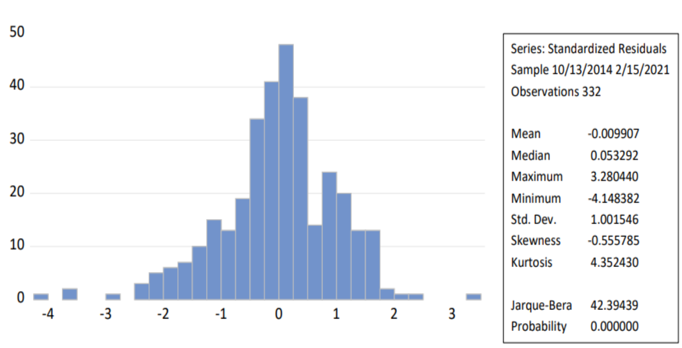
Histogram of model 2 for Exchange and Network volume

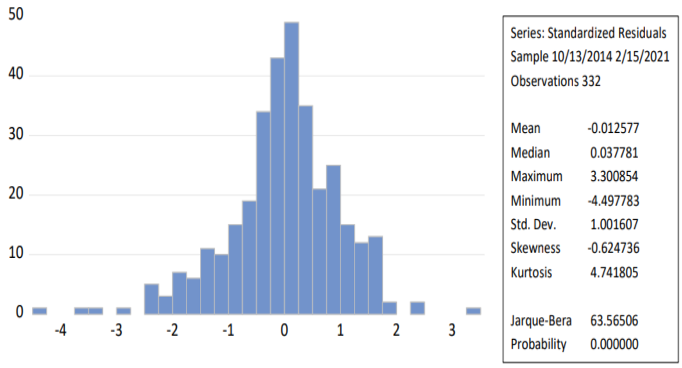




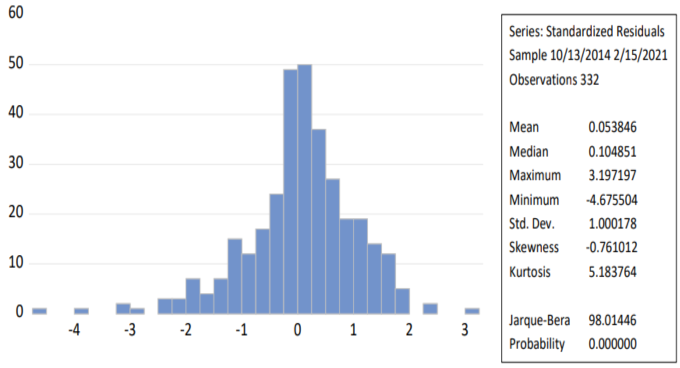
Histogram of model 3 for Exchange and Network volume

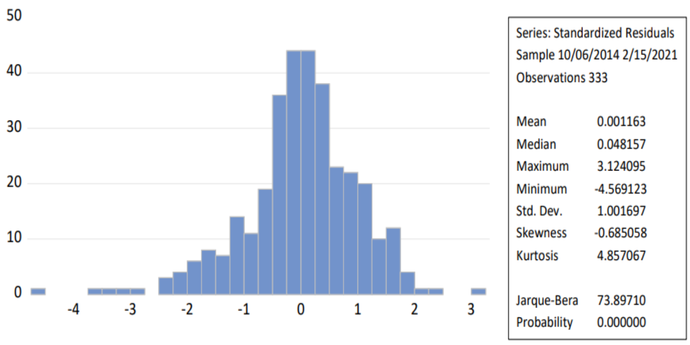
APPENDIX F – Histogram of TABLE II



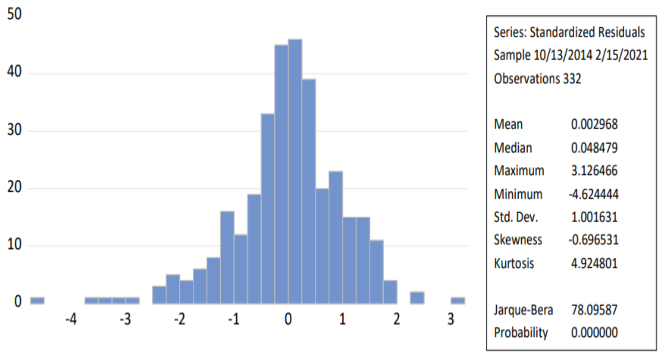


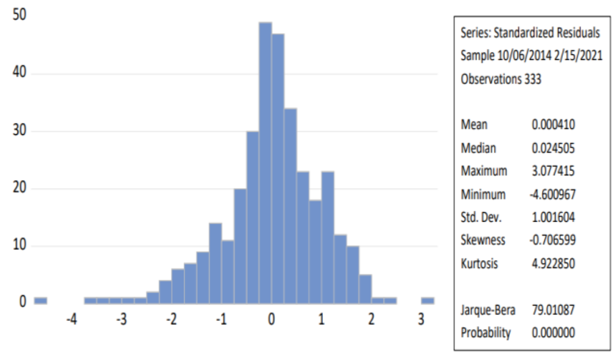
Histogram of Standardized Residuals of equations 10 and 12



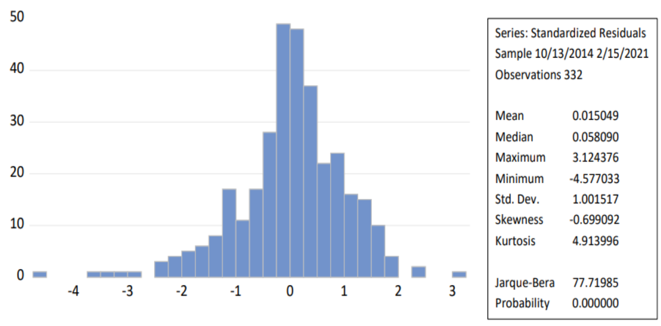


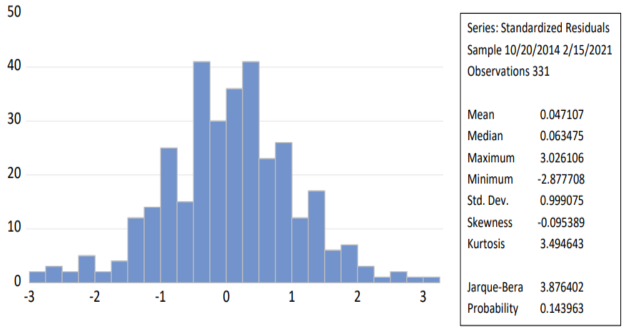
Histogram of Standardized Residuals of equations 14 and 16



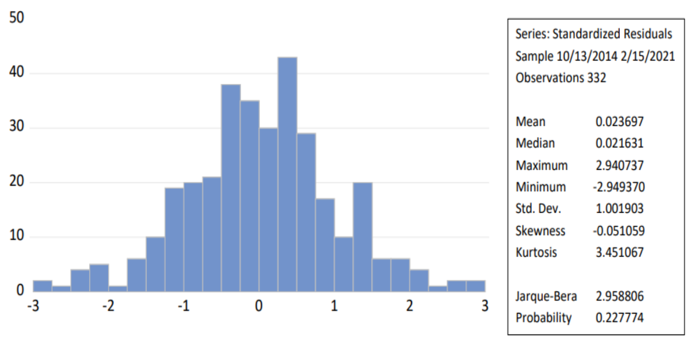


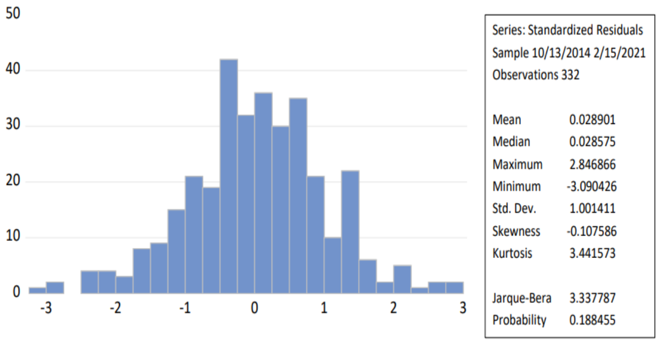
Histogram of Standardized Residuals of equations 18 and 20





Histogram of Standardized Residuals of equations 22 and 24





Histogram of Standardized Residuals of equations 26 and 28