VOLATILITY CONNECTEDNESS OF MAJOR CRYPTOCURRENCY: THE ROLE OF GEOPOLITICAL RISK

SIN YI FENG

BACHELOR OF ECONOMICS (HONOURS)
GLOBAL ECONOMICS

UNIVERSITI TUNKU ABDUL RAHMAN

FACULTY OF ACCOUNTANCY AND MANAGEMENT
DEPARTMENT OF ECONOMICS

MAY 2023

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BY

SIN YI FENG

A research project submitted in partial fulfillment of the requirement for the degree of

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DECLARATION

We hereby declare that:

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

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

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

(4) The word count of this research report is __________14964____________.

Name of Student:	Student ID:	Signature:
1. ____Sin Yi Feng______	____1904308____	Feng

Date: ______3 May 2023______

Acknowledgements

This research project has been successfully carried out and done by the assistance of few parties. I would like to take this golden opportunity to express my gratefulness and appreciation to those who have lend their hand to me throughout the process of completing this research project.

First of all, I would like to express my special thanks of gratitude to my supervisor, Dr. Liew Ping Xin who gave me the opportunity to do this excellent project on the topic of “Volatility Connectedness of Major Cryptocurrencies: The Role of Geopolitical Risk”. Dr. Liew had sacrifice a lot of her valuable time in order to guide and assist me to make sure I can have best performance in this research project. I am so grateful for her valuable assistance and advices. Other than that, Dr. Liew also bring motivation and encourage me whenever I face difficulties throughout the process of completing this research project.

Next, I would like to thank to Universiti Tunku Abdul Rahman (UTAR) for giving me this opportunity to conduct our final year research project. I also feel very grateful to the authority of UTAR who provide me a comfort environment and facilities to carry this research project. Other than that, the complete facilities and database in library also help me in my research project.

DEDICATION

I would like to dedicate this research paper to Universiti Tunku Abdul Rahman (UTAR) for providing me with the opportunity to apply the knowledge I gained to this study. Moreover, I extend my gratitude to Dr. Liew Ping Xin, who served as my Final Year Project (FYP) supervisor, for generously sharing her expertise and answering my questions promptly, even beyond office hours. Without her guidance, support, and patience, completing this research would not have been possible. Additionally, I would like to dedicate this paper to Dr. Lee Hui Shan, who acted as the second examiner of my FYP, and whose suggestions significantly contributed to the enhancement of this research.

Lastly, I would like to express my heartfelt appreciation to my family and friends, who provided me with the motivation and assistance necessary to overcome the challenges I faced during the research period.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

This thesis aims to examine the relationship between geopolitical risk and volatility connectedness of five cryptocurrencies, namely Bitcoin (*BTC*), Ethereum (*ETH*), Ripple (*XRP*), Dogecoin (*DOGE*) and Cardano (*ADA*). Prices and trading volume data of these five cryptocurrencies are collected from Yahoo Finance. The research uses monthly data spanning from February 2018 to October 2022. An additional analysis was also performed using daily data from 1st January 2021 to 31st December 2021. This study uses the TVP-VAR model to calculate the monthly and daily volatility connectedness indices of the five cryptocurrencies. In terms of the level of connectedness, the monthly volatility connectedness was rather high at 74.87% compared to the 2021 daily volatility connectedness at 68.63%. The resulting monthly volatility connectedness index is further utilised as the dependent variable to examine the effect of geopolitical risk (*GPR*) on the level of volatility connectedness among these five cryptocurrencies. In discovering this relationship, time series approach was applied by using E-Views software. The key independent variable in this study – *GPR,* shows a positive and significant impact on the volatility connectedness of the five cryptocurrencies. The estimation of the relationship between GPR and volatility connectedness is controlled by Global Economic Policy Uncertainty (*GEPU*), Volatility Index (*VIX*), World Return (*W_RETURN*), and Energy Return (*E_RETURN*), which are found to be insignificant in explaining volatility connectedness. Instead, volatility connectedness of these five cryptocurrencies is more likely to be affected by their own trading activity such as the return (*AVERET)* and volume (*AVEVOL)* which are also included in this study as control variables. Findings of this research can be utilized by investors who invest in cryptocurrencies market to guide their risk management and diversification strategies. Moreover, the connectedness index of the five cryptocurrencies can provide insights into their potential impact on each other's price movements, and investors can use this information to guide their investment decisions.

CHAPTER 1: INTRODUCTION

1.0 Introduction

This section describes about the price history about five cryptocurrencies, such as Bitcoin (*BTC*), Ethereum (*ETH*), Cardano (*ADA*), Ripple (*XRP*), and Doge coin (*DOGE*) and the geopolitical event in the sample period of this study, and the significance of geopolitical event are mostly highlighted in this section. Moreover, this chapter also included the research objective and question to provide a clear focus for this research.

1.1 Research Background

The first decentralized cryptocurrency was Bitcoin (*BTC*), which was first released on 3 January 2009. Fast-forward to March 2022, there were more than 9,000 other cryptocurrencies in the marketplace, of which more than 70 had a market capitalization exceeding USD1.0 billion. From the year 2009 until 2022, the cryptocurrencies market grew rapidly as it can be seen that the bitcoin was worth only USD0.0009 in 2009 but increased to USD47,063.37 in 2022. The most well-known cryptocurrency by far is Bitcoin, which as of the point of writing this research project, had a market capitalization of USD323.0 billion. Meanwhile, Ethereum (*ETH*) is the second-largest cryptocurrency in terms of market capitalization, which is now valued at USD150.0 billion, despite its relatively recent introduction.[1] In December 2022, Bitcoin and Ethereum, being the two largest cryptocurrencies, made

[1] Data obtained from coinmarketcap.com on 8 December 2022.

up the majority of the total cryptocurrency market capitalization. Although the two cryptocurrencies provide entirely distinct goals and have quite different capabilities, despite the warnings from several financial organisations, both have seen enormous price volatility and are increasingly utilized for investment and speculation (Statista, 2023).

In terms of volatility, Bitcoin is the most volatile asset in the world. The most volatile movement was observed in 2010 to 2013, where the price rose from USD0.10 per *BTC* in 2010 to USD1,200 in 2013. Investors got a whopping 130,000% return in just three years. The fluctuation seen in 2010 to 2013 was nothing compared to the price movement seen in 2021 where *BTC* reached a record high of USD32,149.90 during the year from as low as USD32,149.90 when it was first traded on 1 January 2021. During the year, *BTC* prices fluctuated frequently, giving investors the opportunity to profit from such volatile price movement.

On the other hand, the rest of the cryptocurrencies chosen for this study, which are *ETH*, *ADA*, *XRP*, and *DOGE* also have gained significant popularity in recent years. Their price movements are often similar as few factors may influence the cryptocurrency market which led to similar movement such as market sentiment, adoption rates, and overall demand for cryptocurrencies. Furthermore, they are all traded on major cryptocurrency exchanges and are subject to similar market forces. One of the most significant factors that influence the price movements of these cryptocurrencies is the trend of Bitcoin, which have a significant impact on the entire cryptocurrency market.

For example, in January 2020, *ETH* was trading at around USD140, and by April 2021, it had surged to over USD2,000, a more than 14-fold increase. Similarly, *ADA* was trading at around USD0.04 in January 2020 and had surged to over USD1 in May 2021, a more than 25-fold increase. *DOGE* experienced even more significant gains, with its price increasing from around USD0.002 in January 2020 to over USD0.60 in May 2021, a more than 300-fold increase.

Throughout this period, the price movements of *ETH*, *ADA*, *DOGE*, and *XRP* were closely correlated with the trend of Bitcoin. When Bitcoin's price was increasing, these other cryptocurrencies tended to also see gains, and when Bitcoin's price was decreasing, they tended to see losses. Therefore, while these cryptocurrencies do have their own unique characteristics and factors that can influence their price movements, they have largely followed the trend of Bitcoin in recent years.

Geopolitical events can have a significant impact on the cryptocurrency market, as they can affect global economic stability, investor sentiment, and government regulations. One of the most well-known example of a geopolitical event that had a significant impact on the cryptocurrency market was the COVID-19 pandemic. As the pandemic spread throughout the world in 2020, many countries went into lockdowns, causing a significant economic downturn. This even is geopolitical in nature as tensions were rising among countries, especially with China, as the country is the origin of the deadly virus outbreak. In terms of its effect on cryptocurrencies, this event led to a surge in interest in cryptocurrencies as investors sought to diversify their portfolios and protect their assets from the volatile stock markets which were adversely affected by the pandemic. Furthermore, when the COVID-19 pandemic was improving, many other countries are looking for a chance to reopen their boarder to recover the impact during the lockdowns of 2020 and 2021, but China remained closed to the world, according to Gan (2021). This decision also led to heightened contentions as travelling, be it for business or leisure purposes, were affecting when China’s borders remained closed while the rest of the world had started opening their borders. It will easily led to an increases of geopolitical tension between China and others countries, and China also ban the cryptocurrency trading in 2021 as they knew that cryptocurrencies are pegged to the US dollar. Hence, all these may led to increase tensions of geopolitical between China and other countries especially US.

Hence, geopolitical events that happen between two or more countries can increase the geopolitical tensions that can have a significant impact on the cryptocurrency market. While cryptocurrencies are decentralized and not directly influenced by governments or traditional financial institutions, they are still subject to market forces and investor sentiment, which can be affected by geopolitical events and government regulations. Therefore, investors should be aware of these risks when considering investing or using cryptocurrencies.

1.2 Problem Statement

In Figure 1.1 and Figure 1.2, an increased connectedness in price movements among cryptocurrencies is observed. When the price of a dominant cryptocurrency such as Bitcoin is booming, the prices of other cryptocurrencies tend to follow, and when the dominant cryptocurrency is experiencing a downturn, the prices of other cryptocurrencies tend to follow as well. The possible factor that has been observed as the following example is showing the geopolitical event.

The first event is Elon Musk's involvement in the cryptocurrency market has been notable in recent years, particularly in relation to Tesla's investment in Bitcoin and Musk's tweets about Dogecoin. In February 2021, Tesla announced that it had invested USD1.5 billion in Bitcoin, which caused the price of Bitcoin to rise by more than 25% to USD48,000. This move was seen as a significant endorsement of Bitcoin by one of the world's most valuable companies, and it contributed to the growing acceptance of cryptocurrencies as a legitimate asset class. Musk's tweets about

Figure 1.1: Volatility of the *BTC*, *ETH*, *XRP*, *ADA*, and *DOGE*

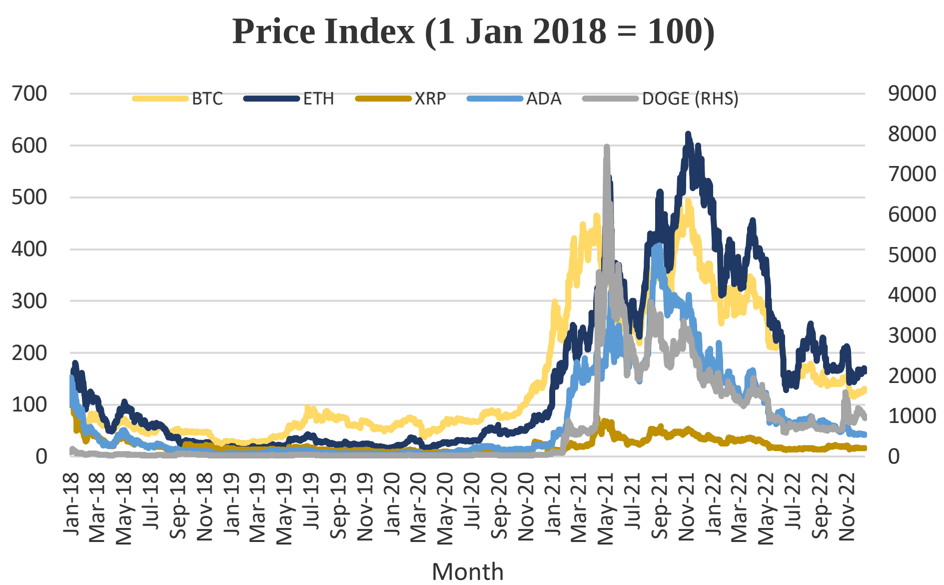
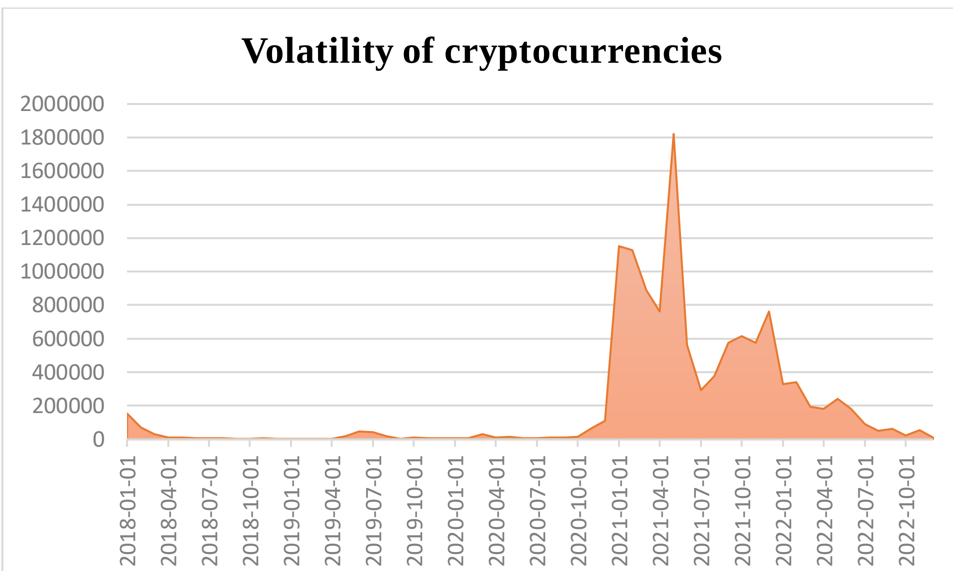


Figure 1.2: Average volatility of the five cryptocurrencies



Dogecoin have also had a notable impact on the price of the cryptocurrency. For instance, in early 2021, Musk tweeted "Dogecoin is the people's crypto" and "No highs, no lows, only Doge" which helped push the price of Dogecoin up by more than 50% to USD0.2. In addition, Musk's tweets about Dogecoin have also contributed to a surge in interest in the cryptocurrency, with many people buying it because of his endorsement (Gautam, 2021).

Meanwhile in June 2021, El Salvador became the first country in the world to adopt Bitcoin as legal tender, alongside the US dollar. The move was announced by El Salvador's President Nayib Bukele, who argued that the adoption of Bitcoin would help to boost financial inclusion and promote economic growth in the country. The adoption of Bitcoin as legal tender in El Salvador has been met with a range of reactions, with some observers hailing it as a ground-breaking move that could pave the way for greater acceptance of cryptocurrencies around the world. Others, however, have raised concerns about the potential risks and challenges of using Bitcoin as a mainstream currency (Hernandez, 2021). With the move by El Salvador in recognizing Bitcoin as a legal tender, if other countries later follow suit, this may undermine the dominance of the US dollar as the world's strongest reserve currency, thereby creating greater geopolitical tensions with the world's largest economy – the US. For example, if more countries adopt cryptocurrencies as legal tender, or if cryptocurrencies become more widely accepted and used in international trade and investment, they could start to pose a threat to the position of the US dollar.

Furthermore, China's ban on cryptocurrency trading is a notable geopolitical event that reflects the country's efforts to maintain control over its economy and financial system. Many cryptocurrencies are pegged to the US dollar and are used as a means of transferring value across borders. By banning cryptocurrency trading, China is seeking to limit the outflow of capital from its economy and reduce the potential risks associated with the use of decentralized digital currencies. In addition, the ban may also reflect China's concerns about the potential use of cryptocurrencies for illicit activities, such as money laundering and financing of terrorism. The ban has significant implications for the global cryptocurrency market, as China has been a major player in this space and has played a significant role in the mining and trading of cryptocurrencies. The ban has also contributed to a shift in the global cryptocurrency market, with many companies and investors looking to other countries and regions for opportunities in this emerging asset class (What's Behind China's Cryptocurrency Ban?, 2022).

Last but not least, Bitcoin experienced a significant one-day jump in value as the war in Ukraine intensified, it is important to note that there may be a variety of factors that contributed to this increase in price. However, Russian individuals and entities may be seeking to use cryptocurrencies like Bitcoin as a means of evading sanctions and laundering funds. This is because cryptocurrencies offer a degree of anonymity and decentralization that traditional financial systems do not, which can make them attractive to those seeking to move money outside of traditional channels. Furthermore, terrorist financing and other illicit activities can also be facilitated through the use of cryptocurrencies due to their relative lack of transparency and regulatory oversight (Cox, 2022).

In general, a high level of volatility connectedness or spillovers among cryptocurrencies can limit the benefits of diversification. If investors have the knowledge on the information transmission mechanism in the cryptocurrency market, they can use it to adjust asset portfolios or create investment or hedging strategies when the market is in a high level of volatility connectedness. Apart on the effect of investor, there are also significant for a countries, when geopolitical tensions among countries is increase, every player may being the trade restriction in the cryptocurrency market. if all cryptocurrency remains to be more volatile, the impacts will be serious.

On the other hands, the increasing geopolitical tensions may have an impact on the volatility connectedness in cryptocurrency market based on anecdotal evidence observed in the study from Aysan et al. (2019), and Nouir and Hamida (2022).

However, no study has thus far looked into potential impact of geopolitical tensions on the volatility connectedness of cryptocurrencies. The only studies available that are closed to this research area are those that examine the impact of geopolitical risk on just the volatility of cryptocurrency market (Aysan et al., 2019; Nouir & Hamida, 2022). Hence, this study is highly warranted to contribute to the literature by shining light on the effect of geopolitical risk on the volatility connectedness of cryptocurrencies.

1.3 Research Objectives

Motivated by the lack of study on the effect of geopolitical risk on volatility connectedness of cryptocurrencies, the study formulates the following research objectives:

1. To compute a volatility connectedness index for Bitcoin (*BTC*), Ethereum (*ETH*), Ripple (*XRP*), Dogecoin (*DOGE*), Cardano (*ADA*).
2. To examine the impact of geopolitical risks on volatility connectedness of Bitcoin (*BTC*), Ethereum (*ETH*), Ripple (*XRP*), Dogecoin (*DOGE*), Cardano (*ADA*).
3. To compute the volatility connectedness index for Bitcoin (*BTC*), Ethereum (*ETH*), Ripple (*XRP*), Dogecoin (*DOGE*), Cardano (*ADA*). using daily data for year 2021.

1.4 Research Questions

Given the research objectives formulated above, the corresponding research questions for this study are as follows:

1. What is the degree of connectedness between the volatility of Bitcoin (*BTC*), Ethereum (*ETH*), Ripple (*XRP*), Dogecoin (*DOGE*), Cardano (*ADA*)?
2. Is there a relationship between geopolitical risk and volatility connectedness of Bitcoin (*BTC*), Ethereum (*ETH*), Ripple (*XRP*), Dogecoin (*DOGE*), Cardano (*ADA*)?
3. What is the degree of connectedness between the daily volatility of Bitcoin (*BTC*), Ethereum (*ETH*), Ripple (*XRP*), Dogecoin (*DOGE*), Cardano (*ADA*) in year 2021?

1.5 Significance of Study

This research contributes to the literature by closing the gap observed whereby no study thus far has looked at the relationship between geopolitical risks and volatility connectedness of cryptocurrencies. The only study which looks at geopolitical risks in the space of cryptocurrencies is the work by Aysan et al. (2019), who examine the relationship between geopolitical risk and volatility of cryptocurrency market.

On the other hand, the methodology used in this study – Time-Varying Parameter Vector Autoregression (TVP-VAR) in coming out with the connectedness index is considered rare in the extant literature. Out of eight studies reviewed, only Hassan et al. (2022) and Elsayed et al. (2022) use TVP-VAR model, whereas the rest mainly use VAR model (Lin, 2021; Hassan et al., 2020; Gozgor et al., 2019; Charfeddine et al., 2022; Mensi et al., 2021; Al Guindy, 2021). The TVP-VAR method is superior to the traditional VAR model as it eliminates the need to set an arbitrary window length for the estimation. Also, it provides individual point estimates for each of the time period in the study instead of just a single average point estimate for the whole sample period, which allows for the examination of the connectedness of volatility of the five cryptocurrencies over time, something that cannot be achieved with VAR.

Moreover, understanding the degree of volatility connectedness among the five main cryptocurrencies can be particularly helpful for investors who are interested in portfolio diversification strategies. By diversifying their portfolio, investors aim to reduce the overall risk of their investments by spreading their money across different assets that are not perfectly correlated with each other. For example, if two cryptocurrencies are highly positively correlated, investing in both of them may not provide as much diversification benefit as investing in two cryptocurrencies that are less correlated with each other. Conversely, if two cryptocurrencies are highly negatively correlated, investing in both of them could help to hedge against the risk of one cryptocurrency experiencing a significant decline in value.

Furthermore, understanding the relationship between the connectedness of cryptocurrencies and geopolitical factors can be immensely valuable for different groups of people. Especially, investors or traders can use this information to make informed decisions when investing in cryptocurrencies. When there are the impact of geopolitical factors on cryptocurrencies, they can predict price movements and take advantage of market fluctuations, this can help them maximize profits while minimizing risk as well.

In term of that, researchers can use this information to deepen their understanding of the relationship between cryptocurrencies and geopolitical factors, and to conduct the further studies. Meanwhile, they can identify specific factors that are most influential in shaping the cryptocurrency market. This can help researchers develop new theories and models that can help predict and explain market behaviour. Lastly, this study discovers the factors affecting volatility connectedness among the five cryptocurrencies which can help in identify potential co-movement of volatility among the five world events mentioned in the section 1.1.

1.6 Chapter Layout

Chapter 2 of the research paper focuses on the literature review, providing a comprehensive overview of the existing research on volatility of cryptocurrency, volatility connectedness of cryptocurrency, return of cryptocurrency, return connectedness of cryptocurrency, liquidity of cryptocurrency, liquidity connectedness of cryptocurrency, and geopolitical risk on the cryptocurrency. This chapter will examine and synthesize the findings of previous studies in these areas, and the calculation on volatility is the main that highlighted in this study, and identifying the gaps in the literature that the current study aims to address.

Chapter 3 details the data and methodology used in the research. The chapter will describe the sources of the data, which will include the five cryptocurrencies, calculation on volatility to generate the dependent variable of Total connectedness index (*TCI*). The chapter will also outline the control variables that will be used, such as Global Economic Policy Uncertainty Index (*GEPU*), volatility index (*VIX*), average volume of five cryptocurrency (*AVEVOL*), average return of five cryptocurrency (*AVERET*), world returns (*W_RETURN*), and energy return (*E_RETURN*). Additionally, the chapter will explain how the TVP-VAR model will be computed and will discuss the stationarity of the five cryptocurrencies and variables. Finally, the chapter will detail the model specifications that will be used in the study.

Chapter 4 presents the results of the study and provide a detailed discussion of these results. The chapter will begin by presenting the descriptive statistics and correlations of variables. Then, the average of the volatility connectedness of the five cryptocurrencies of the sample period in monthly data and the daily data in high volatility in 2021 also conducted that to discuss in this study. Finally, the chapter will present the output estimation of the model specifications outlined in chapter 3.

Chapter 5 concludes the research paper by summarizing the main findings of the study and discussing their implications.

Chapter 2: Literature Review

2.0 Introduction

The purpose of this study is to examine the impact of geopolitical risk on volatility connectedness of cryptocurrency. A comprehensive understanding of this topic requires a thorough review of the existing literature on the geopolitical risk and the cryptocurrency. Section 2.1 presents literature on the returns of cryptocurrencies, including the determinants of cryptocurrency returns - investor attention in section 2.1.1, regulation, and war and terrorist attacks in section 2.1.2 and section 2.1.3, respectively. The following section 2.2 reviews studies on the volatility of cryptocurrencies and the effect of investor attention on volatility in the section 2.2.1. Liquidity of cryptocurrencies is presented in section 2.3. The sections mentioned thus far mainly discuss on the return, volatility, and liquidity of cryptocurrencies but not connectedness. The following sections 2.4, 2.5, and 2.6 discuss about the volatility, liquidity, and return connectedness of cryptocurrencies. Finally, the last section of literature review presents the geopolitical risk and cryptocurrencies.

The research gap in this area of study would be to investigate how geopolitical risk impacts the volatility connectedness of cryptocurrencies. While there have been several studies that have examined the relationship between geopolitical risk and cryptocurrency volatility, there is still a need for research that explores the role of geopolitical risk in the context of volatility connectedness.

Specifically, a potential research question could be: How does geopolitical risk affect the interconnectedness of cryptocurrency markets and what are the implications for volatility transmission? Answering this question would require analysing data on cryptocurrency prices and volumes across different markets, as well as geopolitical events and their potential impact on market behaviours. By addressing this research gap, the findings could contribute to a better understanding of the dynamics of cryptocurrency markets and inform policymakers and investors on how to manage risks associated with geopolitical events.

2.1Returns of Cryptocurrencies

2.1.1 Investor Attention

In the literature examining the relationship between investor attention and cryptocurrency returns and volume has been explored by Lin (2021) and Ante (2022) using data obtained five major cryptocurrencies and their US dollar closing prices from investing.com. The former examines the effect of investor attention, proxied by the probability of these keywords appearing in Google search, on 6 cryptocurrencies, namely Bitcoin, Ethereum, Litecoin, XRP and Tether. Using weekly data from 16/4/2017 to 29/2/2020, the findings show that interaction effects when using Granger Causality tests, but past cryptocurrency returns show a significant effect on future attention and weak reverse results when using the VAR models to fill the gap of the literature. The paper by Ante (2023) uses Elon Musk's Twitter activity as a proxy for investor attention to examine the effect of Musk's social media activity on the returns of 47 cryptocurrencies. As Elon Musk is one of the richest individuals in the world has a social network of over 110 million followers on social media platform Twitter. He regularly uses his social media presence to communicate on various topics, one of which is cryptocurrency, such as Bitcoin or Dogecoin. The author using the API of Twitter to investigate the Elon Musk's activity from April 2019 to July 2021. However, when a tweet by Elon Musk can have a significant short-term impact on the price of Bitcoin or other cryptocurrencies, it is for market participants that cryptocurrency returns have a certain relationship with external information from the twitter account of the world's richest man, so market participants should monitor Musk's account to react to the news, which could pose a risk of market manipulation while also boosting cryptocurrency returns. However, a contrasting finding was obtained by Chokor & Alfieri (2021) found that the less liquidity of cryptocurrency may have less significant effect on investor attention.

2.1.2 Regulation

The paper by Chokor and Alfieri (2021) the long- and short-term impact of market regulation on the return of cryptocurrency. The long- and short-term impact, proxied by market regulation of these keywords that search in FACTIVA database, and the data of cryptocurrency obtained by Coin Market Cap, using the top 13 cryptocurrency from 2015 to 2019 daily data and 10 countries of the world to conduct this research. The author finds that events may increase the probability of regulation but decrease the probability of an unexpected return in cryptocurrency. However, the significant positive effect is shown in risk-adjusted return during events, but not in post-event.

However, a contrasting finding was obtained by Gozgor et al. (2019) examine that the relationship between the returns of Bitcoin and the index of trade policy uncertainty which use the data from United States in the period from July 2010 to August 2018. The author use monthly data of the logarithmic and the difference percentage of price returns of Bitcoin price and the index of Trade Policy Uncertainty (TPI) is capture from the website http://www.policyuncertainty.com. The empirical findings show that VAR Based-Granger-causality (GC) analysis indicate that there are not significant relationship between the returns of Bitcoin and the index of trade policy uncertainty. However, when using the standard VAR analysis also show the same result compare to that VAR Based-Granger-causality (GC) analysis.

2.1.3 War and terrorist attacks

The articles about the effect of terrorist attack and war on the return of cryptocurrency were done by Almaqableh (2022) and Khalfaoui et al. (2022). The paper by Almaqableh (2022) is to study the effect of 21 terrorist attacks on the return of cryptocurrencies. The author obtained the data of 1387 cryptocurrencies daily data from April 2013 to February 2018, using the Capital Asset Pricing Model (CAPM) to conduct this research. This finding shows there are positive significant relationship of the terrorist attacks on the return of cryptocurrency and the effect of short-term risk movement action for every different type of cryptocurrencies. Similar research that conducts by Khalfaoui et al (2022), is to study the impact of Russia-Ukraine War on cryptocurrencies. The data was obtained on the Russia-Ukraine War (War), proxied by Google Trends index capturing public attention and the top four of the data of cryptocurrencies, which is Bitcoin (BTC), Ripple (XRP), Ethereum (ETC), and Litecoin (LTC) for the period from 24 February 2022 to 21 June 2022. The author uses Quantile cross-spectral analysis to examine the effect of public attention to the Russia-Ukraine conflict on the cryptocurrency market. The findings shows that Russia-Ukraine on the four cryptocurrencies (BTC, XRP, ETC, and LTC) and G7 stock market returns, war public attention has a significant positive (negative) causal impact. This effect depends on both market situation and temporal frequency. Overall, we see that market conditions and investment horizon affect how stocks, cryptocurrencies, and War attention move together. While other time horizons are more complex, War attention has a short-term negative (positive) impact on all cryptocurrencies in both bearish and normal (bull) markets. The findings support the hypothesis that the focus on the war has a substantial influence on cryptocurrencies, with short-term cryptocurrency investors responding by looking for liquidity.

2.2Volatility of Cryptocurrencies

2.2.1 Investor Attention

Apart from looking at the returns of cryptocurrencies, Al Guindy (2021) also study about the Investor attention. Al Guindy (2021) examine the relationship of the volatility price of cryptocurrencies and the investor attention. The author use the top 23 of largest cryptocurrencies from 15 November 2017 to 5 November 2018 to conduct the research. The dataset used in this study is collected directly from the API of Twitter that the relate words or sentences that occurred within the sample period. The attention measure used to proxy investor attention in this study. On the other hand, the cryptocurrency data was obtained through the website https://coinmarketcap.com/. There are several ways of volatility measure in this research. First, use the realized volatility of hourly returns. Realized volatility assesses variation in returns for an investment product by analysing its pass returns within the sample period. The additional of realized volatility from this research is to use Heterogenous Auto-Regressive (HAR) model that introduced by Corsi (2009). The HAR model is model accounts for lagged daily, weekly, and monthly volatilities. Second, for robustness, as the second measurement of volatility. The volatility is based on the high and low prices to measure. Similar to the previous finding about the relationship of returns of cryptocurrency and investor attention, this research also using the VAR model to do the analysis. The findings show that using the VAR model is to show the investor attention, so that it might can predict the future price volatility of cryptocurrency. As the result findings suggest that the increase of investor attention may have a negative effect on the volatility price of cryptocurrency.

2.3 Liquidity of Cryptocurrencies

2.3.1 Investor attention

Apart from the study by Lin (2021) and Ante (2022) study about investor attention and return of cryptocurrency and the study from Al Guindy (2021) examine the investor attention and volatility of cryptocurrency, this paper by Yao et al. (2022) study the impact of investor attention on the liquidity of cryptocurrency. This research using two way to capture the investor attention. First, U.S. dollar-denominated cryptocurrency 5-minute order book and tick-by-tick data from Bitfinex exchange and the second is Google search volume index (GSV). The finding show that the static investor attention may significantly increase the buy and sell activity of investors in the market, which has a continuous positive impact on the liquidity of cryptocurrency marketplaces.

2.4 Volatility Connectedness of Cryptocurrencies

2.4.1 Investor attention

Apart from the investor attention in previous studies, there literature conduct from Bouri et al. (2022) is to investigate the investor happiness will effect on the volatility connectedness on cryptocurrencies using the data obtained from https:// coinmarketcap.com/ to capture the daily data of top fifteen cryptocurrencies from 7th August 2015 to 11th March 2020 and using twitter as a proxy to capture the investor sentiment for investor happiness index. This author introducing the DCC-GARCH based volatility connectedness approach of Gabauer (2020) which can be seen as an alternative to the VAR based connectedness approach of Diebold and Yilmaz (2012, 2014). However, for QQ approach to examine the effect of investor sentiment proxied by the investor happiness index on the TCI and common volatility. This finding demonstrates a significant correlation between the lower quantile of investor happiness and the whole conditional distribution of connectedness using Twitter feed data as a proxy for investor sentiment. Additionally, due to the highly connected nature of the market, total market volatility increases when investor unhappiness increases. Because lower total connectivity is matched with high common volatility, increased volatility—possibly caused by higher trading volumes—seems to recommend that cryptocurrencies are being used as a hedge when investor sentiment is low. This is evidence that the behaviour is relatively stronger than the possible speculative motives associated with happy investors. The findings tend to indicate that there are usually more possibilities for diversification when investor sentiment is positive than when it is negative (Bouri et al., 2022).

A similar study by Mensi et al. (2021) examines the dynamic frequency connectedness for volatility differences among eight popular cryptocurrencies from 9 August 2015 to 7 February 2019. Diebold and Yilmas method of VAR model also using for this study. The findings have important implications for investors since they need them to consider the dynamic risk spillovers among cryptocurrency markets as they change. To make the best selections for their portfolios, investors should also consider the risk receiver and transmitter directional spillovers status of cryptocurrencies. The emphasis on risk spillovers over frequency demonstrates the need to change the portfolio structure for short-, medium-, and long-term time horizons. Investors should combine LTC and BTC with other assets and portfolios to create a portfolio with the lowest risk possible in order to reduce risk as much as possible (better diversification benefits). Due to the absence of financial reforms and the lack of regulations, the BTC market remains volatile. For institutional investors, BTC futures might be a smart strategy to protect their investments from the unpredictable price fluctuations of cryptocurrencies.

2.4.2 Dynamic volatility connectedness of cryptocurrency

The paper by Yi et al. (2018) study the static and dynamic volatility connectedness of eight typical cryptocurrencies which is BTC, XRP, LTC, PPC, NMC, FTC, NVC, and TRC. The weekly data of cryptocurrencies obtained from coinmarketcap.com from 4 August 2013 to 1 April 2018. This author further expand his study to 52 cryptocurrencies by using the model of LASSO-VAR for the higher dimension of VARs estimation. In this study, the author uses measures of volatility of Garman and Klass (1980), by capturing the data of high, low, closing, and opening prices to get the volatility price. A contrasting finding from Charfeddine et al. (2022) study the dynamic volatility connectedness between the cryptocurrency market which is the mineable coins, non-mineable coins, and tokens. However, the measure of volatility from this study also similar to previous study. Garman and Klass (1980) measure and (2) the Parkinson (1980) to measure the volatility by capture the data of daily high, low, opening and closing prices. From Yi et al. (2018) finding point out that the overall volatility correlation among the eight cryptocurrencies changes frequently and increases throughout the study period when the market faces uncertain economic shocks or unstable economic conditions. Research shows that the cryptocurrency market is currently undergoing rapid and unpredictable changes. Another interesting conclusion is that market capitalization does not always correlate with volatility correlations or spillover effects. Large volatility shocks are usually propagated by high-cap cryptocurrencies such as Bitcoin, Litecoin, and Dogecoin, but small-cap cryptocurrencies are more susceptible to volatility shocks from other cryptocurrencies. Besides that, LASSO-VAR model suggest a result of the 52 cryptocurrencies' close connections, "mega-cap" cryptocurrencies are more likely to distribute volatility shocks than others. Some hardly recognized cryptocurrencies, however, are also important net-transmitters of volatility connections and even contribute more to volatility spillovers to other cryptocurrencies.

2.5 Liquidity connectedness of cryptocurrency

In the literature examining the dynamics of liquidity connectedness in cryptocurrency has been explored by Hassan et al. (2020) using the six major cryptocurrency daily data from 7 Aug 2015 to 28 Dec 2019. In this research,, using two method to measure the liquidity which is use return divided volatility and the second measure is using the volatility-over-volume to calculate. However, the Liquidity Connectedness is using the spillover approach from Diebold and Yilmaz (2012), which was used by several studies (Bouri et al. 2022; Yi et al. 2018; Hassan et al. 2022; Mensi et al. 2021). On the other hand, the frequency connectedness is using the method explore by Baruník and Křehlík (2018). Following Diebold and Yilmaz (2012), the author use VAR to conduct this study. The finding show the liquid connectedness among our sample cryptocurrencies is moderate, with BTC and LTC playing a significant role in connectivity. Frequency-domain analysis shows that liquidity linkages are more pronounced in short-term time horizons than in medium- to long-term time horizons. In the short term, BTC, LTC, and XRP are the main contributors to the liquidity shock, while in the long term, ETH assumes this role. Short-term and long-term liquidity aggregation is tighter than that in the medium term. The analysis over time shows that liquidity correlations in the cryptocurrency market increase over time, suggesting that increased demand and higher acceptability of this unique asset may be having an effect. Furthermore, more pronounced liquidity connectivity patterns are observed in the short and long run, reinforcing that liquidity connectivity in cryptocurrency markets is a phenomenon that depends on time-frequency connectivity.

2.6 Return connectedness of cryptocurrency

A paper investigates the connectedness of the returns of cryptocurrencies and changes in the cryptocurrency policy uncertainty has been explored by Hassan et al. (2022). This research obtained 7 major cryptocurrencies of weekly data from 10 August 2015 to 15 February 2021. A several studies using the same approach to indicate their studies, spillover approach from Diebold and Yilmaz (2012) also has been used for this study to indicate the return connectedness. However, UCRY Policy Index is proposed by Lucey et al. (2022) also been using for this study, and using the TVP-VAR to conduct the research. The finding suggest that A few cryptocurrencies stand out "from" other cryptocurrencies by having very low "to" connectivity in total directional connectedness measures between the UCRY policy index and those few cryptocurrencies. The study has significant implications since any variation in the returns of Bitcoin, DOGE, and Litecoin increases the risk to other cryptocurrencies as well as UCRY policy index variation.

2.7 Geopolitical Risk and Cryptocurrencies

The paper by Aysan et al. (2019) examine global geopolitical risks (GPR) index on daily returns and price volatility of Bitcoin, using data obtained from http://www.coindesk.com/price/ from 18 July 2010 to 31 May 2018. To conduct the research, Bayesian Graphical Structural Vector Autoregressive (BSGVAR) technique is used to find whether GPR has the impact on both returns and volatility of Bitcoin. This research is using dynamic Standard Deviations of last five day of bitcoin returns to measure the volatility price of bitcoin, the GPR index is capture from webpage of Caldara and Iacoviello (2018). So, the findings show that GPR has a significant impact on volatility price of Bitcoin. In addition, to obtain the further about the significance of the effects of the GPR indexes on the price volatility of Bitcoin, the author also reports the findings of OLS and QQ regressions. When using OLS estimates, we illustrate that the change in the GPR index has a significant negative and positive impact on returns and the volatility of Bitcoin's price, respectively. The influence of the global GPR index movement on the price volatility and returns of Bitcoin, however, is demonstrated using QQ estimation techniques to be positive and statistically significant at higher quantiles.

As similar to Nouir and Hamida (2022), investigate how economic policy uncertainty (EPU) and geopolitical risks (GPR) impact Bitcoin volatility. This author measures the China and US, EPU and GPR index that proposed by Baker et al. (2016) and Caldara and Iacoviello (2018), and both EPU and GPR are capture from policyuncertainty.com. The data of bitcoin volatility is obtained from the monthly data from August 2010 to September 2021 of bitcoin price, using the GARCH model from Samuel Asante (2019) to calculate the volatility of bitcoin. The study is using ADRL model and quantile regression to conduct the research. This finding indicates that in ARDL model, the result show that the relationship between policy uncertainty and bitcoin volatility changes according to different factors. US policy uncertainty has short run effects on Bitcoin volatility, while China's policy uncertainty has rather long run effects, it responds differently to China's EPU and GPR. In extreme quantiles, we find that Bitcoin hedges against US EPU and GPR. Additionally, Bitcoin only hedges against the simultaneous impacts of US uncertainty, not both.

However, a contrasting finding was obtained by Chibane and Janson (2020) to examine the impact of the level of global geopolitical risk on the dynamics of Bitcoin (BTC) price. Similar to the few previous studies, this study also uses the method that proposed by Caldara and Iacoviello (2018) to capture the GPR index. But, this study capture the weekly data of bitcoin return and the monthly data of GPR index within the period from 5 May 2013 to 2 June 2019. The empirical finding indicate that there are strong correlation between BTC dynamics and global geopolitical risk, as well as the fact that GPR has a significant influence on the portfolio allocation of prudent mean-variance investors that consider geopolitical risk in their decision-making. Surprisingly, BTC seems to serve as a geopolitical risk hedge for this investor more than GOLD, which should be sold short when GPR is at its greatest.

Chapter 3: Methodology

3.0 Introduction

This chapter discusses the steps involved in obtaining the volatility connectedness index of *BTC*, *ETH*, *DOGE*, *XRP* and *ADA*. It begins with the discussion of the computation of the volatility index for each of the cryptocurrency, followed by the unit root testing of their stationarity and then the TVP-VAR model for the calculation of the volatility connectedness index. Subsequently, this chapter also outlines the factors which are deemed to be potential determinants of volatility connectedness of *BTC*, *ETH*, *DOGE*, *XRP* and *ADA*, as well as the model used to test the significance of these variables as determinants of the volatility connectedness of these five cryptocurrencies. The correlation between the key independent variable and control variable are also included in this section.

3.1 Theoretical framework

The theoretical framework of this study is divided into two, the first part looks at theory explaining connectedness among cryptocurrencies., and the second part looks at the theory explaining the volatility connectedness and geopolitical risk.

3.1.1 Theory on volatility connectedness

Volatility connectedness of cryptocurrencies refers to the extent to which changes in the volatility of one cryptocurrency affect the volatility of other cryptocurrencies.

This concept is particularly relevant to the study of the cryptocurrency market, which is characterized by a high degree of correlation between different assets. Visible transmission mechanism, which holds the view that the correlation between economic fundamentals and global capital allocation leads to the co-movement of asset prices. It means that when there are changes in economic fundamentals, investor will most likely reallocate their funds between different assets. Hence, this re-allocation will cause asset prices move certain direction (Adler & Dumas, 1983; McQueen & Roley, 1993).

The second theory is invisible transmission mechanism, which includes market inefficiency, the psychological expectation, and behaviors of investors. Supporters of this mechanism consider that investors will seek investment or hedging opportunities in a certain market by assessing other markets' performance, thereby causing contagion through a correlated information channel, which say that investor will use whatever happen to prices of an asset as a guide of the performance of another assets. Therefore, when an asset performs poorly, the investor will reduce exposure of other assets too, thereby causing contagion (Yi et al., 2018).

The third theory is portfolio balance theory which contends that asset prices assimilate anticipated news seamlessly, since rational economic agents in the financial market revise their expectations upon the arrival of new information. Hence, when there are the changes in the expected returns of an asset, it will affect its price and the composition of investors' portfolios. It means that when there is a certain allocation of the portfolio, when one asset is performing well, the investor will re-allocate their funds to another asset, thereby causing co-movement again (Mac-Donald & Taylor, 1992).

3.1.2 Theory of volatility connectedness and geopolitical risk

The rational expectations theory assumes that economic agents are rational and have perfect information. In other words, economic agents make decisions based on their best estimate of future outcomes, given all available information, and they update their expectations when new information becomes available. For example, if there are escalation in geopolitical tensions between two major countries, and investors perceive that this event increases the risk of a global economic downturn. In response to this perceived risk, investors with rational expectations may adjust their investment strategies by reducing their exposure to risky assets. Hence, this will affect the prices of one or more asset causing their volatility to co-movement (Hodrick, 1989).

3.2 Data

This study uses five cryptocurrencies that are well-traded and are the most popular among the 9000 cryptocurrencies available as at the point of writing.[2] The sample period of this study spans from February 2018 to October 2022, with data collected at monthly frequency. The following subsections discuss each of the variables involved in this study, both for the computation of the volatility connectedness index as well as the variables involved in determining the effect of geopolitical risk on volatility connectedness. The sources from which these data are extracted are also outlined in this subsection.

[2] This statistic is valid as of https://www.statista.com/statistics/863917/number-crypto-coins-tokens/#:~:text=How%20many%20cryptocurrencies%20are%20there,might%20not%20be%20that%20significant.

3.2.1 Prices of Cryptocurrencies

The prices of *BTC*, *ETH*, *XRP*, *ADA*, and *DOGE*, mainly the data of high, low, closing and opening prices, are obtained from Yahoo Finance. All the data are downloaded at daily frequency from 1st January 2018 to 31th October 2022 , then only take simple average to obtain monthly prices. Additionally, the closing prices of these cryptocurrencies are also utilized to calculate the average return of all cryptocurrencies, which is further discussed in section 3.2.5.

3.2.2 Geopolitical Risk Index (*GPR*)

The Geopolitical Risk Index (*GPR*) is developed by Caldara and Iacoviello (2018) at the Federal Reserve Board. The workings of the calculation of this index is published as a working paper with the title "Measuring Geopolitical Risk". The GPR index is published on the website https://www.policyuncertainty.com/gpr.html. This index measures the level of political and financial risk associated to a specific nation or area.

3.2.3 Global Economic Policy Uncertainty (*GEPU*)

The Global Economic Policy Uncertainty (*GEPU*) index was created by Scott Baker, Nicholas Bloom, and Steven J. Davis (Baker, Blook & Davis, 2013), who are economists at Stanford University, the University of Chicago, and the University of California, respectively. The *GEPU* index is from https://www.policyuncertainty.co m/, It is designed to provide policymakers, investors, and analysts with a quantitative measure of the level of uncertainty in the global economy, which can help them make more informed decisions.

3.2.4 Volatility Index (*VIX*)

The index is more commonly known by its ticker symbol and is often referred to simply as "the *VIX*" which mean that the Volatility Index that was created by the CBOE Options Exchange (CBOE) and is maintained by CBOE Global Markets. This data was obtained from Refinitiv DataStream. *VIX* represent the expectations of the market regarding the relative strength of movements in the S&P 500 Index's short-term pricing (SPX), and it is important for investment purpose as it is often referred to as the market fear index. During periods of financial or economic crisis, the *VIX* index surges to reflect heightened fear among investors on the future movement of the financial markets.

3.2.5 Average Return (*AVERET*)

This index represents the average return of the five cryptocurrencies - Bitcoin (*BTC*), Ethereum (*ETH*), Cardano (*ADA*), Ripple (*XRP*), Doge coin (*DOGE*) on the sample period from February 2018 until October 2022. The daily data of high, low, opening, and closing price by each of the cryptocurrency is downloaded from yahoo finance, and use the closing price to calculate the daily return percentage of the five cryptocurrencies, then average the data from daily to monthly, and sum up the total monthly return among the five cryptocurrency divided by five to get the average return (AVERET) index.

3.2.6 Average Volume (*AVEVOL*)

This index represents the average volume of the five cryptocurrencies - Bitcoin (*BTC*), Ethereum (*ETH*), Cardano (*ADA*), Ripple (*XRP*), Doge coin (*DOGE*) on the sample period from February 2018 until October 2022. The data of total volume by each of the cryptocurrency is downloaded from Yahoo Finance. The calculation is the total volume among the five cryptocurrency divided by five to get the average volume (*AVEVOL*) index.

3.2.7 Return of MSCI World Index (*W_RETURN*)

The index of *W_RETURN* represents the return of MSCI World Index which is the stock market index that tracks the performance of large- and mid-cap stocks from 23 developed countries across the world. It includes stocks from countries such as the United States, United Kingdom, Japan, Germany, France, Canada, and Australia, among others. The data is downloaded from Refinitiv Datastream. The price index of MSCI WORLD is in US dollar terms and the price difference is calculated in percentage to get the return of MSCI World Index (*W_RETURN*).

3.2.8 Return of MSCI Energy World Index (*E_RETURN*)

The index of *E_RETURN* represents the return of MSCI Energy World Index. The MSCI World Energy Index is calculated using a market capitalization-weighted methodology, which means that companies with higher market capitalizations have a greater impact on the index's performance. The price index of MSCI ENERGY WORLD in US dollar term is downloaded from Refinitiv Datastream. The price difference in terms of percentage is calculated to get the return of MSCI Energy World Index (*E_RETURN*).

3.3 Volatility Index of Cryptocurrency

This study adopts the volatility measure proposed by Garman and Klass (1980) to compute the volatility index of all five cryptocurrencies. The calculation by Garman and Klass (1980) is specified as below:

$$Vol_{i,t} = 0.511\left(H_{i,t} - L_{i,t}\right)^2 - 0.019\left[\left(C_{i,t} - O_{i,t}\right)\left(H_{i,t} + L_{i,t} - 2O_{i,t}\right) - 2\left(H_{i,t} - O_{i,t}\right)\left(L_{i,t} - O_{i,t}\right)\right] - 0.383(C_{i,t} - O_{i,t})^2 \quad (1)$$

$Vol_{i,t}$ denotes the volatility index of cryptocurrency *i* on month *t*. Meanwhile, $H_{i,t}$, $L_{i,t}$ denote the high and low prices of cryptocurrency *i* on month *t*. Lastly $O_{i,t}$ and $C_{i,t}$, are the opening and closing price of cryptocurrency *i* on month *t*, respectively. This calculation has also been adopted by Yi et al. (2018), Charfeddine et al. (2022), Mensi et al. (2021) in their studies of the static and dynamic volatility connectedness of eight cryptocurrencies, the dynamic volatility connectedness between the cryptocurrency market, and the dynamic frequency connectedness for volatility differences among eight popular cryptocurrencies.

This approach is superior to the usual calculation of volatility using standard deviation as adopted by Aysan et al (2019) with a sample period that is characterized by low volatility in the market. However, the sample period of this study is during the bullish season with high degree of volatility. Therefore, the approach by Garman and Klass (1980) may be able to better capture the high volatilility of the cryptocurrency market. The Garman-Klass method is a method for calculating volatility that is commonly used in finance and is considered better than some other methods because it takes into account the presence of gaps in price data, which can affect the accuracy of volatility estimates.

Specifically, the Garman-Klass method calculates volatility by using four pieces of information: the high and low prices for a given time period, as well as the opening and closing prices. It then adjusts for gaps between the opening and closing prices, which can occur when the market is closed or when there is a significant change in price between periods. By accounting for these gaps, the Garman-Klass method provides a more accurate estimate of volatility than some other methods, such as simple close-to-close volatility or Parkinson's volatility, which do not account for gap risk.

3.4 Unit Root Tests

Prior to estimating the volatility connectedness index using the Time-Varying Parameter Vector Autoregression (TVP-VAR) by Antonakakis, Chatziantoniou and Gabauer (2020), it is essential to ascertain the stationarity of all the volatility series so as to avoid potential spurious results arising from non-stationarity of the volatility series.

This study uses two unit root tests to achieve the above purpose. The first unit root test is the Dickey-Fuller GLS by Elliott, Rothenberg and Stock (1996). The second unit root test is the Ng-Perron Unit Root Test by Ng and Perron (1995). The unit root tests employed in this study has the null hypothesis of non-stationarity. Hence, rejection of the null hypothesis indicates that the series is stationary. Based on unit root test results populated in Table 3.1, it is found that *BTC*, *ETH* and *DOGE* are stationary at level given that the test statistics in both the unit root test are all significant at the 1% level. However, *XRP* and *ADA* are not able to achieve stationarity even after being differenced once. Therefore, this study proceeds to perform breakpoint unit root test for all volatility series. This is also supported by the graphical plots of all the cryptocurrencies as shown in Figure 3.1 which show that all the series have signs of structural break, particularly in year 2021. Results from breakpoint unit root test show that all volatility series are stationarity in the presence of structural break. Hence, this study will proceed to using the volatility series at level for the computation of their volatility connectedness index in TVP-VAR model.

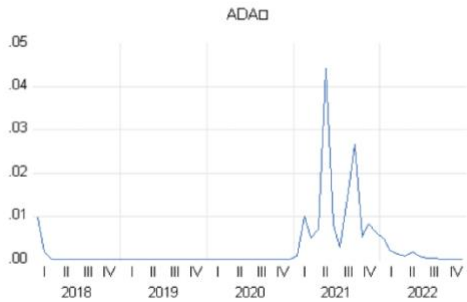
Apart from the volatility series of all the five cryptocurrencies in this study, the factors influencing the strength of connectedness of volatilities among these cryptocurrencies are also examined. In the testing of stationarity of determinants, this study first performs unit root test at level. In the event that the variable at level is not stationarity, a check on the variable's graphical plot will be performed to examine the presence of structural break. If a structural break is observed, the breakpoint unit root test will be performed on the series. Testing of unit root test at first difference will be performed if the null hypothesis of non-stationarity cannot be rejected for both unit root test at level and breakpoint unit root test.

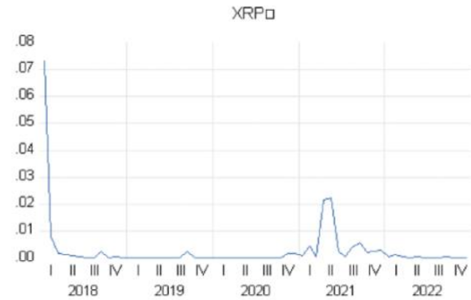
Table 3.1 Unit Root Test Results of Cryptocurrency Volatility Series

Variable	**Dickey-Fuller GLS**	**Ng-Perron Unit Root Test**				**Breakpoint Unit Root Test**
		MZa	**MZt**	**MSB**	**MPT**	
BTC	-3.0616***	-14.2004***	-2.6557***	-0.1870**	1.7597***	-4.782**
ETH	-4.8925***	-24.4387***	-3.4871***	0.1427***	1.0311***	-6.084***
DOGE	-5.6278***	-26.9528***	-3.6708***	0.1362***	0.9097***	-26.635***
XRP	-0.1282	0.2544	0.3355	1.3189	98.2095	-22.375***
Δ*XRP*	0.020	0.0416	1.109	2.668	396.325	
ADA	-1.7583*	-5.134	-1.557	-0.303	4.889	-6.087***
Δ*ADA*	-0.725	-0.285	-0.327	1.147	66.214	

Notes: *BTC* is Bitcoin, *ETH* is Ethereum, *DOGE* is Doge coin, *XRP* is Ripple, and *ADA* is Cardano. All unit root tests are estimated with Intercept and Trend and based on Schwarz Information Criterion (SIC). Null hypothesis for both the unit root test is non-stationarity of the series being tested. Δ indicates first difference operator. ***, ** and * indicate significance at the 1%, 5% and 10% respectively.

Figure 3.1: Graph of structural break for *ADA* and *XRP*





Notes: *ADA* denotes Cardano, and *XRP* denotes Ripple.

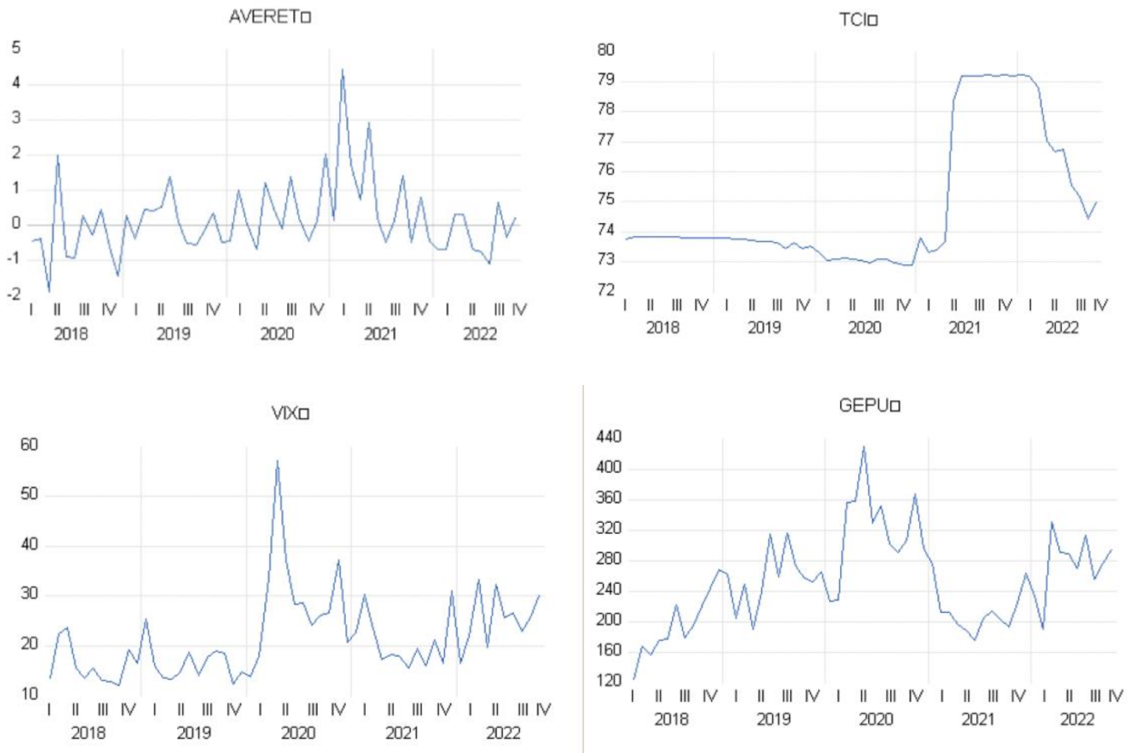
Table 3.2 below presents the results of unit root tests for the potential determinants of volatility connectedness. Based on unit root results populated in Table 3.2, it is found that *GRP*, *W_RETURN*, *AVEVOL* and *E_RETURN* are stationary at level given that the test statistics in both the unit root test are all significant at the 1% level.

Table 3.2 Unit Root Test Results of Determinants of Volatility Connectedness

Variables	**Dickey-Fuller GLS**	**Ng-Perron**				**Breakpoint Unit Root Test**
		MZa	**MZt**	**MSB**	**MPT**	
TCI	-1.461	-2.656	-1.145	0.431	9.195	-11.409***
GPR	-2.634***	-11.4506***	-2.323***	0.203***	2.411***	
GEPU	-1.266	-3.552	-1.215	0.342	6.894	-3.910
Δ*GEPU*	-10.047***	-24.872***	-3.517***	0.141***	3.718***	
VIX	-3.567***	-17.404	-2.875	0.165	1.683	-6.703***
AVEVOL	-2.955***	-25.593***	-3.577***	0.140***	0.958***	
AVERET	-2.432**	-6.638*	-1.816*	0.274*	3.711*	-7.245***
W_RETURN	-7.514***	-27.838***	-3.648***	0.131***	1.143***	
E_RETURN	-7.616***	-27.961***	-3.731***	0.133***	0.903***	

Notes: *TCI* is Total Connectedness Index of the five cryptocurrency, *GPR* represent the Geopolitical Risk Index, and the *GEPU* is Global Economic Policy Uncertainty index, *VIX* is the Volatility Index, *AVEVOL* is the average volume of the five cryptocurrency, and the *AVERET* is the average return of the five cryptocurrency, the *W_RETURN* is represent that the return of MSCI World Index, and the *E_RETURN* is represent the return of MSCI World Energy Index. the All unit root tests are estimated with Intercept and Trend and based on Schwarz Information Criterion (SIC). Null hypothesis for both the unit root test is non-stationarity of the series being tested. Δ indicates first difference operator. ***, ** and * indicate significance at the 1%, 5% and 10% respectively.

Figure 3.2: Graph of Structural break for *TCI*, *GEPU*, *AVERET*, *VIX*



Notes: *AVERET* is the average return of the five cryptocurrency, *TCI* is Total Connectedness Index of the five cryptocurrency, *VIX* is the Volatility Index, and the *GEPU* is Global Economic Policy Uncertainty index.

Meanwhile, *VIX* and *AVERET* have contrasting results from Dickey-Fuller GLS and Ng and Perron unit root tests with the former showing stationarity of these series while the latter shows otherwise. The remaining series – *GEPU* and *TCI* are not stationary at level as shown by the results of both the unit root tests. As mentioned in the previous paragraph, this study tries to avoid using the first difference series of data as using first difference would result in loss of information. Hence, this study proceeds to perform breakpoint unit root test for *VIX*, *AVERET*, *GEPU* and *TCI*. This decision is also supported by the graphical plots of all the cryptocurrencies as shown in Figure 3.2 which show that all the series have signs of structural break.

Results from breakpoint unit root test show that all volatility series are stationarity in the presence of structural break with the exception of *GEPU*, which is not able to achieve stationarity even after considering structural break. Therefore, the stationarity of *GEPU* is tested at first difference for both tests and results show that the differenced series is stationary at first difference. Hence, this study will proceed to using the determinants at level for *GPR*, *VIX*, *TCI*, *AVEVOL*, AVERET, *W_RETURN* and *E_RETURN* and first difference for *GEPU* in testing their significance in explaining volatility connectedness.

3.5 Model Specifications

3.5.1 TVP-VAR for Volatility Connectedness

The time-varying parameter VAR (TVP-VAR) estimation is a statistical technique used to estimate a Vector Autoregressive (VAR) model with time-varying parameters. It is an innovation of Antonakakis and Gabauer (2017) that extends the traditional VAR framework, which assumes that the parameters of the model are constant over time. It employed to examine volatility spillover across the five cryptocurrency of *BTC*, *ETH*, *XRP*, *ADA*, and *DOGE*. The TVP-VAR model allows for changes in the parameters of the VAR model over time, which can capture the dynamic behaviour of the variables in the model more accurately. This approach is particularly useful in modelling economic and financial time series data, where the relationships between variables can change over time due to various factors such as changes in economic policies, technological innovations, or shifts in consumer preferences. While Diebold and Yilmaz (2009, 2012, 2014) have mentioned in their introductory papers that they also compute the time-varying spillover index, it is worth highlighting that they account for time variation in the index using rolling-window and not via a Kalman-Filter estimation. The latter estimation method is superior to the rolling-window estimation in at least three ways. First, the width of rolling window is often arbitrarily determined with little or no statistical backing (Antonakakis & Gabauer, 2017; Ibrahim & Aziz, 2003). Second, the need to set a window size to perform rolling sample analysis also means the loss of valuable observations which commensurate the width of the window. Finally, unlike Kalman-Filter which produces coefficients for all the data points in the sample, rolling-window estimation does not allow the identification of which data points contribute to a spike or a dip in the spillover index in a particular window.

Table 3.3: Total Connectedness Index

	X1	X2	X3	X4	Total FROM
X1	From X1 to X1	From X2 to X1	From X3 to X1	From X4 to X1	Total from X2, X3 & X4 to X1
X2	From X1 to X2	From X2 to X2	From X3 to X2	From X4 to X2	Total from X1, X3 & X4 to X2
X3	From X1 to X3	From X2 to X3	From X3 to X3	From X4 to X3	Total from X1, X2 & X4 to X3
X4	From X1 to X4	From X2 to X4	From X3 to X4	From X4 to X4	Total from X1, X2 & X3 to X4
TOTAL TO	Total from X1 to X2, X3 & X4	Total from X2 to X1, X3 & X4	Total from X3 to X1, X2 & X4	Total from X4 to X1, X2 & X3	TOTAL CONNECTEDNESS INDEX

The spillover index framework of Diebold and Yılmaz (2014) is best understood by analysing the connectedness table as illustrated in Table 3.3. The connectedness index shown in the table 3.3 is a matrix that shows the degree of connection between different variables. In the table, the variables are listed in both rows and columns which consist X1, X2, X3, and X4. The cells show the degree of connection between each pair of variables. Each cell in the table represents the total number of connections from the row variable to the column variable, as well as the total number of connections from other variables to the column variable. The diagonal cells represent the total number of connections from the variable to itself.

The "Total from" row and column in the table represent the total number of connections from each variable to all the other variables. It means that the “Total from” show the influences from others, the higher the value, the higher the influence from others variable. Moreover, the “Total to” mean that the higher the value, the higher influence to other variables. On the other hand, the "Total connectedness index" in the bottom right corner of the table represents the average connectedness index among all the variables.

3.5.2 Determinants of Volatility Connectedness

This study uses the Ordinary Least Squares (OLS) with heteroscedasticity and autocorrelation corrected (HAC) standard errors on monthly data spanning February 2018 to October 2022 to examine the relationship between geopolitical risk and volatility connectedness of the five cryptocurrencies. Prior to specifying the model, the correlation between all independent variables, namely *GRP*, Δ*GEPU*, *VIX*, *AVEVOL*, *AVERET*, *E_RETURN*, and *W_RETURN* is tabulated to ensure that there will be no perfect collinearity among the independent variables. Table 3.4 presents the correlation of the key independent variable and control variable which there are no high correlation among these variables as none of the result shown among these variables that are more that positive value of 0.8. The highest correlation between the variable of *W_RETURN* and *E_RETURN* is 0.697. Besides that, the lowest correlation is the variable of *VIX* and *W_RETURN* resulting the value of -0.485. One of the factor explained that energy is a critical input for economic growth, and its price movements can have a significant impact on the cost of production and transportation of goods and services. This means that changes in energy prices can affect the profitability of many companies, which in turn can influence stock prices which resulting the highest value of correlation between *W_RETURN* and *E_RETURN*. On the other hand, the lowest correlation between *VIX* and *W_RETURN* can be explained by the fact that the *VIX* is primarily focused on the US equity market, while the world price return covers global equity markets. While there may be some spillover effects between the US and global markets, they are not perfectly correlated.

Table 3.4 Correlations of Key Independent Variable and Control Variable

	GPR	Δ*GEPU*	*VIX*	*AVEVOL*	*AVERET*	*W_RETURN*	*E_RETURN*
GPR	1.000						
Δ*GEPU*	0.203	1.000					
VIX	0.077	0.227	1.000				
AVEVOL	-0.044	-0.128	0.019	1.000			
AVERET	-0.178	-0.165	-0.003	0.487	1.000		
W_RETURN	-0.211	-0.393	-0.485	0.094	0.363	1.000	
E_RETURN	-0.222	-0.360	-0.366	0.189	0.276	0.697	1.000

Notes: *GPR* represent the Geopolitical Risk Index, and the *GEPU* is Global Economic Policy Uncertainty index, *VIX* is the Volatility Index, *AVEVOL* is the average volume of the five cryptocurrency, and the *AVERET* is the average return of the five cryptocurrency, the *W_RETURN* is represent that the return of MSCI World Index, and the *E_RETURN* is represent the return of MSCI World Energy Index. Δ indicates first difference operator.

Given that there is no correlation of above 80% among the independent variables, the model to examine significance of these variables in explaining volatility connectedness of *BTC*, *ETH*, *DOGE*, *ADA*, and *XRP*, based on outcome of the unit root tests, is specified as follow:

$$TCI_t = \beta_0 + \beta_1 \mathrm{GPR}_t + \beta_2 \Delta GEPU_t + \beta_3 VIX_t + \beta_4 AVEVOL_t + \beta_5 AVERET_t + \beta_6 W\_RETURN_t + \beta_7 E\_RETURN_t + u_t \quad (2)$$

where TCI_t denotes the monthly time-varying volatility connectedness across the five cryptocurrency of *BTC*, *ETH*, *XRP*, *ADA*, and *DOGE*, obtained by from the TVP-

VAR model calculated in Section 5.3. GPR_t is the by Geopolitical Risk Index developed by Dario Caldara and Matteo Iacoviello, $GEPU_t$ is Global Economic Policy Uncertainty index was created by Scott Baker, Nicholas Bloom, and Steven Davis, VIX_t is Volatility Index created by the CBOE Options Exchange (CBOE) and is maintained by CBOE Global Markets, $AVEVOL_t$ is average volume of the five cryptocurrency of Bitcoin (*BTC*), Ethereum (*ETH*), Cardano (*ADA*), Ripple (*XRP*), Doge coin (*DOGE*) from Yahoo Finance, $AVERET_t$ is average return of the five cryptocurrency of Bitcoin (*BTC*), Ethereum (*ETH*), Cardano (*ADA*), Ripple (*XRP*), Doge coin (*DOGE*), *W_RETURN* is the return of MSCI World Index which is the stock market index that tracks the performance of large and mid-cap stocks from 23 developed countries across the world, *E_RETURN* is the return of MSCI Energy World Index. The MSCI World Energy Index is calculated using a market capitalization-weighted methodology, which means that companies with higher market capitalizations have a greater impact on the index's performance.

CHAPTER 4: RESULTS AND DISCUSSIONS

4.0 Introduction

This chapter provides the interpretation of the findings. Section 4.1 shows the descriptive statistics that summarize the key characteristics of the data. Section 4.2 includes graphical plots of the volatility of the five cryptocurrencies with the graph of the dynamic volatility connectedness of cryptocurrencies. In Section 4.3, the average volatility connectedness from TVP-VAR Model for monthly data with the graph of total connectedness index and the net spillover index for the five cryptocurrencies are illustrated and discussed. Section 4.4 answers the third research question whereby the 2021 daily volatility connectedness of the five cryptocurrencies are illustrated and discussed. Lastly, Section 4.5 discusses the determinants of cryptocurrency volatility connectedness which mean that the result of Ordinary Least Squares (OLS) with heteroscedasticity and autocorrelation corrected (HAC) are presented in this section.

4.1 Descriptive Statistics

Table 4.1 shows the descriptive statistics of the eight variables with data consisting of 57 of monthly observations for the period from February 2018 to October 2022. The mean for *TCI* is 74.86 and its median value is 73.787. *TCI* recorded a highest value of 79.218 on November 2021 that it can be explained from the news that related to the to the cryptocurrency which showing the high volatile market in 2021. The standard deviation of *TCI* is 2.262 and the skewness is 1.168 which is greater than 1, *TCI* distribution is highly skewed. Jarque-Bera's probability is 13.221 which is above than 0.05, so do not reject the null hypotheses and the variable are normally distributed. For the *GPR*, the highest value is 325.394 that happened in March of 2022, it can be explain by the geopolitical event that mentioned in this study, Russian and Ukraine War. Moreover, for the trading volume (*AVEVOL*) and return (*AVERET*) of all these five cryptocurrencies, there are total of 207 billions of USD traded on average during the sample period, with an average return of 0.2%.

Table 4.1: Descriptive Statistics

	TCI	*GRP*	*GEPU*	*VIX*	*AVEVOL*	*AVERET*	*W_RETURN*	*E_RETURN*
Mean	74.860	101.783	251.605	21.621	207053.100	0.188	0.406	0.409
Median	73.787	90.491	251.515	19.340	21551.170	0.130	1.058	1.220
Max	79.217	325.394	430.259	57.060	1821743.000	4.441	25.485	12.548
Min	72.881	60.680	123.860	12.000	534.345	-1.890	-33.592	-19.487
Std. Dev.	2.262	43.280	61.220	8.193	364348.200	1.059	9.368	5.563
Skewness	1.168	2.962	0.451	1.682	2.402	1.446	-0.487	-0.645
Kurtosis	2.662	14.467	3.005	7.407	0.128	6.588	5.297	4.643
Jarque-Bera	13.221	395.627	1.929	73.003	143.987	50.440	14.786	10.372
Observations	57	57	57	57	57	57	57	57

Notes: The dependent variables is the total connectedness index (*TCI*), and the determinants of total volatility connectedness index across the geopolitical risk (*GPR*), economic policy uncertainty index (*GEPU*), volatility index (*VIX*), average volume of five cryptocurrency (*AVEVOL*), average return of five cryptocurrency (*AVERET*), world returns (*W_RETURN*), and energy return (*E_RETURN*).

Next, the average value of *GPR* is 101.783, median value is 73.787, and the highest *GPR* value of 325.394 collected on Mar, and the lowest of *GPR* value is 60.680. The standard deviation of *GPR* is 43.280, and *GPR* distribution is highly skewed since its skewness is 2.962. *GPR* also normally distributed because the Jarque-Bera probability is 395.627.

Other than that, *GEPU* has a mean and median of 251.605 and 251.515 respectively. The highest *GEPU* is the value of 430.259, and the lowest *GEPU* is 123.860. The standard deviation for *GEPU* is 61.220 and its skewness is 0.451 which mean *GEPU* is evenly distributed. *GEPU* are also normally distributed since its Jarque-Bera probability is more than 0.05.

In addition, the results show that the *AVEVOL* and *AVERET* has an average value of 207053.100 and 0.188, with a median value of 21551.170 and 0.130 respectively. The largest value of the *AVEVOL* and *AVERET* is value of 1821743 and 4.441. On the other hand, the lowest value of *AVEVOL* and *AVERET* was recorded 534.345 and -1.890. It is normal that will get the negative value of return as there are always profit in cryptocurrency market, however, volume is just based on the market cap to capture the value. Furthermore, the *AVEVOL* and *AVERET* has a standard deviation of 36438.200 and 1.059, the distribution of *AVEVOL* is highly skewed compare to *AVERET*, with a skewness of 3.0914 and the value of *AVERET* is 1.446. This suggests that both *AVEVOL* and AVERET are normally distributed.

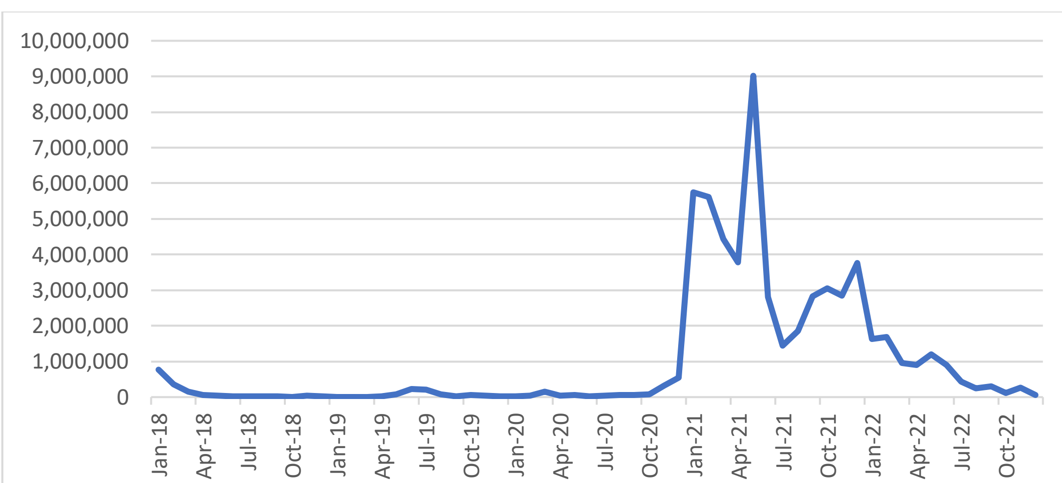
The mean of *VIX*, *W_RETURN*, and *E_RETURN* is 21.621, 0.406 and 0.409 respectively. The median value which are the middle values of variables for *VIX*, *W_RETURN*, and *E_RETURN* is 19.340, 1.058, and 1.220 respectively. *VIX* recorded a highest value of 57.060 and lowest value is 12. The highest value of *W_RETURN* is 25.485 and its lowest value is -33.592, for the *E_RETURN* measured a highest value of 12.548 and lowest value is -19.487. Other than that, the standard deviation for *VIX*, *W_RETURN*, and *E_RETURN* is 8193, 9.368, and 5.563 respectively. The skewness value of *VIX* is greater than 1, the distribution is highly skewed of 1.682, however, the skewness value of *W_RETURN*, and *E_RETURN* is below 1, which recorded the value of -0.487 and -0.645. Furthermore, Jarque-Bera's probability for *VIX*, *W_RETURN*, and *E_RETURN* is more than 0.05, so do not reject the null hypotheses and the variables are normally distributed.

4.2 Graphical Plots of Monthly Volatility

4.2.1 Bitcoin (*BTC*)

According to Figure 4.1 which shows that the monthly volatility of Bitcoin, the first spike point was observed in February of 2021. According to the news gathered, Musk updated his Twitter profile to "#bitcoin" on January 29, 2021. Bitcoin's price increased by more than 18% on the day and crossed the USD38,000 mark. But soon after, Musk made it known that he supported Bitcoin in public. Additionally, he acknowledged that he was a latecomer to the bitcoin trading feast and that he should have purchased bitcoin at least 8 years ago. A few days later, Tesla said that it has bought USD1.5 billion worth of Bitcoin and might continue to buy and keep the virtual currency for an extended length of time. Additionally, Tesla stated that it wished to accept bitcoin as payment for its goods. On that day, the price of bitcoin reached as high as USD56,563.72. The market value was USD1.04 trillion, and the trading volume within 24 hours was around $14 trillion.

Figure 4.1: Monthly volatility plot of *BTC*



Thereafter, the prices of *BTC* in March and April of 2021 show stable and not much news affected to the price of *BTC*, so the market correction the *BTC*'s price on that time. During the time of correction, *BTC* show stable in the market, meanwhile there are not much of important news that affect to the *BTC*.

After that, Tesla's CEO Elon Musk immediately stated on May 13, 2021, that Tesla will stop accepting Bitcoin as payment for cars. The decisions made by Musk and Tesla caused Bitcoin to fall more than USD3,000 in only 40 minutes, to a low of USD51,600, or over 6%. Musk tweeted, "He is working with Dogecoin devs, which has minimal influence on Bitcoin, but Dogecoin has increased a lot, about 10%," the day after Tesla terminated Bitcoin[3]. On May 20, 2021, the U.S. Treasury Department said that it will take action to regulate the cryptocurrency market and transactions, and that any transfers of USD10,000 or more would need to be reported to the Internal Revenue Service. Soon after the statement, Bitcoin's trend changed, and it eventually increased by 1.6%. The 51st meeting of the State Council's Financial Stability and Development Committee (hence referred to as the "Financial Committee") was held in one day after that. In particular, the Financial Committee stressed the need for tougher regulations on bitcoin mining and trading. Resolutely stop personal hazards from spreading to the social sphere. When the news broke, the currency market responded rapidly, and Bitcoin immediately plummeted below USD38,000, down 9.05% in a single day.

The Development and Reform Commission of Changji Prefecture, Xinjiang, said on June 9, 2021, that all businesses involved in virtual "mining" must stop operations for correction. The hash rate of Chinese mining pools fell by 11% to 30% within 24 hours of the news' publication. Similar decreases of 10% were also experienced by other mining pools run by well-known exchanges like Huobi and Binance. El

[3] News extract from thetime.co.uk, on 11 April 2023, available at https://www.thetimes.co.uk/money-mentor/article/is-bitcoin-crash-coming/

Salvador had requested technical support from the World Bank to enable it utilize Bitcoin as its official currency, but the World Bank had already done so owing to environmental and transparency issues, according to Zelaya, El Salvador's finance minister, on June 16, 2021. say no. Bitcoin dropped 21.79% during the following 5 days, from USD41,300 to USD32,300. Major banks and Alipay have made the decision to "resolutely not carry out or engage in any business activity linked to virtual currency" as of June 21, 2021. Bitcoin once dropped to a price of below USD29,000, plunged by nearly 12% in 24 hours, wiping away this year's profits, and then kept on rising until it reached a price of USD33,000. The drop in cryptocurrencies stopped on June 23, 2021. In the short time, Bitcoin increased by about USD1,200, crossing the USD34,000 mark, an increase of 4.2% from the previous night. The price of Ethereum has also risen to USD2,000 per token, up 6.2%, or over USD300, from its 24-hour low. On the other hand, China's pressure strategies have been a significant contributor to the unexpected change in momentum. Financial institutions are not permitted to offer services to bitcoin businesses in China. One of the mining superpowers for bitcoin has been China. After China's crackdown on cryptocurrencies, the network has lost more than 50% of Bitcoin's hash power. Therefore, these unexpected limitations on mining must have some short-term effects on market sentiment.

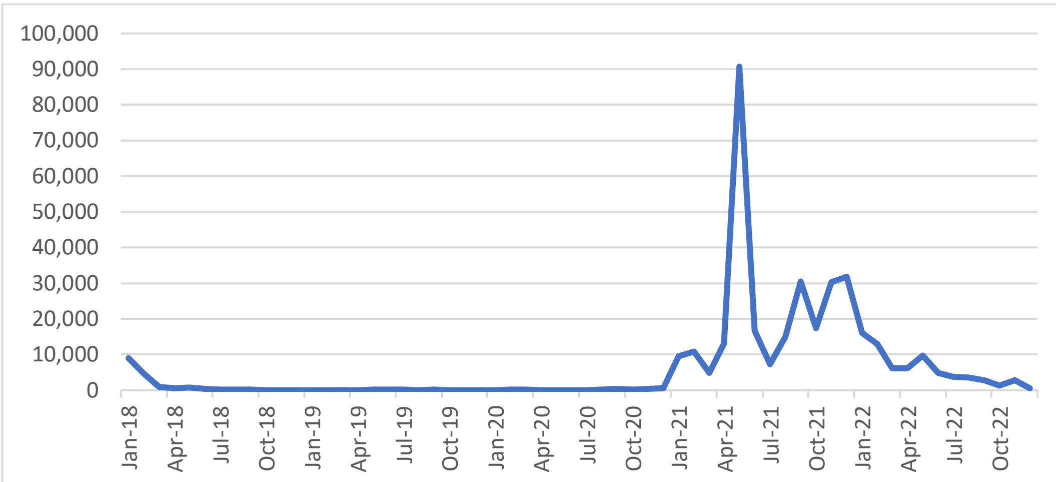
The financial business founded by banking tycoon Soros revealed its entry into cryptocurrency in October 2021, a few months after several factors affected the cryptocurrency and caused its price to fluctuate. At the time, it already had a holding in Bitcoin. In the 24 hours that followed the revelation, the cryptocurrency's price increased by 10%, reaching around USD55,000. On October 13, 2021, data from the Cambridge Alternative Finance Research Center revealed that China's share of the world's computer power has decreased from 44% to zero between May and July of this year. Two months after China outlawed cryptocurrency mining domestically, the United States has surpassed China as the world's top source of bitcoin mining, according to new statistics. "When investing in funds that contain Bitcoin futures contracts, make sure to carefully assess the possible Risks and Benefits," the SEC Office of Investor Education and Advocacy tweeted on October 15, 2021. These comments come as the US SEC is getting ready to release a number of connected goods. On October 15 at 13:20, with an intraday increase of more than 4.5%, Bitcoin once more crossed the USD60,000/coin threshold. Finally, on November 9, 2021, Bitcoin reached a record high when its price crossed the USD68,000 threshold. Ethereum, the second-largest cryptocurrency in the world by market value, also crossed the $4,800 level at the same moment, setting a new record high (Hannah, 2023).

In such experience of bitcoin, it was a crazy year for cryptocurrency in 2021. As the volatile of the bitcoin price may attract a lot of investors to invest in cryptocurrency. Fear and Greed Index is the market sentiment for crypto to show that when the higher the bitcoin price, the higher the fear and greed index. Meanwhile, when the fear and greed index is higher, the market is greed, while the fear and greed index is lower, meaning the market is fear.

4.2.2 Ethereum (*ETH*)

The monthly volatility of ETH is presented in Figure 4.2. In 2021, Ethereum (ETH) experienced a significant increase in value, with its price rising from around USD730 at the start of the year to a peak of around USD4,300 in May 2021. This increase in value was driven by a number of factors, including the growing popularity of decentralized finance (DeFi) applications, the increasing adoption of non-fungible tokens (NFTs), and the launch of Ethereum 2.0. The DeFi ecosystem, which is built on top of the Ethereum network, experienced significant growth in 2021, with a wide range of applications including decentralized exchanges, lending and borrowing platforms, and yield farming protocols. This growth helped to drive demand for Ether, the cryptocurrency associated with the Ethereum network, as users needed to use it for transactions and to pay gas fees.

Figure 4.2: Monthly Volatility of *ETH*



In addition, the growing popularity of NFTs, which are unique digital assets that can be bought and sold on the Ethereum network, also contributed to the increase in demand for Ether. NFTs were used for a wide range of purposes, including digital art, music, and sports memorabilia, and some high-profile NFT sales helped to drive media attention and increase interest in the Ethereum network.

Finally, the launch of Ethereum 2.0, a major upgrade to the Ethereum network that aims to improve scalability and reduce transaction fees, also contributed to the increase in value of Ether (Yahoo Is Part of the Yahoo Family of Brands, n.d.).[4] However, like most cryptocurrencies, Ethereum and Ether experienced significant volatility in 2021, with periods of rapid growth followed by sharp declines in value. In particular, the cryptocurrency market experienced a significant decline

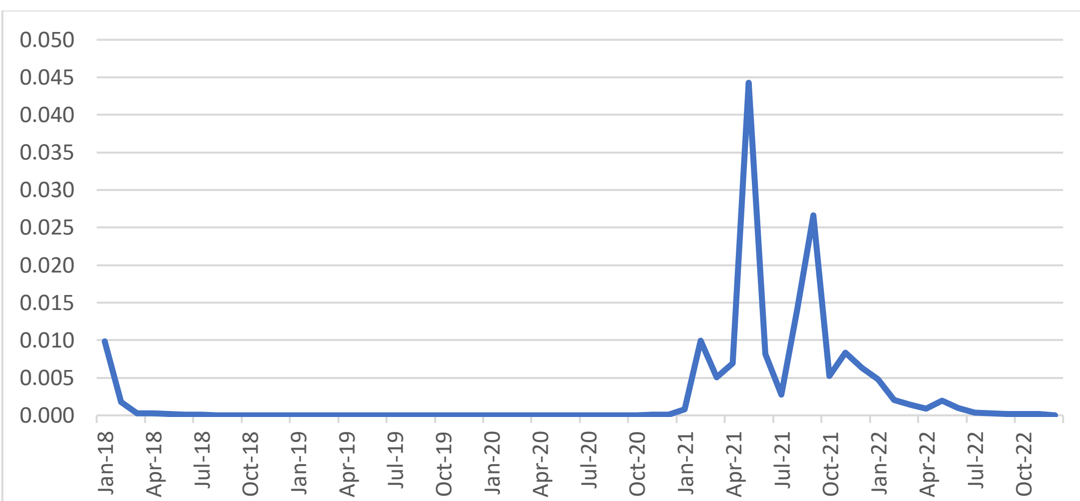
[4] News extract from forkast news, on 27 July 2021, available at https://forkast.news/whats-ethereums-price-outlook-for-2021/

in May 2021, which was driven by a number of factors including increased regulatory scrutiny and concerns about the speculative nature of the market. Despite this, Ethereum has continued to be one of the most widely used and traded cryptocurrencies, and its value has remained relatively high compared to other cryptocurrencies (Lim, 2021).

4.2.3 Cardano (*ADA*)

The monthly volatility plot of ADA is illustrated in Figure 4.3. In 2021, the cryptocurrency ADA (Cardano) experienced significant growth and development. ADA's price started the year at around USD0.18 and saw a significant increase, reaching an all-time high of over USD3.00 in September 2021. The launch of smart contracts is one of the most significant developments for ADA was the launch of the Alonzo hard fork in September 2021, which enabled smart contract functionality on the Cardano blockchain.

Figure 4.3: Monthly volatility plot of *ADA*



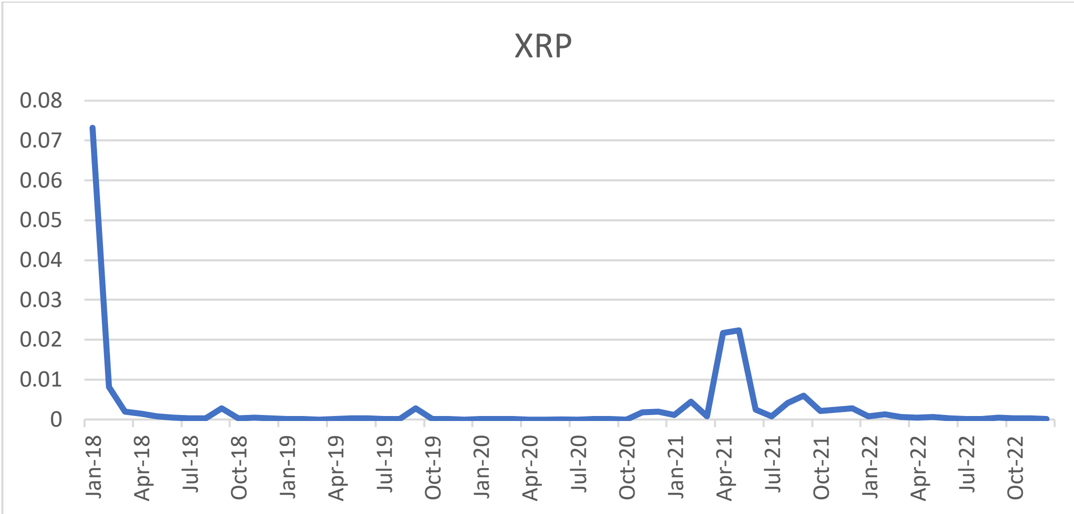
On the other hand, Cardano has seen growing adoption, with more companies and organizations announcing partnerships and collaborations. For example, the Ethiopian government announced a partnership with IOHK, the company behind Cardano, to use the blockchain technology for its education system. Furthermore, Cardano has been promoting sustainability and green energy, with a focus on reducing energy consumption and carbon emissions compared to other cryptocurrencies (Wan, 2021).

4.2.4 Ripple (*XRP*)

Based on Figure 4.4, in 2017, XRP (the cryptocurrency associated with the Ripple network) experienced a significant increase in value, with its price rising from less than USD0.01 at the start of the year to a peak of around USD3.84 in early January 2018. This increase in value was driven by a number of factors, including the growing popularity of cryptocurrencies in general, the perceived value of the Ripple network and its use cases, and the growing interest of investors in XRP as an alternative to other cryptocurrencies like Bitcoin and Ethereum. During this period, Ripple also made several significant partnerships with major financial institutions, including Santander, American Express, and UBS, which helped to increase confidence in the Ripple network and XRP.

However, in early 2018, the value of XRP and other cryptocurrencies experienced a significant decline, with XRP's price dropping to around USD0.50 by the end of the year. This decline was driven by a number of factors, including increased regulatory scrutiny, concerns about the speculative nature of the cryptocurrency market, and a general market correction after the significant increase in value during 2017.

Figure 4.4: Monthly volatility plot of *XRP*



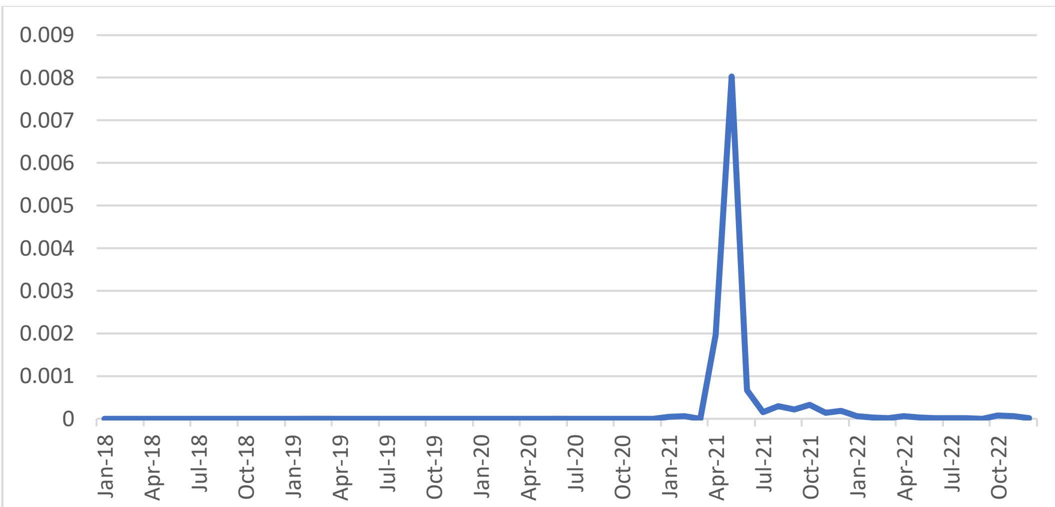
Despite this decline, XRP has continued to be one of the most widely used and traded cryptocurrencies, with a significant presence in the cross-border payments and remittance markets. The Ripple network has also continued to expand its partnerships with major financial institutions, and XRP's value has remained relatively stable in recent years (Daly, 2021).

4.2.5 Dogecoin (*DOGE*)

In 2021, Dogecoin (*DOGE*) experienced a significant increase in value, with its price rising from less than $0.01 at the start of the year to a peak of around $0.70 in early May 2021. This increase in value was driven by a number of factors, including the growing popularity of cryptocurrencies in general, the influence of social media, and the support of high-profile figures like Elon Musk. Musk, the CEO of Tesla and SpaceX, tweeted about Dogecoin several times in early 2021, which helped to increase interest and investment in the cryptocurrency. In addition, the subreddit r/Wall-Streeters', which had previously fuelled the GameStop short squeeze in

January 2021, also began to promote Dogecoin as a potential target for investment, further increasing its value. However, in May 2021, Dogecoin and other cryptocurrencies experienced a significant decline in value, with DOGE's price dropping to around USD0.20 by the end of the month. This decline was driven by a number of factors, including increased regulatory scrutiny, concerns about the speculative nature of the cryptocurrency market, and a general market correction after the significant increase in value during the early part of the year.

Figure 4.5: Monthly volatility plot of *DOGE*



Despite this decline, Dogecoin has continued to be one of the most widely traded cryptocurrencies, with a significant presence on social media and a strong community of supporters. Its value has remained relatively volatile, with significant fluctuations in response to events and trends in the broader cryptocurrency market. In May, just before Elon Musk made his “Saturday Night Live” debut, the price of dogecoin began to spike. On May 8, the day of Musk’s SNL appearance, dogecoin hit an all-time high of about 73 cents, according to Coin Gecko. However, on May 9, 2021, when Elon Musk participated in the well-known American variety show "Saturday Night Live". After repeated questioning by the host, he admitted that Dogecoin is a "scam". The panic was transmitted quickly, and Dogecoin once plummeted by 40%. This was representative of the roller-coaster run that dogecoin had all year, most of which had to do with Musk. The Tesla and SpaceX CEO has been a consistent supporter of the meme-inspired cryptocurrency. Dogecoin's rally first began in February after a series of tweets from Musk, and since, he has continued to hype up the digital coin. Musk suddenly said that Tesla has stopped accepting Bitcoin as payment for vehicles on May 13, 2021. Due to Musk and Tesla's decision, Bitcoin fell more than USD3,000 in only 40 minutes, reaching a low of USD51,600, a decline of about 6%. Musk tweeted, however, "He is working with Dogecoin developers to increase system transaction efficiency," the day after Tesla abandoned Bitcoin. With a 24-hour growth of up to 10.4%, it has increased significantly (Mukherjee & Mukherjee, 2021).[5]

4.3 Average Volatility Connectedness from TVP-VAR Model (Monthly Data)

Table 4.2 shows the monthly average volatility connectedness of the five cryptocurrencies from TVP-VAR Model. Based on the table shown the FROM index, BTC is the least affected by volatility of other cryptocurrency by 60.79%, other than that, XRP is the most affected by volatility of other cryptocurrency by 94.2%. Based on the Total TO index, Bitcoin and Ethereum are almost equally in influencing volatility of Doge, Ripple and Cardano which is because the TO index sum up to 125.22 and 125.12 respectively. The reason of Bitcoin and Ethereum are the most influential among the rest of cryptocurrency is because they two are the most market cap among all the cryptocurrency. However, DOGE is the least spillovers to other coin which mean that the least influencing volatility of others coins. DOGE is the coin that move individually that because it's mainly affected by the richest person in

[5] News extract from News18, on 31 December 2021, available at https://www.news18.com/news/buzz/the-rise-and-rise-of-dogecoin-in-2021-4611008.html

the world, Elon Musk. So, the movement of Bitcoin may not be the main reason influencing DOGE. For the individual spillover index, Bitcoin spillover the most to itself by 39.21% follow by BTC spillover to XRP and ADA by 37.38% and 37.65% respectively. Other than that, DOGE spillover the least to XRP by 2.3%. In overall, the volatility for these five cryptocurrencies is connected by 74.87% which mean that all five cryptocurrencies may have no diversification benefit because those coin itself are highly influenced by each other.

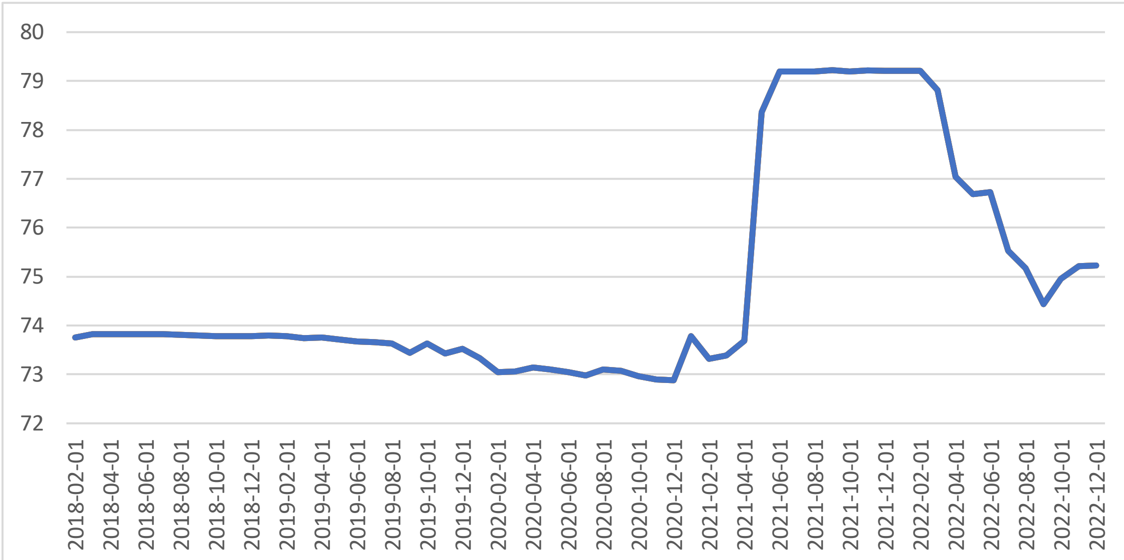
Table 4.2 Average Monthly Volatility Connectedness from TVP-VAR Model

	From (j)					Total FROM
To (i)	*BTC*	*ETH*	*DOGE*	*XRP*	*ADA*	
BTC	39.21	33.48	2.56	4.55	20.2	60.79
ETH	35.36	32.63	2.41	4.85	24.75	67.37
DOGE	14.83	24.41	25.72	5.62	29.42	74.28
XRP	37.38	34.46	2.30	5.80	20.06	94.20
ADA	37.65	32.77	2.54	4.75	22.28	77.72
Total TO	125.22	125.12	9.81	19.78	94.43	374.36
Net spillovers	64.43	57.75	-64.47	-74.42	16.71	**74.87**

Note: BTC denotes volatility series of Bitcoin, ETH is the volatility series for Ethereum, DOGE is the volatility series for Doge Coin, XRP is the volatility series for Ripple, and ADA denotes volatility series of Cardano. Total TO indicates the total directional spillovers from asset j to all other assets i excluding own spillovers. Net spillovers is the Net connectedness that calculated by subtracting total spillovers received (Total FROM) from total spillovers transmitted (Total TO). The number which is bold is the average Total Connectedness Index over the sample period.

Based on the Figure 4.5, it shows that the total connectedness index throughout the sample period from January 2018 until December 2022. It is observed that from January 2018 until March 2021, the volatility connectedness was stable and maintain between around 73% to 74%. However, volatility connectedness among these five cryptocurrencies surged to more than 79% and remained elevated for about a year before slowly falling beginning March 2022 to around 75% in the months of July 2022 to December 2022. The high connectedness of the cryptocurrencies due to the rise of decentralized finance (DeFi) and the use of blockchain technology that mentioned in the section 4.2.2 of the ETH, it can led to the creation of a large number of interconnected networks and protocols that are used to trade and manage cryptocurrencies.

Figure 4.6: Dynamic Total Connectedness Index (%)

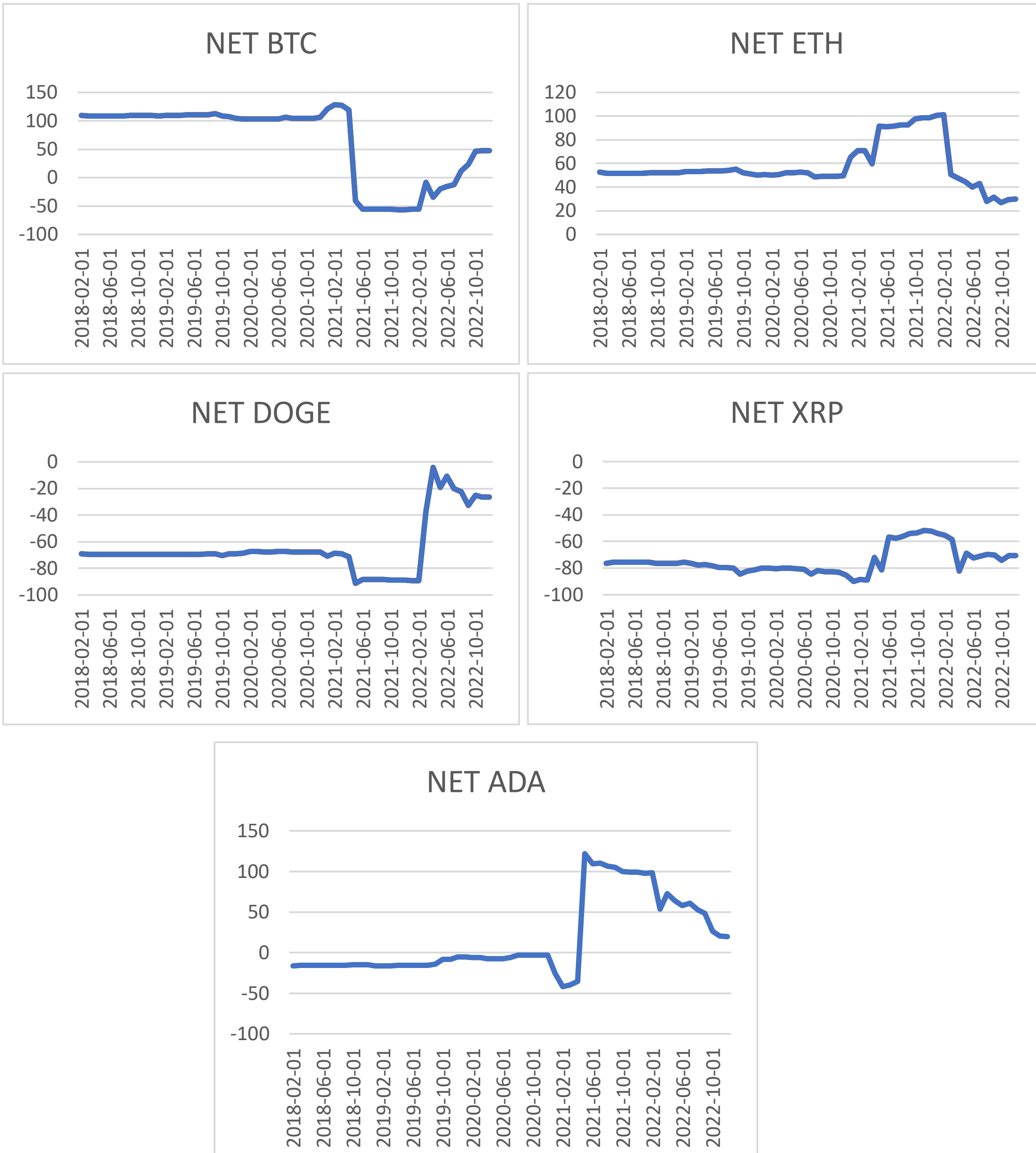


Notes: The graph plots the evolution of total connectedness index (TCI) of the five cryptocurrencies - Bitcoin, Ethereum, Doge Coin, Ripple, and Cardano, based on the TVP-VAR model estimated with lag length of 10 as selected by the Schwarz Information Criterion (SIC).

This has created a complex web of interdependencies between different cryptocurrencies, exchanges, and protocols, which can amplify the effects of price movements. On the other hand, the influx of new retail and institutional investors into the crypto market in 2021 has also contributed to the high level of connectedness. As more investors and traders enter the market, they bring with them their own biases and strategies, which can lead to increased correlation between different cryptocurrencies.

In terms of net volatility connectedness, Figure 4.6 shows that the *BTC*, *ETH*, and *ADA* are the net transmitters of volatility spillovers whereas the *XRP* and *DOGE* are net receivers of volatility spillovers. It can be observed from the graphical plots of the net volatility connectedness that the Bitcoin is a larger transmitter of volatility spillovers than the *ETH* and *ADA* before May 2021 as given that the former's plot

Figure 4.7: Net spillover index for five cryptocurrency



Notes: NET *BTC* represents the net transmitters of volatility spillovers, NET *ETH* represents the net transmitters of volatility spillovers, NET *XRP* represents the net transmitters of volatility spillovers, NET *DOGE* represents the net transmitters of volatility spillovers, and NET *ADA* represents the net transmitters of volatility spillovers has greater incidence of fluctuations above the horizontal zero line. However, after the crash of *BTC* in May 2021, *BTC* is no longer the largest transmitter of volatility spillovers. Instead, *ETH* is the larger transmitter of volatility spillovers after May 2021, followed by *ADA*. However, of the two net receivers of volatility spillovers, the *XRP* is the larger receiver, with its net connectedness index hovers below the horizontal zero line all the time.

4.4 Average Volatility Connectedness from TVP-VAR Model (Daily Data, 2021)

Looking at the graphical plots of all five volatility series as well as the plot of dynamic volatility connectedness among these five cryptocurrencies in the Figures 4.1 to 4.5, the year 2021 exhibits large movement in volatility as well as connectedness. In addition, the year 2021 was also the year of bullish market for cryptocurrencies. Hence, this study further zooms into the year 2021 using data of daily frequency to provide closer examination of the dynamics of spillovers among these five cryptocurrencies.

Table 4.3 shows that the average volatility connectedness of cryptocurrency from TVP-VAR Model, focused on daily data for the year 2021 only. Based on the Total FROM index, *BTC* is the least affected by volatility of other cryptocurrencies with its Total FROM registering 64.19% whereas *ADA* is the most affected by volatility of other cryptocurrencies by 72.06%. This result is not consistent with the monthly data result, which shows that the *ADA* is the most affected by volatility of other cryptocurrencies in the year of 2021, but in overall, XRP is the most affected by volatility of other cryptocurrencies in the period of February 2018 until October 2022. In terms of the exports of spillovers to other cryptocurrencies, the Total TO index show that *ETH* is the most influential, with its Total TO recording 86.44%, followed by *ADA* which has a Total TO of 76.69%. This result is different compared to the result of monthly data shown in Table 4.2. In the monthly data result that the *BTC* is the most influential that with 125.22% of Total TO, but daily data shown in Table 4.3 in the year of 2021 shows only 64.16%. The reason of *ETH* and *ADA* being the most influential among the rest of cryptocurrencies is that both *ETH* and *ADA* are offering advanced smart contract functionality, which has been explained in Section 4.2. Nevertheless, one of the similarities between the monthly data and daily data in the Table 4.2 and Table 4.3 is that the *BTC*, *ETH*, and *ADA* are the top three of Total TO among the five cryptocurrencies.

On the other hand, *XRP* produces the least spillovers to other cryptocurrencies, which means that it is the least influential towards other coins. In overall, the volatility for these five coins is connected by 68.63% which mean that all five cryptocurrencies may have no diversification benefit because those cryptocurrencies itself are influencing by each other as well as the monthly data as shown in Table 4.2

Table 4.3: Average Volatility Connectedness from TVP-VAR Model (Daily Data)

	From (j)					Total FROM
To (i)	*BTC*	*ETH*	*DOGE*	*XRP*	*ADA*	
BTC	35.81	21.39	10.96	13.5	18.34	64.19
ETH	18.51	28.06	16.74	14.32	22.37	71.94
DOGE	11.87	21.19	33.73	15.21	17.99	66.27
XRP	16.22	19.34	15.14	31.31	17.99	68.69
ADA	17.55	24.53	15.31	14.67	27.94	72.06
Total TO	64.16	86.44	58.15	57.7	76.69	343.14
NET Spillover	-0.03	14.5	-8.11	-10.99	4.64	**68.63**

Note: *BTC* denotes volatility series of Bitcoin, *ETH* is the volatility series for Ethereum, *DOGE* is the volatility series for Doge Coin, *XRP* is the volatility series for Ripple, and *ADA* denotes volatility series of Cardano. Total TO indicates the total directional spillovers from asset j to all other assets i excluding own spillovers. Net spillovers is the Net connectedness that calculated by subtracting total spillovers received (Total FROM) from total spillovers transmitted (Total TO).

4.5 Determinants of Cryptocurrency Volatility Connectedness

Results of the OLS regression to examine the relationship between geopolitical risk and volatility connectedness are presented in Table 4.4. The results show that the *GPR* is significant in affecting volatility connectedness of cryptocurrencies at the significance level of 1%. This implies that higher geopolitical risk may lead to increased volatility in the cryptocurrency market, as investors may become more risk-averse and seek safe-haven assets such as cryptocurrencies. This may lead to a higher degree of volatility connectedness between cryptocurrencies and other assets, as investors shift their portfolios in response to changing geopolitical risk.

From another perspective, higher geopolitical risk may also lead to increased connectivity between cryptocurrencies, as investors may adopt more defensive investment strategies and avoid risky assets. In this scenario, the volatility connectedness between cryptocurrencies may increase as investors may collectively reduce their exposure to highly risky assets such as cryptocurrencies during times of heightened geopolitical risk.

This outcome is consistent with other studies like Aysan et al (2019) and Nouir and Hamida (2022), which indicate that the *GPR* have significant impact the volatility of Bitcoin's price. Another similar finding was obtained by Chibane and Janson (2020) which indicates that there is strong correlation between *BTC* dynamics and global geopolitical risk, as well as the fact that *GPR* has a significant influence on the portfolio allocation of prudent mean-variance investors that consider geopolitical risk in their decision-making.

Table 4.4: Ordinary Least Squares (OLS) with heteroscedasticity and autocorrelation corrected (HAC) standard errors

	C	*GPR*	*ΔGEPU*	*VIX*	*AVEVOL*	*AVERET*	*W_RETURN*	*E_RETURN*
Coefficient	72.876***	0.019***	0.001	-0.028	3.940**	-0.687**	-0.001	0.015
	(66.660)	(3.421)	(0.845)	(-1.098)	(2.667)	(-2.304)	(-0.030)	(0.643)
R^2	0.479							
Adjusted R^2	0.404							
Observation	56							

Notes: The results of the ordinary least squares regression for the determinants of total volatility connectedness index across the geopolitical risk (*GPR*), economic policy uncertainty index (*GEPU*), volatility index (*VIX*), average volume of five cryptocurrency (*AVEVOL*), average return of five cryptocurrency (*AVERET*), world returns (*W_RETURN*), and energy return (*E_RETURN*).

C denotes the intercept, GPR_t is the by Geopolitical Risk Index that developed by Dario Caldara and Matteo Iacoviello, $GEPU_t$ is Global Economic Policy Uncertainty index was created by Scott Baker, Nicholas Bloom, and Steven J. Davis, *VIXt* is created by the Cboe Options Exchange (Cboe) and is maintained by Cboe Global Markets, $AVEVOL_t$ is average volume of the five cryptocurrency of Bitcoin (*BTC*), Ethereum (*ETH*), Cardano (*ADA*), Ripple (*XRP*), Doge coin (*DOGE*) get from the yahoo finance, $AVERET_t$ is average return of the five cryptocurrency of Bitcoin (*BTC*), Ethereum (*ETH*), Cardano (*ADA*), Ripple (*XRP*), Doge coin (*DOGE*) get from the yahoo finance, *W_RETURN* is representing the return of MSCI World Index which is the stock market index that tracks the performance of large and mid-cap stocks from 23 developed countries across the world, *E_RETURN* is representing the return of MSCI Energy World Index. The MSCI World Energy Index is calculated using a market capitalization-weighted methodology, which means that companies with higher market capitalizations have a greater impact on the index's performance.

Δ indicates first difference operator. ***, ** and * indicate significance at the 1%, 5% and 10%, respectively. Values in parentheses are standard errors.

Furthermore, other control variables like *AVEVOL* and *AVERET* are significant at 5%. This observation can be explained as cryptocurrency transactions tend to be highly speculative, which can make cryptocurrencies more susceptible to their own trading activities. This is because the prices of cryptocurrencies are largely driven by supply and demand dynamics, which can be influenced by a range of factors, including investor sentiment, market psychology and the behaviour of other traders. However, despite their speculative nature, economic events such as world stock returns and energy returns do not have a significant impact on the cryptocurrency market. For example, changes in global economic conditions, such as recessions or expansions, while they affect investor sentiment and lead to changes in demand for other financial assets, the same is not observed for cryptocurrencies as demonstrated by the lack of significance of variables such as *GEPU*, *VIX*, *W_RETURN* and *E_RETURN*. Based on the result, it showing that the world stock return and energy return is not significantly impact to the volatility connectedness of cryptocurrency. Hence, the volatility connectedness of cryptocurrency are more prone to be influenced by their own trading activity rather than economic events such as world stock return and energy return.

CHAPTER 5: CONCLUSION

5.1 Summary of results

In conclusion, the volatility connectedness among the five cryptocurrencies is rather high at 74.87% throughout the sample period, suggests that there was a strong spillover effect in the volatility movements of the cryptocurrencies during this period. This may be due to the fact that the cryptocurrency market as a whole was still relatively new and less mature, with investors and traders still figuring out how to assess and value the different cryptocurrencies. However, the daily volatility connectedness observed in 2021 was marginally lower at 68.63%, suggesting that the correlation between the volatility movements of the different cryptocurrencies may have weakened slightly. This could be due to several factors, such as the increasing maturity and institutionalization of the cryptocurrency market, the emergence of new cryptocurrencies that may be less correlated with the existing ones, and changes in the regulatory landscape that may affect the behavior of investors and traders. It is important to note that the volatility connectedness of 68.63% is still relatively high, indicating that the volatility movements of the different cryptocurrencies remain strongly related to each other.

On the other hand, the Ordinary Least Squares (OLS) with heteroscedasticity and autocorrelation corrected (HAC) standard errors result in Table 4.4 show that the geopolitical risks contribute to greater volatility connectedness of *BTC*, *ETH*, *ADA*, *DOGE*, and *XRP*. Apart from *GPR*, the volatility connectedness is also driven by participation in the cryptocurrency market (*AVEVOL*) as well as the returns in the cryptocurrency market (*AVERET*), indicating that the volatility connectedness of cryptocurrencies is more prone to be influenced by their own trading activities rather than economic events such as market sentiment (*VIX*), returns of the world's stock markets (*W_RETURN*), and movement in the energy markets (*E_RETURN*).

5.2 Implication

Risk management and diversification are crucial tools for investors of cryptocurrencies and portfolio managers to mitigate the risks associated with cryptocurrency investments. This paper had shown the cryptocurrency markets are highly volatile, and the value of cryptocurrencies can fluctuate rapidly, making them a high-risk investment. Due to this high volatility and interconnectedness of their volatilities, investing in multiple cryptocurrencies may not provide the level of diversification that one would expect from investing in different asset classes. Even if an investor holds multiple cryptocurrencies, they may still be exposed to similar risks and market factors that could impact the prices of all the cryptocurrencies they hold. Therefore, risk management techniques can help investors reduce their exposure to these risks.

One common risk management technique is diversification, which involves spreading investments across different types of assets, such as stocks, bonds, and cryptocurrencies, to reduce overall risk. By diversifying their investments, investors can reduce the impact of a single cryptocurrency's price movements on their overall portfolio. Moreover, based on the Table 4.2, the connectedness table for the five cryptocurrencies provides information of their connectedness index. This information can be used as a guide to anticipate the potential impact of one cryptocurrency on the volatility of another.

For example, if an investor is considering investing in Ethereum (*ETH*), they can look at the connectedness table to see that Bitcoin (*BTC*) is a strongly influencer to

Ethereum. This means that changes in the price of Bitcoin may impact the price of Ethereum as well. Therefore, an investor in Ethereum may want to keep an eye on Bitcoin as a guide for potential price movements in Ethereum. Similarly, if an investor is considering investing in Dogecoin (*DOGE*), they can look at the connectedness table to see that Cardano (*ADA*) is a strong spillover contributor to Dogecoin. This means that changes in the price of Cardano may impact the price of Dogecoin as well. Therefore, an investor in Dogecoin may want to keep an eye on Cardano as a guide for potential price movements in Dogecoin. In the case of *XRP*, the connectedness table shows that it is strongly influenced by both Bitcoin and Ethereum. This means that changes in the price of Bitcoin and Ethereum may impact the price of *XRP* as well. Therefore, an investor in *XRP* may want to keep an eye on both Bitcoin and Ethereum as guides for potential price movements in *XRP*. Finally, if an investor is considering investing in Cardano (*ADA*), they can look at the connectedness table to see that it is strongly influenced by both Bitcoin and Ethereum. Therefore, an investor in *ADA* may want to keep an eye on both Bitcoin and Ethereum as guides for potential price movements in *ADA*.

In terms of determinants, geopolitical events can have a significant impact on the cryptocurrency market as well. During periods of high geopolitical tensions, there is often increased uncertainty and risk, which can cause correlations between cryptocurrencies to increase. This means that previously uncorrelated cryptocurrencies may now move in the same direction, reducing the diversification benefits of holding a portfolio of multiple cryptocurrencies. For example, if there is a sudden increase in tensions between two countries, this could lead to a decline in the value of the fiat currencies of those countries. In turn, this could lead to an increase in demand for cryptocurrencies, as investors look for alternative stores of value. However, during such a period, the prices of different cryptocurrencies may become more closely correlated, reducing the benefits of diversifying across different cryptocurrencies.

Additionally, geopolitical events can also impact the regulatory environment surrounding cryptocurrencies. For example, China banned the trading of cryptocurrencies as most of the cryptocurrencies are pegged against the USD. Hence, banning the trading of these coins will then limit the outflow of capital from the Chinese economy. Therefore, during periods of high geopolitical tensions, it is important for cryptocurrency investors to carefully consider the risks and potential impacts on their portfolio. While diversification across multiple cryptocurrencies is still important, it may not provide the same level of protection as during periods of low uncertainty and risk. Investors should consider their risk tolerance, investment goals, and overall portfolio composition before making any decisions about investing in cryptocurrency.

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