The Hedging Effectiveness of Disruptive Technology ETFs to Asia Emerging Markets

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ความสามารถในการป้องกันความเสี่ยงของกองทุนรวมดัชนีหุ้นเทคโนโลยีต่อตลาดเกิดใหม่ในเอเชีย

นายธีรพงศ์ ธีระสรรพวิทยา

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This study examines the role of hedge and safe haven of four disruptive technology ETFs to six Asia emerging markets and assess whether if COVID-19 pandemic has altered the dynamic conditional correlations and hedge effectiveness between these assets. Using daily return data from February 23, 2018 to January 28, 2022, first, the results indicate that despite the outperformance of disruptive technology ETF's returns during COVID-19 pandemic, these ETFs do not have a hedge or safe haven property against Asia emerging market downturns as their returns were still positively correlated. They can only be used as diversifier tools to the Asia emerging markets. Second, the changes in the dynamic conditional correlations between the ETFs and Asia emerging markets were identified in which majority of the ETFs were found to have higher correlations with the emerging markets during COVID-19 period. This implies that the optimal hedge ratio or hedging cost between these assets were increased during the pandemic. Third, this study found that the disruptive technology ETFs can provide higher hedge effectiveness against Asia emerging markets during COVID-19 period than normal period due to shorting a unit of the ETF can reduce variance of the long-only portfolio in Asia emerging market by larger magnitude. Hence, these ETFs can be used as hedging tools to minimize the risk of Asia emerging market portfolio. This study provides insights for investors to formulate hedging strategies and determine portfolio diversification by thematic technology ETFs.

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1. Introduction

1.1 Background

Exchange-Traded Funds are the financial instruments to track index, sector, industry, or theme as closely as possible at the lowest possible cost. In recent years, there is a fast growing of specialized ETFs called "Thematic ETFs" that focus on investing in a specific theme or trend that is believed to have substantial improvement to life, society, environment and even governance. Unlike the traditional investing, thematic investments are unconstrained by geographies, sectors, and industries as they concentrate the investment into particular trends which are expected to have long-term growth and substantial impacts to the world. While the concept of thematic investment has been around for a while, their popularity and growth of asset under management for these ETFs have enormously increased in recent years. According to data from Bloomberg as of December 31, 2021, the total asset under management of thematic ETFs went up from $21 billion in five years ago to over $160 billion.

For decades, the diversification benefits in term of hedging ability between stock markets and a variety of assets have been long studied. Several research have focused and examined the hedge property of gold, bonds, REITs, global sector ETFs, or even Bitcoin in the normal times and during financial market turbulences (e.g., Baur & Lucey, 2010; Bana, Nedal, & Elie, 2020; Lucey, Akhtaruzzaman, Boubaker, & Sensoy, 2021; Jin, Han, Wu, & Zeng, 2020; Chemkha, Ahmed, Ahmed, & Tahar, 2021). Recently, with the amid of 4th industrial revolution, disruptive technologies such as cloud computing, artificial intelligence, robotics technology, cyber security, and financial technology have been major keys for the development of society and expansion of economy. They are expected to improve the efficiency of production capacity and data processes as well as changing the ways we live, work, and interact with each other (Melnyk et al., 2019). As a result, the disruptive technologies have become one of the mega trends for future investment and being considered as new investment opportunities by investors for hedging risks and optimizing portfolio diversification. The disruptive technology ETFs have been one of the fastest growth thematic ETFs with the largest AUM of $89.92 billion as of Q3, 2021 (Palandrani, 2021). Furthermore, the importance of disruptive technology had been heightened since the novel Coronavirus Disease outbreak COVID-19, originated in Wuhan, China. It has spread around the globe, was declared as global pandemic by World Health Organization on March 11, 2020. Throughout the pandemic period, many governments have been imposing the lockdown policies and travel restrictions to control the infections. the COVID-19 is still out of control. As of 17 January 2022, the COVID-19 pandemic had infected 326,279,424 cases with 5,536,609 cumulative deaths globally. The novel COVID-19 pandemic has created new challenges for businesses and human life. People have to adopt and integrate with technology in the way of working and living more than ever. With the lockdown and travel restriction imposed by governments around the world, the need for accessing online application platform and database has been rapidly increasing. This growth has emphasized the importance of Cloud Computing technology due to innovation and expansion in the area of cloud powered solutions to the not only information technology industry, but also education, healthcare, and many others which can help the industry to handle and synchronize data from different information systems and integrate as a to improve the quality of human life (Sharaf et al., 2021). Artificial Intelligence and robotics are also key technologies of the 4th industrial revolution. Hence, the investment in Artificial Intelligence have been growing very fast. In 2016, many developed companies spent around $18 to $27 billion for internal investment in AI-related projects, while venture capital investment in AI and robotics start-up companies were also increased by 40% from 2013 to 2016. The main aims for AI and robotics adoption are to improve operational efficiency, lower costs while improving quality of productions which can improve the overall country's output and economy subsequently (Webster & Ivanov, 2020). As the world becomes more digitally connected, the role of cyber security in life, business, and society has been amplified to ensure information is accurately and securely stored, transmitted, and proceeded. With the continuous development of innovative technology, security becomes even more concerned. Hence, the cybersecurity companies also must innovate new technologies to prevent cyber threats or mitigate the consequences if there is a breach of information to the lowest possible level . In addition, Financial Technology helps to transform traditional financial services by integrating innovative, user-friendly, automated applications and services to create more transparent and attract customers. It also has become one of the attractive investment choices for investors as traditional financial institutions also put more investments into Financial Technology firms (Le et al., 2021).

In addition, technology is also one of the key successes for emerging economies that can attract more foreign direct investment inflow and lead to economic expansion. In pursuance of advancement, emerging countries recognized the importance of technology and innovation adoption to reduce the economic gap between the developed and emerging countries. Hence, investment diversification from investors in emerging markets to technology businesses can help to reduce investment risks as well as to bring more development and improvement to their businesses and economies in the aggregate level (Borensztein, De Gregorio, & Lee, 1998; and Kayalvizhi & Thenmozhi, 2018).

Therefore, the AI and robotics, financial technology, cyber security, and cloud computing technology are interesting thematic investments which have potential growth in future and their investment have been growing rapidly, especially when these companies benefited largely from the COVID-19 pandemic period. However, the exploration of the investment diversification benefits from these disruptive technologies are still very limited. Previous studies on these technology thematic investments were done in comparison with only developed equity markets or across different asset classes such as commodities, cryptocurrencies or green bond (Huynh, Hille, & Nasir, 2020; Sercan, Hatice, & Selcuk, 2021; and Le, Emmanuel, & Aviral, 2021). In particular, the benefits of diversification in term of the optimal hedging ratio and hedge effectiveness of these disruptive technology ETFs to Asia emerging markets during financial market turbulences and COVID-19 pandemic have not been discovered yet.

1.2 Objectives and Research Hypothesis

This study aims to provide empirical evidence on diversification benefits and the role of disruptive technology ETFs as hedging tools for Asia emerging markets in period before and during COVID-19 pandemic with three main objectives and hypotheses as follows:

First, this study intends to examine the role of disruptive technology ETFs as a hedge or safe-haven asset to Asia emerging markets during extremely negative market return. As the disruptive technologies are essential for the improvement of production and expansion of economy and Asia emerging markets are lacking these companies (Kayalvizhi & Thenmozhi, 2018), investors in these countries can see the disruptive technology ETFs as new opportunities to hedge or diversify their portfolio. Furthermore, a study by Jin, Han, Wu, & Zeng (2020) reveals that technology stocks served as a better hedge for emerging markets during market turmoil. Thus, the first hypothesis is that the hedge or safe-haven property of disruptive technology ETFs should be observed in the times of extremely negative market returns. However, if it turns out that correlation between the ETFs and Asia emerging markets are positive and significant during extremely negative market movement, it may be due to "correlation breakdown phenomenon". It is a situation where there are structure changes in correlations between assets during extreme market turbulence and the correlations tend be greater than tranquil period and emerge to 1. This means that during such period, the assets in the markets tend to comove in the same direction with higher degree than usual (Gallegati, 2012).

Second, this study aims to analyze dynamic co-movement between disruptive technology thematic ETFs and Asia emerging stock market returns and compare the result before and during COVID-19 pandemic period. In particular, it investigates whether if the COVID-19 pandemic period has altered the time-varying correlation structure among these investments. Literatures studied on US and China stock markets found that technology stocks have recovered rapidly and managed to outperform markets and many other sectors during COVID-19 period (He, Sun, Zhang, & Li, 2020; and Mieszko, Man, & Miguel, 2021). In addition, many developed countries have released stimulus monetary and fiscal policies to stimulate economy, causing their stock markets surge up substantially. With a huge increase in disruptive technology stock returns while Asia emerging market returns can be seen to recover slower during COVID-19 period, the second hypothesis is that there should be a structure change in the dynamic conditional correlation between pre and during COVID-19 pandemic in which the lower dynamic conditional correlation between the disruptive technology ETFs and Asia emerging markets should be observed during COVID-19 period.

Third, this study intends to examine the optimal hedge ratio and hedge effectiveness of individual disruptive technology thematic ETF to each Asia emerging market in pre COVID-19 and during COVID-19 period. This is to further analyze the benefit of diversification from each pairwise assets and find the optimal hedge ratio to hedge against each market and whether if the hedge effectiveness of the disruptive technology ETFs to stock markets is higher during COVID-19. As the literature by Jin, Han, Wu, & Zeng (2020) suggested that the optimal hedge ratio and hedge effectiveness vary across time, and the hedge effectiveness of global sector ETFs such as financial, industrial, and technology sector to emerging markets are greater during subprime crisis and European debt crisis period than non-crisis period. The literature then concluded that global sector ETFs including global technology sector ETF preserved a better hedge for emerging markets during crisis period. However, the research on the hedge effectiveness of disruptive technology thematic ETFs to Asia emerging markets is undiscovered, especially during COVID-19 pandemic where the disruptive technology stocks have recovered and outperformed many other traditional sectors. Hence, the third hypothesis is that the higher hedge effectiveness of disruptive technology ETFs against Asia emerging markets should be observed during COVID-19 pandemic period.

1.3 Contribution

Due to very limited studies on disruptive technology thematic ETFs and most of the previous studies on the technology thematic investment only focused on diversification benefits in comparison with only developed stock markets and other asset classes such as MSCI USA, MSCI World, S&P500 index, gold, oil, bitcoin, and green bond (Huynh et al., 2020);(Le et al., 2021);(Sercan et al., 2021). To the best of my knowledge, none of the literature on technology-focus thematic investment has studied the dynamic correlation between individual technology thematic ETFs to Asia emerging markets as well as the hedging effectiveness and optimal hedge ratio across time periods, especially during the COVID-19 period where disruptive technology has benefited greatly from the government's lockdown and social distancing policies. To fill these gaps, this study provides three main following contributions.

First, as there have been several literatures studied on the role of diversifier, hedge and safe-haven property from various asset classes in relation to equity markets. For instance, gold, bonds, and Bitcoin have been concluded that they can serve as hedging tools for stock markets for most of the time and gold do serves as safe-haven in time of market turmoil (Baur & McDermott, 2010);(Baur & Lucey, 2010);(Chemkha et al., 2021);(Lucey et al., 2021). By examining the safe-haven and hedge property of the disruptive technology ETFs will provide an implication whether if disruptive technology thematic ETFs can be used to diversify and hedge against

Asia emerging markets. This study will benefit both foreign and local investors in term of new opportunities for hedging portfolio's risks and diversification benefits.

Second this study contributes to the existing studies on the diversification benefits of thematic investments in several ways by analyzing the dynamic conditional correlation and assess the optimal hedge ratio and hedge effectiveness of disruptive technology ETFs to Asia emerging stock market returns and compare the result before and during COVID-19 pandemic period. This will provide an evidence whether if the COVID-19 carry any implications for hedging effectiveness of these disruptive technology ETFs.

Third, as previous literatures on disruptive technology stocks were done in comparison with only developed stock markets, it lacks an empirical evidence on Asia emerging markets. There have been a number of research examined and concluded that diversification benefits from developed markets to emerging markets can lower risks and optimize portfolio returns due to their low correlations (Meriç et al., 2016); and (Christoffersen et al., 2014). This study examines the diversification benefit from disruptive technology ETFs, in which majority of constitutes are in developed markets to Asia emerging markets to see if the diversification between developed markets and emerging markets through disruptive technology ETFs can be more beneficial to investors during COVID-19 period. Moreover, as there may exist heterogeneity in the degree of a market's exposure to different themes, some Asia emerging markets may be severely affected by a certain theme than the others. This study helps to explore and measure which disruptive technology thematic investment is the best hedge instrument for each country. Thus, considering only one thematic investment like previous studies, may downplay the importance of thematic heterogeneity in portfolio risk management.

2. Literature Review

2.1 Diversification Benefits of Thematic Investments in Mixed Portfolio

Huynh et al. (2020) studied the role of Artificial Intelligence, Robotics stocks, green bonds, and cryptocurrencies in the portfolio diversification with traditional assets like, gold, oil, VIX index, MSCI USA and MSCI World using copulas tail dependence and Generalized Forecast Error Variance Decomposition to examine volatility connectedness. They found that in the time of market turmoil with extreme negative returns, holding a pair of these alternative investments have high probability of significant losses. This result is in align with the finding from Gallegati (2012) that an increase in cross-market linkages and correlations between stock markets is observed during market turbulence. Such phenomenon is called "correlation breakdown" where the movement of assets tend to go in the same direction during extreme market movements. This also means the international diversification benefit is potentially reduced when these benefits are needed the most.

Sercan et al. (2021) studied the interdependence between AI & Robotics stocks and traditional assets like S&P500 index, U.S. government and corporate bond, cryptocurrency index, and commodity index, employing wavelet coherence analysis in time-frequency space. They found that under unconditional correlation, the co-movement between assets can be substantially different across periods. For instance, the correlation between AI and corporate bond index is (-0.18) in pre-covid period but increase to 0.23 in post-covid period. They also concluded that in the long-time horizon, all assets tend to comove together, while in the short run there might be different correlation patterns among assets. Le et al. (2021) had examined the volatility connectedness and also found similar results that in the period of March 2020 where COVID-19 pandemic was announced, the total connectedness between Fintech stocks, MSCI World, MSCI USA, and Bitcoin were high. However, when the sample period was expanded to from 4 - 8 days to 30 days, the degrees of spillover effect of FinTech stocks to the equity markets and other asset classes are subsequently reduced. Hence, this study also confirmed that the volatility transmissions across assets is higher in the very short period after COVID-19 pandemic announcement and the effect is lessen in longer period.

In addition, a study on the performance comparison between disruptive technology thematic ETFs and S&P 500 index by Andersson (2021) found that during period from January 2015 to end of 2020, 11 out of 12 disruptive technology thematic ETFs can outperform S&P500 index in term of risk-adjusted returns based on Sharpe ratio, Jensen's Alpha, and Treynor ratio. When comparing risk-adjusted returns from the equally-weighted portfolio of disruptive technology thematic ETFs with S&P500 index, he also found the same conclusion. The thematic ETFs portfolio can outperform the market by far as its average annualized return is 20.16% p.a., compared with 10.34% p.a. of the S&P500 Index.

2.2 Hedge and Safe-haven Financial Instruments for Stock Markets

Baur & Lucey (2010) defined a safe-haven asset as "an asset that is uncorrelated with another asset or portfolio in times of market turmoil" and a hedge as "an asset that is uncorrelated or negatively correlated with another asset or portfolio on average". Baur & McDermott (2010) further classified a strong (weak) safe-haven asset "as an asset that is negatively correlated (uncorrelated) with another asset or portfolio in times of extremely falling stock markets" and a strong (weak) hedge "as an asset that is negatively correlated (uncorrelated) with another asset or portfolio on average". Several research have studied and examined the hedge or safe-haven property of numerous financial instruments to stock markets. Traditional asset like gold has been one of the most common assets to hedge the stock markets. Many literatures confirmed that gold preserves the hedge property for stock markets and can act as a safe haven during financial market turbulences (Baur & Lucey, 2010; Baur & McDermott, 2010). For emerging stock markets, Chkili (2016) also examined the relationship between gold and BRICS countries (Brazil, Russia, India, China, and South Africa) during global financial crisis and European debt crisis and suggested that gold can serve as a safe haven against extreme negative movements except for China and Brazil during European debt crisis; thus, the hedge and safe-haven property also varied across time. Similarly, Lucey, Akhtaruzzaman, Boubaker, & Sensoy (2021) had conducted dynamic conditional correlation between gold and USA, Europe, Japan, and China stock returns. They found that gold lost its safe haven property because the DCCs between gold and all markets turned positive during period March 17, 2020 to April 24, 2020 when governments intervened the markets with monetary and fiscal stimulus policies to curb with COVID-19 impacts. The hedging and safe-haven property of bonds have also been discussed in many literatures. Baur & Lucey (2009) examine flight-to-quality between stocks and bonds for eight developed countries. The results showed that the flight-to-quality from stocks to bonds existed in many crisies. Moreover, due to rapid growth of cyptocurrencies, many research also tested wether if these new investments can be a hedge or safe-haven for stock markets. For instance, Chemkha, Ahmed, Ahmed, & Tahar (2021) examined and compared the hedging and safe haven role of Bitcoin and gold to stock markets in period before and during COVID-19. The results showed that before COVID-19 pandemic, gold has higher hedge effectiveness to all markets in comparison with Bitcoin. However, during COVID-19 period, the hedge effectiveness of Bitcoin increased and became greater than the hedge effectivness of gold in every stock markets, which showed that Bitcoin seems to be a better hedging tool than gold in times of market turbulence. These results indicated that the COVID-19 pandemic also has an impact on dynamic correlation and hedge effectiveness of assets.

2.3 Diversification Benefits from Technology Stocks

There are numbers of studies on the linkages between technology stocks and oil prices and clean energy sectors. A study had used DECO-GARCH to examine dynamic correlation between these assets and found that DCC between oil and technology stocks varied from (-0.3) to (0.5) during December 2000 to June 26, 2017, which indicates portfolio diversification opportunities to investors. In addition, the correlation between these two assets also became negative (-0.2) in the time of global financial crisis. This enhances the hedging ability of technology to oil movement during market downturn. They also examine the time-varying hedging ratio among these assets and found that the hedge ratio of the pair of oil and technology stocks and the pair of clean energy stocks with technology stocks are more stable than the pair of oil and clean energy stocks. Hence using technology stocks to diversify these energy stocks provides a cheaper cost for rebalancing portfolio over the period (Samia et al., 2020).

Portfolio Diversification Benefit between different sector ETFs to developed markets and emerging markets has been one of the critical issues to investment world. Jin et al. (2020) studied on the portfolio optimization and hedge effectiveness of sectoral Global ETFs such as Financial, Industrial, Energy, and Technology Global ETFs to both developed and emerging markets by employing different multivariate GARCH models to construct the optimal portfolio and hedging ratio based on time-varying correlation. They found that the conditional correlation for all ETFs to emerging markets have been trending downwards after year 2012. The literature suggested that this could be due to the tapering of quantitative easing policy, causing selling-off stocks in emerging markets and shifting investment back to the developed markets. Furthermore, they also investigated the hedging effectiveness by following the model (Ku et al., 2007) to compare variance of unhedged portfolio with the hedged portfolio.

They found that during the full sample period from November 2007 to May 2018, the Global Financials ETF is the best hedge for the risk in the emerging markets as it has the largest average hedge effectiveness value among all the sector ETFs. Moreover, they also investigated the hedging effectiveness of sector ETFs to emerging markets in the crisis period of 2008 global financial crisis and 2010 – 2012 European Debt crisis. The finding is that global financial, industrial, and technology sector ETFs can provide more benefits as a hedging tool for emerging markets in the period of market turmoil. The reason is that they all have higher hedge effectiveness rate in crisis period than non-crisis period, indicating higher ability to hedge against emerging markets.

2.4 Technology Stocks with COVID-19 Pandemic Impact

Mieszko et al. (2021) studied the impact of COVID-19 pandemic to stock prices in S&P 1500 Index and found that during the market crash in March 2020 stock prices in technology, healthcare, and grocery sectors recovered very fast and can outperform other sectors such as petroleum, real estate, entertainment, hospitality sectors that were negatively affected by the COVID-19 pandemic. The reasons that technology sector performed well were because of remote working environment and social distancing. These are factors that triggered a large demand for information technology gadget, data servers, internet usage and online application platforms to facilitate and improve the quality of work and life. He et al. (2020) also studied the impact of COVID-19 to the stock returns across different sectors in Chinese stock markets and found that COVID-19 negatively impacted to most of traditional industries such as transportation, electricity, and mining, causing these stocks performed below market with negative excess return, whereas the high technology stocks can outperform the market. Despite its negative impact to economy, The COVID-19 pandemic created the investment opportunities for technology stocks. This finding is intensified when compare across multiple event window on and after the COVID-19 outbreak. The longer period after COVID-19 outbreak, the greater excess return high technology stocks generated. The excess return of information technology and manufacturing industries were always positive after COVID-19 outbreak, implying the immunity ability of these sectors against COVID-19 pandemic.

3. Data

I collected daily return data from Refinitiv DataStream for four disruptive technology ETFs and six Asia emerging markets for the period 23nd February 2018 to 28th January 2022. The main reason to start at 23nd February 2018 is that the inception date of ROBT ETF starts from this date. I selected ROBT ETF, SKYY ETF, FTEK ETF, CIBR ETF that are passively tracking NASDAQ CTA Artificial Intelligence and Robotics Index, The ISE CTA Cloud Computing Index, NASDAQ Financial Technology Index, and NASDAQ CTA Cybersecurity Index respectively. Table 1 represents the names and descriptions of disruptive technology ETFs for this study.

For the sample of Asia emerging markets, I follow the definition of Asia emerging markets from MSCI Asia emerging market index. I selected a total of six countries. The selected stock indices data include Shanghai Shenzhen CSI 300 Index (CSI 300 Index) for China, Jakarta Stock Exchange Composite Index (JCI Index) for Indonesia, Korea Stock Exchange KOSPI Index (KOSPI Index) for Korea, FTSE Bursa Malaysia KLCI Index (FBMKLCI Index) for Malaysia, Philippines Stock Exchange PSEi Index (PCOMP Index) for Philippines, and Stock Exchange of Thailand (SET Index) for Thailand.

In addition, I further divided the sample period into two sub-periods. “Pre COVID-19” period is from 23nd February 2018 to 10th March 2020, and “During COVID-19” period starts from 11th March 2020 to 28th January 2022 because the COVID-19 was announced as a global pandemic by World Health Organization on 11th March 2020.

3.1 Data Overview

Table 1: Description of Disruptive Technology ETFs

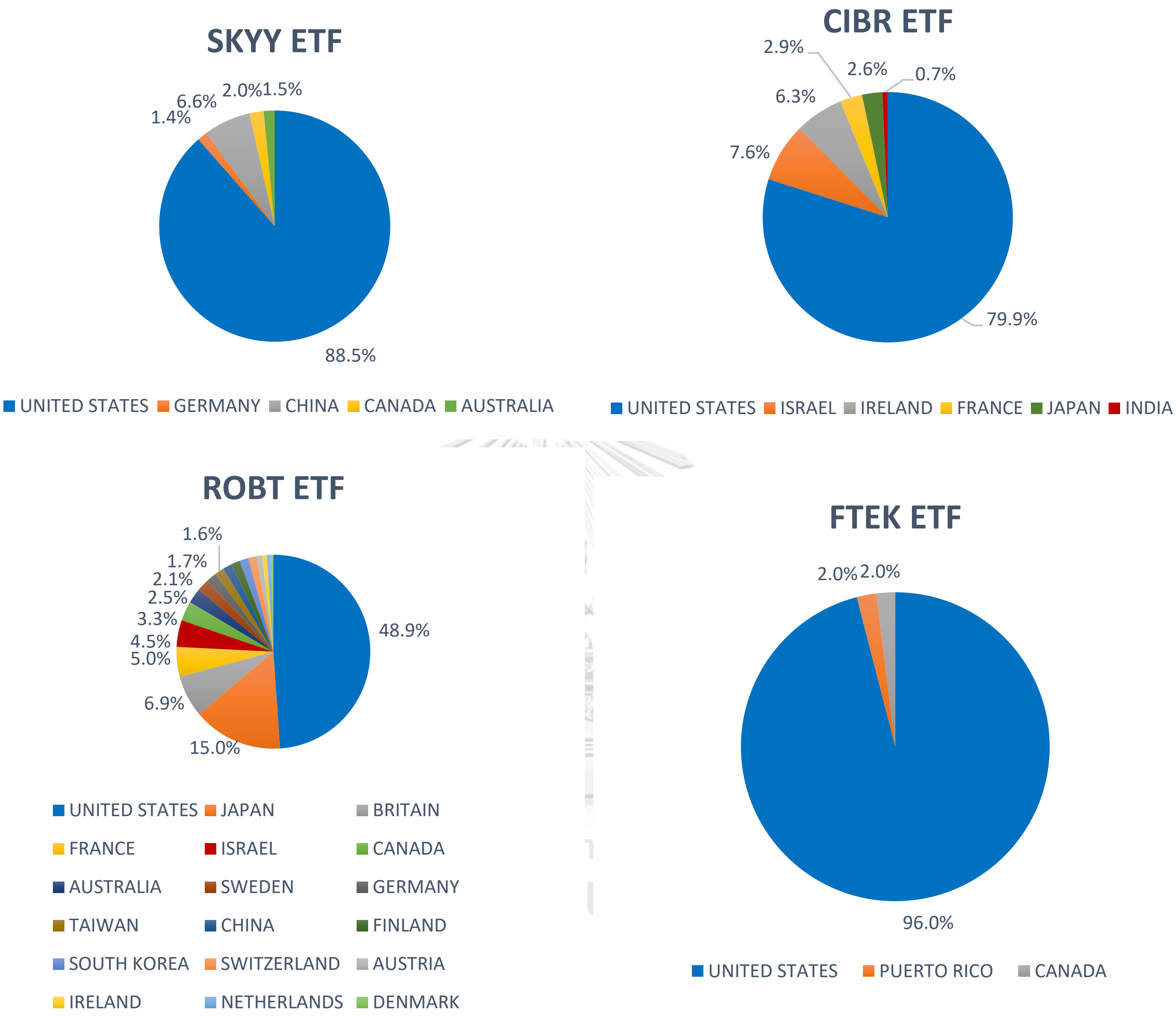
ETF Name	Description
The First Trust Nasdaq Artificial Intelligence and Robotics ETF (ROBT ETF)	It is designed to track the performance of companies engaged in Artificial intelligence (AI), robotics and automation including companies that develop advanced machinery, autonomous systems, self-driving vehicles, semiconductors, and databases used for machine learning or create and integrate programs, or products to AI and robotics.
The First Trust Cloud Computing ETF (SKYY ETF)	It is designed to track the performance of companies involved in the cloud computing industry, including companies that deliver cloud computing infrastructure - servers, storage, and networks as a service, or companies that deliver a service platform for the creation of software in the form of virtualization, or operating systems, and companies that deliver software applications over the Internet allowing other companies to conduct their operations using the application.
The Invesco KBW NASDAQ Fintech UCITS ETF (FTEK ETF)	It is designed to track the performance of companies that use technology to deliver financial products and services, such as payments, financial data, exchanges, internet banks, lending, or funding software.
The First Trust Nasdaq Cybersecurity ETF	It is designed to track the performance of companies that conducted business relating to cybersecurity. It includes companies involved in the building, implementation, and management of security

(CIBR ETF)	protocols applied to private and public networks, computers, and mobile devices in order to provide protection of the integrity of data and network operations.

3.2 Data Descriptive Analysis

Figure 1 represents the geographic breakdown of each disruptive technology ETFs in the sample. It shows that most of the stocks in ETF's baskets are listed in developed markets, especially in United States. The total weights in United States markets for SKYY ETF is 88.5%, 79.9% for CIBR ETF, 48.9% for ROBT ETF, and 96% for FTEK ETF. These market statistics support the notation that majority of stocks in the ETFs are located in developed markets and very little portion in Asia emerging markets. For SKYY ETF and ROBT ETF, there are 6.6% and 1.5% weights in China respectively.

Figure 1: ETFs Geographic Breakdown



Note: The fund constituents are based on market closed as of 18 January 2022.

Figure 2 shows the daily cumulative return for the disruptive technology ETFs and Asia emerging markets. It clearly shows that all four ETFs surged up and outperformed all Asia emerging markets during COVID-19 period. However, looking at the return alone does not take into account of the volatility or risk-adjusted returns on the assets. Hence, more statistical data is provided in table 2 and table 3 for readers to further analyze and compare across assets.

Figure 2: Daily cumulative net total return of disruptive technology ETFs and Asia emerging markets
Note: the daily return data is retrieved from DataStream for period 23 February 2018 to 28 January 2022

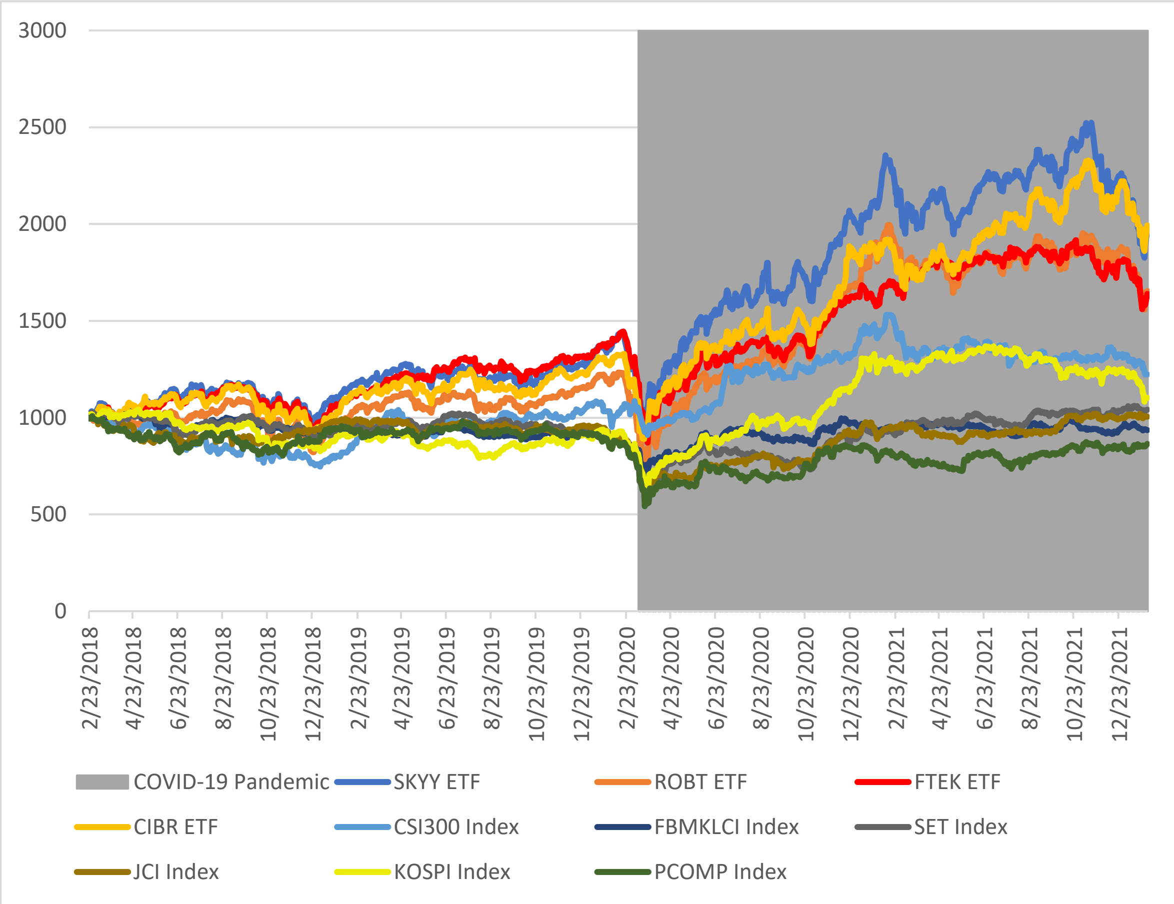


Table 2 represents the descriptive statistics of disruptive technology ETFs and Asia emerging markets. The risk-free rate used to compute the Sharpe ratio is from US treasury bill 3 months retrieved from Bloomberg Terminal. In the full sample period, CIBR ETF has the highest average daily return of 0.06% (15.20% p.a.) with 0.035 daily Sharpe ratio. While Philippines stock market (PCOMP Index) has the lowest average daily return of -0.035% (-8.86% p.a.) and -0.026 daily Sharpe ratio. When comparing the risk-adjusted returns, it shows that all of Asia emerging markets experience negative Sharpe ratio and all disruptive technology ETFs have positive Sharpe ratio. However, the volatility of the ETFs were also more fluctuated than Asia emerging markets. In the pre COVID-19, it can be seen that the returns of all disruptive technology ETFs are still positive, while the return of Asia emerging markets are negative. These differences are even more intensified during COVID-19 period. It is obvious that all of disruptive technology ETF returns outperform every Asia emerging market by further margin. During the period of COVID-19, CIBR ETF provides the highest average daily return of 0.098% (24.68% p.a.) with the highest daily Sharpe ratio of 0.051. Meanwhile, Philippines market provides the lowest daily return of -0.041% (-10.29% p.a.). This statistic data is in line with the literatures of He, Sun, Zhang, & Li (2020) and Mieszko, Man, & Miguel (2021) that technology can outperform markets and many sectors during COVID-19 period.

From the unconditional correlation matrix shown in table 3, it is noted that in the full sample period, the lowest correlations between disruptive technology ETFs and Asia emerging markets are CIBR ETF and Philippines market (0.123) and SKYY ETF and Philippines market (0.125) respectively. In the pre COVID-19 period, Philippines market has the lowest correlation with disruptive technology ETFs. Its correlation with SKYY ETF is (0.065), with CIBR ETF is (0.081), and with ROBT ETF is (0.142). It seems that in this period, Philippines’s stock market do not significantly comove with the disruptive technology stocks. During COVID-19 pandemic period, the lowest correlations are between CIBR and Philippines market (0.146), followed by the correlation with SKYY ETF (0.153). By analyzing these unconditional correlation matrices, it indicates that Philippines stocks have the weakest correlation with the disruptive technology ETFs. On average, these Asia emerging markets seems to have lower unconditional correlations with the disruptive technology ETFs during COVID-19 period. However, the conditional correlations extracted from DCC-GARCH model will be used to summarize whether if the stock markets and ETFs have higher or lower degree of co-movement between pre and during COVID-19 period.

Table 2: Descriptive Statistics of Disruptive Technology ETFs and Asia Emerging Markets

	SKYY ETF	ROBT ETF	FTEK ETF	CIBR ETF	CSI Index	FBMKLCI Index	SET Index	JCI Index	KOSPI Index	PCOMP Index
Full Period: (23 February 2018 to 28 January 2022)										
Daily Mean	0.042%	0.051%	0.037%	0.060%	-0.006%	-0.007%	-0.005%	-0.015%	0.001%	-0.035%
Daily Maximum	7.981%	9.209%	11.106%	7.899%	4.232%	3.275%	6.504%	9.704%	8.251%	7.172%
Daily Minimum	-11.586%	-12.619%	-10.423%	-10.572%	-8.209%	-5.300%	-11.384%	-6.805%	-8.767%	-14.322%
Daily Std. Dev.	1.696%	1.645%	1.460%	1.626%	1.309%	0.801%	1.192%	1.159%	1.184%	1.498%
Daily Sharpe Ratio	0.023	0.029	0.023	0.035	-0.007	-0.013	-0.007	-0.016	-0.002	-0.026
Annualized Mean	10.56%	12.90%	9.33%	15.20%	-1.41%	-1.83%	-1.17%	-3.89%	0.33%	-8.86%
Annualized Std Dev.	26.93%	26.12%	23.17%	25.81%	20.78%	12.72%	18.92%	18.40%	18.79%	23.79%
Pre COVID-19: (23 February 2018 to 10 March 2020)										
Daily Mean	0.030%	0.026%	0.032%	0.026%	-0.008%	-0.020%	-0.044%	-0.050%	-0.027%	-0.030%
Daily Maximum	4.172%	6.972%	3.118%	4.169%	4.232%	1.538%	2.927%	2.893%	2.837%	3.421%
Daily Minimum	-7.865%	-12.245%	-5.927%	-8.958%	-8.209%	-4.055%	-8.272%	-6.805%	-4.541%	-7.001%
Daily Std. Dev.	1.374%	1.433%	1.099%	1.398%	1.375%	0.657%	0.947%	0.981%	0.957%	1.153%
Daily Sharpe Ratio	0.020	0.016	0.026	0.016	-0.008	-0.036	-0.050	-0.054	-0.031	-0.029
Annualized Mean	7.62%	6.63%	8.05%	6.46%	-2.06%	-5.11%	-11.17%	-12.51%	-6.73%	-7.54%
Annualized Std Dev.	21.81%	22.75%	17.45%	22.20%	21.83%	10.43%	15.04%	15.57%	15.19%	18.30%
During COVID-19: (11 March 2020 to 28 January 2022)										
Daily Mean	0.055%	0.078%	0.043%	0.098%	-0.003%	0.007%	0.038%	0.022%	0.032%	-0.041%
Daily Maximum	7.981%	9.209%	11.106%	7.899%	3.112%	3.275%	6.504%	9.704%	8.251%	7.172%
Daily Minimum	-11.586%	-12.619%	-10.423%	-10.572%	-4.890%	-5.300%	-11.384%	-5.341%	-8.767%	-14.322%
Daily Std. Dev.	1.990%	1.850%	1.771%	1.843%	1.235%	0.934%	1.410%	1.326%	1.390%	1.802%
Daily Sharpe Ratio	0.026	0.041	0.022	0.051	-0.005	0.004	0.025	0.014	0.020	-0.024
Annualized Mean	13.76%	19.70%	10.72%	24.68%	-0.71%	1.73%	9.67%	5.47%	7.99%	-10.29%
Annualized Std Dev.	31.60%	29.37%	28.12%	29.25%	19.61%	14.82%	22.39%	21.06%	22.07%	28.60%

Table 3: Unconditional Correlation Matrices Between Disruptive Technology ETFs and Asia Emerging Markets

Full Period (23 Feb 2018 - 28 Jan 2022)										
	SKYY ETF	**ROBT ETF**	**FTEK ETF**	**CIBR ETF**	**CSI300 Index**	**FBMKLCI Index**	**SET Index**	**JCI Index**	**KOSPI Index**	**PCOMP Index**
SKYY ETF	1									
ROBT ETF	0.891	1								
FTEK ETF	0.463	0.577	1							
CIBR ETF	0.932	0.868	0.468	1						
CSI300 Index	0.224	0.286	0.278	0.202	1					
FBMKLCI Index	0.164	0.245	0.286	0.183	0.281	1				
SET Index	0.301	0.424	0.447	0.310	0.342	0.478	1			
JCI Index	0.214	0.287	0.276	0.220	0.279	0.402	0.421	1		
KOSPI Index	0.239	0.368	0.441	0.229	0.465	0.471	0.483	0.435	1	
PCOMP Index	0.125	0.171	0.194	0.123	0.211	0.441	0.441	0.504	0.418	1
Pre-COVID (23 Feb 2018 - 10 Mar 2020)										
	SKYY ETF	**ROBT ETF**	**FTEK ETF**	**CIBR ETF**	**CSI300 Index**	**FBMKLCI Index**	**SET Index**	**JCI Index**	**KOSPI Index**	**PCOMP Index**
SKYY ETF	1									
ROBT ETF	0.890	1								
FTEK ETF	0.576	0.611	1							
CIBR ETF	0.927	0.876	0.572	1						
CSI300 Index	0.237	0.303	0.336	0.213	1					
FBMKLCI Index	0.193	0.302	0.304	0.221	0.322	1				
SET Index	0.295	0.423	0.393	0.320	0.355	0.479	1			
JCI Index	0.249	0.323	0.285	0.255	0.278	0.458	0.435	1		
KOSPI Index	0.332	0.434	0.445	0.327	0.519	0.517	0.502	0.432	1	
PCOMP Index	0.065	0.142	0.203	0.081	0.239	0.478	0.427	0.454	0.444	1
During COVID (11 Mar 2020 - 28 Jan 2022)										
	SKYY ETF	**ROBT ETF**	**FTEK ETF**	**CIBR ETF**	**CSI300 Index**	**FBMKLCI Index**	**SET Index**	**JCI Index**	**KOSPI Index**	**PCOMP Index**
SKYY ETF	1									
ROBT ETF	0.893	1								
FTEK ETF	0.412	0.563	1							
CIBR ETF	0.937	0.863	0.419	1						
CSI300 Index	0.225	0.280	0.255	0.200	1					
FBMKLCI Index	0.149	0.211	0.278	0.160	0.261	1				
SET Index	0.304	0.426	0.472	0.305	0.352	0.477	1			
JCI Index	0.194	0.264	0.274	0.198	0.290	0.370	0.414	1		
KOSPI Index	0.191	0.330	0.440	0.173	0.445	0.446	0.473	0.436	1	
PCOMP Index	0.153	0.188	0.189	0.146	0.204	0.423	0.448	0.533	0.406	1

3.3 Stationery and Heteroscedasticity of Data

Unit Root Test

When analyzing time-series data, there must be a test for unit root or stationarity of data. If a time series has a unit root, it shows a systematic pattern that the data is unpredictable. If the data is non-stationary, the correlation between them can be spurious, which means that the statistical results of their correlation can have high R-squared even if they are uncorrelated. There are numbers of methods to test for stationary such as Dicky Fuller Test, Augmented Dicky Fuller Test (Dickey & Fuller, 1979), and KPSS test (Kwiatkowski et al., 1992). As the Augmented Dicky Fuller Test is one of the most common used methods, this study will employ the ADF test for unit root at level setting with no interception and use the Akaike's information criterion (ACI) to determine the optimal lag. After that, compare the ADF statistic result with critical value at 5%. If p-value is less than 0.05, the data is stationary.

The Augmented Dicky Fuller Test model is shown in equation (1) below.

$$Y_t = \alpha + \theta_1 t + \delta Y_{t-i} + \sum_i^n \beta_i Y_{t-i} + \varepsilon_t \tag{1}$$

Where:

Y_t is the logarithm of daily return from Asia emerging markets and disruptive technology ETFs; θ_1 is a slope coefficient on time trend t, and δ is the coefficient presenting process root.

The hypothesis for Augmented Dicky Fuller Test can be written as follow:

$H_0 : \delta = 0$

$H_1 : \delta < 0$

If it is failed to reject H_0 at 5% significant level, it means that the data Y_t is non-stationary. If reject H_0 at 5% significant level, it means that the data is stationary, and no unit root exists.

ARCH Effect Test

Before estimating the DCC-GARCH model, the ARCH effect test is performed to confirm heteroscedasticity of the all daily return series. The test is conducted by Lagrange Multiplier (LM) statistics with 1st order ARCH effects. The null hypothesis is “there is no ARCH Effect”. If the p-value is less than 10% significance level, it means that there is ARCH effect in the data.

From the table 4, The results of diagnostic checks on all of the daily return series reveal that all the return series have no unit root and are stationary at level. The ARCH effects are also presented at 10%, 5%, 1% significance level. Therefore, the data can be further proceeded and analyzed with DCC-GARCH model.

Table 4: Unit Root Test and ARCH Effect Test

Unit Root Test and ARCH Effect Test						
	Full Period		Pre COVID-19		During COVID-19	
	ADF	ARCH	ADF	ARCH	ADF	ARCH
SKYY ETF	-12.832***	73.633***	-8.952***	17.689***	-20.295***	34.749***
ROBT ETF	-7.366***	36.525***	-6.702***	20.75***	-20.343***	20.095***
FTEK ETF	-12.286***	40.778***	-16.791***	33.906***	-16.489***	32.503***
CIBR ETF	-12.302***	56.332***	-7.008***	7.352***	-19.603***	35.638***
CSI Index	-27.509***	6.596**	-10.556***	5.644***	-19.121***	11.714***
FBMKLCI Index	-16.792***	74.560***	-4.860***	2.670*	-7.434***	50.298***
SET Index	-6.898***	86.812***	-4.468***	6.133**	-11.365***	10.005*
JCI Index	-6.045***	33.071***	-7.506***	24.558***	-10.378***	17.242***
KOSPI Index	-5.413***	89.213***	-12.058***	10.877**	-17.857***	51.1289***
PCOMP Index	-5.652***	30.619***	-4.845***	52.699***	-12.270***	19.082***

Note: For the unit root test using Augmented-Dickey Fuller test, the numbers in the table represent t-statistic values and if absolute t-statistic value is greater than critical value, the data is stationary. Critical value are -2.571 at 1% significance level, -1.941 at 5% significance level, -1.616 at 1% significance level respectively. The ARCH effect test displays the LM statistics with 1^{st} order of ARCH effects. ***, **, and * denote statistical significance level at 1%, 5%, 10% respectively.

4. Methodology

To assess and examine the role of diversifier, hedge and safe haven, the dynamic correlation, the optimal hedge ratio, and hedge effectiveness from disruptive technology thematic ETFs to Asia emerging markets across sample periods, several steps are applied as follows.

4.1 The Diversifier, Hedge, Safe-Haven Property of Disruptive Technology ETFs

To test whether the disruptive technology ETFs possess a hedge, safe-haven, or diversifier property in comparison to Asia emerging stock markets, I followed the approach used by Baur & McDermott (2010) and Chen & Wang (2019). Equation (2), (2a), (2b) presents the regression model to analyze the correlation between disruptive technology ETFs and Asia emerging markets. To control for heteroscadasticity in the data, the conditional variance is modeled by GARCH (1,1). This approach measures the correlation between the ETFs and stock markets by measuring the sensitivity between the ETF's returns with stock market returns during extremely negative stock market return in the 5th, and 1st percentiles of stock return distribution.

$$r_{ETF,t} = a + b_t r_{stock,t} + e_t \tag{2}$$

$$b_t = c_0 + c_1 D(r_{stockq5}) + c_2 D(r_{stockq1}) \tag{2a}$$

$$h_{ii,t} = \beta_{i,0} + \beta_{i,1} h_{ii,t-1} + \beta_{i,2} \varepsilon^2_{i,t-1} \tag{2b}$$

Where Equation 2 shows the relation of the ETF returns and stock market returns. The parameters to be estimated are c_0, c_1, and c_2. The error term is estimated by e_t. The parameter $b_t$is modelled and estimated by equation (2a). The terms$D(r_{stockq5})$ and $D(r_{stockq1})$ represent dummy variables equal to 1 if the returns are in the 5th and 1st of the extremely negative return distribution and 0 otherwise.

The parameter c_0 measures the hedge property of the disruptive technology ETF to stock market. If the sum of the parameters c_1 and c_2 are not jointly positive exceeding the value of c_0 and parameter c_0 is statistically negative, the ETF is considered a strong hedge. If c_0 is equal to zero and the sum of c_1 and c_2 are not jointly positive exceeding the value of c_0, the ETF is considered a weak hedge. However, if c_0 is significantly positive, the ETF can only be a diversifier to stock portfolios.

The parameter c_1 and c_2 measure the sensitivity of ETFs returns to stock market's returns during extremely negative stock market returns at 5% and 1% quantile of return distribution. If the sum of parameters at each quantile that is, the sum of c_0 and c_1 for the 5% quantile is positive and significant at 1%, 5%, 10% level, the disruptive technology ETF cannot act as safe-haven for stock markets. However, if the value is statistically negative, the ETF has a safe-haven property to the stock market.

4.2 The Dynamic Conditional Correlation Between the Disruptive Technology ETFs and Asia Emerging Markets

Several studies in correlation and diversification benefits have used the multivariate dynamic conditional correlation (DCC-GARCH) model of (Engle, 2002) to assess the time-varying correlations between assets and construct hedging strategies in different timeframe (Chang et al., 2011); and (Bouri et al., 2017). Due to its simplicity and widely used, this study will employ the DCC-GARCH model to investigate the dynamic correlations between daily return of disruptive technology ETFs and each Asia emerging market to see whether they are stable over time or have a change in correlation structure during COVID-19 period and used the dynamic correlations to find the optimal hedge ratio and hedge effectiveness for each pair of the ETF and Asia emerging market. The DCC-GARCH model is computed by two steps. First, the univariate GARCH model for each time series of return is estimated to obtain a time-varying standard deviation matrix and standardized residuals. In the second step, the conditional covariance matrix is estimated by using the estimated time series of return from first step, then the dynamic conditional correlations will be obtained.

The DCC-GARCH Model

First step, to estimate univariate GARCH model for time series of return, let r_t and $h_{ii,t}$ in Equation 3 and 4 be the returns and conditional variances of a pair of assets such as SKYY ETF and Asia emerging stock market to be tested at time t. Adding five lags in autoregressive process in return equation to take into account of the day-of-the-week effect. The univariate GARCH (1,1) model is applied where I_{t-1} is the information set at time t–1.

$$r_t = \mu + \Sigma_{p=1}^{5} a_{i,p} r_{i,t-p} + \varepsilon_t \tag{3}$$

$$h_{ii,t} = \beta_{i,0} + \beta_{i,1} h_{ii,t-1} + \beta_{i,2} \varepsilon_{i,t-1}^2 \tag{4}$$

$$\varepsilon_t | I_{t-1} \sim N(0, h_t)$$

In the second step, the conditional covariance matrix is estimated in Equation 5. H_t is an n×n time-varying conditional covariance matrix. In Equation 6, D_t is a diagonal matrix with time-varying standard deviations on the diagonal, obtained from the estimation of univariate GARCH.

$$H_t = D_t R_t D_t \tag{5}$$

$$D_t = diag\{\sqrt{h_{ii,t}}\} \tag{6}$$

$$R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \tag{7}$$

$$z_{i.t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}} \tag{8}$$

R_t in Equation 7 is the time-varying conditional correlation matrix that is formed by the standardized residuals $z_{i,t}$ shown in Equation 8. The $z_{i,t}$ are estimated from univariate GARCH model. Equation 9 represents the process

$$Q_t = (1 - a - b)Q_0 + az_{t-1}z'_{t-1} + bQ_{t-1} \quad (9)$$

where $Q_t = (q_{ii,t})$ is an n×n time-varying covariance matrix of standardized residuals (z_t) and Q_0 represents the unconditional variance matrix of standardized residuals z_t. The non-negative scalar parameters a and b are used to construct the dynamic conditional correlations with a sum of less than unity. a and b capture the effects of the previous shocks and the previous conditional correlation on the current conditional correlation respectively (Jin et al., 2020).

Under DCC-GARCH model, the time-varying correlation $\rho_{ij,t}$ is modelled in Equation 10 as follows.

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii.t}q_{jj,t}}} \quad (10)$$

Where $q_{ij,t}$ is covariance between the return of asset i and return of asset j at time t. $q_{ij,t}$ is the variance of asset i and $q_{jj,t}$ is the variance of asset j at time t.

After the time-varying correlations between each pair of disruptive technology ETF and Asia emerging market are obtained from DCC-GARCH model, the dynamic conditional correlations will be used to examine if there are statistical results showing higher or lower correlations between disruptive technology ETFs and Asia emerging markets during COVID-19 period as well as to find the optimal hedge ratio and hedge effectiveness across pre and during COVID-19 period.

4.3 The Potential Changes in Dynamic Correlation Coefficients Between Disruptive Technology ETFs and Asia Emerging Markets

In order to test the second hypothesis whether if the dynamic conditional correlations between disruptive technology ETF and Asia emerging market becomes lower during COVID-19 period, I construct a dummy variable D_1 equal to 1 if the period is in COVID-19 pandemic or 0 otherwise.

$$DCC_{ij,t} = \alpha + \beta_0 DCC_{ij,t-1} + \beta_1 D_1 + \varepsilon_{ij,t} \quad (11)$$

In Equation 11, $DCC_{ij,t}$ is the DCC between each pair of disruptive ETF and Asia emerging market obtained from Equation (10). α captures the additional sensitivity in period before COVID-19 period and β_0 is the coefficient of first lag of dynamic conditional correlation. β_1 captures the additional sensitivity during COVID-19 period. If β_1 is statistically positive at 10%, 5%, 1% significance level, it indicates that the dynamic conditional correlation between the ETF and Asia emerging market increases during COVID-19 period. However, if β_1 is negative and statistically significant at 10%, 5%, 1% level indicating that the correlations between these pair of assets become lower during COVID-19 period.

4.4 The Optimal Hedge Ratio and Hedge Effectiveness Between Disruptive Technology ETFs and Asia Emerging Markets

As we assume investors and market participants are risk-averse, they seek to minimize the risk of portfolio. To examine the third hypothesis whether if the time-varying hedge effectiveness of disruptive technology ETFs against Asia emerging market is greater during COVID-19 period than in pre COVID-19 period, there are three main steps involved.

First, this study adopted the optimal hedge ratio (HR) strategy based on multivariate GARCH model as defined by Kroner & Sultan (1993) to investigate the time-varying optimal hedge ratio between disruptive technology ETFs to Asia emerging markets in pre COVID-19 period and during COVID-19 period. Equation 12 presents a model to calculate time-varying optimal hedge ratio.

$$\beta_t^{i/(ETF)} = \frac{cov(R_{country,t}, R_{ETF,t})}{var(R_{ETF,t})} \tag{12}$$

Where $\beta_t^{i/(ETF)}$ is the daily optimal hedging ratio at time t. To minimize the risk of portfolio of two assets, a long position of one dollar in an Asia emerging market could be hedged by a short position $\beta_t^{i/(ETF)}$ dollars in the disruptive technology ETF. The lower hedge ratio means that in order to minimize the portfolio risk, it requires lower amount of another asset to hedge the risk. The variable $cov(R_{country,t}, R_{ETF,t})$ is the conditional covariance between each disruptive technology ETF and Asia emerging market daily returns at time t. While the $var(R_{ETF,t})$ is the conditional variance of each disruptive technology ETF at time t. These variance and covariance of the assets can be obtained from the DCC-GARCH model.

Second step, to measure and compare the performance of hedging strategies, I follow Ku, Chen, & Chen (2007) and Chang, McAleer, & Tansuchat (2011) methods to compare the daily variance of the hedged portfolio with the daily variance of the unhedged portfolio and calculate the hedging effectiveness (HE) value as shown in Equation 13.

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \quad (13)$$

Where var_{hedged} is the daily variance of hedged portfolio and $var_{unhedged}$ is the daily variance of unhedged portfolio. Equation 14 represent the method to calculate the variance of hedged portfolio by using the optimal hedge ratio $\beta_t^{i/(ETF)}$ obtained from Equation 12.

$$var(r_{h,t}) = var(r_{i,t}) - 2\beta_t^{i/(ETF)} cov(r_{ETF,t}, r_{i,t}) + (\beta_t^{i/(ETF)})^2 var(r_{ETF,t}) \quad (14)$$

Where $r_{h,t}$ is the daily hedged portfolio return; $r_{ETF,t}$ is daily disruptive technology ETF return and $r_{i,t}$ is the daily Asia emerging market return. The unhedged portfolio includes only a long position of one dollar in an Asia emerging market. While the hedged portfolio includes a long position of one dollar in an Asia emerging market and a short position of $\beta_t^{i/(ETF)}$ dollars in a disruptive technology ETF. The larger HE values, the better hedge effectiveness of disruptive technology ETF to the Asia emerging market.

Third step, after obtaining the hedge effectiveness from each pair of the disruptive ETF and Asia emerging market in pre COVID-19 and during COVID-19, use Equation 15 to compare the hedge effectiveness value between pre COVID-19 period and during COVID-19 period to find if the hedge effectiveness during COVID-19 is greater than the one in pre COVID-19 period.

$$\Delta \mathrm{HE} = \mathrm{HE}_{\mathrm{DuringCovid}} - \mathrm{HE}_{\mathrm{PreCovid}} \quad (15)$$

If ΔHE is positive value, it implies that the disruptive technology ETF can provide more hedge effectiveness to the Asia emerging stock market during COVID-19 period.

5. Empirical Results

5.1 The Diversifier, Safe-Haven, and Hedge Property of Disruptive Technology ETFs

In this section, we provided empirical evidence whether if the disruptive technology ETF is a diversifier, safe-haven or hedge during 5% and 1% quantile of extreme negative returns of Asia emerging markets. Table 5 displays the estimated results of the equation (2), (2a), (2b) respectively. The finding shows that for almost every pair of the disruptive technology ETF and Asia emerging market, the parameter c_0 is statistically positive at 10%, 5%, 1% significance level. This suggests that the ETFs cannot act as a hedge against the stock markets. Although there are some exceptions found negative c_0 on the pair of PCOMP index and three ETFs which are CIBR ETF, ROBT ETF, and SKYY ETF, the sum of parameter c_1 and c_2 for these three pairwise assets still jointly exceed c_0. According to the methodology suggested by Baur & McDermott (2010), it means their hedge properties also do not hold. Therefore, it can be concluded that all disruptive technology ETFs do not have hedge property against Asia emerging markets.

In addition, the Wald test results for most of the pairwise assets indicate that the sum of parameters at 5% and 1% quantile of extremely negative returns are statistically positive and significant at 10%, 5%, and 1% level. It implies that the return of disruptive technology ETFs moves in the same direction as Asia emerging stock markets during period of extreme negative market return. Although the Wald test result at 1% quantile of negative return for the pair of FBMKLCI index with FTEK ETF and CSI300 index with SKYY ETF are negative, the results are not statistically significant.

Therefore, it can be concluded that despite the outperformance of disruptive technology stocks during COVID-19 period, none of the ETF possesses the hedge or safe haven to Asia emerging markets. They can be just diversifier tools to the stock markets. This result is aligned with the finding from Huynh, Hille, and Nasir (2020) and Sercan, Hatice, and Selcuk (2021) and Le, Emmanuel, and Aviral (2021) that artificial intelligence, robotic and fintech stocks positively comove with the equity markets and combining these technology stocks in an equity portfolio can experience large joint loss during the time of market turburence.

Table 5: Empirical Results for Diversifier, Hedge, Safe-Haven Property of Disruptive Technology ETFs

	c_0	c_1	c_2		
	Hedge	**5% quantile**	**1% quantile**	**Wald Test**	
		CIBR ETF			
	0.1307***	-0.083	0.0021		
CSI300 Index	(2.9859)	(-0.9718)	(0.0225)	ΣCi (1%)	0.0498
				ΣCi (5%)	0.0477
	0.2225***	-0.1045	0.0855		
FBMKLCI Index	(3.2998)	(-0.7373)	(0.5966)	ΣCi (1%)	0.2035**
				ΣCi (5%)	0.118
	0.1122*	-0.1120	0.6015***		
JCI Index	(1.8212)	(-0.8804)	(3.7290)	ΣCi (1%)	0.6014***
				ΣCi (5%)	0.0002
	0.1514***	0.1421	0.1425		
KOSPI Index	(2.9231)	(1.5167)	(0.9508)	ΣCi (1%)	0.4359***
				ΣCi (5%)	0.2935***
	-0.0384	0.1957**	0.153		
PCOMP Index	(-0.9219)	(2.1534)	(1.3670)	ΣCi (1%)	0.3103***
				ΣCi (5%)	0.1573*
	0.2362***	-0.0712	0.3525**		
SET Index	(3.9280)	(-0.4532)	(2.2739)	ΣCi (1%)	0.5175***
				ΣCi (5%)	0.165
		FTEK ETF			
	0.2411***	-0.1816**	0.0225		
CSI300 Index	(6.9796)	(-2.4474)	(0.2880)	ΣCi (1%)	0.082**
				ΣCi (5%)	0.0595
	0.267***	0.008	-0.3088**		
FBMKLCI Index	(4.1108)	(0.0680)	(-2.4506)	ΣCi (1%)	-0.0337
				ΣCi (5%)	0.2751***
	0.1623***	0.0496	0.1476		
JCI Index	(3.3026)	(0.6286)	(1.2778)	ΣCi (1%)	0.3595***
				ΣCi (5%)	0.2119***
	0.3127***	0.0152	0.3064**		
KOSPI Index	(6.9994)	(0.2239)	(2.2540)	ΣCi (1%)	0.6342***
				ΣCi (5%)	0.3278***
	0.0586	-0.0125	0.4668***		
PCOMP Index	(1.4785)	(-0.1641)	(5.7772)	ΣCi (1%)	0.5129***
				ΣCi (5%)	0.0461
	0.363***	0.0292	-0.045		
SET Index	(8.1113)	(0.2622)	(-0.4155)	ΣCi (1%)	0.3473***
				ΣCi (5%)	0.3922***

Table 5: Empirical Results for Diversifier, Hedge, Safe-Haven Property of Disruptive Technology ETFs

	c_0	c_1	c_2		
	Hedge	**5% quantile**	**1% quantile**	**Wald Test**	
		ROBT ETF			
	0.2539***	-0.0634	-0.1505*		
CSI300 Index	(6.4513)	(-0.7303)	(-1.6681)	ΣCi (1%)	0.04
				ΣCi (5%)	0.1905**
FBMKLCI	0.2736***	0.005	-0.0891		
Index	(3.9108)	(0.0419)	(-0.7886)	ΣCi (1%)	0.1895**
				ΣCi (5%)	0.2786***
	0.1513**	-0.0585	0.5828***		
JCI Index	(2.5698)	(-0.5597)	(5.4442)	ΣCi (1%)	0.6756***
				ΣCi (5%)	0.0928
	0.3826***	-0.0207	0.3282**		
KOSPI Index	(8.8232)	(-0.2941)	(2.5458)	ΣCi (1%)	0.6901***
				ΣCi (5%)	0.3619***
	-0.0246	0.1527*	0.3823***		
PCOMP Index	(-0.5598)	(1.7648)	(3.8036)	ΣCi (1%)	0.5104***
				ΣCi (5%)	0.1281*
	0.3248***	0.0895	0.0897		
SET Index	(6.5335)	(0.6649)	(0.6772)	ΣCi (1%)	0.504***
				ΣCi (5%)	0.4143***
		SKYY ETF			
	0.1746***	-0.0637	-0.1731*		
CSI300 Index	(4.3682)	(-0.7185)	(-1.8933)	ΣCi (1%)	-0.0622
				ΣCi (5%)	0.1109
FBMKLCI	0.1286*	0.091	-0.1496		
Index	(1.8178)	(0.7242)	(-0.9934)	ΣCi (1%)	0.07
				ΣCi (5%)	0.2195**
	0.0594	-0.0314	0.5904***		
JCI Index	(0.9993)	(-0.2456)	(2.6977)	ΣCi (1%)	0.6183***
				ΣCi (5%)	0.0279
	0.1971***	0.0391	0.1423		
KOSPI Index	(3.6696)	(0.3948)	(0.7891)	ΣCi (1%)	0.3784**
				ΣCi (5%)	0.2362***
	-0.0867**	0.266**	0.1503		
PCOMP Index	(-2.1344)	(2.5469)	(1.0453)	ΣCi (1%)	0.3296***
				ΣCi (5%)	0.1792*
	0.2091***	-0.0226	0.2175		
SET Index	(3.9030)	(-0.1605)	(1.5078)	ΣCi (1%)	0.404***
				ΣCi (5%)	0.1865

Note: Estimated results from equation:

$$r_{ETF,t} = a + b_t r_{stock,t} + e_t \quad (2)$$

$$b_t = c_0 + c_1 D(r_{stockq5}) + c_2 D(r_{stockq1}) \quad (2a)$$

$$h_{ii,t} = \beta_{i,0} + \beta_{i,1} h_{ii,t-1} + \beta_{i,2} \varepsilon_{i,t-1}^2 \quad (2b)$$

Wald test for 5% and 1% quantile is computed as the sum of parameter c_0 and c_1, and c_0, c_1, and c_2 respectively. The numbers in parenthesis are t-statistic. *, **, *** denote statistical significance level at 1%, 5%, 10% respectively.

5.2 The Dynamic Conditional Correlations Between the Disruptive Technology ETFs and Asia Emerging Markets

Table 6 presents descriptive statistics of the dynamic conditional correlations between the disruptive technology ETFs and Asia emerging markets. This result is in line with the unconditional correlations in table 3 and the empirical results in section 5.1 whereby the daily dynamic conditional correlations between disruptive technology

ETFs and Asia emerging markets are positive on average. It helps to confirm that the disruptive technology ETFs do not possess hedge or safe haven properties to Asia emerging markets in any periods. Figure 3 also displays the graph of dynamic conditional correlations between the ETFs and Asia emerging markets with the shaded highlight denoted for COVID-19 period. It is clearly seen that on average the dynamic conditional correlations between country indexes and ETFs are positive throughout the full period. Their correlations significantly increased during a few weeks after WHO announced the COVID-19 virus as a global pandemic. These graphs did well in representing the correlation breakdown phenomenon between the disruptive technology ETFs and Asia emerging markets. Their correlations were generally 0.1 to 0.3 in tranquil period, but they emerged closed to 0.5 to 0.6 during the time of market uncertainty. This study also found that the correlations between disruptive technology ETFs are considerably high especially between SKYY ETF, ROBT ETF, and CIBR ETF. Their correlations were between 0.6 to 0.95. Meanwhile, it is noted that the correlation between FTEK ETF and the other ETFs are lower at the range of 0.3 to 0.75, and this implies that financial technology ETF had some different movements from other disruptive technology thematic.

Despite their positive average correlations, the table 6 also shows that there are few circumstances that the negative correlations between ETFs and Asia emerging markets may occur. In full period, there were cases where the dynamic conditional correlations between SKYY ETF and CSI300 Index, FBMKLCI Index, JCI Index, PCOMP Index went negative. This means that there were times where these two assets moved in opposite directions. However, these events happened in very short period and their correlations quickly reverted to positive again. This phenomenon is known as correlation breakdown where the correlations between assets are extremely and jointly high in short period, especially during crisis period (Gallegati, 2012).

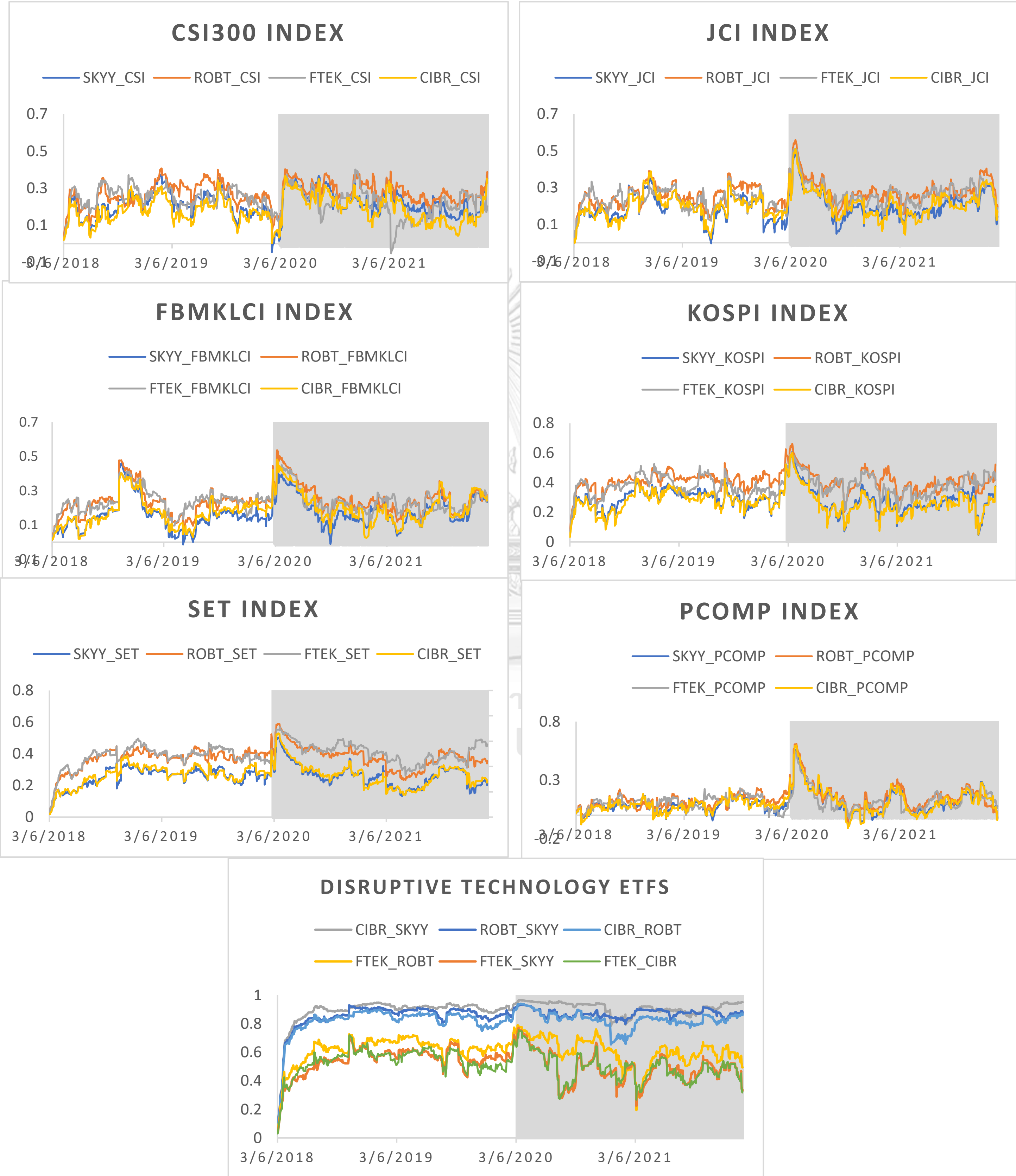
Furthermore, when comparing the volatility of dynamic conditional correlations between each pair, it indicates that most of the pairwise assets experience an increase in dynamic conditional correlation’s volatility, in which it means that their correlations become more volatile during the COVID-19 period. Hence to minimize the portfolio’s volatility, the hedging strategies between the assets need to be cautiously and wisely implemented.

Table 6: Analysis of Dynamic Conditional Correlations

	Full Period						Pre COVID-19 Period						During COVID-19 Period					
	CSI300	FBMKLCI	JCI	KOSPI	PCOMP	SET	CSI300	FBMKLCI	JCI	KOSPI	PCOMP	SET	CSI300	FBMKLCI	JCI	KOSPI	PCOMP	SET
CIBR ETF																		
Mean	0.184	0.188	0.206	0.268	0.107	0.265	0.171	0.176	0.197	0.281	0.087	0.267	0.168	0.202	0.216	0.254	0.128	0.263
Median	0.176	0.178	0.201	0.266	0.093	0.271	0.172	0.175	0.195	0.286	0.082	0.277	0.169	0.182	0.207	0.247	0.113	0.263
Maximum	0.366	0.482	0.512	0.602	0.598	0.529	0.343	0.476	0.458	0.541	0.518	0.450	0.366	0.482	0.512	0.602	0.598	0.529
Minimum	0.003	0.013	-0.001	0.034	-0.110	0.018	0.003	0.013	-0.001	0.034	-0.080	0.018	0.042	0.024	0.044	0.050	-0.110	0.139
Std. Dev.	0.071	0.089	0.075	0.083	0.097	0.072	0.065	0.086	0.071	0.076	0.059	0.068	0.076	0.089	0.078	0.088	0.121	0.077
FTEK ETF																		
Mean	0.231	0.238	0.249	0.380	0.120	0.393	0.245	0.240	0.233	0.377	0.108	0.377	0.217	0.235	0.267	0.382	0.132	0.410
Median	0.240	0.234	0.250	0.378	0.112	0.400	0.251	0.240	0.235	0.375	0.113	0.391	0.223	0.222	0.261	0.381	0.110	0.414
Maximum	0.401	0.450	0.512	0.586	0.550	0.569	0.371	0.431	0.498	0.586	0.418	0.497	0.401	0.450	0.512	0.585	0.550	0.569
Minimum	-0.053	0.016	0.024	0.045	-0.077	0.025	0.020	0.016	0.024	0.045	-0.077	0.025	-0.053	0.086	0.140	0.200	-0.029	0.263
Std. Dev.	0.073	0.070	0.064	0.074	0.083	0.070	0.060	0.070	0.059	0.073	0.059	0.074	0.082	0.070	0.065	0.074	0.101	0.062
ROBT ETF																		
Mean	0.273	0.243	0.266	0.410	0.141	0.373	0.296	0.235	0.251	0.413	0.123	0.368	0.286	0.251	0.282	0.406	0.160	0.378
Median	0.268	0.236	0.264	0.411	0.128	0.387	0.294	0.235	0.253	0.418	0.117	0.388	0.276	0.240	0.268	0.399	0.143	0.380
Maximum	0.407	0.536	0.560	0.662	0.611	0.591	0.407	0.529	0.518	0.625	0.567	0.538	0.402	0.536	0.560	0.662	0.611	0.591
Minimum	0.027	0.017	0.026	0.050	-0.059	0.026	0.027	0.017	0.026	0.050	-0.034	0.026	0.168	0.085	0.119	0.201	-0.059	0.233
Std. Dev.	0.064	0.083	0.069	0.070	0.092	0.073	0.071	0.084	0.065	0.066	0.060	0.073	0.051	0.082	0.069	0.075	0.114	0.072
SKYY ETF																		
Mean	0.215	0.171	0.198	0.282	0.104	0.257	0.235	0.156	0.190	0.291	0.084	0.255	0.231	0.187	0.207	0.272	0.126	0.260
Median	0.213	0.153	0.193	0.284	0.093	0.266	0.200	0.146	0.193	0.299	0.084	0.271	0.225	0.174	0.193	0.263	0.114	0.257
Maximum	0.372	0.460	0.501	0.608	0.561	0.503	0.372	0.460	0.433	0.534	0.452	0.413	0.371	0.416	0.501	0.608	0.561	0.503
Minimum	-0.046	-0.014	-0.003	0.036	-0.102	0.018	-0.046	-0.014	-0.003	0.036	-0.043	0.018	0.099	-0.011	0.048	0.047	-0.102	0.132
Std. Dev.	0.073	0.088	0.075	0.082	0.091	0.067	0.077	0.091	0.072	0.070	0.054	0.064	0.063	0.081	0.076	0.092	0.114	0.071

Note: The data shown is the summary of dynamic conditional correlations data from the multivariate DCC-GARCH model with 5 lags in return equation to capture the day-of-the-week effect. The full period is from 23 February 2018 to 28 January 2022. Pre COVID-19 period is from 23 February 2018 to 10 March 2020. During COVID-19 period is from 11 March 2020 to 28 January 2022.

Figure 3: Dynamic Conditional Correlations between Disruptive Technology ETFs and Asia Emerging Markets



5.3 The Changes in Dynamic Correlation Coefficients between Disruptive Technology ETFs and Asia Emerging Markets

Table 7 represents the estimation results for equation (11). In each pair of Asia emerging market and disruptive technology ETF, the coefficient α is statistically positive at the 1% significance level, meaning that the ETFs and Asia emerging markets are positively correlated during pre COVID-19 period. This result also supports the finding in section 5.1 on the safe haven and hedge property of disruptive technology ETFs against Asia emerging markets that these ETFs cannot act as a hedge or safe haven due to their positive dynamic correlations with the stock markets. The coefficient $ß_1$ measuring additional sensitivity of the dynamic conditional correlations during COVID-19 period are positive in most of pairwise assets and significant for the pair between CSI300 Index with CIBR ETF, ROBT ETF, and SKYY ETF at 10% and 5% respectively. Meanwhile, the coefficient $ß_1$ are found to be negative but not significant in the relationship between FTEK ETF and CSI300 Index, FBMKLCI Index, KOSPI Index, PCOMP Index, and SET Index.

Hence, the result indicates that the dynamic conditional correlations between most of disruptive technology ETFs and Asia emerging markets have increased during COVID-19 period. The exception is only for the relationship between FTEK ETF and the other mentioned five Asia emerging markets that their dynamic conditional correlations tend to be lower during COVID-19 period. This finding indicates that during COVID-19 period, investors in Asia emerging market should consider higher cross-linkages between the disruptive technology stocks and Asia emerging markets. It is consistent with literatures from (Graham et al., 2012) that the correlation between assets can be significantly increased and emerged close to one during crisis period due to higher market integration. In financial research, this is called "correlation breakdown" phenomenon where the correlations between assets are unusually increasing and portfolio diversifications among assets become less beneficial than they are supposed to be (Gallegati, 2012).

Table 7: Empirical Results of Potential Changes in Dynamic Correlation Coefficients

	CSI300 Index	FBMKLCI Index	JCI Index	KOSPI Index	PCOMP Index	SET Index
			CIBR ETF			
α	0.165*** (8.5448)	0.1778*** (6.4457)	0.1964*** (9.5689)	0.2636*** (11.2944)	0.0965*** (3.4977)	0.2472*** (7.8051)
$ß_0$	0.9493*** (76.1265)	0.9669*** (95.3242)	0.9512*** (77.4719)	0.9508*** (76.4830)	0.9589*** (84.7477)	0.9798*** (109.3862)
$ß_1$	0.0374* (1.9200)	0.0123 (0.5628)	0.0082 (0.3985)	0.0018 (0.0789)	0.0071 (0.2770)	0.0014 (0.0819)
			FTEK ETF			
α	0.2321*** (11.0242)	0.2345*** (10.9266)	0.2392*** (13.9060)	0.3787*** (15.9301)	0.1173*** (5.2925)	0.3374*** (2.9935)
$ß_0$	0.9557*** (80.4836)	0.9599*** (83.2997)	0.9439*** (68.0807)	0.9572*** (74.7095)	0.9504*** (78.2516)	0.9953*** (134.7157)
$ß_1$	-0.0159 (-0.8084)	-0.0063 (-0.3328)	0.0078 (0.4138)	-0.0163 (-0.7351)	-0.0023 (-0.1032)	-0.0022 (-0.1452)
			ROBT ETF			
α	0.2498*** (13.8200)	0.2297*** (9.0070)	0.2524*** (13.7381)	0.3949*** (16.0881)	0.1289*** (4.8037)	0.341*** (7.1081)
$ß_0$	0.9494*** (72.8904)	0.9626*** (87.9279)	0.9446*** (69.4091)	0.961*** (75.9566)	0.9597*** (84.1538)	0.9864*** (109.4249)
$ß_1$	0.0404** (2.2158)	0.0124 (0.5700)	0.0137 (0.6916)	0.0137 (0.6412)	0.0067 (0.2740)	0.0017 (0.0973)
			SKYY ETF			
α	0.1925*** (10.0830)	0.1597*** (6.2000)	0.1882*** (9.5755)	0.275*** (11.8936)	0.0924*** (3.7472)	0.2422*** (9.4733)
$ß_0$	0.9459*** (73.3144)	0.9623*** (90.1709)	0.9457*** (73.6224)	0.9508*** (76.2814)	0.9538*** (80.3681)	0.9731*** (96.8431)
$ß_1$	0.0438** (2.2004)	0.0172 (0.7782)	0.0086 (0.4142)	0.0062 (0.2707)	0.0125 (0.5172)	0.0033 (0.1939)

Note: The estimated results are from equation (11) $DCC_{ij,t} = \alpha + \beta_0 DCC_{ij,t-1} + \beta_1 D_1 + \varepsilon_{ij,t}$ where D_1 equals to 1 when the dynamic conditional correlation is in period of COVID-19 pandemic (11 March 2020 – 28 January 2022). The numbers in parenthesis are t-statistic. *, **, *** denote statistical significance level at 1%, 5%, 10% respectively.

5.4 The Optimal Hedge Ratio and Hedge Effectiveness of Disruptive Technology ETFs

In this section, the optimal hedge ratio and hedge effectiveness are computed to examine whether if the hedge effectiveness of disruptive technology ETFs to Asia emerging markets have increased during COVID-19 period. Table 8 reports the average optimal hedge ratio (HR), hedge effectiveness (HE) and variance of hedged portfolio across period. As the dynamic conditional correlations between each pair of assets varied across time, the optimal hedge ratio also varied. The highest optimal hedge ratio (HR) in pre COVID-19 period can be observed in the pair of FTEK ETF and KOSPI Index (0.347), while during COVID-19 period, the pair of FTEK ETF and SET Index had the highest optimal hedge ratio (0.339). This means that in order to minimize the risk of one-dollar long position in KOSPI Index (SET Index), a short position of 0.347 (0.339) dollar of FTEK ETF should be taken. The higher optimal hedge ratio means that investor needs to sell more portion of the ETF to minimize the risk of a long position in Asia emerging market. Thus, the higher hedge ratio, the more expensive the hedging cost. We can see that the optimal hedge ratios between each pair tends to increase during COVID-19 period comparing to pre COVID-19 period. This result is consistent with the literatures from Jin, Han, Wu, & Zeng (2020) that the optimal hedge ratios between global technologies ETF and emerging stock markets are higher in period of crises. However, our result found some exceptions with KOSPI Index that their average optimal hedge ratios are lower during COVID-19 period. This is aligned with the dynamic conditional correlation result in provided table 6, that the average dynamic conditional correlations between the disruptive technology ETFs with KOSPI Index are lower during COVID-19.

In contrast, the lowest optimal hedge ratio in pre COVID-19 period and during COVID-19 period can be observed in the pair of SKYY ETF and FBMKLCI Index at the hedge ratio of 0.077 and 0.097 respectively. The lowest optimal hedge ratio also means that investors is required to sell the least portion of the ETF to minimize portfolio risk. Similarly, it means that investors require more long position in SKYY ETF when investing in Malaysia stock market than any other disruptive technology ETFs to minimize portfolio risk.

For a better analysis of hedging performance, the hedge effectiveness is computed by comparing the reduction in variance of unhedged portfolio with the variance of hedged portfolio. From the table 8, the highest hedge effectiveness (HE) in pre COVID-19 period, observed in the pair of ROBT ETF and KOSPI Index is 17.47%. The pair of FTEK ETF and SET Index provided the highest HE at 17.22%. during COVID-19 period. A higher value of hedge effectiveness indicates a greater risk reduction in hedged portfolio in comparison to unhedged portfolio. The implication is that when an investor takes a short position of a highly correlated asset to minimize the variance of long position of another highly correlated asset, the variance of portfolio can be reduced by a greater margin because selling out a highly correlated asset helps to reduce more degree of variance. When hedge effectiveness is close to one hundred percent, it means that the hedge strategy is perfect. This finding implies a one-dollar long position in KOSPI Index in pre COVID-19 period can be hedged by shorting 0.322 dollar of ROBT ETF to reduce 17.47% of its portfolio variance. Similarly, during COVID-19 period, a one-dollar long position in SET Index can be hedged by shorting 0.339 dollar of FTEK ETF to reduce 17.22% of its portfolio variance. Furthermore, it found that ROBT ETF have provided the highest hedge effectiveness for five out of six Asia emerging markets during COVID-19 except SET index that shorting FTEK ETF can provide the highest hedge effectiveness and lowest variance of portfolio. The explanation for this result is that ROBT ETF has the highest average dynamic conditional correlations with these five emerging markets during COVID-19 period as shown in table 6, so it requires more short position of ROBT ETF than other ETFs to minimize the variance of hedged portfolio. In addition, the reason for the high correlation between ROBT and the five markets is that there are some stocks from the Asia equity markets like China, Korea, Japan, and Taiwan as parts of constituents inside ROBT ETF. Asia emerging stock markets co-movement tend to be more correlated among each other rather than the co-movement with developed markets (Peng, 2018). Therefore, taking short position in ROBT ETF tends to provide more hedge effectiveness than the others. From figure 3, this study also found that the dynamic conditional correlation between FTEK ETF and other three ETFs were clearly lower than other pairs. It implies that FTEK ETF had movement that is quite different from the other ETFs, so investors cannot just use any disruptive technology ETFs to hedge but they need to selectively choose the ETF that can provide the highest hedge effectiveness to a particular market to formulate the hedging strategies.

To compare the hedge effectiveness of ETFs between pre COVID-19 and during COVID-19 period, the results are shown in the last column of table 8. A positive ΔHE indicates a better hedging performance during COVID-19 period, while the negative value means poorer hedging ability of the ETF during COVID-19 compared to pre COVID-19 period. We find that the values of ΔHE are positive for most of pairwise assets. This finding indicates that the hedge effectiveness of disruptive technology ETFs to Asia emerging markets are greater during COVID-19 period for most cases. The explanation for these results is that the disruptive technology ETFs and stock markets had higher dynamic conditional correlation during the COVID-19 period, so when investors take a short position of a unit of the ETF, it can reduce variance of long portfolio in emerging stock markets by greater margin than pre COVID-19 period. This is similar to the finding by Jin, Han, Wu, & Zeng (2020) that global technologies ETF can provide higher hedge effectiveness to emerging markets during time of crises. However, this study also found negative values of ΔHE on FBMKLCI Index and FTEK ETF, SET Index and CIBR ETF, KOSPI Index and SKYY ETF, ROBT ETF, and CIBR ETF. The negative ΔHE implies that the ability of shorting the disruptive technology ETFs to reduce variance of hedged portfolio during COVID-19 period is less than pre COVID-19. This due to lower dynamic conditional correlations between these pairwise assets during COVID-19.

With some exceptions on the pair with negative ΔHE, this study concludes that the disruptive technology ETFs are considered useful hedge tools for many Asia emerging markets during COVID-19 period where a higher short position in the ETFs can better offset adverse movement from a long position in Asia emerging stock markets.

Table 8: Optimal Hedge Ratio and Hedge Effectiveness of Disruptive Technology ETFs

		Full period		Pre COVID-19 period			During COVID-19 period			$HE_{DuringCovid}$ - $HE_{PreCovid}$
		HR	HE	HR_{Before}	HE_{Before}	Var Hedge	HR_{During}	HE_{During}	Var Hedged	ΔHE
CSI300 Index	SKYY	0.194	5.149%	0.188	4.582%	1.721	0.199	5.755%	1.498	1.1728%
	ROBT	0.269	7.838%	0.281	7.297%	1.678	0.286	8.418%	1.458	1.1217%
	FTEK	0.263	3.945%	0.199	3.415%	1.745	0.323	4.513%	1.541	1.0989%
	CIBR	0.166	3.876%	0.163	3.352%	1.740	0.170	4.438%	1.520	1.0859%
FBMKLCI Index	SKYY	0.087	3.699%	0.077	3.281%	0.423	0.097	4.146%	0.685	0.8652%
	ROBT	0.133	6.591%	0.126	6.252%	0.410	0.141	6.994%	0.655	0.7420%
	FTEK	0.148	6.141%	0.153	6.215%	0.411	0.142	6.022%	0.668	-0.2307%
	CIBR	0.096	4.332%	0.087	3.833%	0.421	0.107	4.866%	0.676	1.0325%
SET Index	SKYY	0.174	7.064%	0.159	6.895%	0.680	0.190	7.245%	1.730	0.3503%
	ROBT	0.268	14.452%	0.248	14.104%	0.629	0.289	14.823%	1.550	0.7190%
	FTEK	0.320	15.952%	0.302	14.770%	0.627	0.339	17.218%	1.536	2.4477%
	CIBR	0.182	7.556%	0.198	7.586%	0.674	0.168	7.523%	1.708	-0.0624%
JCI Index	SKYY	0.138	4.471%	0.135	4.118%	0.881	0.142	4.849%	1.391	0.7312%
	ROBT	0.198	7.552%	0.191	6.721%	0.857	0.206	8.441%	1.326	1.7195%
	FTEK	0.215	6.636%	0.215	5.769%	0.862	0.216	7.565%	1.348	1.7965%
	CIBR	0.145	4.814%	0.138	4.372%	0.879	0.152	5.288%	1.385	0.9160%
KOSPI Index	SKYY	0.204	8.616%	0.214	8.980%	0.804	0.193	8.227%	1.202	-0.7527%
	ROBT	0.315	17.274%	0.322	17.469%	0.729	0.307	17.066%	1.083	-0.4034%
	FTEK	0.329	14.956%	0.347	14.745%	0.751	0.310	15.182%	1.122	0.4365%
	CIBR	0.195	7.859%	0.206	8.451%	0.807	0.183	7.226%	1.220	-1.2248%
PCOMP Index	SKYY	0.096	1.912%	0.078	0.998%	1.365	0.116	2.890%	2.319	1.8927%
	ROBT	0.139	2.836%	0.122	1.877%	1.352	0.158	3.863%	2.261	1.9857%
	FTEK	0.131	2.122%	0.124	1.518%	1.359	0.138	2.768%	2.341	1.2498%
	CIBR	0.102	2.080%	0.081	1.112%	1.363	0.125	3.117%	2.295	2.0057%

Note: Estimated results are from equation (12), (13), (15) as follows:

$$\beta_t^{i/(ETF)} = \frac{cov(R_{country,t}, R_{ETF,t})}{var(R_{ETF,t})} \quad (12)$$

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \quad (13)$$

$$\Delta\text{HE} = \text{HE}_{\text{DuringCovid}} - \text{HE}_{\text{PreCovid}} \quad (15)$$

HR stands for the optimal hedge ratio computed from equation (12) and HE represents hedge effectiveness, computed from equation (13). Var Hedged represents variance of hedged portfolio. ΔHE is the difference between hedge effectiveness during COVID-19 period and pre COVID-19 period. Pre Covid-19 period is from 23 February 2018 to 10 March 2020. During Covid-19 period is from 11 March 2020 to 28 January 2022.

6. Conclusion

In this study, we evaluated the role of disruptive technology ETFs in Asia emerging stock portfolios. Particularly, we examined the safe-haven and hedge property of the ETFs against stock markets and investigated whether if COVID-19 pandemic carried any implications on dynamic conditional correlations between these two assets. We also further analyzed on the hedge effectiveness of the ETFs to stock markets across pre COVID-19 period and during COVID-19 period to assess the time-varying hedging performances. The study of dynamic conditional correlation and hedging performance is an essential part to assist investor's decision-making process on asset allocation and hedging portfolios. The main findings of this study are summarized as follow:

First, all of disruptive technology ETFs in this study do not possess a safe haven or hedge property to Asia emerging markets due to their positive co-movement in both tranquil period and during the period of extremely negative market returns. They can only act as diversifier tools for Asia emerging markets. This result is consistent with numbers of literatures that equity markets are positively correlated in general and diversification among the same asset class does not provide a flight to safety or safe-haven property to stock markets (Graham et al., 2012), (Christoffersen et al., 2014), (Jin et al., 2020), and (Bana et al., 2020).

Second, the result from investigating on potential changes in dynamic conditional correlations between the ETFs and Asia emerging markets suggests that the DCCs between the ETFs and stock markets tend to increase during COVID-19 period. This phenomenon is generally known as correlation breakdown where during crisis period, the correlation between assets extremely increased and emerged closed to one due to higher market integration (Gallegati, 2012). This finding is also align with many literatures that the correlations or linkages between robotic and artificial intelligence stocks or global technology ETFs with stock indexes increased significantly during crise or time of high volatility.(Huynh et al., 2020; Jin et al., 2020), and (Le et al., 2021; Sercan et al., 2021). Nevertheless, this study found a few exceptions on the dynamic conditional correlations between fintech ETF and five stock markets, China, Malaysia, Korea, Philippines, and Thai markets that their correlations tend to decrease during COVID-19 period, but the results are not statistically significance.

Third, further finding on the optimal hedge ratio and hedge effectiveness of the disruptive technology ETFs reveals that the average hedge ratios substantially increased during COVID-19 period, implies investors need to short more portion of ETF to minimize the variance of hedged portfolio. It indicates that the process for investors to offset losses, on average, was more expensive during COVID-19 period. The results also indicated the most risk reduction that by shorting ROBT ETF can provide the lowest variance of hedged portfolio and the highest hedge effectiveness for every Asia emerging market except Thai stock market. Our finding also notes that the hedge effectiveness of ETFs has increased during COVID-19 period in comparison with pre COVID-19 period for almost every pair of assets due to shorting a unit of the ETF provides higher degree of variance reduction to Asia emerging market portfolio.

Lastly, the limitation of this study is that it covered the period from February 2018 to January 2022 which included only period of COVID-19 crisis. Therefore, it is advised for the future study to expand the period of study in which it might provide different outcomes.

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