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What are the main determinants of the valuation of top 5 cryptocurrencies?

By

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Chapter 1: Introduction

1.1 BACKGROUND RESEARCH

In the past decade, a new asset class called "Bitcoin" attracted vast interest among investors, researchers and academics. Having been launched in 2009, popularity of Bitcoin and the blockchain technology has surged dramatically which was largely attributed to unique media coverage and reporting over this new asset type as well as increasing number of other crypto assets. While bitcoin is still dominating the cryptocurrency market, there remains alternative popular crypto coins that are considered promising as well (e.g Ethereum, Tether, Ripple). Digital finance has been a hot topic of interest in the last decade (Ozili, 2018). The reason why cryptocurrencies captured significant interest among investors, researchers, politicians and also general public is associated with its solemn pledge to ensure reduced costs of money transfer. Another presumed advantage of the cryptocurrencies was linked to their nature that is independent from a controlling mechanism such as countries' central banks. Unlike other asset classes such as stocks, bonds, foreign exchanges, digital currencies appeared as an asset type that is free from a regulatory body.

Given the technological advancements and ever-more connected financial system of the global economy, transition to digital finance and its advantageous offerings are widely considered mandatory and inevitable. Cryptocurrencies, especially the Bitcoin, is believed to have the underlying technology that is capable of taking the global payment mechanism to the next level (Al Mamun et al., 2020). Despite the initial hype over the potential contribution cryptocurrencies may offer to transition to digital finance, significant concerns exist around cryptocurrencies' speculative nature (Baek and Elbeck, 2015). The key thing about crypto currency market is that it lacks quantitative fundamentals which informs its valuation. Generally, cryptocurrencies do not offer cash flow underpinning their valuations which largely explains the investor and speculative funds inflow into this asset class (Berentsen and Schär, 2018). Accordingly, cryptocurrency returns are generated through capital gains alone, thus, this asset class is deemed more speculative than other asset types such as bonds, equities etc.

Having mentioned the speculative nature of cryptocurrencies, it is safe to note that cryptocurrencies provided significant data flow from the behavioral trading perspective. Market for cryptocurrencies demonstrated the characteristics of a strong bull market which was largely attributed to several renown media outlets publishing stories on how early investors of this new asset class made significant fortune. Regardless of the significant investor inflow until 2018, market was destined to go bearish early in the first quarter of 2018 (Gurdgiev and O'Loughlin, 2020). Due to lack of financial fundamentals to estimate the direction of the market for cryptocurrencies, behavioral research has gained significant interest among researchers. The primary interest of these researches were to investigate and discover how retail investors and their financial decisions were being considerably influenced by social media posts concerning cryptocurrencies (Corbet et al., 2019). It is safe to say that sentiment analysis has been at the center of analyzing cryptocurrency investor behaviors thus far, and provided evidence that investor sentiment and opinion mining is indeed an effective predictor of the direction of the crypto market (Bollen et al., 2011). Besides the popularity of profound analysis of investor sentiment, some studies have attempted to investigate the price formation of cryptocurrencies based on other events such as elevated geopolitical tensions (Al Mamun et al., 2020) or uncertainties regarding country-specific or global monetary policies (Shaikh, 2020). Similarly, these studies provided evidence that there is a correlation between such events and cryptocurrency valuations (Al Mamun et al., 2020; Shaikh, 2020; Lucey et al., 2021).

Given the academic literature and research that has been conducted so far, it seems reasonable to suggest that there is no solid quantitative formulation that informs cryptocurrency valuation effectively. Existing literature has mainly focused on the impact of investor opinion about the future of the market on the valuation of this particular asset via analyzing investor sentiment on social media platforms and crypto-specific blogs. In addition, there has been studies that examined the relationship between well-known indices and cryptocurrency valuation and found significant correlation between some of the most commonly used financial indices and cryptocurrency valuation (Walther et al., 2019).

1.2 CONTRIBUTION

Cryptocurrencies has not been introduced to our lives so long ago. It has been slightly more than a decade since the most popular cryptocurrency, the “Bitcoin” has been mined. Despite being launched in 2009, it was early 2017 when Bitcoin first broke the $1000 valuation and begin the bull market, attracting more and more customers over time, hitting the all time record of nearly $64000 in April, 2021 which was followed by a significant drop in valuation later on. Given the above information and data on cryptocurrency, it is safe to suggest that volatility is a big reality that no investor can ignore when it comes to cryptocurrency investing. Due to its volatile nature in valuation, cryptocurrencies are regarded by many to be a speculative asset type that may rather be incorporated in investors’ hedging strategies.

In this research paper, we will be investigating the relationship between cryptocurrency valuation and a number of well-know financial indices that has previously been covered in other studies. This paper will not only analyze the impact of financial indices on cryptocurrencies but also assess how economic policy uncertainty affects cryptocurrency prices. In addition, our model will include geopolitical risk index to evaluate how geopolitical tensions influence prices. To address the impact of customer sentiment on cryptocurrency prices, our model will include the VIX index which is considered as investor fear index. Put/Call ratio will help this study discover if cryptocurrency prices can be predicted based on the general equity market direction. Furthermore, oil prices and US dollar index will be examined to see if an hedging relationship exists.

This research aims to reveal potentially existing correlation between a significant number of financial, economic and geopolitical indices with cryptocurrency pricing mechanism. This research paper has implications for investors, retail traders, hedge fund managers and stock brokers in formulating their trading strategy by providing insights on a relatively recent asset class. This paper also aims to discover hedging patterns in order to effectively inform investors and facilitate the construction of a winning portfolio. At the end of this research, we will also distinguish between indices and be able to communicate which financial, economic or geopolitical index has the most determinative impact on cryptocurrency valuation.

1.3 RESEARCH QUESTION

It has been made clear in the parts above, the purpose of the study is to identify the determinants of cryptocurrency prices. Thus, the research question is:

> “What are the determinants of the value of the top 5 cryptocurrencies?”

1.4 AIMS AND OBJECTIVES

This research paper aims to discover the underlying relationship between the valuation of top 5 cryptocurrencies and well-known financial indices as well as economic and geopolitical uncertainties. In order to do that, following aims will have to be satisfied:

- Extensive literature review will be conducted to identify theories, empirical researches and gaps,
- Literature will be analytically examined to figure out how this research can be improved further to make a solid contribution,

- An appropriate econometric analysis tool will be selected to ensure that our research delivers results that are relevant and informatory,
- Carry out a critical discussion of the empirical results derived from the econometrics analysis and discuss whether they are in line with previous studies conducted.

1.5 RESEARCH STRUCTURE

To ensure that our research meets its objectives and discusses the empirical results in a precise way, this paper is structured in 5 chapters, all of which are described in detail below.

- Chapter 1: is basically the introduction chapter and provides brief information about research topic. It also introduces the research question as well as how this research is likely to contribute to the existing literature.
- Chapter 2: is the chapter for literature review. Relevant theories and empirical research that has previously been done will be critically examined and discussed how they shaped the construction of our model.
- Chapter 3: Research methodology will be disclosed in this chapter. Data sources, variables and the econometric model chosen for this research will be revealed and justified as to why they have been considered appropriate for this research.
- Chapter 4: This chapter will be dedicated to presenting and interpreting results derived from the econometric analysis.
- Chapter 5: will be the extension chapter to chapter 4 as more discussions regarding the empirical results will be made.
- Chapter 6: This chapter will be the conclusion chapter providing the last remarks of this research and deliver recommendations for further research purposes.

Chapter 2: Literature Review

This chapter will make an explicit assessment of the existing literature with respect to cryptocurrency valuation and its correlation with some of the renown indices. The aim is to reveal whether cryptocurrency prices can be forecasted with the help of various indices most of which are widely used financial indices whilst others are macroeconomic, geopolitical and investor sentiment-analyzing measures.

The existing literature so far indicated 2 groups of price determinants for cryptocurrencies which can be grouped as internal and external drivers of cryptocurrency valuation. Regarding the internal factors, studies mainly look at measures such as supply and demand factor (Buchholz et al., 2012; Bouoiyour & Selmi, 2015; Ciaian et al., 2016). Also, Ciaian et al. (2016) suggests that price level is another determinant of cryptocurrency valuation as it is directly linked with investors's expectations over future cryptocurrency prices. Note that internal drivers of cryptocurrency valuation is not going to be analyzed in this paper.

In contrast, this paper will focus on and evaluate potential external drivers of cryptocurrencies. What is meant by external drivers are financial and macroeconomic developments, economic policy uncertainties, escalated geopolitical tensions and changing investor sentiment.

2.1 Sentiment Analysis and Behavioral Drivers of Cryptocurrencies

In terms of investigating cryptocurrency valuation and price movements of cryptocurrencies, investor sentiment analysis and behavioral aspects of decision making process remain some of the most popular and commonly analyzed tools. Some of the most preferred indices that are investigated in existing literature are VIX index, CBOE Put/Call Ratio and Equity Uncertainty Index. VIX index is known to measure fear in the equity market and often an increase in the index leads to decrease in the stock market. CBOE Put/Call Ratio is regarded as a signal (indicator) to upcoming bullish or bearish market. Lastly, the Equity Uncertainty Index measures the uncertainty towards equity market across investors.

Fear and uncertainty are two primary determinants of investor behavior. These factors lead market participants to avoid risk and loss (rational and behavioral economics models). In this context, Ciner et al. (2013) explains safe haven characteristics of cryptocurrencies. Ciaian et al. (2016) and Dyhrberg (2016) also studied cryptocurrencies' safe haven properties and found that Bitcoin actually promises hedging capacity in the short-run against equities and dollars. Similarly, Bouri et al. (2016) discovered bitcoin's hedging relationship with the CBOE VIX index ahead of the BTCUSD crash of 2013. Akyildirim et al. (2020) revealed that when investors' fear is escalated, cryptocurrency market experiences increase in volatility — CBOE VIX and VSTOXX indices are used to measure fear across the US and the European financial markets respectively. Also, Fang et al. (2020) investigated the impact of News-based Volatility Index (NVIX) on cryptocurrency returns and provided evidence that NVIX is a more accurate tool than Global Economic Policy Uncertainty Index (GEPU) in predicting long-term volatility in given cryptocurrencies.

Gurdgiev and O'Loughlin (2020) analyzed the behavioral aspects of cryptocurrency valuation using VIX index, put/call ratio, advanced analysis of a cryptocurrency blog and Equity Uncertainty Index (EUI). The study accounted for bull and bear markets, thus split the data into two groups to provide more precise information and implications. According to the study, there is a negative correlation between cryptocurrency prices and VIX, meaning that cryptocurrencies are not a promising hedge for the stock market during times of fear. That result held true for both bear and bull markets of cryptocurrencies. Lucey et al. (2021) also provided results that supports the existing literature that

VIX and cryptocurrency prices are negatively correlated. However, they argued that Cryptocurrency Uncertainty Index (UCRY) might be more accurate than other tools in predicting the future direction of cryptocurrency valuation. Shaikh (2020) analyzed Bitcoin returns based on a number of financial and economic indices and demonstrated a high degree of inverse association between VIX and Bitcoin returns.

The reality of highly dynamic and rather unstable hedging relationships are attributed to high level of uncertainty in financial markets (Gurdgiev & O'Loughlin, 2020). Hence, another index that is used in various research as a tool to analyze the impact of investor sentiment on cryptocurrency valuation is proposed by Baker et al. (2016), the Equity Market Uncertainty Index (Chulia et al., 2017). In terms of measuring uncertainty, academics use wide range of factors. For instance, Shaikh (2020) and Al Mamun et al. (2020) involves into their models and analyzes country specific economic policy uncertainty (EPU) as well as EPU at global scale. Al Mamun et al. (2020) also describes VIX as uncertainty benchmark while Gurdgiev and O'Loughlin (2020) regarded VIX as fear index — as is widely regarded by financial actors — and incorporated into their model a distinct equity related uncertainty index to analyze its impact on cryptocurrency valuation. Among the uncertainty indicators, it is important to note that VIX and Equity Uncertainty Index are the ones to use for analyzing investor sentiment towards cryptocurrency. Equity Uncertainty Index is suggested to reflect sentiment of investor uncertainty towards risky assets. In that regard, Kristoufek (2015) found that bitcoin prices soar when financial market uncertainty increases. Likewise, Gurdgiev and O'Loughlin (2020) discovered that during the times of uncertainty concerning the US Equity Market, cryptocurrencies were to go up in terms of valuation. According to the study, this result is particularly significant during bull market period as bear market conditions indicate weaker correlation. Despite the absence of a consensus over the hedging ability of cryptocurrencies, Gurdgiev and O'Loughlin (2020) suggested that cryptocurrencies can well serve as a hedge against stock market during bull market conditions.

Although not as widely used as VIX in research projects and financial studies, Put/Call Ratio (PCR) is also useful to measure the possible direction of the market. An increase in PCR suggests that the market is likely to enter bearish trend. Bandopadhyaya and Jones (2008) analyzed the extent to which the CBOE Put/Call Ratio is capable of predicting investor sentiment and found that PCR performed better then VIX in predicting non-economic factors which can cause changes in equity prices. Numerous other studies that investigated the use of Put/Call Ratio and its ability to measure investor sentiment have concluded that PCR can indeed provide investors an edge in formulating their trading strategy on a short-term horizon (Houlihan & Creamer, 2019; Jena et al., 2019; Gang et al., 2020). For the fact that CBOE PCR is commonly accepted as the proxy for market direction, it will be exciting to test the interaction between the equity market expectations and cryptocurrency valuation.

Indicators that will be used in this paper to analyze sentiment aspect of change in cryptocurrency valuation are VIX, Equity Uncertainty Index and CBOE Put/Cal Ratio (PCR). All the reasoning for choosing these measures are explicitly described in paragraphs above via referencing a range of academic sources existing in the literature. By including 3 different measures of uncertainty, this paper will also be investigating whether different indicators will produce different results in terms of the underlying relationship between cryptocurrency valuation and the uncertainty factor.

2.2 Geopolitical Uncertainty and Risk Factor

Geopolitical risk has been considerably popular factor which many paper has accounted for to analyze its interaction with stock returns, crude oil prices and gold in particular (Balcilar et al., 2018; Das et al., 2019; Hoque & Zaidi, 2020; Antonakakis et al., 2017; Alqahtani et al., 2020; Yang et al., 2021; Triki & Maatoug, 2021). In terms of examining geopolitical risks (GPR) on the stock return of emerging economies (BRICS countries), Balcilar et al. (2018), Das et al. (2019) and Hoque and Zaidi (2020) has produced invaluable results. Balcilar et al. (2018) found out that the impact of GPR is not homogenous across the BRICS counties and also GPR is discovered to more consistently impact market volatility instead of market returns. Similar to the findings of Balcilar et al. (2018), Hoque and Zaidi (2020) also revealed that despite the volatility level of the domestic stock market, GPR has negative effect on the performance of various stock markets across emerging countries. Yet, the research noted that the impact of the GPR on returns varies based on the prevailing volatility regime. Das et al. (2019) uncovered that GPR, Economic Policy Uncertainty (EPU) and Financial Stress Index (FSI) are consistent predictors of mean of returns rather than the variance. All 3 papers reported inverse effects of geopolitical tensions.

Since Geopolitical tensions are often associated with the region of middle east which is known to be the most oil-rich region of the world, some papers aimed to investigate the correlation between geopolitical risks and energy stock returns such as crude oil as well as renewables (Yang et al., 2021; Alqahtani et al., 2020). Alqahtani et al. (2020) has provided empirical evidence that crude oil returns which are directly linked with geopolitical tensions is an effective predictor of Gulf Cooperation Countries' (GCC) stock returns. Conversely, Yang et al. (2021) reported that GPR does not demonstrate a positive or negative impact on renewable energy stock prices, yet can be used to monitor volatility in order to formulate optimal hedging and portfolio management strategies. Triki and Maatoug (2021) studied the gold's designated hedging (safe-haven) capacity during the periods of increased GPR and found that gold remains to serve investors as safe-haven during elevated geopolitical tensions.

In the context of cryptocurrency, there has not been done many research concerning the correlation between the geopolitical risk and cryptocurrency price movement. Yet, there still exists a number of papers that investigated how cryptocurrency valuation has been impacted by geopolitical risks and uncertainty which are often associated with war and terrorism. In this respect, Aysan et al. (2019) reported that Geopolitical Uncertainty Index (GPR) is capable of successfully predicting Bitcoin returns and volatility. In contrast, Colon et al. (2021) also investigated the potential correlation between GPR and cryptocurrency returns, yet failed to find statistically significant relationship. Similarly, Al Mamun et al. (2020) studied geopolitical risk and other uncertainty measures' impact on Bitcoin volatility and risk premium, and discovered that geopolitical risk is far ahead of other measures in determining the volatility and risk premium of Bitcoin. According to the same study, the impact of geopolitical risk on Bitcoin volatility and risk premium are far superior in worsening economic conditions.

Given the exiting literature about geopolitical risk and its impact on various asset classes, including cryptocurrencies, suggested that the inclusion of geopolitical uncertainty index would produce valuable insights and implications for investors, traders, and stock brokers. The study will also report how geopolitical risk factor compares to the other indices in terms of the scope of the impact on cryptocurrency valuation.

2.3 Macroeconomic Uncertainty Factor (Indices)

Many financial research today incorporate macroeconomic uncertainty factor into their models when analyzing its interaction with financial trends and impact on particular asset classes. One of the most commonly used macroeconomic uncertainty indices has recently been developed by Bali et al. (2015). The macroeconomic uncertainty index (MUI) of Bali et al. (2015) is generated by considering inconsistency in survey forecasts for some macroeconomic variables. Asgharian et al. (2015) used that index and provided empirical evidence that macroeconomic uncertainty has direct correlation with long-run stock and bond volatility, and added that investors flee from the risky assets such as stock investment and prefer the less profit yielding, yet safer bonds. Furthermore, Baker et al. (2016) has developed a novel news-based Economic Policy Uncertainty (EPU) index which has gained tremendous interest among researchers. Azqueta-Gavaldón (2017) has utilized the same approach and further developed the index by supplementing with advanced machine learning technology.

Following the same approach of Baker et al. (2016), Ghirelli et al. (2019) have made a number of adjustments to construct an index which has been empirically proven to produce statistically significant predictive capacity with less volatility in comparison to the original index.

EPU index is used to understand and analyze a wide variety of economic and financial variables. Pastor and Veronesi (2012) used EPU to evaluate its role in determining stock prices and found that stock prices wander up and down depending on the set of economic policy changes. Brogaard and Detzel (2015) have also examined the impact of EPU on stock market and achieved similar results that the financial market negatively prices EPU given that prices drop as sentiment of uncertainty towards economic policy builds up in the market. Pástor and Veronesi (2013) examined the effects of political uncertainty on risk premium and concluded that political uncertainty contributes to the risk premium, volatility and correlations of stock returns. The impact is proven to be larger in weaker economic circumstances. At firm level, Gulen and Ion (2016) documented a strong negative relationship between macroeconomic uncertainty and US corporate investments. This basic correlation also held true for the UK, Germany, France, Italy and Canada. A study by Rubio-Ramírez et al. (2011) assessed the impact of fiscal uncertainty on the US economic performance and presented empirical evidence that economic uncertainty could easily shrink the Gross Domestic Product (GDP) by 0.15 percentage point. The study admitted to have ignored various factors such as budgetary issues over the long-term that could further deepen the financial frictions and damage the economic performance, thus notes that the impact of fiscal uncertainty can be significantly larger in reality. Similar findings that are reported by Bachmann et al. (2013) suggested that a decline in output is likely during economic uncertainty periods which impose long-run implications. In relation to labor market dynamics, Bakas et al. (2016) investigated and uncovered the inverse relationship between fiscal uncertainty and employment whereas Choi and Loungani (2015) argued sectoral shocks having more deterministic effects on unemployment than the aggregate economic uncertainty.

Al Mamun et al. (2020) and Lucey et al. (2021) investigated the impact that the US EPU and Global EPU have on Bitcoin and cryptocurrency respectively. Al Mamun et al. (2020) reported that the US EPU has no predictive power on Bitcoin, however Global EPU is significant in explaining risk premium of Bitcoin. Shaikh (2020) has extended the scope of the reserach and included EPU for European Union (EU), China, Hong Kong and Japan. According to the findings of this research, which is in line with previous research, that Global EPU is the most deterministic on Bitcoin valuation. Yet, unlike the previous paper, this research documented that the US EPU is significant in explaining Bitcoin behavior. The research findings indicated that EPU for China and EU are positively correlated with Bitcoin pricing while EPU for the US, Japan, Hong Kong and Globe are negatively priced by Bitcoin traders.

Literature about fiscal uncertainty and its effects on economic and financial variables which are mentioned above suggested that the inclusion of economic policy uncertainty into our research to assess its relationship with cryptocurrency valuation would contribute to the overall quality of the research and provide significant insights that can be utilized by investors, traders and hedge-fund managers.

2.4 Financial Indices

As cryptocurrencies become more popular among traders, wealth managers, hedge funds and stock brokers, a growing interest appeared towards assessing the volatility of cryptocurrencies as they are characterized by their volatile nature. This is particularly important due to the formulation of effective hedging strategies and providing optimal portfolio management. In this dissertation, we will be looking at the underlying relationship between cryptocurrency returns and S&P500 index (SPX), Dow Jones Industrial Average Index (DJIA), Oil Prices, Euro/Dollar, MSCI Emerging Markets 50

Index (MSCI EM50), Monetary Policy Uncertainty Index (MPU), Financial Stress Indicator (FSI) and Global Real Economic Activity (GREA).

A study conducted by Walther et al. (2019) investigated Bitcoin and cryptocurrency volatility using the most prominent financial indices. This research is remarkably important due to employing GARCH-MIDAS approach as its methodology to analyze data that are observed in different frequencies (e.g. daily, weekly, monthly). According to the study, different cryptocurrencies are best predicted by different indicators. For instance, Global Economic Policy Uncertainty (GEPU) predicted Bitcoin volatility best among other indicators while Dow Jones Precious Metals (DJPM) was the best predictor for Etherium. Best predictors for other cryptocurrencies were; Global Financial Stress Index (GFSI) for Litecoin, GREA for Ripple and CRIX (whole cryptocurrency market) and Chinese Economic Policy Uncertainty (CEPU) for Stellar. Unlike Gurdgiev and O'Loughlin (2020), Lucey et al. (2021) and Shaikh (2020), the findings of Walther et al. (2019) suggested that VIX is not significant in predicting cryptocurrency volatility. Furthermore, over the long horizon, the research reported that GREA is the best predictor of the cryptocurrency market. Shaikh (2020) studied the factors influencing Bitcoin returns and found that S&P500 returns do not predict Bitcoin returns significantly.

Teker et al. (2019) and Teker et al. (2020) investigated whether there is a cointegrating relationship between gold and oil prices and various cryptocurrencies. The study involved Bitcoin, Tether, Ethereum, Litecoin and EOS as cryptocurrencies to study, yet only found cointegration with Tether. Consequently, it reported that changes in oil and gold prices have not impacted daily price movements of Bitcoin, Ethereum, Litecoin and EOS. Another study that is performed by Zhang et al. (2018) examined the correlation between Cryptocurrency Composite Index (CCI) and DJIA. The study uncovered the persistent cross-correlation between DJIA index and CCI. In terms of MSCI EM50 index, Kartal et al. (2020) examined the factors that are most influential on the direction of Turkish Stock Market (XU100) and identified MSCI EM50 index as the 4th most impactful determinant, following government bonds interest rates (third), CDS spreads (second) and foreign investors in the equity market (first). According to the study, during the pandemic, rankings of the factors based on the scope of their impact on XU100 has shifted and MSCI EM50 made it to the top of the list.

Economic policy uncertainty (EPU) indices have been demonstrated to be included in many papers to analyze its impact or relationship with certain economic and financial variables. Although not as popular as EPU, monetary policy uncertainty (MPU) has recently gained interest among academics and researchers (Kurov & Stan, 2018; Bauer et al., 2019; Husted et al., 2020; De Pooter et al., 2021). There seems to be a consensus over the fact that uncertainty towards monetary policy similar to fiscal policy is negatively linked with economic activity. Another index that is regarded highly crucial in estimating financial risks is the financial stress index (FSI). Emerging economies in particular attract growing interest among researchers as FSI is utilized to analyze countries' economic and financial stability (Balakrishnan et al., 2011; Cevik et al., 2013; Cevik et al., 2016). Due to providing significant information about the economic well-being of countries, the inclusion of FSI will be exciting to test its correlation with cryptocurrency valuation. The last financial index that our research will encompass is Global Real Economic Activity (GREA). Ratti and Vespignani (2013) used GREA to analyze why crude oil prices are high during periods when GREA is weak. Similarly, Charles et al. (2021) assessed the underpinning relationship between oil shocks and global economic activity and discovered far-reaching indirect effects EU crisis has had on economic activity.

Chapter 3: Methodology

In this chapter, general overview and research details regarding this paper will be provided. To better understand how this research will be conducted, econometric approach to model specification is going to be outlined. Null and alternative hypothesis will be defined explicitly. To establish reliability, data sources will be mentioned. Variables that are specifically chosen for this research are going to be demonstrated with fair explanation to what they stand for and why they are important for this research. Lastly, descriptive statistics for the data will be illustrated.

3.1 Research Method

As mentioned in the Literature Review, there is a tremendously growing research interest in cryptocurrencies and their possible underlying relationship with a number of indices ranging from finance, economics and geopolitics. It is most common in the literature that the time-series often comes in handy effectively examining and explaining short-term and long-term relationship between explanatory variables and the chosen dependent variable (Ciaian et al., 2016; Lucey et al., 2021). Despite that, OLS and some variations of least squares such as GLS remains an alternative in investigating the underpinning correlation among different time-series data that become stationary in first-differences (Gurdgiev & O'Loughlin, 2020; Shaikh, 2020).

In time series analysis, there are several ways to analyze data which depends on the features of the data collected. Fist, it necessary to visualize data by graph to see if data is stationary or non-stationary which is traditionally non-stationary when dealing with time series data. There is also formal tests such as Dickey-Fuller (1970) tests and Philips Perron (2001) test to see if data is indeed non-stationary. It is just as important to observe and recognize the type of non-stationarity whether is trend non-stationary or stochastically non-stationary. Introducing the trend term to the model is usually enough to model an ARDL when non-stationarity is caused by trend. However, in the existence of stochastic trend, Johansen (1991) cointegration test is necessary to determine whether the time-series are co-integrated or not. Then, if cointegration between the series are detected, it is advised to estimate a long-run equation with least squares and estimate error correction model (VECM) for the short-run relationship. In the absence of cointegration however, it is simply recommended to estimate Autoregressive Distributed Lag (ARDL) model in first differences.

Time series data that has been collected for this research is non-stationary and it follows a stochastic trend. Therefore, Johansen cointegration test has been conducted and found that there is no cointegration between the series. Hence, the ideal econometric approach has been determined to be ARDL model in first differences.

3.2 Econometric Analysis and Model Specification

The ARDL model specified to reach research objectives of this paper is given below:

$$Yt = \beta0 + \beta1Yt\text{-}1 + \beta2Xt + \beta3Xt\text{-}1 + Vt$$

Number of lags for the dependent and the explanatory values will be determined after the "ARDL" regression is run. By doing so, not only the effect of the current value of explanatory variables will be revealed, but also how the lagged values impact the dependent variable will be manifested. Both dependent and explanatory variables are explicitly described below.

3.3 Data Source

Data that is going to be used in this research to analyze underlying factors affecting cryptocurrency valuation is collected from a variety of sources that are regarded highly reliable, hence been used in many academic research papers most of which are referenced in the literature review. The main sources of data for this dissertation will be the Federal Reserve Bank of St. Louis (FRED) database, The Chicago Board Options Exchange (CBOE), www.coindesk.com and policyuncertainty.com.

Dependent variable of this research is top 5 cryptocurrencies, thus the data for cryptocurrency prices will be sourced from coindesk.com. Besides, the research involves a long list of explanatory variables hoping to explore correlations between crypto valuation and bunch of indices. Volatility Index (VIX), Equity Market-related Uncertainty Index, S&P500 Index (SPX500), Dow Jones Index (DJI), Euro/Dollar and Oil prices are going to be sourced from the Federal Reserve Bank of St. Louis (FRED). The CBOE Put/Call Ratio will gather data from the CBOW database. Then, data for Geopolitical Risk Index, Economic Uncertainty Index for the US, China, the EU and the globe, Monetary Policy Uncertainty, Financial Stress Indicator and Global Real Economic Activity will be collected from policyuncertainty.com. Lastly, the paper will cite msci.com for the MSCI Emerging Markets 50 Index.

3.4 Variable Selection and Description

3.4.1 Dependent Variable

Given the research title, it is not difficult to guess that the dependent variables for this dissertation are going to be the top 5 cryptocurrencies which are namely as Bitcoin, Ethereum, Binance Coin, Tether and Ripple. It is particularly important to note that these cryptocurrencies are not chosen solely based on their market capitalization despite the fact that Bitcoin and Ethereum are still dominating the market by exceptionally large margins. All these cryptocurrencies are among top 5 by market cap except for the Ripple which made it top 10. Coins change places often basically because the market is quite volatile and Ripple made it to this research due to its popularity among crypto investors. For each cryptocurrency, the econometric model constructed will be run to test whether a correlation exists between the valuation of the coins and indices.

3.4.2 Independent Variables

Volatility Index (VIX)

VIX is one of the most commonly used indices in financial research. It is also commonly referred to as the fear index. It demonstrates the volatility expectations of the market over the next 30 days. It would not be false to suggest that VIX is perhaps used more than any other indices due to the fact that it reflects market expectations which directly has to do with market trading psychology. In an era where corporate investors make exceptional use of data to analyze investor behavior in order to position themselves before the actual market reaction, VIX truly stands out. Many research that tested the impact of VIX on cryptocurrency valuation found results that proved the underlying relationship (Akyildirim et al., 2020; Shaikh, 2020; Ghorbel & Jeribi, 2021; Malladi & Dheeriya, 2021; Kim et al., 2021). Data for VIX will be gathered from the Federal Reserve Bank of St. Louis (FRED).

Equity Market-Related Uncertainty Index (EMUI)

Uncertainty with regards to equity market is measured and announced by the Federal Reserve Bank of St. Louis (FRED) on a daily and weekly basis. The index first proposed by Baker et al. (2016) and has been incorporated into models of research papers (Chulia et al., 2017; Gurdgiev & O'Loughlin, 2020). What is unique about this index is that it measures investors' interest into risky assets during the times of high uncertainty which makes it a great tool for analyzing investor behavior potentially revealing investor biases in investment decision making. This will be particularly interesting to analyze due to the emergence of recent Covid-19 pandemic, seeing how the pandemic with devastating economic consequences altered investors' risk and return appetite compared to pre-pandemic period.

CBOE Put/Call Ratio (CBOE PCR)

The Put/Call ratio derived from the Chicago Board Options Exchange (CBOE) is a widely used indicator that measures bullishness or bearishness of the general financial markets. The hypothesis is that an increase in the bullishness of the financial markets will lead to an increase in the valuation of cryptocurrencies (Mao et al., 2015; Li & Wang, 2017; Gurdgiev & O'Loughlin, 2020). The model including the put/call ratio is especially important to find out how investors respond to general financial markets leading towards either direction. This indicator just like VIX has to do with investor sentiment over the financial markets, hence are widely incorporated into models of research that study behavioral finance.

Geopolitical Risk Index (GRI)

In comparison with other indices, geopolitical risk index is relatively new to financial studies. The geopolitical risk index that will be used in tis paper will be sourced from policyuncertainty.com. The GRI follows the most popular and internationally recognized 11 newspapers and magazines such as The Guardian, Financial Times, The Wall Street Journal, The Washington Post, etc. The way the GRI functions is that it captures words such as tension and war which are linked with geopolitical risks and come up with and index number. Increase in the use of these word in the content of the given newspapers and magazines translates to higher GRI. Given that there is not many studies that investigate the impact GRI may have on cryptocurrency valuation, this study will provide invaluable insights.

US/China/EU/Global Economic Policy Uncertainty (EPU)

Uncertainty for Economic Policy for the US, the EU, China and the whole globe will also be retrieved from policyuncertainty.com. Similar to the Geopolitical Risk Index (GRI), the automation that is set up looks for words that might potentially signal economic policy uncertainty from the content of 10 newspapers that are most widely recognized. For Chine EPU, the local newspapers will be analyzed. For the UK, database offers several options, yet this paper will again choose local newspapers content due to the notion that British newspapers might reflect the policy-sets government is enforcing in more depth. However, it is crucial to note that patriotism might arise as a bias which this research chooses to ignore. Al Mamun et al. (2020) and Lucey et al. (2021) studied the possible effects EPUs may have over cryptocurrency prices and found results that have implications for investors.

S&P 500 Index (SPX500)

S&P 500 Index tracks the equity prices of the 500 largest companies in the US financial markets across a range of industries from technology to defense. Federal Reserve Bank of St. Louis (FRED) provides the data for this index, hence our data is highly reliable. S&P 500 is one of the most prominent indices whose relationship with other financial assets are research quite aggressively. That obviously has to do with S&P 500 being the largest equity market in the world. Shaikh (2020) investigated whether a correlation exists between the S&P 500 returns and Bitcoin returns, yet found no relationship. Considering the size and the liquidity of S&P 500, it is useful to test if any cryptocurrency can stand a hedge against the largest equity market in the world.

Dow Jones Index (DJIA)

The Dow Jones Industrial Average (DJIA) is a benchmark index that is widely-watched by investors. Companies DJIA tracks consist of 30 large and publicly owned firms that are traded in the New York Stock Exchange (NYSE) and Nasdaq. Taking into account that companies that are tracked by DJIA are mostly technology companies or companies that rely on technology for their growth agenda, it will be useful to analyze if investors can make a better use DJIA for their optimal investment decision making and portfolio management strategy. Zhang et al. (2018) researched the possible correlation between the DJIA and Cryptocurrency Composite Index (CCI) and discovered persistent correlation. Data for DJIA will be sourced from the FRED.

Oil Prices

Oil prices is another index that will be incorporated in this research to examine if cryptocurrency prices have an underpinning relationship with oil prices. It is safe to say that there are not many research regarding the impact change in oil prices may have in cryptocurrency valuation. Therefore, this study might potentially deliver invaluable results that are informative and have implications for cryptocurrency traders. It is also exciting to see which one between the Geopolitical Risk Index and oil prices is more influential on determining crypto valuation since oil prices are dramatically impacted by geopolitical risks. Data for crude oil prices will be extracted from the FRED.

Euro/Dollar

The foreign exchange (forex) market is the world’s largest financial market with trillions being traded everyday. Forex is not only the largest but also the most liquid market among all the markets in finance. Given the size and liquidity of forex, the potential underlying relationship between euro and dollar is even more important for traders to ensure optimal portfolio construction and diversification. It is important to put emphasis on the fact that finding of a possible correlation would significantly leverage investors in terms of their risk aversion strategies. The reason euro/dollar has been chosen for this research is due to being the most traded benchmark currency pair. Data for euro/dollar will be sourced from wsj.com.

MSCI Emerging Markets 50 (MSCI EM50)

The Index of MSCI Emerging Markets 50 is a passively managed fund which tracks equity market indices of emerging economies. Including emerging markets index is particularly important for this research due to the fact that emerging markets have also been experiencing high volatility post-Covid era, thus requiring an advanced formulation to successfully manage the short and long strategies. There is a shortage of studies that emphasize on how cryptocurrency valuation is affected by volatility in the financial markets of emerging economies. Especially the post-Covid performance of emerging financial markets will be exciting to analyze with regards to its possible interaction with cryptocurrencies. MSCI EM50 data will be collected from msci.com.

Monetary Policy Uncertainty (MPU)

Monetary policy is directly influential on the supply of money in the financial system which is likely to have a direct impact on increasing asset prices including cryptocurrencies. Hence, results that our research will produce are critical to understanding how cryptocurrencies respond to uncertainty with regards to monetary policy. It is important to note that monetary policy for this research will be FED's monetary policy, thus it can also be referred to as US monetary policy uncertainty. Uncertainty for monetary policy is news-based which means that word that are signaling monetary policy uncertainty are identified to drive an index number. The index is developed by Baker et al. (2016). Data for the MPU will be cited from policyuncertainty.com.

Financial Stress Indicator (FSI)

Financial Stress indicator that has been chosen for this research is newspaper-based and developed by Lukas Puttmann. This indicator is for the US, hence only covers 5 U.S newspapers. Data is available at monthly and quarterly frequencies. Unfortunately, there remains a key limitation of this indicator which is that it only covers data from 1889 to 2016. Index is constructed through counting in relevant words and labelling each word positive or negative depending on the word itself. FSI is a popular indicator that help analyze countries' economic and financial risks, emerging countries in particular (Balakrishnan et al., 2011; Cevik et al., 2013; Cevik et al., 2016). It will be interesting to see how investors react when risks associated with financial markets increase and whether or not they consider cryptocurrency a safe haven during high financial stress. Data will be sourced from policyuncertainty.com.

Global Real Economic Activity (GREA)

Global real economic activity (GREA) index is developed by senior economic policy advisor, Lutz Kilian (2009) working at the Federal Reserve Bank of Dallas. The index is developed by tracking data from 34 OECD countries. This index will offer a rather wider framework for the reader to look at the world economic circumstances and understand how the overall world economic outlook is associated with cryptocurrency prices. It will interesting to look at post-Covid era in particular to comprehend how devastated economic activity and disrupted supply chains have, if at all, affected crypto valuation. Data for GREA will be collected from the FRED.

3.5 Descriptive Statistics

Table illustrated below provides descriptive information with respect to variables to be used to in the dissertation.

	Mean	Std. Dev.	Min	Max
GPR	148.9027	55.45577	65.41	380.6
USMPU	79.86617	59.36548	20.14998	304.0693
GlobalEPU	240.4294	72.63423	126.3877	437.0496
USEPU	196.9247	87.35892	109.6864	503.9633
ChinaEPU	573.2348	225.9096	122.9374	970.8299
EUEPU	222.57	45.17353	135.1637	361.3689
EMUI	81.11265	78.95338	13.4	476.3336
FSI	-0.3903557	0.7067179	-0.97328	3.767925
GREA	-13.42202	49.21121	-122.0738	109.2519
BrentOil	60.30589	13.14498	23.33727	83.65
DJIA	26931.61	4259.471	20424.14	35848.57
SP500	3132.147	660.04	2329.911	4667.387
VIX	18.53191	8.191809	10.12545	57.73682
EURUSD	1.152957	0.0443883	1.06	1.23
MSCIEM50	1107.853	127.8058	848.58	1376.21
Bitcoin	15590.9	17292.76	1068.0	60968.0
Ethereum	773.1886	1074.686	15.63	4453.8

	Mean	Std. Dev.	Min	Max
BinanceCoin	101.5992	179.03	1.28358	624.08
Ripple	0.4992745	0.4005351	0.1651	1.99
Tether	0.9990649	0.0126233	935.0	1.0571

Chapter 4: Empirical Results

This chapter will be dedicated to disclosing and interpreting the empirical results derived from the econometric analysis whose tools and methods have been mentioned in the previous chapter. To avoid the distraction of having several tables, tables illustrating empirical results will be provided in the Appendix.

4.1 Bitcoin

As previously mentioned, the econometric approach chosen for this research paper is the Autoregressive Distributed Lags (ARDL). It is just as important to clarify that in order to prevent multicollinearity, independent variables are grouped in 5 then the ARDL has been run. The number of lags chosen for each ARDL model has been dictated by considering the optimal R_squared as well as Root MSE. Lastly, it is critical to note that by including error correction (ec), the empirical results were able to show both short and long-run estimates for each independent variable which are subsequently supported by the ARDL Bounds Test results.

The first group of independent variables consist of Geopolitical Risk Index (GPR), US Monetary Policy Uncertainty (USMPU), Global Economic Uncertainty (GEPU), US Economic Policy Uncertainty (USEPU) and China Economic Policy Uncertainty (CEPU). For this group of variables, the optimal lag selection has been 4 for each variable including the dependent variable.

The results show no short-run correlation between the independent variables and the dependent variable except for the China Economic Policy Uncertainty (CEPU). Second and third lag of CEPU has proven to be significantly correlated with Bitcoin prices in the short-run. Yet, it is crucial note that the correlation is significant only at 10% significance level (see Table.1). Both lags are positively correlated with Bitcoin prices, 46.18 and 36.51 respectively. That means that uncertainty in Chinese Economic Policy in previous periods (t-2, t-3) leads to an increase in Bitcoin prices in current period (t). Results show no long-run (LR) relationship with any variable and it is supported with ARDL Bounds Test findings.

The second group of variables are European Union Economic Policy uncertainty (EUEPU), Equity Market Related Uncertainty (EMUI), Financial Stress Indicator (FSI), Global Real Economic Activity (GREA) and Brent Oil prices. It is only the FSI that seems to be correlated with Bitcoin prices in the short-run (see Table.2). The second lag of FSI is negatively correlated at -3000.958 which means that increase in financial stress in t-2 will cause a decline in Bitcoin valuation in t. Yet again, no LR relationship is observed.

The last group of variables are Dow Jones Industrial Average (DJIA), S&P500 (SP500), Volatility Index (VIX), Euro/Dollar (EURUSD) and MSCI Emerging Markets Index (MSCIEM50). Results show that all variables are highly significantly correlated with Bitcoin prices. DJIA and SP500 are correlated with 3 lags, VIX and EURUSD with one whereas MSCIEM50 shows correlation with 2 lags (see Table.3). DJIA is positively correlated with all lags meaning DJIA going up, Bitcoin follows same trend. On the other hand, SP500 is negatively correlated, thus an increase in US equity market causes a decline in Bitcoin prices. EURUSD is positively correlated while VIX and MSCIEM50 seems to have a reverse relationship with Bitcoin valuation.

4.2 Ethereum

Quite similar to Bitcoin, Ethereum also did not indicate significant correlation with first group of variables neither in the short-run (SR) nor in the long-run (LR). That finding is supported by Bounds Test result.

In terms of the second group, Ethereum seems to have a relationship with Brent Oil in the short-run as the first lag of Brent oil is statistically significant at 5% significance level (see Table.5). Coefficient for the estimate for Brent oil is -37.6 which means that increase in Brent oil prices in t-1 translates to decrease in Ethereum prices in the current time period (t). According to the results, Brent oil is not only correlated in the short-run but also seems to have an underlying relationship with Ethereum in the long-run. However, it is essential to emphasize that despite the inverse correlation in the short-run, the relationship seems to be positive over the long-run with coefficient being +36.5. Bounds test also confirmed the long-run relationship at 10% significance level.

With respect to the last group of variables, none of the variables showed any evidence of determining the price of Ethereum in the short-run (see Table.6). However, benchmark volatility index (VIX) provided results that suggest correlation with Ethereum valuation in the long-run. The coeeficient estimate is significant at 5% and the coefficient estimate is +64.85. That translates to an increase in equity volatility and so the VIX will lead to an increase in Ethereum prices. Bounds test confirmed the long-run relationship at 10% significance level.

4.3 BinanceCoin

According to the results, first group of variables have not demonstrated any significant relationship with BinanceCoin's price formation neither in the short-run nor in the long-run (see Table.7). Bounds test confirmed the absence of long-term relationship. The second group of indicators perform no better than the ones in the first group (see Table.8). The results indicate no statistically significant correlation between any of the indicators and the valuation of BinanceCoin.

On the other hand, third group of variables seem promising in terms of their correlation with BinanceCoin valuation (see Table.9). DJIA is correlated with BinanceCoin along with its 3 lags which are all significant and positive which means that an increase in DJIA (t-1, t-2, t-3) will trigger an increase in BinanceCoin prices (t). In a similar way, S&P500 manifests its underlying relationship with 3 lags all of which are statistically significant but negative compared to the DJIA. That means that an increase in SP500 (t-1, t-2, t-3) will shift BinanceCoin prices (t) downwards. MSCIEM50 is also correlated with 3 lags which are all negatively signed, hence it is safe to argue that an increase in emerging markets' equity market will lead to a decline in the valuation of BinanceCoin.

VIX is correlated with BinanceCoin prices the second and third lags both of which are significant at 5% and negatively signed similar to the SP500 and MSCIEM50. EURUSD also provides evidence that it has an underlying relationship with BinanceCoin, the first and the second lags both of which are statistically significant and positively correlated. That means if EURUSD goes up (Euro strengthens against dollar), the price of BinanceCoin will go up as well.

An interesting finding emerges in the long-run relationship between the variables and the coin. DJIA and EURUSD were positively correlated with BinanceCoin valuation in the short-run, however they become negatively correlated in the long-run equation. Moreover, S&P500 and MSCIEM50 which were both negatively correlated with BinanceCoin prices in the short-term, become positively linked with the valuation of BinanceCoin over the long horizon. Also, VIX is no longer a significant determinant of the valuation of BinanceCoin in the long-run.

4.4 Tether

First group variables which are mostly economic uncertainty indices remain irrelevant in estimating cryptocurrency valuation so far. However, US monetary policy uncertainty (USMPU) and US economic policy uncertainty (USEPU) seem promising in estimating Tether’s valuation in the third and forth lags which are significant at 10% and 5% respectively (see table.10). Despite the similar results, the main difference is that USMPU is positively correlated whereas USEPU indicates an inverse correlation. Therefore, increase in the USMPU is estimated to soar Tether's price while an increase in the USEPU tend to cause a decline in Tether’s valuation. It is important to note that there is no evidence of long-term relationship between Tether and any of the variables in the first group including USMPU and USEPU.

In the second group, only Brent oil seems to estimate the valuation of Tether in the short-run. It is positively correlated and significant only at 10% (see Table.11). There is again no significant relationship over the long horizon.

The last group of variables that is dominated by financial indicators seems not to be as efficient in predicting Tether's price as in predicting the previous 3 cryptocurrencies, Bitcoin, Ethereum and BinanceCoin. With respect to short-run relationship, it is only the EURUSD in the third lag that has a correlation with Tether (see Table.12). The coefficient estimate is negative meaning that increase in the EURUSD (stronger Euro against Dollar) will lead to a fall in Tether’s price. Yet, the estimate is only significant at 10% significance level. Despite the short-run relationship of EURUSD, the only variable that significantly predicts Tether’s price over the long horizon is the DJIA and is negatively correlated.

4.5 Ripple

There is no independent variable in the first group that is statistically significantly predicting Ripple’s price over the long-run. On the other hand, USMPU and USEPU effectively predict the valuation of Ripple over the short horizon (see Table.13). USMPU provides evidence that it is correlated with Tether’s price in its second lag which is significant at 5% and negatively signed. USEPU is also correlated with 3 lags and positively signed. The second and the third lags are significant at 5% whereas the first lag is only significant at 10% significance level.

Surprisingly, there is no evidence that any variable in the second group has an underlying relationship with the valuation of Tether neither in the short nor in the long-term (see Table.14).

In terms of the third group, the results suggest that variables that predict Tether’s price in the short-run are different than those effective in the long-run (see Table.15). DJIA is significant in the third lag and positively correlated meaning an increase in the DJIA will translate to an increase in Tether’s price. S&P500 also demonstrates statistically significant relationship in the third lag. Correlation is negative suggesting that an increase in SP500 is likely to cause a fall in Tether’s valuation. EURUSD also indicates a relationship in the second lag which is significant at 10% and positively signed.

Regardless of the efficiency of DJIA, SP500 and EURUSD over the short horizon, the only variable that indicates a correlation over the long-run is VIX. It is positively correlated with Tether’s valuation and significant at 10%.

Chapter 5: Discussion

According to the results derived from the econometric analysis that has been carried out, it is safe to argue that there are certain underpinning relationship between some variables which might have an effective use in optimal portfolio construction, risk management and asset management. This is particularly important due to proposing investors that alternative asset classes exist and they can well serve as a hedge against particular investment types. It is important to note at this point that since cryptocurrencies are highly volatile the main area of interest will be on rather the short-run correlation between the variables.

Starting off with Bitcoin, ChinaEPU reveals correlation in the second and third lag which suggests that investors can track economic uncertainty data for China and can position themselves 2 or 3 months ahead. The correlation is positive, thus anticipating increasing uncertainty in China must trigger an upward price movement. FSI is negatively correlated with bitcoin in the second lag meaning that data of the month of 2 months prior can be exploited to take earlier positions in the bitcoin market as increase in financial stress is likely to cause a downward shift in prices.

In relation to other asset classes, Bitcoin seems positively correlated with DJIA in 3 lags meaning that an anticipated increase in DJIA will lead to an upward trend in bitcoin prices. In contrast, S&P500 exhibits negative correlation in three lags, therefore it is reasonable to assume that bitcoin can serve as a hedge against S&P500. Similarly the equity market index of emerging markets MSCIEM50 seems to have a negative relationship with bitcoin prices demonstrating another hedging opportunity for investors that seek optimal risk management. The EURUSD is positively linked with bitcoin prices which may mean that the anticipation of strengthening Euro against dollar is likely to increase bitcoin prices as well. VIX coefficient estimate is signed negative, hence increase in equity volatility tend to devalue bitcoin. Yet, the estimate is only significant at 10%.

An interesting finding arises in the coefficient estimates in the long-run which are all signed exact opposite those of short-run. Positive correlation of DJIA turns negative in the long-run while S&P500 goes positive, EURUSD becomes negative and MSCIEM50 indicates positive relationship over the long horizon.

In the case of Ethereum, Brent oil seems to predict Ethereum's price both in the short and long horizon. It is negatively correlated in the first lag which means that an increase in the price of Brent oil in the previous month tends to cause a decline in Ethereum prices today. However, the long-run estimates suggest that Brent oil and Ethereum are positively correlated. Companies that engage in Brent oil trading can optimize their risks by incorporating Ethereum in their portfolio. The key thing to consider here is to determine on what horizon the risk management is being constructed. That is due to Ethereum's hedging feature agains Brent oil in the short-run is no longer the case in the long-run. VIX also presents positive correlation with Ethereum prices in the long-run which translates to an increase in equity volatility tends to come with higher Ethereum prices over the long horizon.

BinanceCoin, similar to Ethereum, have not presented so much of promising results in terms of explanatory variables in the first 2 groups effectively predicting the price of the coin. It is observed that BinanceCoin itself is a solid predictor of its own price being impacted by its previous price (t-2). That may support the narrative that cryptocurrencies are speculative assets and many go into market basically hoping the market to continue to soar without having a legitimate rationale.

Similar to Bitcoin, BinanceCoin also presents significant hedging opportunities for investors. Both S&P500 and MSCIEM50 indicates inverse correlation with BinanceCoin prices in 3 lags. That is to suggest US equity market and emerging equity markets can be hedged by incorporating BinanceCoin into portfolio. In comparison, DJIA and EURUSD contributes positively to the valuation of BinanceCoin. DJIA allows prices to be predicted as early as 3 months while EURUSD is significant in 2 lags. VIX also significantly predicts BinanceCoin prices in the second and third lag. It is important to emphasize on the fact that second and third lag being significant means that prices can be estimated based on VIX figures of 2 to 3 months, not the prior month. Same finding of Bitcoin that the contradiction between the estimate results over the short and long horizon also applies to BinanceCoin's trading data. Therefore, traders must profoundly take into consideration whether they are formulating their trading strategy in the short or the long-run. Also, the VIX is no longer correlated with the valuation of BinanceCoin in the long-term.

Tether's valuation seems to be correlated with USMPU and USEPU, both in the third lag. This means that FED's monetary policies as well as general economic policy uncertainty in the US (t-3) has an impact on Tether's price today (t). FED's policy uncertainty shows positive correlation meaning that increase in monetary policy uncertainty soars Tether's price whereas economic policy uncertainty has a descending impact on the valuation of Tether. It is important to remind that both variables provide insignificant results for the long-run estimates. Equity Market-related uncertainty (EMUI) also demonstrates an underlying relationship with Tether's price in the third lag. The relationship is positive, hence it can inferred that an increase in EMUI will pick up the price of Tether. However, it is critical to emphasize that significance in the third lag requires a strategy that takes into consideration the prices of Tether can be estimated 3 months ahead, not the prior month. Brent oil is also positively associated in the first lag allowing investors to determine position a month ahead. Regardless of the short-run correlation, none of these variables above indicate a relationship over the long horizon.

EURUSD index presents negative correlation with Tether's price in the third lag. This represents a safe heaven for Euro investors given that as Euro strengthens against dollars, Tether price goes down.Yet, the hedging opportunity of EURUSD remains only in the short-run. Similarly, the DJIA indicates a negative relationship in the long-term, offering investors another tool to use as a part of risk aversion strategies. Tether is also highly correlated with its own price, hence it might be reasonable to suggest that the investors lack proper investment strategies and rather follow the crowd when it comes to purchasing crypto assets such as Tether.

In the analysis of Ripple, it is observed that USMPU predicts Ripple's price in the second lag and is significant at 5%. The correlation is negative, hence uncertainty regarding FED policies is proven to decrease Ripple's price. The USEPU is also correlated in all three lags, second and third lag being significant at 5% and signed positive. Therefore, overall economic policy uncertainty in the US leads to increased valuation of Ripple. Despite the short-term estimates, there is no proof of correlation over the long-term. DJIA seems to be positively correlated in the third lag, thus an anticipation of increasing DJIA might also trigger price hikes in Ripple. In comparison, S&P500 is negatively correlated in the third lag and significant at 5%, presenting a significant hedging opportunity against the US equity market. In addition, EURUSD in the second lag shows positive relationship with Tether's price. However, the estimate is only significant at 10%.

Chapter 6: Conclusion

This dissertation has been dedicated to research both short-term and long-term relationship of the most popular cryptocurrencies with a number of indices from a wide range areas such as geopolitics, finance, economics etc. To be able to conduct a research that is valuable and scientifically informative, an econometric tool of Autoregressive Distributed Lag (ARDL) has been chosen. Also to prevent multicollinearity, variables have been grouped into 3 and ran regression.

According to the findings of the econometric models, this paper suggests that cryptocurrencies can serve as hedge against particular asset class. This is particularly important to know in order to construct a proper risk management strategy and build a portfolio that offers the optimal yield to risk ratio. Bitcoin has proven to be a hedge against S&P500 and MSCIEM50 in the short-run, yet over the long-term it was DJIA and EURUSD which Bitcoin could present hedging opportunities against. Ethereum also indicated potential to serve as a hedge against Brent oil both in the short and long run.

BinanceCoin provided evidence that it is similar to Bitcoin in dynamics as it was negatively correlated with S&P500 and MSCIEM50 in the short-run and DJIA and EURUSD in the long-run. It can also be said that following VIX might be useful in making inferences over BinanceCoin's price as VIX is negatively associated with the valuation of BinanceCoin. There remains a key detail that must be considered is that coefficient estimates vary dramatically depending on whether short-term or long-term, hence investors must determine their trading horizon in order to come up and study with the relevant variable.

Tether did not seem to offer much of hedging opportunities with other asset classes. According to the regression, its price was best predicted by its previous price, USMPU and USEPU. Similarly, Ripple also provided evidence that its price is effectively determined by the uncertainty in the US monetary policy and general economic policy. As opposed to Tether though, Ripple showed hedge features against the S&P500 and the MSCIEM50 in the short-run and S&500 and EURUSD in the long-run.

Based on the findings of this research, it is explicitly observed that some cryptocurrencies inherited similar trading features given that they demonstrated capacity to be incorporated in risk management strategies in order to offer advanced risk aversion mechanism. This research is, in particular, important due to providing invaluable insights to investors of all types whether crypto investors, hedge funds, corporate traders or retail traders. There are certainly key takeaway from this research as both short-term and long-term trading psychology of the most popular cryptocurrencies have been revealed to a certain extent. It is recommended that investors must first determine why they are willing to add crypto assets to their portfolio then build up the strategy accordingly considering the investment horizon as well.

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APPENDIX

ARDL(4,4,4,4,4,4) regression

Sample:	2017m7 - 2021m5	Number of obs =	47
		R-squared =	0.6160
		Adj R-squared =	-0.0391
Log likelihood = -430.37849		Root MSE =	3814.3203

D.d_Bitcoin	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Bitcoin						
L1.	-.8668687	.4746706	-1.83	0.085	-1.868336	.1345987
LR						
d_GPR	-60.29237	70.50585	-0.86	0.404	-209.0467	88.46196
d_USMPU	131.0794	101.7742	1.29	0.215	-83.64544	345.8042
d_GlobalEPU	45.70314	181.6651	0.25	0.804	-337.5767	428.9829
d_USEPU	-123.4838	103.2029	-1.20	0.248	-341.2229	94.25521
d_ChinaEPU	-49.50224	45.65885	-1.08	0.293	-145.834	46.82952
SR						
d_Bitcoin						
LD.	.3276265	.466039	0.70	0.492	-.6556297	1.310883
L2D.	-.0481185	.5654052	-0.09	0.933	-1.241019	1.144782
L3D.	.3614559	.4695033	0.77	0.452	-.6291095	1.352021
d_GPR						
D1.	46.96844	58.02533	0.81	0.429	-75.45431	169.3912
LD.	29.14747	47.40125	0.61	0.547	-70.86042	129.1554
L2D.	.2126569	30.01888	0.01	0.994	-63.12164	63.54695
L3D.	-2.539265	15.99741	-0.16	0.876	-36.29086	31.21233
d_USMPU						
D1.	-78.25314	99.80515	-0.78	0.444	-288.8236	132.3173
LD.	-55.53702	76.33127	-0.73	0.477	-216.5819	105.5079
L2D.	-4.986259	41.69057	-0.12	0.906	-92.94567	82.97315
L3D.	-13.66567	26.2283	-0.52	0.609	-69.00255	41.6712
d_GlobalEPU						
D1.	-94.24074	133.0677	-0.71	0.488	-374.989	186.5075
LD.	-70.75108	106.4992	-0.66	0.515	-295.4448	153.9427
L2D.	-97.31592	73.94419	-1.32	0.206	-253.3245	58.69268
L3D.	-25.65195	44.30821	-0.58	0.570	-119.1341	67.83021
d_USEPU						
D1.	97.09971	82.3418	1.18	0.255	-76.62631	270.8257
LD.	44.77189	62.37141	0.72	0.483	-86.82027	176.3641
L2D.	25.58052	42.38059	0.60	0.554	-63.83472	114.9958
L3D.	4.752836	19.97565	0.24	0.815	-37.3921	46.89777
d_ChinaEPU						
D1.	45.6766	29.75326	1.54	0.143	-17.09729	108.4505
LD.	46.18503	26.15163	1.77	0.095	-8.990092	101.3601
L2D.	36.50867	18.51826	1.97	0.065	-2.561448	75.57878
L3D.	17.96672	12.79259	1.40	0.178	-9.023301	44.95673
_cons	1048.402	713.1047	1.47	0.160	-456.1178	2552.921

Table.1

Sample: 2017m7 - 2021m11

Log likelihood = -516.67634

Number of obs	=	53
R-squared	=	0.6921
Adj R-squared	=	0.5552
Root MSE	=	5029.4108

D.d_Bitcoin	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Bitcoin						
L1.	-1.520777	.301667	-5.04	0.000	-2.132587	-.9089683
LR						
d_EUEPU	-28.33514	40.05305	-0.71	0.484	-109.5665	52.8962
d_EMUI	-5.652319	17.87053	-0.32	0.754	-41.89543	30.59079
d_FSI	3838.654	2715.221	1.41	0.166	-1668.069	9345.378
d_GREA	26.42026	20.76452	1.27	0.211	-15.69215	68.53267
d_BrentOil	312.9008	204.3172	1.53	0.134	-101.4737	727.2753
SR						
d_Bitcoin						
LD.	.4868487	.2684206	1.81	0.078	-.0575334	1.031231
L2D.	.5664673	.2209308	2.56	0.015	.1183988	1.014536
L3D.	.5106051	.1596236	3.20	0.003	.1868734	.8343369
d_EUEPU						
D1.	12.4455	50.35887	0.25	0.806	-89.68703	114.578
LD.	25.7861	37.00618	0.70	0.490	-49.26591	100.8381
L2D.	24.27173	20.24325	1.20	0.238	-16.78349	65.32694
d_FSI						
D1.	-3888.205	2897.169	-1.34	0.188	-9763.937	1987.527
LD.	-3000.958	1738.674	-1.73	0.093	-6527.151	525.236
d_BrentOil						
D1.	-377.6665	250.1464	-1.51	0.140	-884.9868	129.6539
LD.	-77.95183	179.1578	-0.44	0.666	-441.3007	285.397
_cons	1075.912	745.0202	1.44	0.157	-435.0591	2586.883

Table.2

Sample: 2017m7 - 2021m11		Number of obs =	53
		R-squared =	0.8056
		Adj R-squared =	0.7192
Log likelihood = -504.49279		Root MSE =	3996.5223

D.d_Bitcoin	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Bitcoin						
L1.	-.9907266	.1343909	-7.37	0.000	-1.263284	-.7181692
LR						
d_DJIA	-9.386979	3.977173	-2.36	0.024	-17.45306	-1.320898
d_SP500	81.88668	30.92745	2.65	0.012	19.16291	144.6105
d_VIX	495.4407	389.3828	1.27	0.211	-294.2641	1285.146
d_EURUSD	-211220.3	73404.24	-2.88	0.007	-360091	-62349.57
d_MSCIEM50	141.1008	41.90762	3.37	0.002	56.10825	226.0934
SR						
d_DJIA						
D1.	16.26965	3.487609	4.66	0.000	9.196445	23.34285
LD.	11.4304	3.41675	3.35	0.002	4.500914	18.35989
L2D.	7.966968	2.284025	3.49	0.001	3.33475	12.59919
d_SP500						
D1.	-148.1712	30.59789	-4.84	0.000	-210.2266	-86.11577
LD.	-93.35105	30.50148	-3.06	0.004	-155.2109	-31.49119
L2D.	-79.68816	20.13113	-3.96	0.000	-120.516	-38.86033
d_VIX						
D1.	-483.1511	281.1694	-1.72	0.094	-1053.389	87.08686
d_EURUSD						
D1.	167101.6	56537.39	2.96	0.005	52438.43	281764.7
d_MSCIEM50						
D1.	-107.7441	30.97609	-3.48	0.001	-170.5665	-44.92167
LD.	-53.42087	16.24927	-3.29	0.002	-86.37591	-20.46582
_cons	-27.44953	801.9036	-0.03	0.973	-1653.785	1598.886

Table.3

Sample: 2017m7 - 2021m5		Number of obs	= 47
		R-squared	= 0.3552
		Adj R-squared	= 0.2585
Log likelihood = -313.46237		Root MSE	= 206.6667

D.d_Ethereum	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Ethereum						
L1.	-.6101048	.1539139	-3.96	0.000	-.9211765	-.2990331
LR						
d_GPR	.7332347	.7917323	0.93	0.360	-.8669161	2.333385
d_USMPU	-.6352328	1.155677	-0.55	0.586	-2.970943	1.700478
d_GlobalEPU	1.120701	2.55477	0.44	0.663	-4.042682	6.284084
d_USEPU	-.732375	1.153283	-0.64	0.529	-3.063248	1.598498
d_ChinaEPU	.0466021	.5185315	0.09	0.929	-1.001389	1.094593
SR						
_cons	36.3464	31.30832	1.16	0.253	-26.93007	99.62288

Table.4

```
Sample:  2017m5 - 2021m11                       Number of obs     =         55
                                                R-squared         =     0.6193
                                                Adj R-squared     =     0.4444
Log likelihood = -386.81501                     Root MSE          =   334.3771
```

D.d_Ethereum	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Ethereum						
L1.	-1.214563	.2761146	-4.40	0.000	-1.774025	-.6551019
LR						
d_EUEPU	-.5710855	2.56344	-0.22	0.825	-5.765108	4.622937
d_EMUI	3.350841	4.356616	0.77	0.447	-5.476501	12.17818
d_FSI	44.8427	360.4776	0.12	0.902	-685.5543	775.2397
d_GREA	2.259579	2.700494	0.84	0.408	-3.212142	7.731301
d_BrentOil	36.50162	18.03205	2.02	0.050	-.0347811	73.03802
SR						
d_Ethereum						
LD.	.0670972	.2003144	0.33	0.740	-.3387784	.4729728
d_EUEPU						
D1.	-.8623174	2.396888	-0.36	0.721	-5.718874	3.99424
LD.	-.8347734	1.372505	-0.61	0.547	-3.615733	1.946186
d_EMUI						
D1.	-2.011712	3.888791	-0.52	0.608	-9.89115	5.867726
LD.	-.4911075	2.227483	-0.22	0.827	-5.004416	4.022201
d_FSI						
D1.	-153.2205	318.1065	-0.48	0.633	-797.7654	491.3244
LD.	-120.0464	191.2341	-0.63	0.534	-507.5235	267.4307
d_GREA						
D1.	-.0306406	2.878205	-0.01	0.992	-5.862438	5.801156
LD.	-.1033679	2.15001	-0.05	0.962	-4.459702	4.252966
d_BrentOil						
D1.	-37.60096	16.78435	-2.24	0.031	-71.60929	-3.592638
LD.	-8.598776	13.16373	-0.65	0.518	-35.27102	18.07347
_cons	63.37058	49.61914	1.28	0.210	-37.16734	163.9085

Table.5

Sample: 2017m5 - 2021m11		Number of obs	= 55
		R-squared	= 0.6772
		Adj R-squared	= 0.5289
Log likelihood = -382.27675		Root MSE	= 307.8940

D.d_Ethereum	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Ethereum						
L1.	-1.14824	.2605911	-4.41	0.000	-1.676248	-.6202322
LR						
d_DJIA	.0525505	.2239309	0.23	0.816	-.4011765	.5062776
d_SP500	2.294825	1.881426	1.22	0.230	-1.517307	6.106956
d_VIX	64.84624	28.65958	2.26	0.030	6.776423	122.9161
d_EURUSD	-7023.137	5151.223	-1.36	0.181	-17460.51	3414.233
d_MSCIEM50	1.865469	2.635825	0.71	0.484	-3.47522	7.206157
SR						
d_Ethereum						
LD.	.0215613	.1904831	0.11	0.910	-.3643942	.4075168
d_DJIA						
D1.	.2097845	.2411278	0.87	0.390	-.2787868	.6983559
LD.	.1520829	.1755837	0.87	0.392	-.2036836	.5078493
d_SP500						
D1.	-2.888697	2.074745	-1.39	0.172	-7.09253	1.315135
LD.	-1.705188	1.661748	-1.03	0.311	-5.072209	1.661833
d_VIX						
D1.	-35.95289	23.49649	-1.53	0.134	-83.56131	11.65552
LD.	-24.67098	16.66085	-1.48	0.147	-58.42906	9.087109
d_EURUSD						
D1.	6045.579	4948.676	1.22	0.230	-3981.391	16072.55
LD.	3694.803	3728.385	0.99	0.328	-3859.624	11249.23
d_MSCIEM50						
D1.	-.2883649	2.490046	-0.12	0.908	-5.333677	4.756947
LD.	-1.148552	1.496358	-0.77	0.448	-4.180463	1.883358
_cons	-34.14562	64.90763	-0.53	0.602	-165.661	97.36972

Table.6

```
Sample:  2018m1 -  2021m5                       Number of obs     =        41
                                                R-squared         =    0.9302
                                                Adj R-squared     =    0.9127
Log likelihood = -193.50625                     Root MSE          =   30.7117

------------------------------------------------------------------------------
D.            |
d_BinanceCoin |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+---------------------------------------------------------------
ADJ           |
d_BinanceCoin |
           L1. |  -2.374415   .3174044    -7.48   0.000    -3.020947   -1.727883
--------------+---------------------------------------------------------------
LR            |
        d_GPR |   .0420126    .029275     1.44   0.161    -.0176186    .1016437
      d_USMPU |  -.0212125   .0426957    -0.50   0.623    -.1081808    .0657558
  d_GlobalEPU |  -.1164587   .0955288    -1.22   0.232    -.3110444    .0781271
      d_USEPU |   .0531684   .0446299     1.19   0.242    -.0377398    .1440766
    d_ChinaEPU |   .0144193   .0206415     0.70   0.490     -.027626    .0564646
--------------+---------------------------------------------------------------
SR            |
d_BinanceCoin |
          LD. |   1.896516     .48868     3.88   0.000     .9011077    2.891925
         L2D. |   3.619252   .4067787     8.90   0.000     2.790671    4.447833
              |
        _cons |   6.295036   5.013839     1.26   0.218    -3.917819    16.50789
------------------------------------------------------------------------------
```

Table.7

Sample: 2017m12 - 2021m11	Number of obs	=	48
	R-squared	=	0.7413
	Adj R-squared	=	0.4934
Log likelihood = -261.63811	Root MSE	=	79.7127

D. d_BinanceCoin	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_BinanceCoin						
L1.	-1.616991	.3918823	-4.13	0.000	-2.425796	-.8081854
LR						
d_EUEPU	-.7025343	.8851133	-0.79	0.435	-2.529318	1.12425
d_EMUI	1.409008	1.133664	1.24	0.226	-.9307595	3.748775
d_FSI	-6.832989	90.5196	-0.08	0.940	-193.6563	179.9903
d_GREA	.8048585	.670847	1.20	0.242	-.5797016	2.189419
d_BrentOil	6.862331	4.188693	1.64	0.114	-1.782707	15.50737
SR						
d_BinanceCoin						
LD.	.4392709	.2961229	1.48	0.151	-.1718968	1.050439
L2D.	.3817531	.1882654	2.03	0.054	-.0068075	.7703138
d_EUEPU						
D1.	.7043654	1.019053	0.69	0.496	-1.398856	2.807587
LD.	.8118926	.808756	1.00	0.325	-.8572977	2.481083
L2D.	.2278275	.5677233	0.40	0.692	-.9438958	1.399551
d_EMUI						
D1.	-1.371604	1.476337	-0.93	0.362	-4.418613	1.675406
LD.	-.8559226	1.032007	-0.83	0.415	-2.98588	1.274035
L2D.	-.3694385	.5826671	-0.63	0.532	-1.572004	.8331273
d_FSI						
D1.	-38.15632	120.1503	-0.32	0.754	-286.1343	209.8217
LD.	-32.70214	86.05647	-0.38	0.707	-210.314	144.9097
L2D.	15.86518	54.40381	0.29	0.773	-96.41876	128.1491
d_GREA						
D1.	-.8948486	1.0314	-0.87	0.394	-3.023553	1.233856
LD.	-.7216953	.8772814	-0.82	0.419	-2.532315	1.088924
L2D.	-.6791683	.6649629	-1.02	0.317	-2.051584	.6932476
d_BrentOil						
D1.	-8.734878	6.061194	-1.44	0.162	-21.24457	3.774812
LD.	-3.302815	4.775539	-0.69	0.496	-13.15904	6.553413
L2D.	3.708675	4.307556	0.86	0.398	-5.181684	12.59903
_cons	8.899299	12.62702	0.70	0.488	-17.1616	34.96019

Table.8

Sample: 2018m1 - 2021m11				Number of obs	=	47
				R-squared	=	0.9182
				Adj R-squared	=	0.7788
Log likelihood = -229.6132				Root MSE	=	53.2456

D. d_BinanceCoin	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_BinanceCoin						
L1.	-1.770723	.6208402	-2.85	0.011	-3.080581	-.460865
LR						
d_DJIA	-.1000472	.0514283	-1.95	0.068	-.2085513	.008457
d_SP500	.7190364	.3196991	2.25	0.038	.0445303	1.393542
d_VIX	-1.113148	5.677655	-0.20	0.847	-13.09195	10.86566
d_EURUSD	-3650.143	1347.347	-2.71	0.015	-6492.797	-807.4889
d_MSCIEM50	1.857074	.6623258	2.80	0.012	.4596888	3.254459
SR						
d_BinanceCoin						
LD.	.4986702	.4496594	1.11	0.283	-.4500282	1.447369
L2D.	.2728709	.3126151	0.87	0.395	-.3866894	.9324312
L3D.	-.222333	.2555937	-0.87	0.396	-.7615886	.3169226
d_DJIA						
D1.	.127481	.0688751	1.85	0.082	-.0178328	.2727949
LD.	.2246236	.0658893	3.41	0.003	.0856094	.3636378
L2D.	.205094	.0665349	3.08	0.007	.0647177	.3454703
L3D.	.083397	.0582346	1.43	0.170	-.0394672	.2062612
d_SP500						
D1.	-1.143168	.5699252	-2.01	0.061	-2.345605	.0592691
LD.	-2.695784	.6382718	-4.22	0.001	-4.04242	-1.349148
L2D.	-2.44211	.7105816	-3.44	0.003	-3.941306	-.9429144
L3D.	-.6544703	.7264631	-0.90	0.380	-2.187173	.8782329
d_VIX						
D1.	-6.675498	8.555243	-0.78	0.446	-24.72548	11.37449
LD.	-16.98542	7.58673	-2.24	0.039	-32.99202	-.9788188
L2D.	-15.92746	6.585525	-2.42	0.027	-29.8217	-2.033217
L3D.	-1.794732	6.211219	-0.29	0.776	-14.89926	11.30979
d_EURUSD						
D1.	7618.144	2309.275	3.30	0.004	2746	12490.29
LD.	5807.772	2465.12	2.36	0.031	606.8233	11008.72
L2D.	3067.292	1859.794	1.65	0.117	-856.5298	6991.114
L3D.	806.1481	1123.699	0.72	0.483	-1564.65	3176.947
d_MSCIEM50						
D1.	-3.73927	1.046237	-3.57	0.002	-5.946636	-1.531903
LD.	-3.185165	1.096777	-2.90	0.010	-5.499163	-.8711679
L2D.	-1.748565	.8954458	-1.95	0.068	-3.637791	.1406602
L3D.	-.4193028	.5174056	-0.81	0.429	-1.510933	.6723277
_cons	2.800433	16.70011	0.17	0.869	-32.43371	38.03458

Table.9

Sample: 2017m8 - 2021m5		Number of obs =	46
		R-squared =	0.9020
		Adj R-squared =	0.7243
Log likelihood =	192.74772	Root MSE =	0.0062

D.d_Tether	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Tether						
L1.	-2.262028	.5433944	-4.16	0.001	-3.413973	-1.110084
LR						
d_GPR	.0000168	.0000444	0.38	0.710	-.0000774	.0001111
d_USMPU	-.0000588	.0000682	-0.86	0.401	-.0002033	.0000857
d_GlobalEPU	-.0000569	.0001073	-0.53	0.603	-.0002843	.0001705
d_USEPU	.0000561	.0000676	0.83	0.419	-.0000872	.0001994
d_ChinaEPU	.0000209	.0000258	0.81	0.430	-.0000337	.0000754
SR						
d_Tether						
LD.	.9170634	.3990203	2.30	0.035	.0711782	1.762949
L2D.	.3491504	.2152232	1.62	0.124	-.1071025	.8054032
L3D.	.035487	.0872926	0.41	0.690	-.1495651	.2205391
d_GPR						
D1.	-.000071	.000087	-0.82	0.427	-.0002554	.0001135
LD.	-.0000849	.0000687	-1.24	0.234	-.0002304	.0000607
L2D.	-.0000706	.0000452	-1.56	0.138	-.0001665	.0000253
L3D.	-.0000392	.0000248	-1.58	0.134	-.0000917	.0000134
d_USMPU						
D1.	.0001433	.0001292	1.11	0.284	-.0001305	.0004171
LD.	.0001392	.0001065	1.31	0.209	-.0000865	.0003649
L2D.	.000135	.0000704	1.92	0.073	-.0000143	.0002843
L3D.	.0001189	.0000474	2.51	0.023	.0000183	.0002194
d_GlobalEPU						
D1.	-.0000873	.0002142	-0.41	0.689	-.0005414	.0003668
LD.	.000018	.0001633	0.11	0.914	-.0003282	.0003642
L2D.	.0000934	.0001218	0.77	0.454	-.0001649	.0003517
L3D.	.0000137	.0000709	0.19	0.849	-.0001365	.000164
d_USEPU						
D1.	-.0000747	.0001248	-0.60	0.558	-.0003393	.0001899
LD.	-.000122	.0000989	-1.23	0.235	-.0003317	.0000877
L2D.	-.0001461	.0000725	-2.02	0.061	-.0002998	7.56e-06
L3D.	-.0000864	.0000345	-2.51	0.023	-.0001595	-.0000134
d_ChinaEPU						
D1.	3.62e-07	.0000477	0.01	0.994	-.0001007	.0001015
LD.	-.0000116	.0000391	-0.30	0.770	-.0000945	.0000713
L2D.	-.0000172	.0000279	-0.62	0.545	-.0000763	.0000418
L3D.	-2.75e-07	.0000192	-0.01	0.989	-.0000409	.0000404
_cons	-.0006213	.0009437	-0.66	0.520	-.0026219	.0013792

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Table.10

Sample:	2017m7 - 2021m11	Number of obs =	53
		R-squared =	0.8691
		Adj R-squared =	0.7652
Log likelihood =	210.23225	Root MSE =	0.0062

D.d_Tether	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Tether						
L1.	-2.094428	.3146244	-6.66	0.000	-2.737907	-1.450949
LR						
d_EUEPU	.0000213	.0000472	0.45	0.655	-.0000753	.0001179
d_EMUI	-.000047	.000068	-0.69	0.495	-.0001861	.0000921
d_FSI	.0042129	.0055262	0.76	0.452	-.0070895	.0155152
d_GREA	.0000445	.0000396	1.12	0.270	-.0000365	.0001254
d_BrentOil	-.0002649	.0002506	-1.06	0.299	-.0007773	.0002476
SR						
d_Tether						
LD.	.5436404	.1798891	3.02	0.005	.175726	.9115549
L2D.	.14818	.0803192	1.84	0.075	-.0160911	.3124512
d_EUEPU						
D1.	-.0000896	.0000701	-1.28	0.211	-.000233	.0000538
LD.	-.0000482	.000054	-0.89	0.380	-.0001586	.0000623
L2D.	-.0000119	.0000318	-0.37	0.712	-.0000768	.0000531
d_EMUI						
D1.	.000159	.0001118	1.42	0.166	-.0000697	.0003877
LD.	.0001283	.0000768	1.67	0.106	-.0000289	.0002854
L2D.	.0000892	.0000434	2.05	0.049	3.66e-07	.000178
d_FSI						
D1.	-.0095411	.0092766	-1.03	0.312	-.0285138	.0094316
LD.	-.0066396	.0065824	-1.01	0.321	-.0201021	.0068229
L2D.	-.0039659	.003954	-1.00	0.324	-.0120528	.0041209
d_GREA						
D1.	-.0000228	.0000747	-0.31	0.762	-.0001757	.00013
LD.	-.0000812	.0000657	-1.24	0.226	-.0002155	.0000531
L2D.	-.0000146	.0000497	-0.29	0.771	-.0001161	.000087
d_BrentOil						
D1.	.0007828	.0004473	1.75	0.091	-.0001321	.0016976
LD.	.0005363	.0003456	1.55	0.132	-.0001705	.0012432
L2D.	.0005215	.0003225	1.62	0.117	-.000138	.0011811
_cons	-.000096	.0009717	-0.10	0.922	-.0020834	.0018914

Table.11

Sample: 2017m7 - 2021m11		Number of obs =	53
		R-squared =	0.8742
		Adj R-squared =	0.7745
Log likelihood = 211.2956		Root MSE =	0.0061

D.d_Tether	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Tether						
L1.	-2.009896	.3358801	-5.98	0.000	-2.696848	-1.322944
LR						
d_DJIA	-5.97e-06	3.00e-06	-1.99	0.056	-.0000121	1.72e-07
d_SP500	.0000236	.0000235	1.00	0.324	-.0000245	.0000717
d_VIX	-.0005706	.0003945	-1.45	0.159	-.0013775	.0002362
d_EURUSD	-.0585541	.0734658	-0.80	0.432	-.2088084	.0917003
d_MSCIEM50	.0000339	.0000381	0.89	0.381	-.000044	.0001118
SR						
d_Tether						
LD.	.4233012	.1753585	2.41	0.022	.0646527	.7819496
L2D.	.1240917	.0695119	1.79	0.085	-.018076	.2662594
d_DJIA						
D1.	8.10e-06	5.99e-06	1.35	0.186	-4.14e-06	.0000203
LD.	5.53e-06	5.41e-06	1.02	0.315	-5.53e-06	.0000166
L2D.	1.97e-06	3.74e-06	0.53	0.603	-5.69e-06	9.62e-06
d_SP500						
D1.	-.0000481	.0000485	-0.99	0.329	-.0001473	.000051
LD.	-.0000408	.000048	-0.85	0.402	-.0001389	.0000573
L2D.	-.000015	.0000369	-0.41	0.688	-.0000905	.0000605
d_VIX						
D1.	.0005743	.0007037	0.82	0.421	-.0008648	.0020135
LD.	.0003819	.0004924	0.78	0.444	-.0006252	.0013891
L2D.	.0002409	.0003729	0.65	0.523	-.0005217	.0010035
d_EURUSD						
D1.	.0881465	.1404805	0.63	0.535	-.1991683	.3754613
LD.	-.025584	.1121104	-0.23	0.821	-.2548757	.2037076
L2D.	-.1527009	.0833123	-1.83	0.077	-.3230937	.0176919
d_MSCIEM50						
D1.	-.00008	.0000701	-1.14	0.263	-.0002234	.0000634
LD.	-.0000234	.0000572	-0.41	0.685	-.0001403	.0000935
L2D.	.0000166	.0000343	0.48	0.632	-.0000535	.0000868
_cons	.0009032	.0015148	0.60	0.556	-.002195	.0040014

Table.12

Sample: 2017m9 - 2021m5			Number of obs	=	45
			R-squared	=	0.7852
			Adj R-squared	=	0.5500
Log likelihood = -3.9841271			Root MSE	=	0.3870

D.d_Ripple	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Ripple						
L1.	-2.147524	.4713506	-4.56	0.000	-3.127751	-1.167296
LR						
d_GPR	-.0020675	.0021511	-0.96	0.347	-.0065409	.0024059
d_USMPU	.0041536	.0031032	1.34	0.195	-.0022998	.010607
d_GlobalEPU	-.0005208	.0054911	-0.09	0.925	-.0119403	.0108986
d_USEPU	-.0039519	.0033903	-1.17	0.257	-.0110023	.0030985
d_ChinaEPU	-.0005794	.0012075	-0.48	0.636	-.0030905	.0019318
SR						
d_Ripple						
LD.	.6522694	.3695163	1.77	0.092	-.1161818	1.420721
L2D.	.3617634	.2187466	1.65	0.113	-.0931451	.8166718
d_GPR						
D1.	.0040823	.0038435	1.06	0.300	-.0039106	.0120752
LD.	.003128	.0026297	1.19	0.248	-.0023407	.0085967
L2D.	.0014668	.0013911	1.05	0.304	-.0014262	.0043598
d_USMPU						
D1.	-.008262	.0054128	-1.53	0.142	-.0195187	.0029946
LD.	-.0073885	.0035001	-2.11	0.047	-.0146673	-.0001096
L2D.	-.0029227	.0021186	-1.38	0.182	-.0073286	.0014832
d_GlobalEPU						
D1.	-.0049999	.0095315	-0.52	0.605	-.0248218	.0148221
LD.	-.0052713	.0071722	-0.73	0.470	-.0201868	.0096442
L2D.	-.0034932	.004142	-0.84	0.409	-.012107	.0051206
d_USEPU						
D1.	.0105259	.0056636	1.86	0.077	-.0012523	.0223041
LD.	.0091265	.0038737	2.36	0.028	.0010706	.0171823
L2D.	.0045395	.0018585	2.44	0.024	.0006745	.0084045
d_ChinaEPU						
D1.	.0015315	.0021755	0.70	0.489	-.0029928	.0060557
LD.	.0010811	.0016445	0.66	0.518	-.0023388	.004501
L2D.	.000076	.0010444	0.07	0.943	-.002096	.002248
_cons	.059027	.0592934	1.00	0.331	-.0642803	.1823344

Table.13

Sample: 2017m9 - 2021m11 | Number of obs = 51 | R-squared = 0.7674 | Adj R-squared = 0.5692

Log likelihood = -7.5826149 | Root MSE = 0.3859

D.d_Ripple	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Ripple						
L1.	-2.206201	.4149816	-5.32	0.000	-3.057673	-1.354729
LR						
d_EUEPU	-.0019149	.0030167	-0.63	0.531	-.0081046	.0042748
d_EMUI	.0065836	.0038911	1.69	0.102	-.0014003	.0145674
d_FSI	-.3494285	.3216968	-1.09	0.287	-1.009496	.3106388
d_GREA	.0029707	.00236	1.26	0.219	-.0018715	.007813
d_BrentOil	.0207472	.0145708	1.42	0.166	-.0091495	.050644
SR						
d_Ripple						
LD.	.7664969	.2968068	2.58	0.016	.1574997	1.375494
L2D.	.2924205	.1853772	1.58	0.126	-.0879422	.6727831
d_EUEPU						
D1.	.0003577	.0048533	0.07	0.942	-.0096005	.010316
LD.	-.0009533	.0035679	-0.27	0.791	-.008274	.0063674
L2D.	-.0006297	.0020734	-0.30	0.764	-.0048839	.0036245
d_EMUI						
D1.	-.010762	.0073059	-1.47	0.152	-.0257525	.0042284
LD.	-.005243	.0050028	-1.05	0.304	-.015508	.0050219
L2D.	-.0021653	.002781	-0.78	0.443	-.0078715	.0035409
d_FSI						
D1.	.532179	.5863014	0.91	0.372	-.6708121	1.73517
LD.	.2631684	.4179245	0.63	0.534	-.5943419	1.120679
L2D.	.2500998	.2543218	0.98	0.334	-.2717254	.771925
d_GREA						
D1.	-.001713	.0048111	-0.36	0.725	-.0115846	.0081586
LD.	-.0025068	.0041341	-0.61	0.549	-.0109892	.0059756
L2D.	-.0031457	.0032573	-0.97	0.343	-.0098291	.0035377
d_BrentOil						
D1.	-.0465771	.0293897	-1.58	0.125	-.1068797	.0137255
LD.	-.0170808	.0230417	-0.74	0.465	-.0643584	.0301969
L2D.	-.0018912	.0207528	-0.09	0.928	-.0444724	.04069
_cons	-.0159725	.0600298	-0.27	0.792	-.1391435	.1071985

Table.14

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Sample:  2017m9 - 2021m11                       Number of obs     =         51
                                                R-squared         =     0.8593
                                                Adj R-squared     =     0.7395
Log likelihood =  5.2425157                     Root MSE          =     0.3001
```

D.d_Ripple	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ADJ						
d_Ripple						
L1.	-2.497583	.4240609	-5.89	0.000	-3.367684	-1.627482
LR						
d_DJIA	.0001983	.0001244	1.59	0.123	-.0000571	.0004536
d_SP500	-.000399	.000956	-0.42	0.680	-.0023604	.0015625
d_VIX	.0284095	.0165645	1.72	0.098	-.0055779	.062397
d_EURUSD	-2.430324	3.243936	-0.75	0.460	-9.086331	4.225682
d_MSCIEM50	.001379	.0015376	0.90	0.378	-.001776	.0045339
SR						
d_Ripple						
LD.	.8771085	.3112964	2.82	0.009	.2383811	1.515836
L2D.	.3341201	.1869437	1.79	0.085	-.0494568	.717697
d_DJIA						
D1.	-.0003675	.0003364	-1.09	0.284	-.0010578	.0003228
LD.	.0001966	.0002942	0.67	0.510	-.0004071	.0008002
L2D.	.0003838	.0001877	2.04	0.051	-1.41e-06	.000769
d_SP500						
D1.	.0012146	.0025419	0.48	0.637	-.0040009	.0064301
LD.	-.002903	.0024687	-1.18	0.250	-.0079683	.0021623
L2D.	-.0042192	.001805	-2.34	0.027	-.0079228	-.0005156
d_VIX						
D1.	-.0503854	.039491	-1.28	0.213	-.1314143	.0306434
LD.	-.03605	.0265714	-1.36	0.186	-.09057	.0184701
L2D.	-.0046202	.02065	-0.22	0.825	-.0469905	.0377502
d_EURUSD						
D1.	9.415625	7.169424	1.31	0.200	-5.294819	24.12607
LD.	10.18776	5.720084	1.78	0.086	-1.54888	21.92441
L2D.	-4.209871	4.570007	-0.92	0.365	-13.58675	5.167009
d_MSCIEM50						
D1.	-.0028607	.0034767	-0.82	0.418	-.0099943	.0042729
LD.	-.0034037	.002845	-1.20	0.242	-.0092411	.0024338
L2D.	-.0001158	.0017521	-0.07	0.948	-.0037109	.0034792
_cons	-.066916	.0816445	-0.82	0.420	-.2344367	.1006047

Table.15