CRYPTOCURRENCIES AND TRADITIONAL ASSETS: THE EMPIRICAL STUDY IN DYNAMIC LINKAGES AND PORTFOLIO OPTIMIZATION

Watcharaporn Kantaphayao

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Watcharaporn Kantaphayao

School of Development Economics

.... Major Advisor
(Associate Professor Sorasart Sukcharoensin, D.B.A.)

.... Co-Advisor
(Associate Professor Yuthana Sethapramote, Ph.D.)

.... Co-Advisor
(Associate Professor Pariyada Sukcharoensin, D.B.A.)

The Examining Committee Approved This Dissertation Submitted in Partial Fulfillment of Requirements for the Degree of Doctor of Philosophy (Economics).

.... Committee Chairperson
(Associate Professor Tanachote Boonvorachote, D.B.A.)

.... Committee
(Associate Professor Yuthana Sethapramote, Ph.D.)

.... Committee
(Associate Professor Pariyada Sukcharoensin, D.B.A.)

.... Committee
(Associate Professor Sorasart Sukcharoensin, D.B.A.)

.... Dean
(Associate Professor Amornrat Apinunmahakul, Ph.D.)

_____/_____/_____

ABSTRACT

Title of Dissertation	CRYPTOCURRENCIES AND TRADITIONAL ASSETS: THE EMPIRICAL STUDY IN DYNAMIC LINKAGES AND PORTFOLIO OPTIMIZATION
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The paper generates the top 5-coin index and the top 5-token index and treats them as the cryptocurrency price to investigate for three main objectives. First, it has to investigate the short-term dynamic spillover between cryptocurrency and main traditional assets. Second, it has to examine the fundamental characters of both coin and token by long-term relationships with other traditional assets, as well as forecasting price ability. Third, it has to analyze the asset allocation for the portfolio optimization approach by applying the dynamic conditional correlations, calculated by the Dynamic Conditional Correlation (DCC)-GARCH (1,1) model.

The results reveal that coin and token are positively long-term related to each other. The developed stock market also has a negative long-term relationship with coin, while it has a positive long-term relationship with token. The fixed income asset has a positive long-term relationship with coin and token. Meanwhile, the commodity asset has a positive long-term relationship with token. For the short-term spillover, coin return causes token, stock and gold returns. Meanwhile, stock return causes token return. Coin and token return immediately highest responded by the shock of each other by the first period. The responses of coin and token returns from the shock of other markets are not significant. Besides, the shock of main traditional assets does not affect the cryptocurrency volatility. Therefore, the cryptocurrencies might be of benefit to portfolio diversification due to their minor linkages with other financial assets.

Due to the long-term cointegration relationship and some short-term dynamic spillover among coin, token, and developed stock market through MSCI international world price market, these assets will be acted as an exogenous variable for price forecasting. Using data from January 2017 To December 2019, the results reveal that

the ARIMAX model with the developed stock market as an exogenous variable and the VAR model depended on lagged variable of developed stock market are relatively reliable to forecast coin and token comparing to RW and ARIMA models using out-of-sample forecasting period over 20 days horizon ahead. However, longer forecasting horizon has provided higher estimation errors; therefore, the forecasting ability of cryptocurrency would be effective in the short-term period.

Then, this paper has focused on the discussion of the portfolio optimization and diversification benefits by investment in coin and token. The static correlation and dynamic conditional correlation have been applied to form portfolio optimization. The dynamic conditional correlation has been calculated from DCC-GARCH (1,1) model. As the results of the static and dynamic conditional correlations, this paper finds that coin and token are moderately positive correlated with each other. Meanwhile, they have extremely low correlations with the other traditional assets. Therefore, the cryptocurrency might be an alternative asset class to benefit for portfolio diversification.

The optimal portfolios formed by the DCC-GARCH (1,1) model have provided the huge Sharp Ratio rather than the static portfolios. Furthermore, this paper also finds that the actively adjusted weight portfolios provide a huge average annual return and higher standard deviation rather than fixed weights of the investment portfolio. The higher standard deviation is tiny when comparing to the huge increase of the average return. So, the Sharpe Ratio of actively adjusted weight portfolios then is better than the fixed weight portfolio. The portfolios performed well, which presented in terms of average annual return, Sharpe Ratio, and Compound Annual Growth Rate (CAGR), always have either coin or token in there. Nonetheless, due to the high-risk level of cryptocurrencies, including coin and token, the investors should be careful to invest. They should have always re-considered about the weights of investment in either coin or token. The optimal weights of investment in coin and token of each period should be quite low rather than other traditional assets, which are well-known about fundamental movement.

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CHAPTER 1

INTRODUCTION

Due to the technology advancement in the digital era, especially blockchain technology, many cryptocurrencies have been generated and acted as a new investment asset segment. The cryptocurrency is a subclass of the digital currencies (Rose, 2015, p. 617). It is also one of the digital assets created on blockchain technology and mainly used as a medium of exchange for goods and services as well as the other digital assets (Howell, Niessner, & Yermack, 2020, p. 3926). However, cryptocurrency is not qualified with three functions of fiat money, including medium of exchange, unit of account, and store of value, because its price is too fluctuated to use as a store of wealth and widely used as a medium of exchange (Bank of Thailand, 2019, p. 25).

Cryptocurrency can be explained in terms of broad and narrow definition. In cases of a broad definition, the cryptocurrency includes both coin and token. The coin is standalone cryptocurrency that operate on its own blockchain and will be used as a medium of exchange purpose. Meanwhile, the token has to require the existing blockchain or platform to operate (Amsden & Schweizer, 2018; Wu, Wheatley, & Sornette, 2018). The token is divided to two types including security token and utility token. The security token gives holders the rights to participate in any activity or project investment to create a record of ownership, while the utility token represents the right to access or receive specific goods and services or as agreed that mostly provided via a new network. Furthermore, the token is usually sold to the public through Initial Coin Offering (ICOs) in order to raise capital on blockchain technology (Howell et al., 2020, pp. 3925-3926).

In terms of a narrow definition, the cryptocurrency focuses on the coin only and excludes token from its category. In other words, both security token and utility token are separated from cryptocurrency. Nonetheless, most of the recent papers concentrate on cryptocurrency in broadly defined. The data of all cryptocurrencies that have shown on the popular websites also includes coin and token. Currently, the cryptocurrency market is very interesting among investors and speculators because it may be a new category of investment asset (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018, p. 28).

Bitcoin is the first and the most popular of cryptocurrency created by Satoshi Nakamoto in 2008. It has dominated the cryptocurrency market as over 60 percent during 2020. During 2016 – 2017, the value of total cryptocurrency market capitalization has the highest growth rate. It dramatically increased from US$17.7 billion at the end of 2016 to US$565.1 billion at the end of 2017, increasing as the highest growth rate of around 3,090.8 percent. Such high growth rate might be purely driven by demand side and supply side. Furthermore, the demand and supply for the cryptocurrency (Andrianto & Diputra, 2017, p. 229) as well as power of the speculation (Alam, 2017, p. 2285) are significant factors to affect prices.

Demand for cryptocurrency rise continually because most investors always seek to invest in new financial assets during the unpredictable prices of other traditional assets, including stock, bond, currency, and commodity. Cryptocurrency is one of the new assets or alternative assets to be attractive to investors who are acceptable for high risk, although the cryptocurrency price quite fluctuates and the intrinsic value is difficult to evaluate (Alam, 2017; Sontakke & Ghaisas, 2017). The investors expect that cryptocurrency could create a desirable investment opportunity for investors in this era and also improve the performance of their portfolio as well as support portfolio diversification (Andrianto & Diputra, 2017; Chuen, Guo, & Wang, 2017). Some cryptocurrencies with high liquidity and large market capitalization seem a safe haven asset for major indices in the developed market (Pengfei Wang, Zhang, Li, & Shen, 2019, p. 1). Meanwhile, many online retailers have accepted some cryptocurrencies, especially Bitcoin, for payment.

Most of new users also tend to perceive Bitcoin as an alternative investment vehicle (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014, p. 2). Although the Bitcoin's returns are high volatility, Bitcoin is also mainly used as a speculative investment and not as an alternative currency for medium of exchange (Baur, Hong, & Lee, 2018, p. 177). For the supply side, there are lots of new cryptocurrencies. In December 2017, there are 1,335 cryptocurrencies, increasing around 107.3 percent from December 2016, with the rising trend of pricing. As a result, the cryptocurrency market capitalization has severely increased as well.

However, in 2018, the cryptocurrencies' prices are quite volatile and move to downward direction. Its market capitalization tends to decrease around 78.6 percent from 2017. There are many reasons involve with cryptocurrencies' prices, especially Bitcoin, intensely fall in this period. The investors have concerned about bad news such as the trading securities are attacked, or the government of China has banned any activity related to the trade and exchange of cryptocurrency in China, while the Central Bank of many countries is drafting laws or regulations for cryptocurrency usages, etc. Furthermore, the "Whales" or the holders who hold large amounts of cryptocurrency sell cryptocurrency on hand. The panic selling among retail investors has also risen.

According to Glaser et al. (2014) paper, due to lack of intrinsic valuation method of Bitcoin, so the Bitcoin's price is based on some information including news, article analysis paper, internet communities as well as social media. The negative news will affect to investors who apply Bitcoin for operational transaction or speculative approach. Those investors will reevaluate Bitcoin utility and usability from their expectation and eventually sell their Bitcoin. It might be the main factor to cause decreases in Bitcoin's price and make cryptocurrency market capitalization decreases as well.

Recently, the cryptocurrency market has been in an early stage (Alam, 2017, p. 2285). There are lots of new cryptocurrencies, including coin and token. Some of them have achieved, particularly in coins like Bitcoin, Ethereum, and Litecoin, because they have been accepted as a medium of exchange as well as popularly in the investment. Some of them have failed because they cannot be accepted and cannot overspread for investment. Meanwhile, most people's perception of cryptocurrency investment is limited due to the new digital asset and the volatility of price. Therefore, currently, investment in the cryptocurrency market is still among risk lovers who interested in an investment of new assets.

Nonetheless, owing to an unpredictable price of traditional assets, the cryptocurrency would be expected to invest and overspread in public increasingly hereafter. Furthermore, it is expected to be an alternative asset class (Burniske & White, 2016; Chuen et al., 2017; Y. Liu & Tsyvinski, 2021; Sontakke & Ghaisas, 2017).

Bruniske & White (2017) explore that Bitcoin, which is one of cryptocurrencies, exhibits as a unique asset class because it meets four characteristics that are distinct from other assets. First, Bitcoin can be sufficiently investable. Second, it has the different profiles, compared to the other assets, including the basic of value, governance, and use cases. Third, it fluctuates independently from the other assets because there is low correlation between Bitcoin and other assets. Finally, Bitcoin has the risk and return differing from other assets, exhibiting return outperformance in some period.

Moreover, Sontakke & Ghaisas (2017) also view that the Bitcoin and Ethereum, representing cryptocurrency, are a potential asset class because there is no any correlation with any other asset class. It is consistent with a paper of Chuen et al. (2017) which explores that there is a very low correlation between cryptocurrencies and traditional assets, so it implies that the cryptocurrency will be an alternative asset class and also be a good asset for traditional portfolio diversification.

Thanks to an alternative asset class of cryptocurrency as mentioned above, the demand for cryptocurrency is still interesting during high return and volatility. The recent papers have then attempted to find the time-varying relationship or conditional linkages between cryptocurrency and other traditional assets so as to analyze the movement and effect of cryptocurrency prices from other assets in some periods. However, most of the recent papers have only selected Bitcoin to analyze in many approaches, including new asset class analysis, correlation with traditional assets, investment opportunity, risks and returns analysis as well as portfolio diversification. Bitcoin is sometime used as a medium of exchange for any goods or service. Meanwhile, sometime, it is suitable for diversification purpose (Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017, p. 192).

Although bitcoin meets the criteria as a medium of exchange for goods or services just about any fiat money such as the U.S. dollar, it fails as a store of value and a unit of account. Unlike fiat currencies, bitcoin has demonstrated to be too volatile to make it a reliable vehicle in which to store value over long periods of time. Bitcoin has been gained attention from investment community during this period because it is the well-known among the people and its market share dominates the cryptocurrency market during high volatility periods. Bitcoin's explosion in prominence has led to the growth of dozens of other cryptocurrencies.

This paper consequently focuses on other cryptocurrencies apart from Bitcoin for testing the forecasting ability, the long-term relationship to other traditional assets, the short-term dynamic spillover analysis, the dynamic conditional correlation of the cryptocurrencies as well as portfolio optimization. It then concentrates on both popular coin and token to analyze them by separately because they have some different characteristics, particularly of usages. Due to the technology advancement and special properties of token, the security token and utility token are more popular among the startup entrepreneurs in order to raise fund through Initial Coin Offerings (ICOs) (Howell et al., 2020, p. 3925). Although the tokens market capitalization share is now lower than 10 percent of all cryptocurrency market capitalization, the token is still attractive to investors and speculators because the issuers will give some rights to those investors and speculators. Such rights are unique characteristics that make investors and speculators get more benefit than holding coins only.

Due to lots of existing coins and tokens, this paper will concentrate on the top 5 coins and top 5 tokens by market capitalization, which contributes to the existing literatures. As of January 2020, the top 5 coins market capitalization is nearly 88.5 percent of all coin market capitalization, while the top 5 tokens market capitalization is approximately 31.1 percent of all token market capitalization. The top 5 coins and top 5 tokens by market capitalization would be generated to coin index and token index, respectively, by using the market-capitalization weighted index. The top 5-coin index and the top 5-token index would represent the cryptocurrency market and could reduce the unsystematic risk from only one cryptocurrency selected, especially Bitcoin.

Furthermore, currently, most recent papers have only selected some financial models to investigate or analyze in some approach. Some of them select one or two popular cryptocurrencies to analyze the static or the Dynamic Conditional Correlation (DCC) with the traditional assets. Some of them use the Vector Autoregression Model (VAR) to analyze the volatility of the popular cryptocurrencies, especially Bitcoin. Therefore, this paper will use various models to forecast the cryptocurrency prices as well as analyze the short-term and long-term linkages with other traditional assets. It also examines the dynamic interdependence correlation among the returns of the cryptocurrencies and traditional assets as well as the diversification gains from adding coin and token to the portfolio.

This paper has three main objectives. First, this paper has to investigate mean and variance spillover in the short-term period. It then applies the Vector Autocorrelation (VAR) model to test the direction of the causality, which is mean spillovers, between coin or token returns and main traditional asset class returns including stock, bond, and commodity in the short-term period. It also applies the VAR model to analyze the impulse response function, which is mean spillovers, to measure the impacts of the shocks from main traditional asset returns to the coin or token returns of the system in the short-term period. Furthermore, the variance spillover approach will be applied to study the volatility linkages of the coin and token markets in the short-term period when any shock occurs. Those results of the dynamic linkage analysis among coin and token, as the new digital assets, and other traditional assets in the short-term period could be significant information to the investors to decide better for investing in the cryptocurrency market.

Second, it has to examine the fundamental characters of both coin and token. Those characters include the long-term relationship with other traditional assets and the price forecasting ability and. This paper will use the cointegration method to examine the long-term fundamental relationship among cryptocurrencies, including coin and token, and main traditional asset classes. The long-term linkages results could be significant information for investors to analyze the fundamental movement of the coin and token markets. Moreover, this paper will apply the random walk process (RW), Autoregressive Integrated Moving Average (ARIMA), Autoregressive Integrated Moving Average with Exogenous variables (ARIMAX), and Vector Autoregressive (VAR) models to forecast out-of-sample period. After that, the Diebold-Mariano test (Diebold & Mariano, 1995) will be applied in order to test the difference in the predictive accuracy between the forecasting models – including ARIMA, ARIMAX, and VAR – and the Random Walk process, which is the benchmark. The appropriate forecasting model would be useful for investors and speculators to do trading strategy.

Third, this paper will analyze the asset allocation for the portfolio optimization approach by applying the static and dynamic conditional correlations, calculated by the Dynamic Conditional Correlation (DCC)-GARCH (1,1) model. Those results of time-varying or conditional correlation measurement could be the benefits for investors to diversify the assets. The low dynamic conditional correlation could be great for asset diversification purpose to decrease the investment risks during high volatility. As the results, the investors could have more information to allocate and diversify their assets better. In other words, the results of the dynamic linkage analysis including the mean and variance spillover effects as mentioned above are very significant information for the risk management to the optimal portfolio investment.

Furthermore, the results of portfolio optimization will be expected to show the proper weight of cryptocurrency investment in the portfolio to meet the optimized risk and return, as well as to exhibit that whether cryptocurrencies, including coin and token, will be appropriate to invest or not. If the cryptocurrency would be appropriate to invest, the investors will gain the benefits from the portfolio diversification. Furthermore, the investors will have the significant information to make an investment strategy with the weight for each asset class in their portfolio. The optimized weight for each asset class could lead the investors to meet the portfolio optimization approach.

CHAPTER 2

LITERATURE REVIEW

2.1 The Long-term Cointegration and Short-term Dynamic Linkages between Cryptocurrencies and Traditional Assets

Due to without intrinsic valuation of cryptocurrency, many recent papers thus try to investigate the short-term and long-term relationship between cryptocurrency and other financial assets, as well as macroeconomic indicators by using various methodology. The results of each paper have some differences depending on selected explanatory variables as well as the sample period. However, most of the recent papers still focus on Bitcoin, which has the largest market capitalization, and find that Bitcoin price has a significant long-term relationship with some financial assets. The Vector Error Correction Model (VECM) has been applied to examine long-term relationship between Bitcoin price and the number of Bitcoins, as well as between Bitcoin price and S&P500 index (Georgoula, Pournarakis, Bilanakos, Sotiropoulos, & Giaglis, 2015). The number of Bitcoins has a positive long-term impact on their own prices, while the S&P500 index has a negative long-term impact on Bitcoin price. It implies that the investors would sell their stocks and replace them for Bitcoin. That result seems consistent with Conrad et al. (2018), who prove the long-term Bitcoin volatility and other financial asset volatility by using a GARCH-MIxed Data Sampling (MIDAS). The S&P 500 volatility has a negative and significant effect on long-term Bitcoin volatility (Conrad, Custovic, & Ghysels, 2018, p. 23).

Zwick and Syed (2019) investigate the two-regime long term relationship between Bitcoin and the gold price by using the threshold regression model, which concerns with non-linear variables (Syed Zwick & Syed, 2019). They found that, before the turning point as of October 2017, there is a weak negative impact of gold on Bitcoin prices in the long-term period. However, after October 2017, the gold has a significant positive impact on Bitcoin prices in the long-term period. It indicates that an increase in demand for gold would raise demand for Bitcoin as well. At this period, the perception of the investors has thus changed to use Bitcoin for hedging investment strategy. Meanwhile, some paper use an Error Correction Model (ECM) to analyze the short-term and long-term effects of traditional financial assets on Bitcoin price and finds that many financial assets, including Dow Jones, West Texas Intermediate (WTI) crude oil price, and Euro to U.S. Dollar exchange rate, have significantly influenced on Bitcoin price in the long-term period (van Wijk, 2013, p. 13).

Furthermore, the research topic on the short-term dynamic linkages between cryptocurrencies, as digital assets, and traditional assets is quite popular during 2017 – 2019. Many papers have also focused on some popular cryptocurrencies particularly in coin during the high price volatility. Those papers thus examine the dynamic linkages, between cryptocurrencies and other traditional assets in cases of return and volatility to find that whether the cryptocurrencies could be the speculative assets or alternative assets and could offer the diversification benefits from investment or not. Most of the recent papers have also shown that there are very low relationships between cryptocurrencies and other traditional assets. Meanwhile, the cryptocurrencies have highly dynamic linkages with each other. (e.g.,(Baur et al., 2018; Bianchi, 2020; Chuen et al., 2017; Corbet et al., 2018; Yi, Xu, & Wang, 2018))

The volatility among cryptocurrencies could be connected one another (Yi et al., 2018, p. 98). Yi et al. (2018) uses volatility spillover index and variants to investigate the volatility connectedness of eight cryptocurrencies. Those eight cryptocurrencies include Bitcoin Ripple, Litecoin, Peercoin, Namecoin, Feathercoin, Novacoin, and Terracoin which divided by three tiers cryptocurrencies of the market capitalization. The top-tier represents large market capitalization. The second tier represents middle cryptocurrencies, while the third tier represents the minor cryptocurrency with small market capitalization. As a result, the volatility connectedness of each cryptocurency periodically fluctuates. Meanwhile, the volatility connectedness or spillover effect is not necessarily linked to the market capitalization. Furthermore, Yi et al. (2018) also apply LASSO-VAR to measure the volatility connectedness in term of high dimension data of 52 cryptocurrencies and to estimate VAR parameters. They found that the small market capitalization cryptocurrencies usually receive the volatility shocks from others. Bitcoin which dominates the cryptocurrency market capitalization is not the key player of the volatility connectedness in the cryptocurrency market.

Corbet et al. (2018) select three popular coins as the cryptocurrencies comprise of Bitcoin, Ripple, and Litecoin to explore the dynamic relationships between those coins and other financial assets consisting of bonds (Markit ITTR110 index), stocks (S&P500 index), gold (COMEX closing gold price), currencies (U.S. broad index), commodities (MSC GSCI Total Return Index), and volatility index from S&P500. They employ the Diebold and Yilmaz (2012) method to measure and analyze spillover effects across assets. Those spillovers of both assets' prices and volatility will imply the dynamic relationship among assets. As a result, they found that Bitcoin's price intensely affects both Ripple and Litecoin's prices. In contrast, the Ripple and Litecoin's prices affect a bit of the Bitcoin's price. In cases of volatility spillover, they found that the Bitcoin volatility has fewer effects to Ripple and Litecoin volatility than price spillover effect. However, the volatility spillover value from Litecoin to Ripple and Bitcoin are quite high. It means that both Ripple and Bitcoin are sensitive to volatility shock transmitted from Litecoin. Furthermore, Corbet et al. (2018) also found that the linkages between the selected cryptocurrencies and other financial assets are very low. In other words, the cryptocurrencies and other financial assets are not connected in short-term. Therefore, it might conclude that cryptocurrencies are a new investment asset class and give the investment opportunity to the investors from portfolio diversification in short-term.

It is consistent with the paper of Bianchi (2018) which found that there is no significant relationship between returns of cryptocurrencies and other traditional asset classes, though there is a little correlation between returns of cryptocurrencies and returns on future contracts of gold and crude oil. This paper uses a random-coefficient panel regression which explains the unit specific average response and cross-sectional heterogeneity of selected cryptocurrencies to investigate the linkages with other traditional asset classes. It also focuses on large market capitalization by selecting fourteen cryptocurrencies which their market capitalization is over 85 percent of all cryptocurrency market capitalization. Meanwhile, the traditional assets used for analysis include equity (FTSE global all-cap value-weighted index), bonds (Global Broad Market Index), gold (S&P GSCI Gold index), energy (S&P GSCI Energy index), foreign exchange (nominal effective exchange rate of U.S. dollar), real estates (MSCI World REITs index), and volatility (S&P 500 VIX short-term futures index. Bianchi (2018) also explores the volatility spillover effects and finds that the cryptocurrencies' risk is not correlated with other traditional assets' risk, while the volatility is correlated with trade volume. Moreover, this paper uses VAR model to analyze the impulse response function of macroeconomic factors consisting of the inflation, yield spreads, credit default swap, U.S. real effective exchange rate, and one-period changes in VIX. As a result, those macroeconomic factors do not drive the trading volume of cryptocurrency market.

Baur et al. (2018) select only the Bitcoin to analyze the static correlation with the other financial assets comprising of equities (S&P 500 index and S&P600 index), precious metals (gold spot and silver spot), currencies (e.g., Euro to U.S. dollar exchange rate; Australian to U.S. dollar exchange rate; Japanese Yen to U.S. dollar exchange rate; British Pounds to U.S. dollar exchange rate; Chinese Yuen to U.S. dollar exchange rate; Hungarian Forint to U.S. dollar exchange rate; trade weighted U.S. dollar index), energy (crude oil index and natural gas index), and bond (e.g., U.S. corporate bond index; U.S. treasury bond index; USD high yield corporate bond index). Finally, they found that Bitcoin' returns do not correlate to those financial assets. It implies that Bitcoin has different characteristics comparing to traditional asset classes. Furthermore, they also investigate the holding transaction data of Bitcoin holders and analyzes that Bitcoin is mainly used for speculative investment rather than for medium of exchange. The correlation results are quite similar to the paper of Briere et al. (2015) which also use the static correlation to analyze the relationship between Bitcoin and traditional assets comprising of the EUR and JPY currencies, developed equities (MSCI world index), emerging equities (MSCI emerging index), developed government bonds (J.P. Morgan GBI), emerging government bonds (JPM EMBI plus), world corporate bonds (Merrill Lynch Global Broad Market Corporate and High Yield), world inflation-linked bonds (Barclays Global Inflation World), gold bullion, oil (WTI crude oil), hedge funds (HFRX Hedge Fund Index), and real estate (FTSE Global NAREIT). They found that the correlation between Bitcoin and traditional assets is very low, Bitcoin then could be one of the safe-haven assets. However, Bitcoin as a safe-haven asset might be uncertain.

Those results of the correlation between targeted cryptocurrencies and traditional assets are similar to paper of Chuen et al. (2017). However, paper of Chuen et al. (2017) uses the Dynamic Conditional Correlation model (DCC) to examine the time-varying conditional correlation of the targeted assets' returns. This paper focuses on the CRyptocurrency Index (CRIX) and the ten cryptocurrencies that have mostly been included in CRIX consisting of Bitcoin, Ethereum, Litecoin, Dash, Dogecoin, Monero, Bitshare, MaidSafeCoin, Nxt, and Bytecoin. Meanwhile, the traditional assets are composed of S&P 500, gold, oil, commodity (GSCI commodity index), real estate (Real Estate Investment Trusts: REITs, and private equity. As a result, there is very low correlation between CRIX and those traditional assets. Therefore, cryptocurrency investment could improve the portfolio's performance.

2.2 The Cryptocurrency Price Forecasting

The cryptocurrency is too volatile and also provides the high returns to the investors and speculators during unpredictable of intrinsic value. Therefore, the cryptocurrency price and volatility analysis especially forecasting are still appealing because they are significant information for the investors and speculators who interested in cryptocurrency investment and need such information for hedging strategies. There are many research questions to ask for the appropriate models to forecast the cryptocurrencies' prices during high volatility. Currently, there are various models to forecast the assets' price and volatility based on time series models. Furthermore, the Bitcoin still spotlights to be a sample for analysis because its price abundantly varies all the time, and its market capitalization also dominates the cryptocurrency market as mentioned in the last section.

The objective to generate Bitcoin is for the medium of exchange, so the Bitcoin's price is represented by the exchange rate to U.S. dollar (Bakar & Rosbi, 2017, pp. 130-131). Bakar and Rosbi (2017) investigate the Bitcoin exchange rate prediction and analyze the Bitcoin volatility by using the Autoregressive Integrated Moving Average model (ARIMA). They conclude that the ARIMA model is reliable to forecast Bitcoin exchange rate with high volatility environment. Nevertheless, the forecasting as high volatility also creates a large error.

The existing papers also apply various models, especially the ARIMA model, to forecast the cryptocurrency prices. When the ARIMA model is compared to other models, most of the existing papers find that the ARIMA model still provides the best results with lower error rather than others. The ARIMA model should be predictable in case of the overreaction as well (Chen, Härdle, Hou, & Wang, 2018, p. 7). The cryptocurrency prices response to the news and tend to overreact to both good and bad news. Moreover, Chen et al. (2018) also use GARCH and EGARCH models to analyze the change in conditional volatility of the cryptocurrency market, and they found that the EGARCH model is better to use for analysis than the GARCH model. In cases of forecasting Bitcoin, the ARIMA model is better than the seasonal decomposition model because the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) are quite low (Sudarchan & Manu, 2019, p. 118).

2.3 The Cryptocurrency Investment and Portfolio Optimization

The asset allocation for portfolio optimization is still a popular research topic in this decade. Due to the high volatility of the traditional assets during the uncertainty of the economic growth, the expected returns on those assets are quite unpredictable. The asset allocation to meet the optimized returns also challenges for investors as well as fund managers. Both investors and fund managers always find the targeted assets consisting of the traditional assets and new assets to diversify such assets for risk minimization approach. Moreover, the cryptocurrencies are very interesting and attractively to invest as a new asset class. Nevertheless, the cryptocurrencies returns are exceedingly volatile, so there are many questions that whether cryptocurrencies could be a good diversifier asset and properly to invest or put them in the portfolio or not. The recent papers still focus on allocation of the traditional assets especially stocks, bonds, real estate, and commodities in various markets. In 2015 – 2018, some papers have shifted to focus on new asset class particularly cryptocurrencies to investigate the benefits of the investment diversification and the optimization portfolio with various models.

However, currently, Bitcoin is mostly considered to examine the portfolio diversification and optimization. Bitcoin can provide outstandingly high diversification benefits over the period consideration during 2010 – 2013 (Briere, Oosterlinck, & Szafarz, 2015, p. 365). Briere et al. (2015) use the mean-variance spanning test developed by Huberman and Kandal (1987) and Ferson et al. (1993) to test the investment opportunities from putting Bitcoin in investors' portfolio. The portfolio under this research consideration follows to U.S. investors who usually hold the traditional assets consisting of stocks, bonds, currencies, and the alternative assets consisting of commodities, hedge fund, and real estate. When the Bitcoin was added in the traditional assets' portfolio, the alternative assets portfolio as well as all assets portfolio, they found that Bitcoin can span all asset categories. It implies that the portfolio with Bitcoin has a superior mean-variance than the portfolio without Bitcoin. Therefore, Bitcoin offers high risk and high return as well as the significant diversification benefits due to low correlation with other assets. In the other word, Bitcoin may improve the risk and return of the investors' portfolio.

Although the Bitcoin returns are very volatile, the investors should select and hold Bitcoin in their portfolio because it can generate higher risk-adjusted returns (Platanakis & Urquhart, 2018, p. 2). According to U.S. investors who usually hold stocks and bonds in their portfolio, so Platanakis and Urquhart (2018) explore the effects of holding Bitcoin on the stocks and bonds portfolio performance by setting the out-of-sample framework. Furthermore, they select eight asset allocation strategies consisting of the Markowitz mean-variance portfolio optimization, Markowitz mean-variance portfolio optimization with Gens, Bayes-Stein shrinkage portfolio approach, Bayes-Stein shrinkage portfolio approach with Gens, Black-Litterman portfolio construction model, Minimum-Variance with lower generalized constraints, equally weighted portfolio or 1/N with re-balancing, and combination of portfolio techniques or 3-fund portfolio combination. Each asset allocation strategy generates the different weights of the targeted assets. As a result, the risk-adjusted returns of all portfolios formed by those asset allocation strategies are higher when adding the Bitcoin in the portfolio. Meanwhile, the excess return of the Minimum-Variance with lower generalized constraints provides the most value.

The out-of-sample method is better than the in-sample method because the parameters of the out-of-sample method are evaluated through the rolling window at each rebalancing date instead of using the whole period, while the in-sample method cannot reflect the real investment decisions (W. Liu, 2019, p. 200). W.Liu (2019) concentrates the performance of ten cryptocurrencies comprising of the Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Monero, Dash, Tether, NEM, and Verge to analyze the portfolio diversification across those cryptocurrencies approach. He compares the out-of-sample performance of six portfolio models consisting of the 1/N equal weighted rule, minimum variance, risk parity, Markowitz, maximum sharp ratio, and maximum utility. Finally, he found that the portfolio diversification across those cryptocurrencies can improve the cryptocurrency portfolio performance. Moreover, the minimum variance model is less risk. Meanwhile, the maximum utility model also provides higher return and utility.

According to the low liquidity of the cryptocurrencies, the liquidity issue should be considered when adding the cryptocurrencies with the traditional assets, especially stocks which have high volatility, in the same portfolio (Trimborn, Li, & Härdle, 2018, pp. 280-281). Trimborn et al. (2018) use 42 cryptocurrencies with over 10,000 U.S. dollars of the market capitalization as well as some traditional assets comprising of the stocks (S&P 100 index), bonds (U.S. bond index), and commodities (S&P GSCI) in order to examine the optimal portfolio. They use the Liquidity Bounded Risk-return Optimization (LIBRO) method that concerns about risk optimization and expands some restrictions, which impede big investment weight of the assets with low liquidity. They also analyze the optimization portfolio according to the mean-variance analysis developed by Markowitz in 1952 as well as the Conditional Value-at-Risk measures. For the asset allocation in the sample portfolio, they divide into two types. First, the portfolio includes only traditional assets consisting of stocks, bonds, and commodities. Second, the portfolio includes cryptocurrencies and those traditional assets. As a result, the investment weights in cryptocurrencies depend on the liquidity upper bound. In case of the liquidity constraint consideration, the portfolio’s returns which include cryptocurrencies still outperform although the cryptocurrency returns are quite volatile. Therefore, cryptocurrencies can improve the risk-return trade-off of the investors’ portfolio.

Due to the recent research papers related to cryptocurrency topic, there is still some research gap in this area especially the token dynamic linkages and investment analysis. The token has been evolved after coin and has different characteristics, comparing to the coin. The issuers who are mostly startup entrepreneurs usually launch token through ICOs to raise funds. Those funds are substantially for a new digital project investment such as digital platform development, network as well as system development. Meanwhile, the issuers will give token with some rights to the holders. The rights could permit the holders to participate in digital project investment to feel like the ownership or allow them to receive some specific goods and services which mentioned as the last section. Furthermore, the token holders could trade their token on hand in the secondary market, while coin holders will mostly trade purpose only. However, the recent papers have concentrated on the cryptocurrency analysis in terms of coin. In other words, the research papers of the cryptocurrency analysis area still lack the analysis of the token dynamic linkages and investment opportunity in spite of being new and very interesting.

Accordingly, this paper focuses on other cryptocurrencies apart from Bitcoin and separates token from coin analysis to make a difference from the existing papers. This paper extends Trimborn and Härdle (2016) for their CRIX (CRyptocurrency IndeX), which created based on roughly 30 cryptocurrencies and captures high coverage of available market capitalization and modify to bundle the top 5 coins and the top 5 tokens by market capitalization as an index. Moreover, this paper covers the short-term dynamic spillover analysis of the token, the long-term relationship between token and other traditional assets, token price forecasting, the dynamic conditional correlation among token and other assets, as well as the portfolio optimization when adding token to the investors' portfolio. The main results would answer the questions that whether the token is suitable assets to invest or whether they can improve the portfolio's performance and can offer the investment opportunity from token diversification. In addition to the model utilization, this paper will seek the various models to examine the dynamic approach appropriately following by the cryptocurrency characteristics which their price and return are too volatile. Those appropriate models lead the results are reliable. The results could be the significant information for the investors as well as the speculators to create the investment strategies. Both investors and speculators could gain the investment opportunity from new asset class investment and hedging the risks.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Data

This paper uses two groups of secondary data as follows.

3.1.1 The cryptocurrency data

The cryptocurrency data, including coin and token, has been downloaded from CoinMarketCap website. This paper uses the daily data of the coin and token market capitalization calculated by circulating supply from 1 January 2017 – 31 December 2019.

3.1.2 The traditional assets data

The traditional assets data has been collected the daily close prices from Thomson Reuters since 1 January 2017 – 31 December 2019. The traditional assets include equity, commodity, and bond. The equity assets include MSCI International World Price Index, MSCI Emerging Markets Price Index, MSCI All Country World Price Index, S&P 500 Index, Dow Jones Industrial Average Index, NASDAQ 100 Index, FTSE 100 Index, Deutsche Boerse DAX Index, Nikkei 225 Index, and Hang Seng Index. The Thomson Reuters Global Gold Index, ICE Brent, and NYMEX WTI crude oil represent the commodity asset class. In addition, the Thomson Reuters U.S. 10-Year Government Benchmark Index and Merrill Lynch U.S. Corporate Master Index represent the fixed income asset class. Those data are mostly from the popular markets or developed markets with high trading volume.

This paper generates the top 5- coin index and top 5- token index, respectively, by using the market capitalization-weighted index. The top 5- coin and the top 5- token indices are reviewed every three months by using top 5- average market capitalization ranking in the last three months. The components of those indices have shown in table 3.1.

Table 3.1 The Components of Top 5- Coin Index and Top5- Token Index

Top 5- coin index	Top 5- token index
The top 5- coin index mostly includes Bitcoin, Ethereum, Dash, XRP, Monero, Litecoin, IOTA, Bitcoin Cash, Cardano, and EOS. Its components depend on the top 5- average coin market capitalization ranking in the last three months.	The top 5- token index mostly includes Tether, MaidSafeCoin, Augur, Golem DigixDAO, Gnosis, Basic Attention, Veritaseum, OmiseGo, Kyber Network, Populous, QASH, Status, 0x, Maker, USD Coin, True USD, UNUS SED LEO, Crypto.com coin, Chainlink, and Huobi Taken. Its components depend on the top 5- average token market capitalization ranking in the last three months.

The market capitalization-weighted index has calculated by using the following formula.

$$Market\ Capitalization - Weighted\ Index\ = \frac{\sum_{i=1}^{5} CMV_{it}}{\sum_{i=1}^{5} BMV_{i0}} \times Base\ Value$$

Where CMV_{it} = Current Market Value of asset i at time t (calculation date)

BMV_{i0} = Base Market Value of asset i at base date (as of April 1, 2017)

Base Value = 1,000

However, this paper has always adjusted the base value when there is any new index's component at the reviewing period. The review period is in every three months by using the market capitalization from the last three months. Every three months reviewing is consistent with the CRyptocurrency IndeX (CRIX) generation presented by (Trimborn & Härdle, 2018) as s collaboration of Humboldt University Berlin, Germany; SKBI at Singapore Management University; and CoinGecko who provide cryptocurrency data for CRIX generation.

$$BMV_n = \frac{\sum_{i=1}^{5} CMV_{it}}{\sum_{i=1}^{5} CMV_{i0}} \times \sum_{i=1}^{5} BMV_{i0}$$

Where BMV_n = Base Market Value after adjustment

CMV_{it} = Current Market Value of asset i after adjustment

CMV_{i0} = Current Market Value of asset i before adjustment

BMV_{i0} = Base Market Value of asset i before adjustment

Due to transformation of the top 5-coin and top 5-token, there is the reviewing period in every three months. This paper has to set up the data of cryptocurrency market capitalization since 1 January 2017 - 31 March 2017 to generate the top 5-coin index and top 5-token index. Therefore, all asset indices have to start since 1 April 2017.

After that, all asset indices or asset prices will be generated to be the asset return by using the following formula.

$$R_i = logP_{it} - logP_{it-1}$$

where R_i is the return of asset i

P_{it} is the index or price of asset i at time t

P_{it-1} is the index or price of asset i at time t-1

This paper then uses the assets' indices and return to examine in various objectives including the cryptocurrency price forecasting, the investigation of the long-term relationship among cryptocurrencies and traditional assets, the dynamic spillover analysis of coin and token in the short-term period, the dynamic conditional correlation among cryptocurrencies and traditional assets, as well as the portfolio optimization to show investment opportunity from coin and token. Moreover, all variables representing the index and return have shown in Table 3.2.

Table 3.2 Variable Explanations

No.	Variable	Asset Class	Explanation
1	TOKEN	Digital Asset	TOKEN represents the top 5- token index or token price. It is generated by the average top 5- token market capitalization every three months.
2	TR	Digital Asset	TR represents daily return of the top 5- token index.
3	COIN	Digital Asset	COIN represents the top 5- coin index or coin price. It is generated by the average top 5- coin market capitalization every three months.
4	CR	Digital Asset	CR represents the daily return of top 5- coin index.
5	WORLD	Equity	WORLD represents the MSCI International World Price Index, which describes the large and middle market capitalization of 23 developed markets countries[1].
6	WD	Equity	WD represents the daily return of the MSCI International World Price Index.
7	EMERG	Equity	EMERG represents the MSCI Emerging Markets Price Index, which describes the large and middle market capitalization of 24 emerging markets countries[2].
8	EM	Equity	EM represents the daily return of the MSCI Emerging Markets Price Index.

[1] The developed markets countries consists of Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom and United States.

[2] The emerging markets countries consists of Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates.

No.	Variable	Asset Class	Explanation
9	ACWI	Equity	ACWI represents the MSCI All Country World Price Index which describes the large and middle market capitalization of 23 developed market countries and 24 emerging markets countries.
10	AC	Equity	AC represents the daily return of the MSCI All Country World Price Index.
11	SP500	Equity	SP500 represents the S&P 500 Index which captures 500 largest market capitalization of New York Stock Exchange or Nasdaq market.
12	SP	Equity	SP represents the daily return of S&P 500 index.
13	DOWJONES	Equity	DOWJONES represents the Dow Jones Industrial Average Index which measures 30 large companies in New York Stock Exchange or Nasdaq market.
14	DOW	Equity	DOW represents the daily return of Dow Jones Industrial Average Index.
15	NASDAQ	Equity	NASDAQ represents the Nasdaq 100 Index which captures 100 largest non-financial companies of the Nasdaq market. The Nasdaq market shows the leading technology and innovative companies of the world.
16	ND	Equity	ND represents the daily return of Nasdaq 100 Index.
17	DAXINDEX	Equity	DAXINDEX represents the DAX Index which captures 30 largest companies of the Frankfurt Stock Exchange.

No.	Variable	Asset Class	Explanation
18	DAX	Equity	DAX represents the daily return of DAX Index.
19	FTSE100	Equity	FTSE100 represents the FTSE 100 Index which captures 100 large companies of the London Stock Exchange.
20	FTSE	Equity	FTSE represents the daily return of FTSE 100 Index.
21	NIKKEI	Equity	NIKKEI represents the Nikkei 225 Index which captures 225 large companies of the Tokyo Stock Exchange.
22	NK	Equity	NK represents the daily return of Nikkei 225 Index.
23	HANGSENG	Equity	HANGSENG represents the Hang Seng Index which measures the market capitalization weighted index of the Hong Kong Stock Exchange.
24	HSI	Equity	HSI represents the daily return of Hang Seng Index.
25	BRTOIL	Commodity	BRTOIL represents the ICE Brent Crude Electronic Energy Future.
26	BRT	Commodity	BRT represents the daily return of ICE Brent Crude Electronic Energy Future.
27	WTIOIL	Commodity	WTIOIL represents the NYMEX Light Sweet Crude Oil Electronic Energy Future.
28	WTI	Commodity	WTI represents the daily return of NYMEX Light Sweet Crude Oil Electronic Energy Future.
29	GOLD	Commodity	GOLD represents the Global Gold Index generated by Thomson Reuters.

No.	Variable	Asset Class	Explanation
30	GD	Commodity	GD represents the daily return of the Global Gold Index.
31	CORPBOND	Fixed Income	CORPBOND represents the Merrill Lynch U.S. Corporate Master Index.
32	CORP	Fixed Income	CORP represents the daily return of the Merrill Lynch U.S. Corporate Master Index.
33	GOVBOND	Fixed Income	GOVBOND represents the U.S. 10 Year Government Benchmark Index generated by Thomson Reuters, which measures the long-term government bond.
34	GOV	Fixed Income	GOV represents the daily return of the U.S. 10 Year Government Benchmark Index.

3.2 Descriptive Statistics

Table 3.3 shows the descriptive statistics of all variables including cryptocurrencies and other traditional assets. In the sample period, token and coin have higher average daily returns, as 0.25 percent and 0.31 percent respectively, rather than others. Meanwhile, all traditional assets offer a bit positively average daily return. According to the preliminary volatility analysis, token and coin have a high standard deviation as 5.35 percent and 5.67 percent, respectively. The standard deviation of the other traditional assets is in a range of 0.23 percent to 1.93 percent. The returns of the U.S. corporate bond and the U.S. 10-year government bond have quite low standard deviation as 0.23 percent and 0.35 percent, respectively, while NYMEX crude oil has the highest standard deviation of all traditional assets. It implies that the return of the cryptocurrency as a new asset class is volatile rather than the other traditional assets.

For the data distribution, the returns of the token, gold, and U.S. 10-year government bond is positively skewed. Meanwhile, all assets' returns have high kurtosis, which exhibits fat tail with higher peak rather than a normal distribution. Furthermore, the Augmented Dickey-Fuller test has been applied to examine a unit root process. All assets' returns are stationary and do not have a unit root process.

Table 3.3 Descriptive Statistics and Unit Root Test of All Variables

Asset	Mean	Max	Min	Standard Deviation	Skewness	Kurtosis	ADF Test
TR	0.0025	0.3141	-0.2447	0.0535	0.2398	9.2471	-26.2425 (0.0000)
CR	0.0031	0.2919	-0.2603	0.0567	-0.2203	6.8635	-25.2070 (0.0000)
WD	0.0004	0.0185	-0.0318	0.0068	-0.8706	5.6587	-21.6433 (0.0000)
EM	0.0002	0.0290	-0.0354	0.0087	-0.3435	4.2584	-21.0549 (0.0000)
AC	0.0004	0.0198	-0.0300	0.0067	-0.7936	5.2722	-20.8936 (0.0000)
SP	0.0005	0.0294	-0.0418	0.0084	-0.9749	6.7656	-25.6865 (0.0000)
DOW	0.0005	0.0304	-0.0471	0.0087	-1.0293	7.1480	-25.0617 (0.0000)
ND	0.0008	0.0392	-0.0474	0.0115	-0.5987	5.2574	-26.5537 (0.0000)
DAX	0.0001	0.0332	-0.0474	0.0092	-0.5917	5.0816	-24.7557 (0.0000)
FTSE	0.0001	0.0224	-0.0464	0.0076	-0.7507	6.6758	-23.6059 (0.0000)
NK	0.0004	0.0320	-0.0484	0.0099	-0.6459	5.5452	-24.7675 (0.0000)
HSI	0.0003	0.0413	-0.0525	0.0107	-0.3594	4.9046	-23.6743 (0.0000)
BRT	0.0004	0.0890	-0.0744	0.0184	-0.4583	5.6018	-25.4470 (0.0000)
WTI	0.0003	0.0787	-0.0823	0.0193	-0.4782	4.7925	-24.9565 (0.0000)
GD	0.0004	0.0620	-0.0525	0.0141	0.1191	4.3566	-21.3231 (0.0000)
CORP	0.0003	0.0078	-0.0085	0.0023	-0.0755	3.8730	-26.4631 (0.0000)
GOV	0.0002	0.0145	-0.0122	0.0035	0.0961	4.0332	-24.7441 (0.0000)

Note: All variables as Table 3.3 analyzed in terms of daily data

3.3 Static Correlation between Cryptocurrencies and Traditional Assets

In the sample period, the returns of cryptocurrencies, including coin and token, are extremely low correlated with the other traditional assets' returns. However, tokens' return moderately positive correlate to coins' return as of 62.07 percent. Coin and token returns have a low positive relation to the returns of stock and commodity markets, including MSCI international world price, MSCI emerging market price, MSCI all country world price, S&P 500, Dow Jones, Nasdaq 100, DAX, FTSE 100, Nikkei 225, Hang Seng, Brent crude oil, NYMEX crude oil, and gold. Meanwhile, they have a low negative relation to bond market returns, including the U.S. corporate bond as well as the U.S. 10-year government bond.

The traditional assets' returns are highly correlated with other assets' returns in the same asset classes. The return of the MSCI international world price has extremely high positive relations with the return of the MSCI all country world price as around 99.29 percent as well as the other developed market returns, including S&P 500, Dow Jones, and Nasdaq 100 as 94.63 percent, 91.14 percent, and 86.38 percent, respectively. Meanwhile, the return of the MSCI all country price is highly positive correlated to S&P 500, Dow Jones, and Nasdaq 100 as 91.87 percent, 88.56 percent, and 84.20 percent, respectively. The return of S&P 500 is highly positively correlated to the returns of Down Jones and Nasdaq 100 as 95.66 percent and 92.92percent, respectively. The MSCI emerging market index return also has a high positive correlation with the MSCI all country price and Hang Seng as 70.55 percent and 82.18 percent, respectively. The return of Dow Jones is high positive related to Nasdaq 100 as 83.81 percent. Many pairs of the stock markets have quite low correlations to each other as well. The returns of S&P 500, Dow Jones, and Nasdaq are quite positively low correlated to Nikkei 225 and Hang Seng as the range of 17 – 25 percent. Meanwhile, the return of FTSE 100 is also quite low related to S&P 500, Dow Jones, and Nasdaq as 38.24 percent, 38.62 percent, and 30.34 percent, respectively.

The return of Brent crude oil is too positively high correlated with the return of NYMEX crude oil as 91.41 percent. However, the returns of Brent and NYMEX crude oil have quite positively low correlations with gold as around 7.50 percent and 9.53 percent, respectively. The U.S. corporate bonds' return has an exceedingly positive correlation with the U.S. 10-year government bonds' return as 92.72 percent. In addition, the static correlations between two different asset classes are too low. The returns of Brent and NYMEX crude oil are too positively low correlated with all stock markets. Meanwhile, the return of gold is too positively low correlated with the stock markets excepting for a low negative correlation with DAX, FTSE 100, and Nikkei 225. Nonetheless, the returns of the U.S. corporate and U.S. 10-year government bonds have a very low negative correlation with all asset classes' returns, excluding gold, in range of 0.40 – 33.50 percent. The gold return has a low positive correlation with the U.S. corporate bond and the U.S. 10-year government bond as around 35.49 percent and 35.76 percent, respectively.

Table 3.4 Static Correlation Coefficients of Daily Asset Returns

	CR	WD	EM	AC	SP	DOW	ND	DAX	FTSE	NK	HSI	BRT	WTI	GD	CORP	GOV
TR	0.6207	0.0871	0.0511	0.0861	0.0635	0.0646	0.0650	0.0445	0.0351	0.0756	0.0366	0.0154	0.0120	0.0243	-0.0043	-0.0250
CR		0.0666	0.0202	0.0629	0.0500	0.0473	0.0535	0.0578	0.0597	0.0001	0.0049	0.0164	0.0121	0.0540	-0.0398	-0.0449
WD			0.6164	0.9929	0.9463	0.9114	0.8638	0.6547	0.5446	0.3796	0.4081	0.2914	0.2676	0.0690	-0.1726	-0.3216
EM				0.7055	0.4455	0.4352	0.4288	0.5251	0.5093	0.5535	0.8372	0.2157	0.2176	0.1277	-0.0814	-0.2301
AC					0.9187	0.8856	0.8420	0.6684	0.5670	0.4254	0.4936	0.2948	0.2738	0.0814	-0.1675	-0.3241
SP						0.9566	0.9292	0.4975	0.3824	0.2012	0.2396	0.2323	0.2154	0.0359	-0.1928	-0.3039
DOW							0.8381	0.4950	0.3862	0.2054	0.2249	0.2369	0.2192	0.0330	-0.2171	-0.3319
ND								0.4313	0.3034	0.1710	0.2411	0.1760	0.1575	0.0446	-0.1322	-0.2249
DAX									0.7182	0.3415	0.3856	0.2233	0.1942	-0.0991	-0.1508	-0.2967
FTSE										0.3132	0.4167	0.2989	0.2743	-0.0193	-0.1078	-0.2431
NK											0.5718	0.1106	0.1165	-0.1006	-0.0922	-0.2289
HSI												0.1402	0.1423	0.0538	-0.0845	-0.2087

	CR	WD	EM	AC	SP	DOW	ND	DAX	FTSE	NK	HSI	BRT	WTI	GD	CORP	GOV
BRT													0.9141	0.0750	-0.0909	-0.1634
WTI														0.0953	-0.0949	-0.1565
GD															0.3549	0.3576
CORP																0.9272

3.4 Research Assumptions and Models

This paper has to investigate the eleven assumptions involving with the cryptocurrency analysis, including short-term dynamic spillover and long-term cointegration to other traditional assets, price forecasting, dynamic conditional correlation with the other traditional assets, as well as the investment opportunity when adding coin and token to the portfolio. Those research assumptions have been investigated by using various models as follows.

Table 3.5 Research Assumptions and Models

Research Objectives	Research Assumptions	Models
To analyze the direction of the causality, which is the mean spillover, between coin and main traditional asset in the short-term period.	The coin return might have causality with the returns of token and main traditional assets, including MSCI international world price, gold, and U.S. 10-year government bond.	Granger Causality Test
To analyze the direction of the causality, which is the mean spillover, between token and main traditional asset in the short-term period.	The token return might have causality with the returns of coin and main traditional assets, including MSCI international world price, gold, and U.S. 10-year government bond.	Granger Causality Test
To analyze the impulse response function, which is mean spillover, of coin return in the short-term period.	The coin return might respond from their own shock or the other assets' shock. Those other assets include token, MSCI internal world price, gold, and U.S. 10-year government bond.	Impulse response function by applying Vector AutoRegressive (VAR) model.

Research Objectives	Research Assumptions	Models
To analyze the impulse response function, which is mean spillover, of token return in the short-term period.	The token return might respond from their own shock or the other assets' shock. Those other assets include token, MSCI internal world price, gold, and U.S. 10-year government bond.	Impulse response function by applying Vector AutoRegressive (VAR) model.
To examine the variance spillover of the coin volatility in the short-term period.	The volatility of coin return might be affected by the other assets' shock. Those other assets include the token, MSCI internal world price, gold, and U.S. 10-year government bond.	The Univariate Volatility Spillover model
To examine the variance spillover of the token volatility in the short-term period.	The volatility of token return might be affected by the other assets' shock. Those other assets include the coin, MSCI internal world price, gold, and U.S. 10-year government bond.	The Univariate Volatility Spillover model
To investigate the long-term relationship between coin and main traditional assets.	The coin index might have the long-term relationship with token index and main traditional assets, including MSCI international world price index, gold index, and U.S. 10-year government bond index.	Johansen Cointegration Test

Research Objectives	Research Assumptions	Models
To investigate the long-term relationship between token and main traditional assets.	The token index might have the long-run relationship with coin index and main traditional assets, including MSCI international world price index, gold index, and U.S. 10-year government bond index	Johansen Cointegration Test
To forecast cryptocurrency price with the reliable model.	Both coin and token price could be forecasted in the short-term period.	1. Random Walk Process (RW) 2. AutoRegressive Integrated Moving-Average (ARIMA) 3. AutoRegressive Integrated Moving Average with Exogenous Variables (ARIMAX) 4. Vector AutoRegressive (VAR)
To analyze the dynamic conditional correlation between cryptocurrencies and other traditional assets.	The returns of coin and token could have low dynamic conditional correlation with the other traditional assets.	The Dynamic Conditional Correlation (DCC) model.

Research Objectives	Research Assumptions	Models
To examine the proper weights of cryptocurrency investment in the portfolio to meet the optimal return, and to exhibit whether the cryptocurrency will be appropriate to invest.	The cryptocurrencies, including coin and token, are a new asset class to be an alternative investment in investors' portfolios.	Markowitz mean-variance portfolio optimization method.

3.5 Short-term Dynamic Spillover Analysis between Cryptocurrencies and Traditional Assets

3.5.1 Mean Spillover by Using the Granger Causality Test

The Granger causality has usually applied for testing the causality between variables. The value movement of one variable in the past can explain the current value movement of another variable. The causality implies for the spillover effect from one variable to another through the mean equation. It offers the significant information to explain the directions of the causes and effects among variables better. It is the benefits for the investors and speculators to use that information to be indicators for forecasting approach. However, it is appropriate to explain the casual relation in the short run only. Currently, there are many financial and economic papers which apply the Granger causality to explain the causes and effects among financial and economic indicators such as stock prices and exchange rate in various markets (Granger, Huangb, & Yang, 2000), the stock returns and trade volumes (Hiemstra & Jones, 1994), the energy consumption and economic growth (Paul & Bhattacharya, 2004), etc.

This paper uses the Granger causality to analyze the direction of the causality, which are mean spillover linkages, among cryptocurrencies and main traditional asset returns in the short-term period. The main traditional assets have been focused according to different asset classes. The MSCI international world price index represents the equity asset class, the gold index represents the commodity, and the U.S. 10-year government bond index represents the fixed income asset class. The Granger causality test divides into two steps. The first step is the unit root process, and all time-series variables have to be stationary. The second step is the Granger causality test by using the bivariate VAR model as follow.

The causality between coin and token:

$$CR_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} CR_{t-i} + \sum_{i=1}^{m} \beta_{2i} TR_{t-i} + \varepsilon_{1t}$$
$$TR_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} TR_{t-i} + \sum_{i=1}^{m} \alpha_{2i} CR_{t-i} + \varepsilon_{2t}$$

The null hypothesis (H_o): $\beta_{21} = \beta_{22} = \ldots = \beta_{2m} = 0$, the token return does not cause the coin return.

The null hypothesis (H_o): $\alpha_{21} = \alpha_{22} = \ldots = \alpha_{2m} = 0$, the coin return does not cause the token returns.

The causality between coin and main traditional asset classes:

Causality between coin and MSCI international world index returns:

$$CR_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} CR_{t-i} + \sum_{i=1}^{m} \beta_{2i} WD_{t-i} + \varepsilon_{1t}$$
$$WD_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} WD_{t-i} + \sum_{i=1}^{m} \alpha_{2i} CR_{t-i} + \varepsilon_{2t}$$

The null hypothesis (H_o): $\beta_{21} = \beta_{22} = \ldots = \beta_{2m} = 0$, the stock return does not cause the coin returns

The null hypothesis (H_o): $\alpha_{21} = \alpha_{22} = \ldots = \alpha_{2m} = 0$, the coin return does not cause the stock return.

Causality between coin and gold returns:

$$CR_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} CR_{t-i} + \sum_{i=1}^{m} \beta_{2i} GD_{t-i} + \varepsilon_{1t}$$
$$GD_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} GD_{t-i} + \sum_{i=1}^{m} \alpha_{2i} CR_{t-i} + \varepsilon_{2t}$$

The null hypothesis (H_o): $\beta_{21} = \beta_{22} = \ldots = \beta_{2m} = 0$, the gold return does not cause the coin return.

The null hypothesis (H_o): $\alpha_{21} = \alpha_{22} = \ldots = \alpha_{2m} = 0$, the coin return does not cause the gold return.

Causality between coin and U.S. 10-year government bond returns:

$$CR_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} CR_{t-i} + \sum_{i=1}^{m} \beta_{2i} GOV_{t-i} + \varepsilon_{1t}$$
$$GOV_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} GOV_{t-i} + \sum_{i=1}^{m} \alpha_{2i} CR_{t-i} + \varepsilon_{2t}$$

The null hypothesis (H_o): $\beta_{21} = \beta_{22} = \ldots = \beta_{2m} = 0$, the government bond return does not cause the coin return.

The null hypothesis (H_o): $\alpha_{21} = \alpha_{22} = \ldots = \alpha_{2m} = 0$, the coin return does not cause the government bond return.

The causality between token and main traditional asset classes:

Causality between token and MSCI international world price index returns:

$$TR_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} TR_{t-i} + \sum_{i=1}^{m} \beta_{2i} WD_{t-i} + \varepsilon_{1t}$$
$$WD_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} WD_{t-i} + \sum_{i=1}^{m} \alpha_{2i} TR_{t-i} + \varepsilon_{2t}$$

The null hypothesis (H_o): $\beta_{21} = \beta_{22} = \ldots = \beta_{2m} = 0$, the stock return does not cause the token return.

The null hypothesis (H_o): $\alpha_{21} = \alpha_{22} = \ldots = \alpha_{2m} = 0$, the token return does not cause the stock return.

Causality between token and gold returns:

$$TR_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} TR_{t-i} + \sum_{i=1}^{m} \beta_{2i} GD_{t-i} + \varepsilon_{1t}$$
$$GD_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} GD_{t-i} + \sum_{i=1}^{m} \alpha_{2i} TR_{t-i} + \varepsilon_{2t}$$

The null hypothesis (H_o): $\beta_{21} = \beta_{22} = \ldots = \beta_{2m} = 0$, the gold return does not cause the token return.

The null hypothesis (H_o): $\alpha_{21} = \alpha_{22} = \ldots = \alpha_{2m} = 0$, the token return does not cause the gold return.

Causality between token and U.S. 10-year government bond returns:

$$TR_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} TR_{t-i} + \sum_{i=1}^{m} \beta_{2i} GOV_{t-i} + \varepsilon_{1t}$$
$$GOV_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} GOV_{t-i} + \sum_{i=1}^{m} \alpha_{2i} TR_{t-i} + \varepsilon_{2t}$$

The null hypothesis (H_o): $\beta_{21} = \beta_{22} = \ldots = \beta_{2m} = 0$, the government bond return does not cause the token return.

The null hypothesis (H_o): $\alpha_{21} = \alpha_{22} = \ldots = \alpha_{2m} = 0$, the token return does not cause the government bond return.

3.5.2 Mean Spillover by Using Impulse Response Function

The impulse response function has usually applied VAR model to measure the impact of the shock of one variable to another in the system through the mean equation. In other words, it is also used to explain the short-run dynamic interaction between the time-series variables in the system when the shock occurs. Most papers also usually use the impulse response function together with the cointegration as well as causality tests to analyze the spillover effect between time-series variables in the system (e.g., (Chang, Fang, & Wen, 2001; Chevallier, 2010; Granger et al., 2000).

The impulse response function is the coefficient of vector moving average in the VAR model. VAR models are written as below:

$$y_{1,t} = \mu_1 + \varphi_{11} y_{t-1,1} + \varphi_{12} y_{t-1,2} + \ldots + \varphi_{15} y_{t-1,5} + \varepsilon_{1,t}$$
$$Y_{2,t} = \mu_2 + \varphi_{21} y_{t-1,1} + \varphi_{22} y_{t-1,2} + \ldots + \varphi_{25} y_{t-1,5} + \varepsilon_{2,t}$$
$$\vdots \quad \vdots \quad \ldots \quad \ldots \quad \ldots \quad \vdots$$
$$y_{5,t} = \mu_5 + \varphi_{51} y_{t-1,1} + \varphi_{52} y_{t-1,2} + \ldots + \varphi_{55} y_{t-1,5} + \varepsilon_{5,t}$$

where $y_{i,t}$ represents the endogenous variable at time t

$\varphi_{ij}(L)$ represents the matrix in Backshift Operator (L)

μ_i represents the constant value

$\varepsilon_{i,t}$ represent the error term.

The VAR model then has been transformed as the vector moving average as below.

$$y_t = \mu + \sum_{i=0}^{\infty} \varphi_i \varepsilon_{t-i}$$

where y_t represents the vector of the time-series variables in the system
μ represents the mean of y_t
φ_i represents the impulse response function or impact spillover
ε_t represents the vector of the error terms

According to the cointegration and causality tests as the previous analysis, this paper also uses the impulse response function to analyze the short-run dynamic linkages among the cryptocurrencies, including coins and tokens, and main traditional asset classes. It also focuses on the movement of the coin and token returns, including current and future returns, when there are shocks from their own or the other sample assets. The results are benefits for the investment strategies on cryptocurrencies. The impulse response function procedures start with the unit root process. All sample variables should be stationary. The VAR model and the impulse response function then have been estimated. The variables in the system include CR, TR, WD, DOL, GD, and GOV. Therefore, y_t consists of those variables as follow and the φ_i will be estimated and plotted to the graph.

$$y_t = \begin{bmatrix} CR_t \\ TR_t \\ WD_t \\ GD_t \\ GOV_t \end{bmatrix} = \begin{bmatrix} \overline{CR}_t \\ \overline{TR}_t \\ \overline{WD}_t \\ \overline{GD}_t \\ \overline{GOV}_t \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} \varphi_i^{11} & \varphi_i^{12} & \dots & \varphi_i^{15} \\ \varphi_i^{21} & \varphi_i^{22} & \dots & \varphi_i^{25} \\ \vdots & \vdots & & \vdots \\ \varphi_i^{51} & \varphi_i^{52} & \dots & \varphi_i^{55} \end{bmatrix} \begin{bmatrix} \varepsilon_{CR,t-i} \\ \varepsilon_{TR,t-i} \\ \vdots \\ \varepsilon_{GOV,t-i} \end{bmatrix}$$

3.5.3 The Volatility Spillover Model

The volatility spillover model is one of the dynamic linkage analysis models. It describes the shocks' impact of one variable to another through the error terms. Most of the recent financial papers have usually used the volatility spillover to analyze the volatility linkages among the variances of the assets' returns in various markets such as stocks, bonds, oil, etc. (e.g., (Christiansen, 2007; Ji & Fan, 2012; Korkie, Sivakumar, & Turtle, 2006; Skintzi & Refenes, 2006)). The volatility spillover is applied based on the GARCH (1,1) model.

This paper applies the concept of the univariate volatility spillover model, which follows by (Ng, 2000), to analyze the dynamic impact from the main traditional assets to the cryptocurrency market, as well as coin or token to each other, through the error terms. In other words, the shock of the main traditional assets might influence the volatility of coin and token returns. Meanwhile, the shock of coin or token might affect the volatility of each other. The univariate volatility spillover model for the volatility of asset returns i, $\sigma_{i,t}^2$, is specified as follow.

Conditional return with AR(1):

$$R_{i,t} = \beta_{i,0} + \beta_i R_{i,t-1} + \delta_{i,t-1} R_{j,t-1} + \varepsilon_{i,t}$$
$$\varepsilon_{i,t} = e_{i,t} + \varphi_{i,t-1} e_{j,t}$$
$$e_{i,t} \sim N(0, \sigma_{i,t}^2)$$

Conditional variance with GARCH (1,1):

$$\sigma_{i,t}^2 = c_{i,0} + c_{i,1}\sigma_{i,t-1}^2 + c_{i,2} e_{i,t-1}^2$$

where $e_{i,t}$ represents the purely idiosyncratic shock which is the conditional normal distribution with mean zero and variance, and also assumed to be uncorrelated to the shocks of the asset j return, $e_{j,t}$.

This paper applies the univariate volatility spillover model as mentioned above to examine the volatility spillover linkages among cryptocurrencies, including coin and token, and main traditional assets. All sample variables in the model should be stationary, so they have to test for unit root process at first. After that, the conditional variance with univariate GARCH (1,1) model is estimated for the endogenous variable in each model. According to cointegration, causality as well as impulse response function analysis, this paper also applies the univariate volatility spillover model with five aspects. The first aspect, the shock from cryptocurrencies, either coin or token, will influence the volatility of each other because they are in the same market. Furthermore, the investors or the speculators who usually invest in coin and token might be the same person. Therefore, the coin volatility could show the co-movement of the token volatility as the same direction when shock occurs.

Volatility spillover linkages between coin and token:

$$\sigma_{CR,t}^2 = c_{CR,0} + c_{CR,1}\sigma_{CR,t-1}^2 + c_{CR,2}e_{CR,t-1}^2 + \gamma_1\sigma_{TR,t-1}^2$$
$$\sigma_{TR,t}^2 = c_{TR,0} + c_{TR,1}\sigma_{TR,t-1}^2 + c_{TR,2}e_{TR,t-1}^2 + \gamma_2\sigma_{CR,t-1}^2$$

The null hypothesis (H_o): γ_1 = 0, there is no variance spillover. It implies that the token volatility does not affect the volatility of the coin return.

The null hypothesis (H_o): γ_2= 0, there is no variance spillover. It implies that the coin volatility does not affect the volatility of the token return.

For the second aspect, the shock from the MSCI international world return, which represents the equity asset class in the developed market, could affect the volatility of both coin and token returns.

Volatility spillover linkages among coin, token, and MSCI international world returns:

$$\sigma_{CR,t}^2 = c_{CR,0} + c_{CR,1}\sigma_{CR,t-1}^2 + c_{CR,2}e_{CR,t-1}^2 + \gamma_1\sigma_{WD,t-1}^2$$
$$\sigma_{TR,t}^2 = c_{TR,0} + c_{TR,1}\sigma_{TR,t-1}^2 + c_{TR,2}e_{TR,t-1}^2 + \gamma_2\sigma_{WD,t-1}^2$$

The null hypothesis (H_o): γ_1 = 0, there is no variance spillover. It implies that the stock market volatility does not affect the volatility of the coin return.

The null hypothesis (H_o): γ_2 = 0, there is no variance spillover. It implies that the stock market volatility does not affect the volatility of the token return.

For the third aspect, the shock from the gold return, which represents the commodity asset, could affect the volatility of both coin and token returns.

Volatility spillover linkages among coin, token, and gold return:

$$\sigma^2_{CR,t} = c_{CR,0} + c_{CR,1}\sigma^2_{CR,t-1} + c_{CR,2}e^2_{CR,t-1} + \gamma_1\sigma^2_{GD,t-1}$$
$$\sigma^2_{TR,t} = c_{TR,0} + c_{TR,1}\sigma^2_{TR,t-1} + c_{TR,2}e^2_{TR,t-1} + \gamma_2\sigma^2_{GD,t-1}$$

The null hypothesis (H_o): γ_1 = 0, there is no variance spillover. It implies that the gold volatility does not affect the volatility of the coin return.

The null hypothesis (H_o): γ_2 = 0, there is no variance spillover. It implies that the gold volatility does not affect the volatility of the token return.

For the final aspect, the shock from the U.S. 10-year government return, which represents the fixed income asset class, could affect the volatility of both coin and token returns.

Volatility spillover linkages among coin, token, and U.S. 10-year government bond return:

$$\sigma^2_{CR,t} = c_{CR,0} + c_{CR,1}\sigma^2_{CR,t-1} + c_{CR,2}e^2_{CR,t-1} + \gamma_1\sigma^2_{GOV,t-1}$$
$$\sigma^2_{TR,t} = c_{TR,0} + c_{TR,1}\sigma^2_{TR,t-1} + c_{TR,2}e^2_{TR,t-1} + \gamma_2\sigma^2_{GOV,t-1}$$

The null hypothesis (H_o): γ_1 = 0, there is no variance spillover. It implies that the long-term government bond volatility does not affect the volatility of the coin return.

The null hypothesis (H_o): γ_2 = 0, there is no variance spillover. It implies that the long-term government bond volatility does not affect the volatility of the token return.

3.6 Long-run Relationship between Cryptocurrencies and Traditional Assets by using the Johansen Cointegration Method

The Johansen cointegration method proposed by Johansen (1988, 1995) has been usually applied to examine the long-run relationship among time-series variables based on the Vector AutoRegressive (VAR) model proposed by Sim (1980). It develops from cointegration test proposed Engle and Granger (1987). The long-run relationship implies the fundamental characteristics or movement of the time-series variables. Currently, there are many financial or economics papers which apply the cointegration to explain the long-term linkages among assets, especially assets' prices, and macroeconomic indicators ((e.g., (M.-H. Liu & Shrestha, 2008; Maghyereh & Al-Kandari, 2007; Maysami, Howe, & Rahmat, 2004; Nieh & Lee, 2001)).

This paper focuses on applying the Johansen cointegration to test the long-run relationship between cryptocurrencies and main traditional assets including stock, commodity, and bond. The results of the long-run relationship between those assets will give an answer that whether the coin and token have the long-term fundamental movement with the main traditional asset class. The Johansen cointegration test has the advantages that it can apply for the full system, which has more than two variables, with the maximum likelihood method to estimate the number of the cointegration vectors. However, the full system of the VAR model is well specified (Ericsson & MacKinnon, 2002). Meanwhile, the Engle and Granger cointegration is proper to examine the cointegration vectors of only two variables. Furthermore, it has two procedures which are long-run equilibrium estimation by using the unit root process to estimate the error term for the stationary approach, and the estimation of the short-run relationship by using the error-correction model (ECM) for adjustment toward the long-run equilibrium. This leads disequilibrium in the short run when the shock occurs.

According to the recent papers involved the cryptocurrency topic, most of them conclude that the cryptocurrency is as a new alternative asset class (e.g., (Burniske & White, 2016; Chuen et al., 2017; Y. Liu & Tsyvinski, 2021; Sontakke & Ghaisas, 2017)). Some of the popular cryptocurrencies, especially, Bitcoin is compared to gold (Dyhrberg, 2016, p. 139), or claimed as the virtual currency (Briere et al., 2015, p. 365) for mainly as a medium of exchange purpose (Bakar & Rosbi, 2017, p. 130). Therefore, this paper has to apply the Johansen cointegration to examine the long-run relationship among cryptocurrencies including coins and tokens, as a new alternative asset class, and main traditional asset classes.

The procedures of the Johansen cointegration test include three steps. The first step is the unit root process for checking the stationary of all variables and all variables must be non-stationary. The second step is the cointegration test to explore the possible cointegration between the variables in the equation. The trace and maximum eigenvalue tests are applied to find out the amount of the cointegrating vectors. The null hypothesis of the trace test is that there are k cointegrating vectors at most. Meanwhile, the null hypothesis of the maximum eigenvalue is that there are cointegrating vectors not less than k. The third step is the cointegration estimation by using the least square method to estimate the long-run coefficients in each equation. The null hypothesis is that the long-run coefficient is equal to zero, or there is no long-run relation between the sample assets. This paper expects that the null hypothesizes are rejected, and there are long-run relations among cryptocurrencies and other main traditional asset classes.

The cointegration test in this section separates to two purposes. The first purpose is the investigation of whether the top 5-coin index has the long-term linkages with the token, stock, commodity, and bond. The second purpose is the investigation of whether the top 5-token index have the long-term linkages with the coin, stock, commodity, and bond. Due to the lack of the fundamental of token and coin, therefore, those two proposes are transformed to the equations which are tested by pairs of assets as below.

The cointegration between coin and token:

$$COIN_t = \beta_0 + \beta_1 TOKEN_t + \varepsilon_t$$
$$TOKEN_t = \alpha_0 + \alpha_1 COIN_t + \varepsilon_t$$

The null hypothesis (H_o): β_1= 0, the top 5-token index (TOKEN) does not have the long-term relationship to the top 5-coin index (COIN).

The null hypothesis (H_o): α_1 = 0, the top 5-coin index (COIN) does not have the long-term relationship to the top 5-token index (TOKEN).

The cointegration between coin and main traditional asset classes:

Cointegration between top 5-coin index and MSCI international world price index:

$$COIN_t = \beta_0 + \beta_1 WORLD_t + \varepsilon_t$$

The null hypothesis (H_o): β_1= 0, the MSCI international world price index (WORLD) does not have the long-term relationship to the top 5-coin index (COIN).

Cointegration between top 5-coin index and gold index:

$$COIN_t = \beta_0 + \beta_1 GOLD_t + \varepsilon_t$$

The null hypothesis (H_o): β_1= 0, the gold index (GOLD) does not have the long-term relationship to the top 5-coin index (COIN).

Cointegration between top 5-coin index and U.S. 10-year government bond index:

$$COIN_t = \beta_0 + \beta_1 GOVBOND_t + \varepsilon_t$$

The null hypothesis (H_o): β_1= 0, the U.S. 10-year government bond index (GOVBOND) does not have the long-term relationship to the coin index.

The cointegration between token and main traditional asset classes:

Cointegration between top 5-token index and MSCI international world price index:

$$TOKEN_t = \beta_0 + \beta_1 WORLD_t + \varepsilon_t$$

The null hypothesis (H_o): β_1= 0, the MSCI international world price index (WORLD) does not have the long-term relationship to the top 5-token index (TOKEN).

Cointegration between top 5-token index and gold index:

$$TOKEN_t = \beta_0 + \beta_1 GOLD_t + \varepsilon_t$$

The null hypothesis (H_o): β_1= 0, the gold index (GOLD) does not have the long-term relationship to the top 5-token index (TOKEN).

Cointegration between top 5-token index and U.S. 10-year government bond index:

$$TOKEN_t = \beta_0 + \beta_1 GOVBOND_t + \varepsilon_t$$

The null hypothesis (H_o): β_1= 0, the U.S. government bond index (GOVBOND) does not have the long-term relationship to the top 5- token index (TOKEN).

3.7 Forecasting Cryptocurrency Price: A Comparative Study

3.7.1 Random Walk (RW)

This paper applies the random walk process as the benchmark for forecasting coin and token prices. The coin price at time t is forecasted by its price at time t-1. Meanwhile, the token price at time t is also forecasted by its price at time t-1 as well. The random walk model can be written as follows.

$$Y_t = Y_{t-1} + u_t$$

Forecasting coin price by random walk:

$$COIN_t = COIN_{t-1} + u_t$$

Forecasting token price by random walk:

$$TOKEN_t = TOKEN_{t-1} + u_t$$

3.7.2 AutoRegressive Integrated Moving Average (ARIMA)

The ARIMA model is well known as Box and Jenkins (1976) method. It is widely applied for time-series models to forecast the trends of the variables (Zhang, 2003, pp. 159-160). According to the financial study, most of the recent papers use the ARIMA model to forecast the assets' prices or returns in the future to make the trading strategy (e.g., (Bakar & Rosbi, 2017; Virtanen & Yli-Olli, 1987; Zhang, 2003)). Some economic papers also use the ARIMA model to predict macroeconomic indicators such as inflation, exchange rate, consumers' expenditure, investment, employment, import, and export (e.g., (Harvey & Todd, 1983; Meyler, Kenny, & Quinn, 1998)). The ARIMA model has suitably applied for forecasting in the short-term only. However, the techniques of the model identification are quite subjective, so it needs the specialists or experts to select the model appropriately (Meyler et al., 1998, p. 4).

This paper applies the ARIMA model to forecast coin and token prices. The ARIMA model uses the data from the previous period to forecast the trend and also can be used to explain the volatility at the first moment or explain the equilibrium. The ARIMA model is specified as AR(p) and MA(q) models.

AR(p) model:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \cdots + \beta_p Y_{t-p} + u_t$$

MA(q) model:

$$Y_t = \alpha + u_t - \theta_1 u_{t-1} - \cdots - \theta_q u_{t-q}$$

ARIMA(p,d,q) model:

$$Y_t^* = \alpha + \beta_1 Y_{t-1}^* + \cdots + \beta_p Y_{t-p}^* + u_t - \theta_1 u_{t-1} - \cdots - \theta_q u_{t-q}$$

Where $Y_t^* = \Delta^d Y_t$

Forecasting coin price by ARIMA model:

$$\Delta\log(COIN_t) = \alpha + \beta_1 \Delta\log(COIN)_{t-1} + \cdots + \beta_p \Delta\log(COIN)_{t-p} + u_t - \theta_1 u_{t-1} - \cdots - \theta_q u_{t-q}$$

Forecasting token price by ARIMA model:

$$\Delta\log(TOKEN_t) = \alpha + \beta_1 \Delta\log(TOKEN)_{t-1} + \cdots + \beta_p \Delta\log(TOKEN)_{t-p} + u_t - \theta_1 u_{t-1} - \cdots - \theta_q u_{t-q}$$

According to the research objective to forecast coin and token prices in the short-term period, this paper has to follow the Box-Jenkins methodology which has four steps. The first step is the model identification to transform time-series variable to be stationary with checking the unit root process and also find out the appropriate value of lagged p, d, and q in the ARIMA (p,d,q) model by analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF). Moreover, the information criteria with the lowest value including the Akaike Information Criterion (AIC), the Schwarz Criterion (SIC), and the Hannan-Quinn Criterion have been required to determine the proper ARIMA (p,d,q) model. The second step is the parameter estimation of the optimal ARIMA (p,d,q) model selected from the first step. The parameters have been estimated by using the Ordinary Least Square (OLS) in the AR process and the Non-linear Least Square (NLS) estimation method in the MA process to make the errors minimize. The third step is the diagnostic checking in residual by using the Breusch-Godfrey LM test and Ljung–Box Q statistics to examine whether the selected model is fit to the variable data. The optimal ARIMA (p,d,q) model should not have the serial correlation problem. The fourth step is the forecasting variable and checks the reliability of forecasting in the optimal ARIMA (p,d,q) model.

3.7.3 AutoRegressive Integrated Moving Average with Exogenous Variables (ARIMAX)

The AutoRegressive Integrated Moving Average with Exogenous Variables model (ARIMAX) applies the ARIMA model and adds some exogenous variables into it. The spillover effects, or dynamic linkages, might be useful for forecasting price and volatility purposes (Chatziantoniou, Degiannakis, Delis, & Filis, 2019, p. 2). Due to the cointegration relationships and dynamic linkages among top 5- coin, top 5- token, and MSCI international world price, so this paper will take the WORLD and TOKEN as the exogenous variables into an ARIMA model for forecasting coin price. Meanwhile, the WORLD and COIN will act as the exogenous variables into an ARIMA model for forecasting token price as well. The ARIMAX model for out-of-sample forecasting coin and token prices can be written as follows.

Forecasting coin price by ARIMA with exogenous variable (WORLD):

$$\Delta\log(COIN_t) = \alpha + \beta_1 \Delta\log(WORLD)_{t-1} + \cdots + \beta_p \Delta\log(WORLD)_{t-p} + u_t - \theta_1 u_{t-1} - \cdots - \theta_q u_{t-q}$$

Forecasting coin price by ARIMA with exogenous variable (TOKEN):

$$\Delta\log(COIN_t) = \alpha + \beta_1 \Delta\log(TOKEN)_{t-1} + \cdots + \beta_p \Delta\log(TOKEN)_{t-p} + u_t - \theta_1 u_{t-1} - \cdots - \theta_q u_{t-q}$$

Forecasting token price by ARIMA with exogenous variable (WORLD):

$$\Delta\log(TOKEN_t) = \alpha + \beta_1 \Delta\log(WORLD)_{t-1} + \cdots + \beta_p \Delta\log(WORLD)_{t-p} + u_t - \theta_1 u_{t-1} - \cdots - \theta_q u_{t-q}$$

Forecasting token price by ARIMA with exogenous variable (COIN):

$$\Delta\log(TOKEN_t) = \alpha + \beta_1 \Delta\log(COIN)_{t-1} + \cdots + \beta_p \Delta\log(COIN)_{t-p} + u_t - \theta_1 u_{t-1} - \cdots - \theta_q u_{t-q}$$

3.7.4 Vector AutoRegressive (VAR)

This paper also applies the VAR model for out-of-sample forecasting coin and token prices. The VAR model is common model to forecast the financial assets' price and macroeconomic indicator. It also treats all variables as the endogenous variable and considers them at the same time. The endogenous variable will be determined by own lagged variable and also explained by lagged variable of other endogenous variables. Therefore, this paper has to investigate that the coin and token prices could be forecasted by own lagged variables and others or not. Furthermore, because of the cointegration relationship and dynamic spillover between coin, token, and MSIC world international world price, this paper will take the WORLD and TOKEN as other endogenous variables for out-of-sample forecasting coin prices. Meanwhile, it will take the WORLD and COIN as other endogenous variables for out-of-sample forecasting token prices. The VAR models for forecasting coin and token prices are written as bellows.

Forecasting coin price by VAR model:

$$\Delta\log(COIN_t) = \beta_0 + \sum_{i=1}^{n} \beta_{1i}\Delta\log(COIN_{t-i}) + \sum_{i=1}^{n} \beta_{2i}\Delta\log(WORLD_{t-i}) + \varepsilon_{1t}$$

$$\Delta\log(COIN_t) = \beta_0 + \sum_{i=1}^{n} \beta_{1i}\Delta\log(COIN_{t-i}) + \sum_{i=1}^{n} \beta_{2i}\Delta\log(TOKEN_{t-i}) + \varepsilon_{1t}$$

Forecasting token price by VAR model:

$$\Delta\log(TOKEN_t) = \beta_0 + \sum_{i=1}^{n} \beta_{1i}\Delta\log(TOKEN_{t-i}) + \sum_{i=1}^{n} \beta_{2i}\Delta\log(WORLD_{t-i}) + \varepsilon_{1t}$$

$$\Delta\log(TOKEN_t) = \beta_0 + \sum_{i=1}^{n} \beta_{1i}\Delta\log(TOKEN_{t-i}) + \sum_{i=1}^{n} \beta_{2i}\Delta\log(COIN_{t-i}) + \varepsilon_{1t}$$

3.8 The Dynamic Conditional Correlation (DCC) Model

The Dynamic Conditional Correlation (DCC) is a family of multivariate GARCH model to estimate the time-varying correlation across assets (Engle, 2002). It allows the correlation across the pairs of assets to change overtime. Moreover, it also has usually applied for analyzing conditional correlation among assets through the conditional variance in GARCH model. The DCC model is quite popular for the financial and economic papers in this decade to investigate the co-movement of conditional correlations among financial assets as well as macroeconomic indicators (e.g., (Bali & Engle, 2010; Corbet et al., 2018; Lee, 2006; Lyócsa, Výrost, & Baumöhl, 2012; Ping Wang & Moore, 2008)). This paper will apply the DCC model proposed by Engle (2002) to examine the time-varying conditional correlation between all pairs of assets, such as coin and token returns, either coin or token and other traditional assets returns.

The DCC model can be estimated in two steps from univariate GARCH estimation of mean and variance equation. Firstly, the univariate GARCH (1,1) model is estimated. Secondly, the conditional correlation matrix is calculated by using the standardized residuals which obtain from the first step.

The first step, in the case of the univariate GARCH (1,1) estimation, the mean and the variance equations must be estimated as follows.

The mean equation is written as below:

$$y_t = \mu + \omega y_{t-1} + \varepsilon_t$$

where y_t is the vector of all sample assets' returns

μ is the vector of conditional mean of all sample assets' return

ε_t is the vector of residuals to represent shock

The variance equation is written as below:

$$h_t = \gamma + a\varepsilon_{t-1}^2 + bh_{t-1}$$

where h_t is the conditional variance

γ is the constant

a is the parameter to represent the short-run persistence of volatility or ARCH effect

b is the parameter to represent the long-run persistence of volatility or GARCH effect

The second step, the covariance matrix is decomposed to the conditional standard deviation and the conditional correlation as follow.

$$H_t = D_t R_t D_t$$

where $D_t = diag\{\sqrt{h_{i,t}}\}$ or diagonal matrix of conditional standard deviation which estimated from the univariate GARCH (1,1)

H_t is the conditional covariance matrix

R_t is the conditional correlation matrix

The DCC model can be formulated, so the conditional correlation matrix must be estimated as follow.

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}$$

$$Q_t = S(1 - \alpha - \beta) + \alpha(\varepsilon_{t-1}\varepsilon'_{t-1}) + \beta Q_{t-1} \text{ since } \alpha + \beta < 1$$

where Q_t is the conditional covariance matrix which is positive definite matrix

S is the unconditional correlation matrix of ε_t

ε_t is the vector of the standardized residual obtained from the first step

α is the parameter to represent the effects of previous shock on current covariance matrix

β is the parameter to represent the effects of the previous covariance matrix on current covariance matrix

The conditional correlation estimator, calculated from the conditional covariance matrix model, between asset i and j will be estimated as follow.

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}}$$

where $\rho_{i,j,t}$ is the dynamic conditional correlation estimator

$q_{i,j,t}$ is the conditional covariance

$q_{i,i,t}$ is the conditional variance

Therefore, this paper has to apply the DCC concept as above to estimate the time-varying conditional correlation of totally 136 pairs of the sample assets, including cryptocurrencies and other traditional assets.

3.9 The Markowitz mean-variance portfolio optimization

The final approach of this paper is that whether the cryptocurrency, including coin and token, is appropriate to invest in the portfolio or not. This paper has to investigate the portfolio performance improvement from investing in coin and token. Therefore, it applies the conditional variance and conditional correlation which is calculated from the DCC GARCH (1,1) model to examine the optimization portfolio following as the modern portfolio theory proposed by Markowitz (1952). The efficient portfolio is on the efficient frontier, and its creation depends on asset allocation strategy, optimal weights of each asset, and risk management. The modern portfolio theory has assumed that the investors are rational and risk aversion. It means that the investors always choose the less risky portfolio if it offers the same expected return when comparing to another portfolio. In contrast, the investors who need higher expected returns have to except more risk of investment. However, the asset diversification can reduce the investment risks of the portfolio as well. The conditional correlations among sample assets are significantly related to the portfolio's variances or risks. The assets which have very low correlation or have contradictory correlate to the others can reduce the investment risks.

This paper follows the Markowitz mean-variance portfolio optimization, which is the most popular of the asset allocation strategies to generate the optimization portfolio by using mean and variance approach. The mean and variance portfolio allows the rational investors for the tradeoff and balance between the profits and the investment risks (Steinbach, 2001). The recent papers have mostly applied the Markowitz mean-variance portfolio for the empirical research to examine the optimal portfolio selection as well as the optimal assets allocation in various markets (e.g., (Bessler, Opfer, & Wolff, 2017; Fisher & Statman, 1997; Gökgöz & Atmaca, 2012; Gorman & Jorgensen, 2002; Konno & Kobayashi, 1997)). The optimal portfolio should offer the minimum variance as some level of the returns, while it should offer the best returns as some level of the investment risks.

For proving the diversification benefits of investing coin and token to the portfolio, this paper thus generates 23 portfolios with four types underlying the concept of risk level. First is the fixed income portfolio, which includes the government bond and the corporate bond, at the risk level of 4. Second is the balanced portfolio, which includes the government bond, the corporate bond, and equity, at the risk level of 5. Third is the equity portfolio at the risk level of 6. Fourth is an alternative portfolio, which includes alternative assets such as coin, token, commodity, at the risk level of 8.

All portfolios would be tried to examine the portfolio performance by including and excluding fixed-income assets because of risk-free in government bond and low risk in corporate bond, comparing to other assets. Furthermore, the U.S. corporate bond index, which represents for corporate bond, offers high return rather than some of traditional assets during the sample period. Therefore, the different setting of assets with and without fixed-income assets would reduce bias to analysis. However, this paper will screen out of some of high correlation assets. All details are explained as follows.

Table 3.6 Portfolio Information

No.	Type of Portfolio	Assets	Risk Level[1)]
1	Fixed-income portfolio	▪ Government bond ▪ Corporate bond	Level 4
2	Balanced portfolio	▪ Government bond ▪ Corporate bond ▪ Equity	Level 5
3	Equity portfolio	▪ Equity	Level 6
4	Alternative portfolio	▪ Commodity	Level 8
5	Alternative portfolio	▪ Government bond ▪ Corporate bond ▪ Commodity	Level 8
6	Alternative portfolio	▪ Equity ▪ Commodity	Level 8

No.	Type of Portfolio	Assets	Risk Level[1)]
7	Alternative portfolio	▪ Government bond ▪ Corporate bond ▪ Equity ▪ Commodity	Level 8
8	Alternative portfolio	▪ Coin ▪ Token	Level 8
9	Alternative portfolio	▪ Equity ▪ Coin	Level 8
10	Alternative portfolio	▪ Commodity ▪ Coin	Level 8
11	Alternative portfolio	▪ Government bond ▪ Corporate bond ▪ Coin	Level 8
12	Alternative portfolio	▪ Equity ▪ Commodity ▪ Coin	Level 8
13	Alternative portfolio	▪ Government bond ▪ Corporate bond ▪ Equity ▪ Commodity ▪ Coin	Level 8
14	Alternative portfolio	▪ Equity ▪ Token	Level 8
15	Alternative portfolio	▪ Commodity ▪ Token	Level 8
16	Alternative portfolio	▪ Government bond ▪ Corporate bond ▪ Token	Level 8
17	Alternative portfolio	▪ Equity ▪ Commodity ▪ Token	Level 8
18	Alternative portfolio	▪ Government bond ▪ Corporate bond ▪ Equity	Level 8

No.	Type of Portfolio	Assets	Risk Level[1)]
		▪ Commodity ▪ Token	
19	Alternative portfolio	▪ Equity ▪ Coin ▪ Token	Level 8
20	Alternative portfolio	▪ Commodity ▪ Coin ▪ Token	Level 8
21	Alternative portfolio	▪ Government bond ▪ Corporate bond ▪ Coin ▪ Token	Level 8
22	Alternative portfolio	▪ Equity ▪ Commodity ▪ Coin ▪ Token	Level 8
23	Alternative portfolio	▪ Government bond ▪ Corporate bond ▪ Equity ▪ Commodity ▪ Coin ▪ Token	Level 8

Note: Risk level is based on financial assets invested. Risk level 1 = Investment in domestic money market. Risk level 2 = Investment in money market, partially in foreign bond, Risk level 3 = Investment in government bond, Risk level 4 = Investment in fixed income security or general bond, Risk level 5 = Investment in equity and bond, Risk level 6 = Investment in equity, Risk level 7 = Investment in some specific sector of equity, Risk level 8 = Investment in alternative assets with higher risk and more complicated structure such as commodity, derivatives, as well as cryptocurrency.

This paper calculates the quarterly asset returns to analyzes the portfolio diversification and optimization under the maximization of the Sharpe Ratio. According to Markowitz mean-variance portfolio optimization, the Sharpe Ratio has always been applied to analyze the optimal assets diversification of portfolio. The maximized Sharpe Ratio exhibits the minimized risk as well as the maximized return of the portfolio.

The Sharpe Ratio equation:

$$S_p = \frac{R_p - r_f}{\sigma_p}$$

where R_p is the total expected return of the portfolio

r_f is the risk-free rate calculated by the U.S. 3-year treasury bill.

σ_p is the standard deviation of the portfolio

Furthermore, all portfolios have set two constraints. Firstly, the total weights of asset investment in each portfolio is equal to one. Secondly, all portfolios are not allowed to short sell.

The total expected return and variance of each portfolio are calculated by quarterly average and specified as follows.

The total expected return of the portfolio:

$$R_p = \sum_{i=1}^{n} W_i R_i$$

where $R_p$is the total expected return of the portfolio

W_i is the weights of asset his in portfolio investment, and $\sum_{i=1}^{N} W_i = 1$

R_i is the expected return of asset i

The variance of the portfolio:

$$\sigma_p^2 = \sum_{i=1}^{n} W_i \sigma_i^2 + \sum_{i=1}^{N}\sum_{j=1}^{N} W_i\, W_j \rho_{i,j}\sigma_i\sigma_j$$

where σ_p^2 is the variance of the portfolio

$\rho_{i,j}$ is the correlation coefficient, and $\rho_{i,j} = \frac{\sigma_{ij}}{\sigma_i\,\sigma_j}$

σ_{ij} is the covariance between asset his and asset j

Furthermore, this paper sets two procedures of portfolio diversification and optimization analysis. Firstly, all portfolios will be compared the efficient portfolio between the applying of the static and the dynamic conditional statistics during the whole sample period. The static portfolio will be generated by using the static or simple moving average correlations, variance, and covariance. Meanwhile, the dynamic conditional portfolio will be generated by applying the Dynamic Conditional Correlation (DCC) GARCH (1,1) model as previous section. The DCC GARCH (1,1) model has generated the coefficients of conditional correlations and the conditional variance. Therefore, the conditional covariance will be calculated by conditional correlations and conditional variance as well. This paper will then compare the portfolio performance between static and dynamic portfolio.

Secondly, this paper has to analyze the dynamic portfolio performance through asset allocation technique. All dynamic portfolios generated by dynamic conditional correlation, variance, and covariance will be analyzed the asset allocation by actively adjusting the weights of asset investment, in ranges of 0 – 100 percent, in every three months. The adjusted weights of asset investment in each quarterly period is based on the dynamic conditional correlation, variance, and covariance data as the previous period. The optimal weights of the asset investment in the fourth quarter of 2017 (4Q17) are based on the conditional correlations, variance, and covariance statistics in the third quarter of 2017 (3Q17). Then, the rolling quarterly adjusted weights are based on update rolling data from the fourth quarter of 2017 (4Q17) to the third quarter of 2019 (3Q19). Furthermore, this paper will also analyze the portfolio performance by fixed weights of the asset investment during a whole of the sample period. The fixed weights of all dynamic portfolios since the fourth quarter of 2017 (4Q17) to the fourth quarter of 2019 (4Q19) will be calculated by the optimal weights of the third quarter of 2017 (3Q17). This paper will compare the portfolio performance between fixed and actively adjusted weights of the asset investment as well. Furthermore, all portfolios performance will be plotted with benchmark index. The Bloomberg Barclays US Treasury Index represents as a benchmark for the fixed income portfolio. The MSCI International World Index represents as a benchmark for the balanced and equity portfolios. Meanwhile, the Bloomberg Commodity Index represents as a benchmark for all alternative portfolios, which includes commodity, coin, or token.

According to the portfolio performance of the static and dynamic conditional portfolio as well as the fixed and actively adjusted weights of the asset investment, the portfolio, offering the highest Sharpe Ratio, will be the optimization portfolio. If the portfolio which includes coin and token offers the highest Sharpe Ratio, it implies that the coin and token can be good diversification assets to benefit for optimization portfolio.

CHAPTER 4

EMPIRICAL RESULTS

According to the objectives and the assumptions of this paper, the empirical results have explained the competency of forecasting cryptocurrency price through four models, including Random Walk, ARIMA, ARIMAX, and VAR. They have also shown the results of long-term relationship and short-term dynamic spillover between cryptocurrency and other traditional assets. Furthermore, the empirical results have analyzed the investment opportunity in cryptocurrency. Therefore, the results in this section are divided into five topics. Firstly, this paper shows the dynamic spillover between cryptocurrencies and other traditional assets in the short-term period. Secondly, it shows the cointegration between cryptocurrencies and other traditional assets to imply for long-term relationship. Thirdly, it shows the forecasting cryptocurrency price study. Fourthly, it analyzes the dynamic conditional correlation among all sample assets. Finally, this paper shows the portfolio optimization to analyze the investment opportunity.

4.1 Short-term Dynamic Spillover between Cryptocurrencies and Other Traditional Assets

4.1.1 Granger Causality Test

As the results of causality test as table 4.1 – 4.2, this paper finds that the movement of the coin return can cause the direction of token, stock, and gold returns in the short-term period at the 5 percent level. It implies that the coin return movement might determine the cryptocurrency market in terms of the token, stock market, and commodity market as well. However, coin return movement does not cause the direction movement of the U.S. 10-year government bond return. It means that the coin return movement cannot determine the bond market in the short-term period.

Meanwhile, the movement of all main traditional asset does not cause the movement direction of coin return in the short-term period.

In terms of causality of the token return, the stock return movement can affect the token return movement in the short-term period at the 10 percent level. Meanwhile, the returns of gold, and U.S. 10-year government bond do not affect the movement of token return in the short-term period. Furthermore, the token return does not cause the movement direction of coin and all main traditional assets in the short-term period as well.

Table 4.1 Causality Direction between Coin and Main Traditional Assets

Causality between coin and other assets			
Causality between CR and TR			
Dependent Variable: CR		Dependent Variable: TR	
- Chi-Sq	1.8979	- Chi-Sq	7.8284
- Prob.	0.3871	- Prob.	0.0200**
Causality between CR and WD			
Dependent Variable: CR		Dependent Variable: WD	
- Chi-Sq	1.7327	- Chi-Sq	6.3900
- Prob.	0.1881	- Prob.	0.0115**
Causality between CR and GD			
Dependent Variable: CR		Dependent Variable: GD	
- Chi-Sq	5.5755	- Chi-Sq	11.9071
- Prob.	0.2332	- Prob.	0.0181**
Causality between CR and GOV			
Dependent Variable: CR		Dependent Variable: GOV	
- Chi-Sq	2.4744	- Chi-Sq	2.9069
- Prob.	0.2902	- Prob.	0.2338

Note: * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

Table 4.2 Causality Direction between Token and Main Traditional Assets

Causality between token and other assets			
Causality between TR and WD			
Dependent Variable: TR		Dependent Variable: WD	
- Chi-Sq	2.8757	- Chi-Sq	0.7084
- Prob.	0.0899*	- Prob.	0.4000
Causality between TR and GD			
Dependent Variable: TR		Dependent Variable: GD	
- Chi-Sq	1.4592	- Chi-Sq	1.7317
- Prob.	0.2271	- Prob.	0.1882
Causality between TR and GOV			
Dependent Variable: TR		Dependent Variable: GOV	
- Chi-Sq	0.4217	- Chi-Sq	2.4962
- Prob.	0.5161	- Prob.	0.1141

Note: ***** Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

4.1.2 Impulse Response Function

As the results of the impulse response function as figure 4.1 – 4.3, this paper shows that coin return and token return immediately positively respond from their own shock by the first period. Those own shock responses are the highest value comparing to shock from other assets. The coin return and token return are quite high positively responded from the shock of each other by the first period as well. Then, coin return is back to the equilibrium by the third period, but token return is back to the equilibrium by the fourth period. In other words, the coin return has high positively linkage response to the shocks' token return by only two period. Meanwhile, the token return has high positively linkage response to the shocks' coin return by only three period as well. This result is consistent with the causality test to show that the coin return movement can affect the token return movement. Furthermore, it implies that both coin return and token return are rapidly adaptable although there is the shock transmission of each other.

Furthermore, the impulse responses of coin return and token return from the shock of main traditional market are quite small. It implies that the impulse response functions of coin return and token return from the shock of other traditional market are not significant. In other words, the shocks in main traditional markets, including stock, commodity, and bond markets, do not affect the movement of the cryptocurrency return. Meanwhile, the impulse responses of those main traditional asset from the shocks of the coin and token returns are not significant as well. It means that shocks of cryptocurrency market do not affect to the movement of the traditional asset returns.

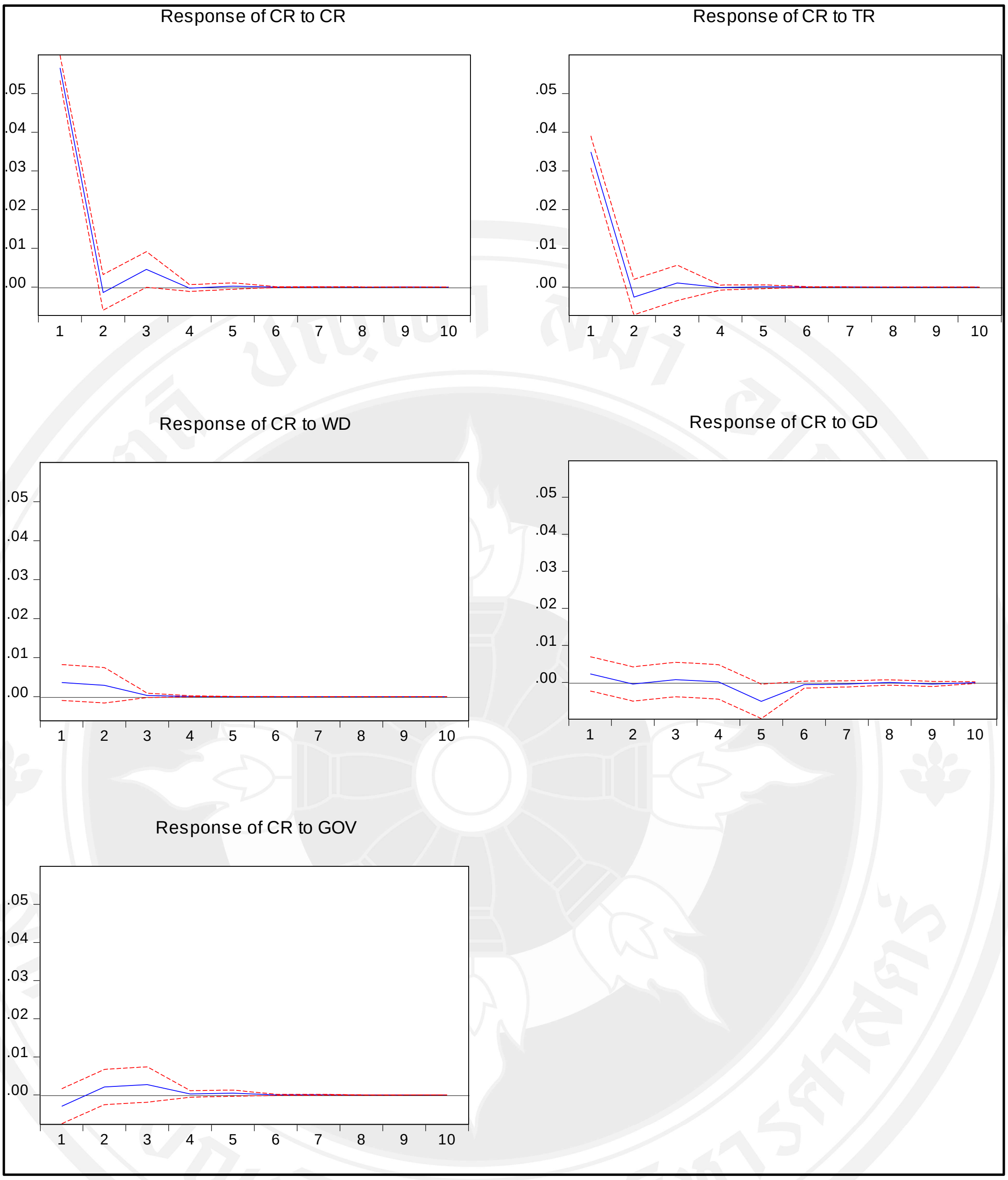

Figure 4.1 The Impulse Response Function of Coin Return

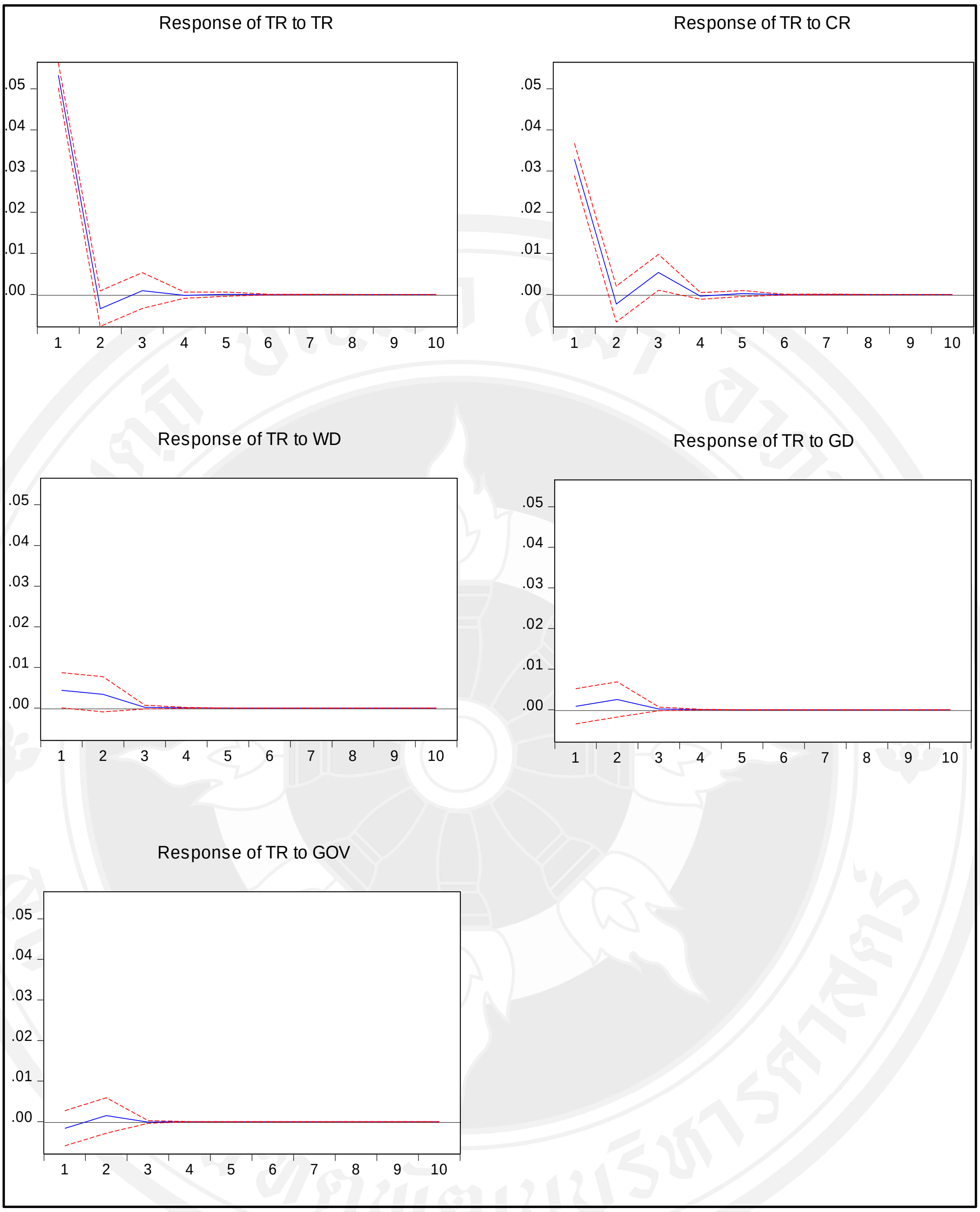

Figure 4.2 The Impulse Response Function of Token Return

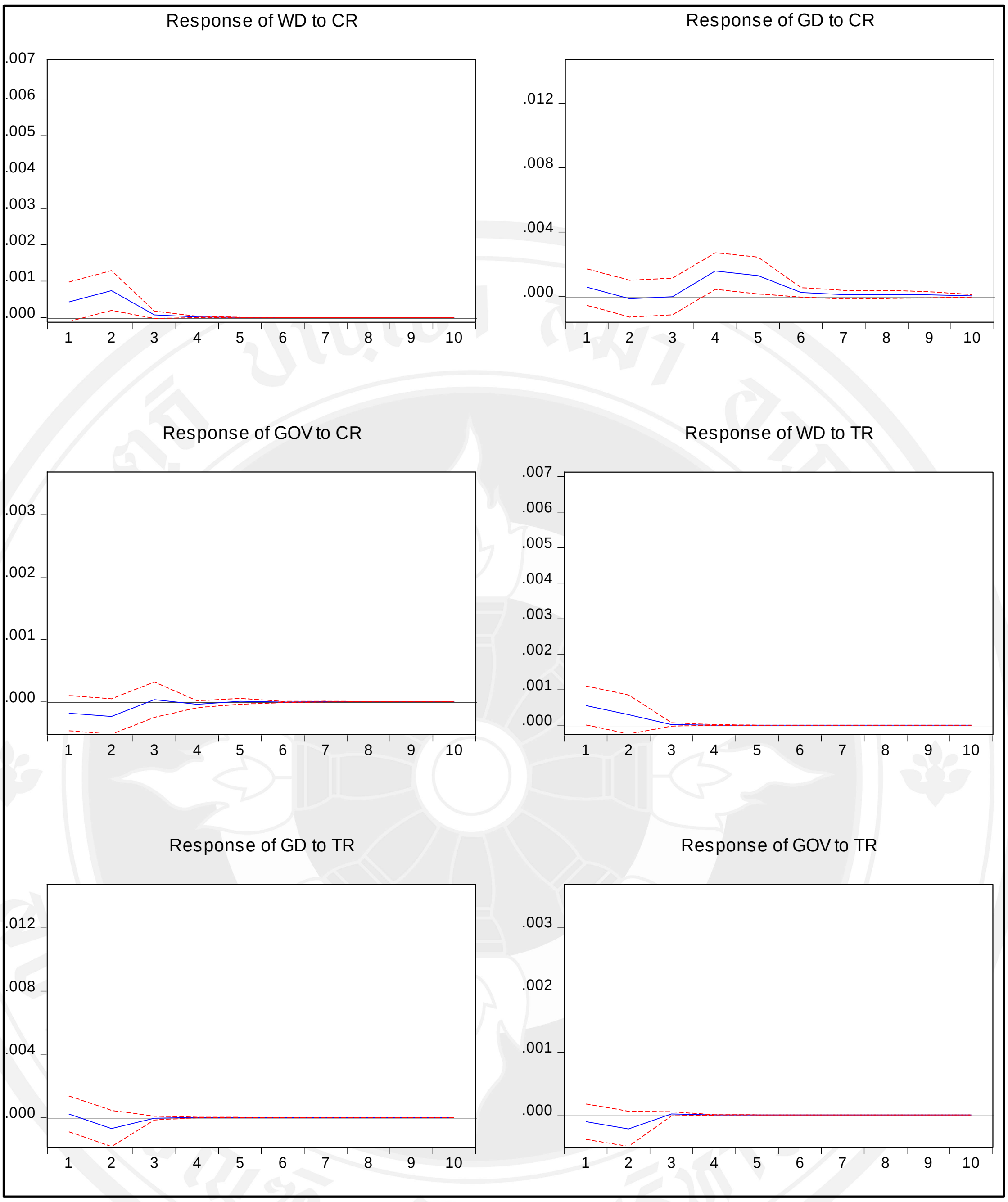

Figure 4.3 The Impulse Response Function of Other Traditional Asset Returns

In cases of spillover index as table 4.3, it shows that the coin return and token return have spillover effects of each other rather than the main traditional assets. The coin return affects to token return as 26.8 percent, while the token return influences to coin return as 27.4 percent. Both coin return and token return have extremely small affected to the main traditional assets in ranges of 1.1 – 1.7 percent. Furthermore, the returns of all main traditional assets have extremely small influenced to coin return and token return in ranges of 0.5 – 1.0 percent as well.

Table 4.3 Diebold-Yilmaz Index of Spillover (Connectedness)

Asset Return	**CR**	**TR**	**WD**	**GD**	**GOV**	**From Others**
CR	69.9	27.4	0.9	1.0	0.8	30.1
TR	26.8	71.2	0.5	0.7	0.8	28.8
WD	1.2	1.7	86.7	1.7	8.7	13.3
GD	1.6	2.0	0.9	82.7	12.7	17.3
GOV	1.1	1.2	8.5	11.4	77.8	22.2
Contribution to others	30.7	32.3	10.8	14.9	23.0	111.6
Contribution including own	100.6	103.5	97.5	97.6	100.8	22.3%

4.1.3 Volatility Spillover

As the results of volatility spillover as table 4.4 – 4.5, this paper finds that there is volatility spillover from token return volatility to coin return volatility at the 1 percent level. The shock of the token return affects the volatility of coin return with one and two optimal lags. Meanwhile, the shock from coin return affects to token return volatility with one optimal lag at the 10 percent level. Furthermore, there is no any volatility spillover from all traditional asset returns to both coin and token returns. It implies that the shock of all traditional asset markets does not affect the volatility of cryptocurrency market.

Table 4.4 Volatility Spillover (Dependent Variable = CR)

	TR	**WD**	**GD**	**GOV**
Wald Test: Lag = 1				
- F-Statistic	7.6319	0.0013	0.0453	1.9353
- Prob.	(0.0059)***	(0.9710)	(0.8315)	(0.1647)
Wald Test: Lag = 2				
- F-Statistic	4.8295	1.2230	0.7018	1.6049
- Prob.	(0.0083)***	(0.2951)	(0.4961)	(0.2018)

Note: ***** Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

Table 4.5 Volatility Spillover (Dependent Variable = TR)

	CR	**WD**	**GD**	**GOV**
Wald Test: Lag = 1				
- F-Statistic	3.4631	1.2572	0.0183	0.7327
- Prob.	(0.0632)*	(0.2626)	(0.8925)	(0.3923)
Wald Test: Lag = 2				
- F-Statistic	2.2309	1.0222	0.4093	0.4764
- Prob.	(0.1083)	(0.3604)	(0.6643)	(0.6213)

Note: ***** Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

4.2 Cointegration between Cryptocurrencies and Other Traditional Assets

The empirical results of the cointegration relationship between cryptocurrencies and other financial assets are shown as table 4.6 – 4.7. According to the probability of the Trace and Max-Eigen statistics, this paper finds that, in the sample period, there are long-term relationships of some financial assets on the top 5-coin index and top 5-token index. There are six pairs of the cointegration relationship between two assets. The top 5-coin index has the long-term relationship with the top 5-token index at 1 percent level. The top 5-coin index has the long-term relationship with the MSCI international world price index and the U.S. 10-year government bond at 10 percent and 5 percent level, respectively. Furthermore, the top 5-token index has the long-term relationship with the MSCI international world price index and the U.S. 10-year government bond at 5 percent level. Meanwhile, it has the long-term relationship with gold at 10 percent level.

To analyze the cointegrating relationship as table 4.8, it could interpret that the top 5-token index has a positive impact on the top 5-coin index in the long-term period. Meanwhile, the MSCI international world index has a negative impact on the top 5-coin index but it has a positive impact on the top 5-token index. The U.S. 10-year government bond index has a positive impact on the top 5-coin and top 5-token indices. Furthermore, gold index has a positive impact on the top 5-token index.

Table 4.6 Johansen Cointegration between Coin and Main Traditional Assets

Cointegration between coin and other assets				
Cointegration between Coin and Token				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	18.1455	0.0048***	17.4174	0.0037***
At most 1	0.7280	0.4519	0.7280	0.4519
Cointegration between Coin and MSCI international world index				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	19.3177	0.0670*	15.3401	0.0609*
At most 1	3.9776	0.4155	3.9776	0.4155
Cointegration between Coin and Gold				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	14.7666	0.2400	13.6705	0.1083
At most 1	1.0961	0.9386	1.0961	0.9386

Cointegration between coin and other assets				
Cointegration between Coin and U.S. 10-year government bonds				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	17.8391	0.1042	17.4101	0.0287**
At most 1	0.4290	0.9972	0.4290	0.9972

Note: * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

Table 4.7 Johansen Cointegration between Token and Main Traditional Assets

Cointegration between token and other assets				
Cointegration between Token and MSCI international world index				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	21.0564	0.0388**	16.1024	0.0464**
At most 1	4.9540	0.2885	4.9540	0.2885
Cointegration between Token and Gold				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	17.3517	0.1199	15.7593	0.0524*
At most 1	1.5924	0.8566	1.5924	0.8566
Cointegration between Token and U.S. 10-year government bond				
Cointegration	Trace Statistic	Prob.	Max-Eigen Statistic	Prob.
None	17.7403	0.1072	17.1794	0.0313**
At most 1	0.5609	0.9919	0.5609	0.9919

Note: * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

Table 4.8 Normalized Cointegrating Coefficients

Cointegration between two assets	**Cointegrating Equation (t-statistic)**
Cointegration between Coin and Token	$COIN_t$ = 1.8482$TOKEN_t$ (15.2519)
Cointegration between Coin and MSCI International world index	$COIN_t$ = 73.3854 – 8.4032$WORLD_t$ (1.9628) (1.7173)
Cointegration between Coin and U.S. 10-year government bond	$COIN_t$ = 2.1692$GOVBOND_t$ (0.7170)
Cointegration between Token and MSCI international world index	$TOKEN_t$ = -10.5508 + 2.4736$WORLD_t$ (0.8958) (1.6047)
Cointegration between Token and gold	$TOKEN_t$ = 0.7715$GOLD_t$ (0.8831)
Cointegration between Token and U.S. 10-year government bond	$TOKEN_t$ = 2.0879$GOVBOND_t$ (0.1385)

In case of the speed of adjustment in error correction process as shown in table 4.9, this paper first considers the movement between coin and token. The results imply that token adjust toward the cointegrating vector, but not vice versa. The speed of adjustment in token is significant and exhibit a quick adjustment (11 percent per day). For the case of relationship between coin and other traditional assets. The results show that coin could adjust toward long-term equilibrium with the stock and bond markets. Meanwhile, the token could adjust along with traditional financial markets, including stock, gold, and bond. The error correction coefficients show that speed of adjustments in tokens are quicker than those of the coins. Lastly, the error correction process of token toward long-term equilibrium with coin is quicker than those of the adjustment between token and other traditional assets (world equity, gold and the U.S. long-term bond).

Table 4.9 Adjustment Coefficient

Cointegration between two assets	Adjustment Coefficient (t-statistic)			
Cointegration between Coin and Token	COIN	0.1112 (1.1139)	TOKEN	0.1112 (3.9086)
Cointegration between Coin and MSCI International world index	COIN	-0.0087 (3.7857)	WORLD	-0.0003 (1.2778)
Cointegration between Coin and U.S. 10-year government bond	COIN	-0.0144 (3.5401)	GOVBOND	-0.0003 (1.2560)
Cointegration between Token and MSCI international world index	TOKEN	-0.0267 (4.0189)	WORLD	-0.0006 (0.6482)
Cointegration between Token and gold	TOKEN	-0.0210 (3.7418)	GOLD	0.0010 (0.6757)
Cointegration between Token and U.S. 10-year government bond	TOKEN	-0.0201 (3.6495)	GOVBOND	-0.0004 (1.1833)

4.3 Forecasting Cryptocurrency Price

Those forecasting cryptocurrency price results have shown in terms of Root Mean Square Error (RMSE) for out-of-sample forecasting. Table 4.10 – 4.11 have shown the RMSE of four cases by using four models, including Random Walk, ARIMA, ARIMAX, and VAR, for forecasting the coin price. The lowest value of RMSE also implies for the reliable forecasting model.

As the results, this paper finds that the Random Walk model provides the worst RMSE at every horizon ahead. The ARIMA with the WORLD as an exogenous variable (ARIMAX) provides the best of average RMSE, comparing to ARIMA, VAR, and ARIMA with the TOKEN as an exogenous variable. The ARIMA model provides the best of coin price forecasting performance at the horizon of 6 days ahead only. The ARIMA with the WORLD as an exogenous variable (ARIMAX) provides the lowest RMSE at the horizon of 4, 9, 11, 12, 13, 14, 16, 17, 18, and 19 days ahead. It also provides the best of forecasting the coin price over 20 forecasting horizons because the average RMSE is the lowest value as well. The ARIMA with the TOKEN as an exogenous variable (ARIMAX) provides the lowest RMSE at the horizon of 1 day ahead only. The VAR model considering the lagged WORLD variable provides the best results at the horizon of 2, 3, 7, 8, 10, and 20 days ahead. Meanwhile, the VAR model considering the lagged TOKEN variable provides the lowest RMSE at the horizon of 5 and 15 days ahead.

In terms of forecasting token price, the Random Walk model provides the worst results of forecasting due to the immense RMSE values at all horizons ahead. Meanwhile, the ARIMA with WORLD as an exogenous variable (ARIMAX) provides the best forecasting at all horizons ahead and over 20 days forecasting horizons because the average RMSE is the lowest value rather than other models. However, all models for forecasting coin and token prices provide the larger value of RMSE in the long forecasting horizon. Furthermore, all out-of-sample forecasting results of coin and token prices have plotted as figure 4.4 – 4.7. They show that the forecasting coin and token prices from ARIMA, ARIMAX, and VAR models have an increasing trend at 20 days ahead.

Table 4.10 RMSE for Out-of-Sample Forecasting for Coin

Horizon	**RW**	**ARIMA**	**ARIMAX[1)]**	**ARIMAX[2)]**	**VAR[3)]**	**VAR[4)]**
1	538.31	395.35	395.08	**395.07**	396.02	395.81
2	725.62	485.79	487.01	491.94	**483.80**	486.28
3	923.92	544.20	544.63	550.13	**543.81**	544.95
4	1,075.11	605.91	**601.64**	615.94	604.10	605.78
5	1,234.12	673.60	676.26	686.88	673.13	**671.81**
6	1,356.65	**715.40**	723.20	732.53	716.75	717.59
7	1,462.26	848.00	846.90	870.79	**844.92**	851.55
8	1,558.75	800.16	793.79	820.33	**792.83**	802.14
9	1,670.98	942.42	**937.60**	966.00	939.77	947.21
10	1,772.56	1,015.95	1,015.79	1,050.42	**1,011.43**	1,015.70
11	1,888.74	1,076.09	**1,072.44**	1,113.01	1,077.27	1,078.43
12	1,992.11	1,011.55	**1,007.71**	1,046.30	1,018.03	1,013.45
13	2,102.55	1,117.28	**1,116.42**	1,147.36	1,121.26	1,121.85
14	2,207.15	1,256.79	**1,240.58**	1,306.52	1,246.33	1,261.35
15	2,308.29	1,184.11	1,180.61	1,228.21	1,183.77	**1,177.45**
16	2,406.38	1,215.56	**1,207.53**	1,263.48	1,209.17	1,221.93
17	2,507.96	1,199.70	**1,185.60**	1,233.98	1,198.70	1,196.98
18	2,594.17	1,322.81	**1,303.83**	1,371.39	1,326.08	1,326.05
19	2,673.54	1,437.57	**1,426.77**	1,493.44	1,443.98	1,439.50
20	2,737.13	1,197.65	1,205.99	1,260.36	**1,194.78**	1,201.40
Average	**1,786.82**	**952.30**	**948.47**	**982.20**	**951.30**	**953.86**

Note: 1) WORLD acts as an exogenous variable.

2) TOKEN acts as an exogenous variable.

3) Forecasting coin price depends on lagged WORLD variable.

4) Forecasting coin price depends on lagged TOKEN variable.

Table 4.11 RMSE for Out-of-Sample Forecasting for Token

Horizon	RW	ARIMA	ARIMAX 1)	ARIMAX 2)	VAR 3)	VAR 4)
1	223.90	102.66	**100.88**	102.52	102.01	102.68
2	294.92	131.06	**129.63**	135.71	130.68	130.65
3	371.16	145.31	**142.03**	151.75	142.19	145.99
4	435.69	159.53	**155.29**	166.88	158.48	159.54
5	485.43	177.35	**166.92**	189.57	170.71	178.28
6	527.34	193.19	**187.51**	205.50	190.53	193.73
7	560.25	232.15	**221.43**	249.42	225.66	232.43
8	592.70	219.01	**202.84**	232.63	212.42	219.13
9	626.72	257.10	**239.31**	275.82	247.22	257.30
10	653.90	294.26	**275.50**	317.93	285.94	294.63
11	697.43	309.23	**288.15**	334.75	305.06	310.00
12	735.53	292.93	**277.21**	318.79	296.67	293.78
13	779.80	329.70	**304.94**	353.04	323.10	329.28
14	824.63	358.71	**333.05**	392.94	353.31	360.41
15	862.11	372.53	**339.21**	411.38	362.83	372.71
16	901.23	326.21	**304.48**	360.38	321.44	326.14
17	940.64	348.81	**329.55**	380.86	348.03	348.39
18	976.82	419.70	**384.93**	447.91	406.89	420.99
19	1,007.99	440.84	**424.32**	483.77	439.41	439.60
20	1,040.00	435.35	**426.68**	473.76	434.72	435.72
Average	**676.91**	**277.28**	**261.69**	**299.27**	**272.87**	**277.57**

Note: 1) WORLD acts as an exogenous variable.

2) COIN acts as an exogenous variable.

3) Forecasting token price depends on lagged WORLD variable.

4) Forecasting token price depends on lagged COIN variable.

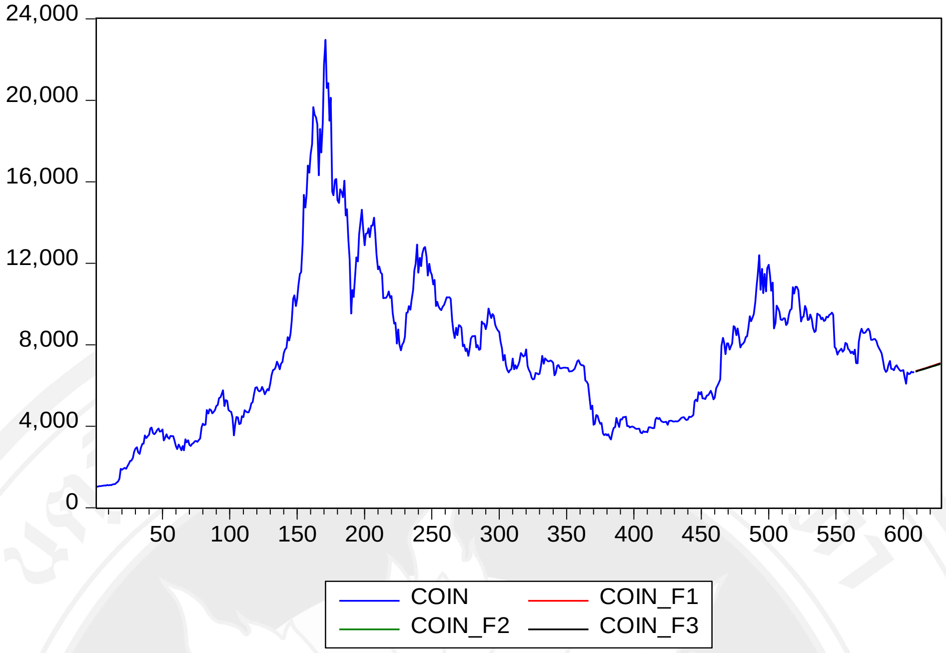

Figure 4.4 Out-of-Sample Forecasting for Coin Price with WORLD as an Exogenous

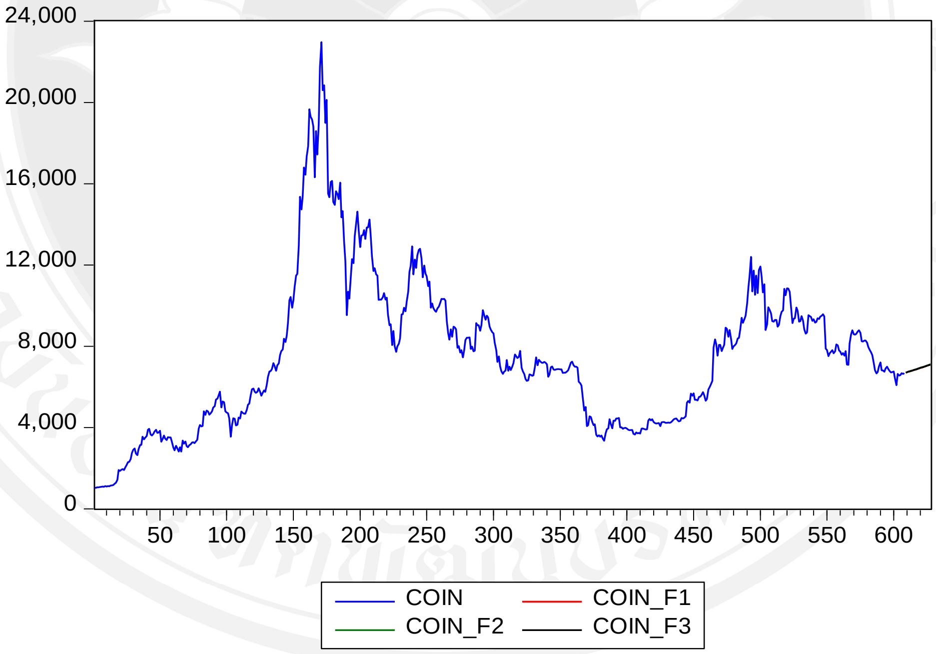

Figure 4.5 Out-of-Sample Forecasting for Coin Price with TOKEN as an Exogenous

Note: COIN is the top 5-coin index. COIN_F1 is out-of-sample forecasting from the ARIMA model. COIN_F2 is out-of-sample forecasting from the ARIMAX model. COIN_F3 is out-of-sample forecasting from the VAR model.

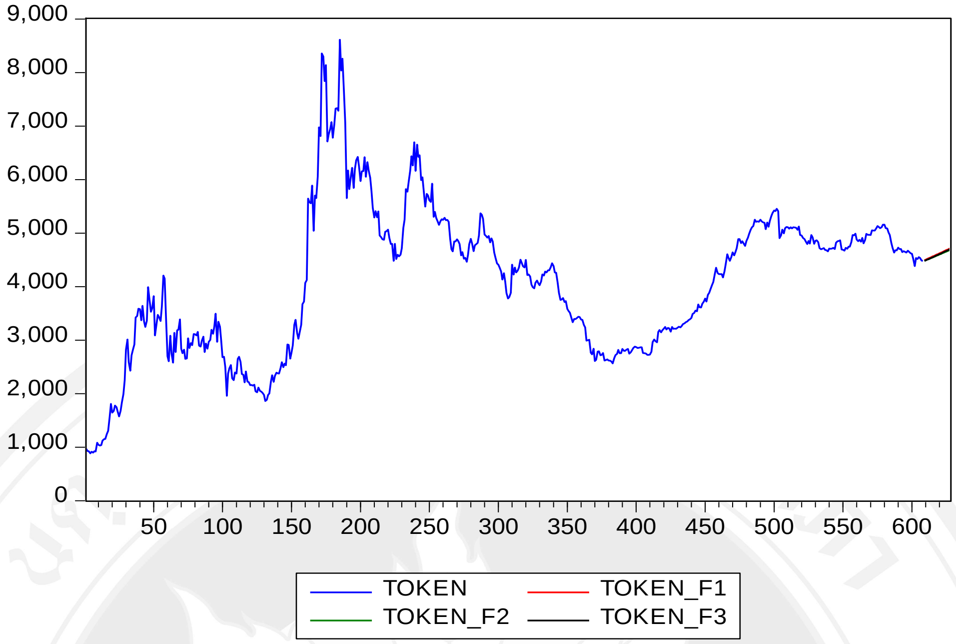

Figure 4.6 Out-of-Sample Forecasting for Token Price with WORLD as an Exogenous

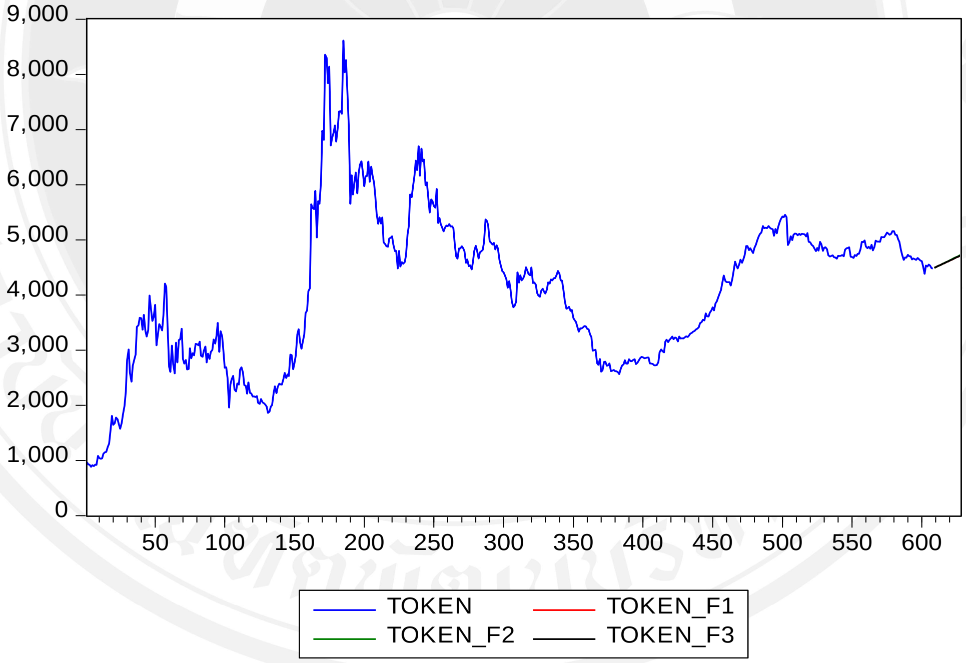

Figure 4.7 Out-of-Sample Forecasting Token Price with COIN as an Exogenous

Note: TOKEN is the top 5-token index. TOKEN_F1 is out-of-sample forecasting from the ARIMA model. TOKEN_F2 is out-of-sample forecasting from the ARIMAX model. TOKEN_F3 is out-of-sample forecasting from the VAR model.

Table 4.12 Correlation Table Test for Significant

Correlation t-Statistic (Probability)	COIN	TOKEN	WORLD
COIN	1.0000 - -		
TOKEN	0.8178 34.9813 (0.0000)	1.0000 - -	
WORLD	0.5577 16.5401 (0.0000)	0.7054 24.4993 (0.0000)	1.0000 - -

Note: If p-value is less than 0.05, it indicates that the there is a linear relationship between two variables.

This paper also emphasizes to do the correlation test for significant among COIN, TOKEN, and WORLD. Finally, it finds that they have a linear relationship among COIN and TOKEN, COIN and WORLD, as well as TOKEN and WORLD. It is consistent with the previous section that there are long-term relationship and some short-term dynamic spillovers among coin, token, and MSCI international world indices. Therefore, the top 5-token index and the MSCI international world index are used as an exogenous variable to forecast the out-of-sample coin price. Meanwhile, the top 5- coin index and the MSCI international world index are used as an exogenous variable for forecasting out-of-sample token price as well.

Furthermore, this paper applies the Diebold-Mariano test to test the difference in the predictive accuracy between the forecasting models – including ARIMA, ARIMAX, and VAR – and the Random Walk process, which is the benchmark. In this case, the null hypothesis is that the forecast results of the second model have less predictive accuracy than the forecast results of the first model. If p-value is less than 0.05, the null hypothesis will be rejected. Therefore, the forecast results of the second model have more predictive accuracy than the forecast results of the first model. As the results in table 4.13 – 4.14, it emphasizes that all forecasting models – including

ARIMA, ARIMAX, and VAR – perform significantly better than the benchmark as of 5 percent level.

Table 4.13 Diebold-Mariano Test (Forecasting Model for Coin Price)

Model Comparison	Diebold-Mariano Statistic	p-value[1)]
RW vs. ARIMA	4.2625	0.0002
RW vs. ARIMAX (TOKEN as an exogenous variable)	4.2580	0.0002
RW vs. VAR (on lagged TOKEN variable)	4.2645	0.0002
RW vs. ARIMAX (WORLD as an exogenous variable)	4.2507	0.0002
RW vs. VAR (on lagged WORLD variable)	4.2401	0.0002

Note: If p-value is less than 0.05, it indicates that the forecast results of the second model is better than the first model.

Table 4.14 Diebold-Mariano Test (Forecasting Model for Token Price)

Model Comparison	Diebold-Mariano Statistic	p-value[1)]
RW vs. ARIMA	5.3737	0.0000
RW vs. ARIMAX (COIN as an exogenous variable)	5.3650	0.0000
RW vs. VAR (on lagged COIN variable)	5.3731	0.0000
RW vs. ARIMAX (WORLD as an exogenous variable)	5.2954	0.0000
RW vs. VAR (on lagged WORLD variable)	5.2919	0.0000

Note: If p-value is less than 0.05, it indicates that the forecast results of the second model is better than the first model.

4.4 Dynamic Conditional Correlation among All Sample Assets

The dynamic conditional correlations are calculated from DCC-GARCH (1,1) model. The results of pairwise of dynamic conditional correlations is consistent with the static correlations. The cryptocurrencies, including coin and token, are moderately positive correlated with each other as around 68.11 percent. Meanwhile, they also have extremely low positive correlations to mostly traditional assets, excluding the negative correlation with the U.S. 10-year government bond. Moreover, the most of traditional assets as the same asset class have quite high correlations; for instance, S&P 500 and Dow Jones as 91.63 percent, S&P 500 and Nasdaq as 88.99 percent, Dow Jones and Nasdaq as 74.63 percent, DAX and FTSE as 70.21 percent, Brent crude oil and WTI crude oil as 90.91 percent, the U.S. government bond and the U.S. 10-year government bond as 91.20 percent. The MSCI international world price is also extremely high correlated with the MSCI all country world price, S&P 500, Dow Jones, and Nasdaq as around 99.18 percent, 93.70 percent, 88.79 percent, and 83.01 percent, respectively.

However, there is the moderate correlation between some pairwise of the traditional assets; for instance, S&P 500 and DAX as 53.36 percent, Dow Jones and DAX 100 as 54.51 percent, Nikkei 225 and Hand Seng as 55.75 percent. Some of traditional assets as the same asset class are quite low correlated to other traditional assets; for instance, S&P 500 and Nikkei 225 as 25.52 percent, FTSE 100 and Nasdaq as 35.47 percent, Nasdaq and Nikkei 225 as 22.78 percent, gold and Brent crude oil as 9.09 percent, gold and WTI crude oil as 11.07 percent.

The traditional assets as the different asset class have the quite low correlations. The equity asset class has quite low positive correlation with the commodity asset class excepting the negative correlations among DAX, FTSE 100, Nikkei 225 and gold. Meanwhile, the fixed income asset class is quite low negative correlated with the equity and commodity asset classes, excluding the gold. The U.S. corporate bond and the U.S. government bond have a positive correlation with gold as around 33.06 percent and 32.87 percent, respectively.

In case of the monthly period of positive and negative correlation, this paper finds that, all periods, the token has positive dynamic conditional correlation with coin, MSCI international world price, MSCI emerging market price, MSCI all country world price, S&P 500, Dow Jones, DAX, FTSE 100, Nikkei 225, Hang Seng, and gold. There are some months that token has a negative correlation with Nasdaq, BRT, WTI, and U.S. corporate bond; for instance, token has negative correlation with Nasdaq during February - April in 2018 and 2019. The token has negative correlation with the U.S. government bond at the almost period. Meanwhile, the coin has positive dynamic conditional correlation with DAX during all periods. However, the coin has negative correlation with the U.S. corporate bond and the U.S. government bond all periods. It also has negative correlation with the MSCI international world price, the MSCI emerging market price, the MSCI all country world price, S&P 500, Dow Jones, Nasdaq, and gold at the same period during May - August 2019.

Furthermore, the DCC-GARCH (1,1) model has also generated the conditional variance. The average monthly of conditional variance has shown as figure 4.9. During the sample period, coin and token returns have extremely high volatility, especially in July 2017 – March 2018, comparing to other traditional assets. At that period, the token return volatility is higher than token return. However, it has lightly decrease since March 2018 and nearby move to other traditional assets since December 2018. Meanwhile, the movement of coin return volatility is always high during a whole sample period. Therefore, the cryptocurrency, especially coin, has been highlighted to high-risk asset. Nonetheless, due to low dynamic conditional correlation with the traditional assets as mentioned before, both coin and token might be a good asset for portfolio diversification as well.

Table 4.15 Average Monthly Dynamic Conditional Correlations of Asset Returns

	CR	WD	EM	AC	SP	DOW	ND	DAX	FTSE	NK	HSI	BRT	WTI	GD	CORP	GOV
TR	0.6811	0.0883	0.0478	0.0865	0.0665	0.0571	0.0405	0.0659	0.0217	0.0832	0.0487	0.0384	0.0350	0.0923	0.0006	-0.0338
CR		0.0660	0.0283	0.0636	0.0399	0.0332	0.0567	0.0664	0.0705	0.0114	0.0116	0.0065	0.0013	0.0460	-0.0400	-0.0484
WD			0.6098	0.9918	0.9370	0.8879	0.8301	0.6576	0.5617	0.4009	0.4097	0.2758	0.2570	0.0892	-0.1736	-0.3245
EM				0.7013	0.4622	0.4442	0.4475	0.5172	0.5031	0.5414	0.8194	0.1942	0.2044	0.1260	-0.0732	-0.2205
AC					0.9112	0.8670	0.8159	0.6662	0.5772	0.4393	0.4934	0.2766	0.2617	0.1004	-0.1673	-0.3233
SP						0.9163	0.8899	0.5336	0.4415	0.2552	0.3235	0.2346	0.2217	0.0392	-0.2118	-0.3373
DOW							0.7463	0.5451	0.4436	0.2329	0.2698	0.2333	0.2165	0.0319	-0.2479	-0.3758
ND								0.4637	0.3547	0.2278	0.2803	0.1809	0.1669	0.0477	-0.1370	-0.2376
DAX									0.7021	0.3371	0.3709	0.1975	0.1751	-0.0933	-0.1468	-0.2926
FTSE										0.3121	0.4215	0.2708	0.2566	-0.0125	-0.0923	-0.2302
NK											0.5575	0.1043	0.1138	-0.1016	-0.1007	-0.2370
HSI												0.1247	0.1375	0.0480	-0.0850	-0.2105

	CR	WD	EM	AC	SP	DOW	ND	DAX	FTSE	NK	HSI	BRT	WTI	GD	CORP	GOV
BRT													0.9091	0.0909	-0.0953	-0.1647
WTI														0.1107	-0.0972	-0.1579
GD															0.3306	0.3287
CORP																0.9120

Note: The pairwise of dynamic conditional correlations are represents in terms of average monthly conditional correlations since April 2017 – December 2019.

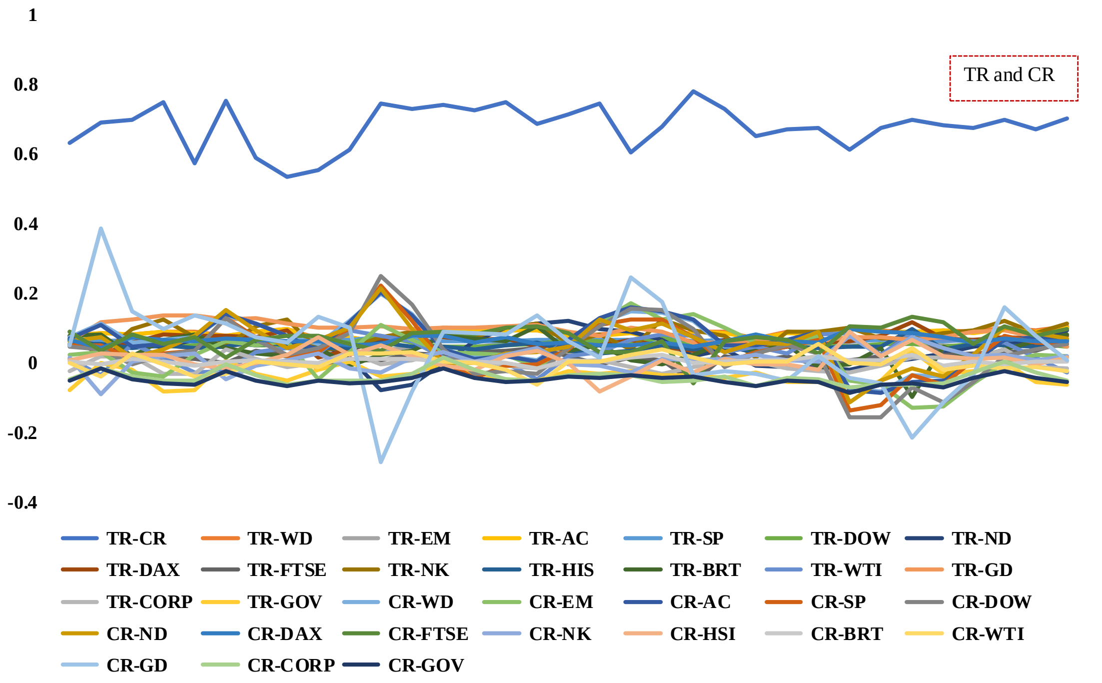

Figure 4.8 Average Monthly Dynamic Conditional Correlation Moving of Cryptocurrency Returns

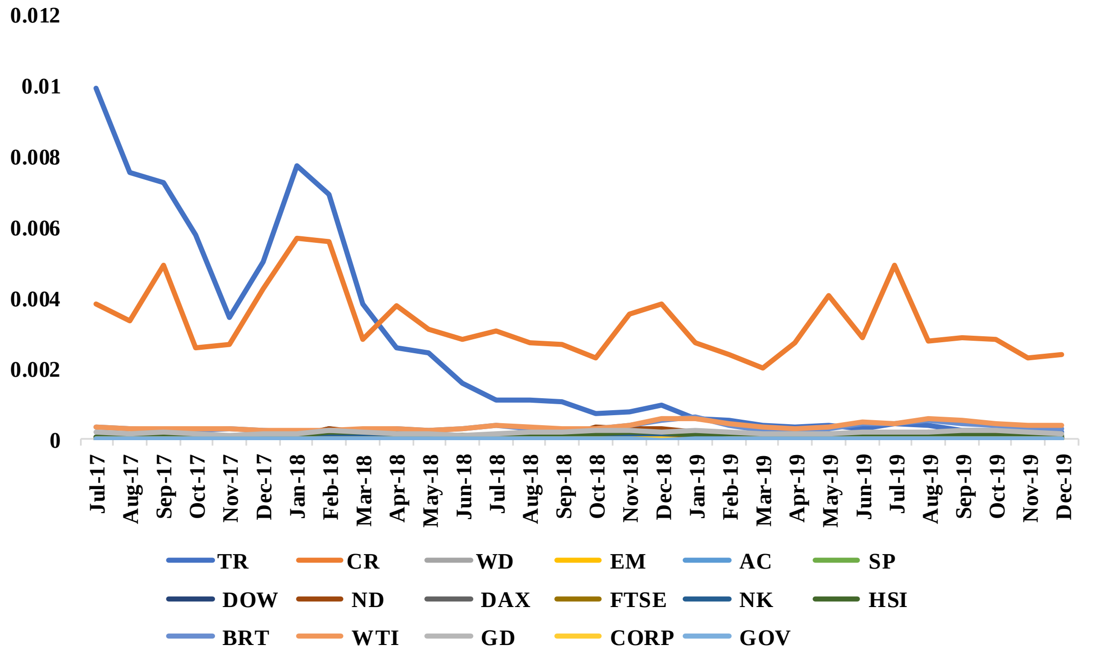

Figure 4.9 Average Monthly Conditional Variance generated by GARCH (1,1) model

4.5 Portfolio Optimization

In this section, this paper presents the portfolio performance to analyze the optimization and diversification. The static and dynamic conditional correlation will be applied to form portfolio diversification to analyze the investment opportunity in coin and token. So, this paper also screens out of some high correlation assets. It has selected the S&P 500, FTSE 100, Nikkei 225, and Hang Seng to represent in the equity assets class because they have quite low correlations. The WTI and gold have been represented for the commodity assets class because they are popular to invest and have a low correlation as well. The U.S. corporate bond and the U.S. government bond have been represented for the fixed-income assets class, even though there is a high correlation between them because these assets have different risk.

This section shows two frameworks to prove the investment opportunity in coin and token through the portfolio optimization approach. First, it shows all portfolio performance between static and dynamic conditional portfolio to analyze the portfolio diversification benefits by investment in coin and token, as well as the risk of each portfolio through standard deviation. The efficient portfolio has presented the optimal weights of asset investment as well as the maximize Sharpe Ratio. Second, it also shows the portfolio performance, through asset allocation technique, when actively adjusting weights of asset investment in every three months. The weights of asset investment in each period are based on the conditional correlations, variance, and covariance calculated by DCC-GARCH (1,1) model as the previous period. Then, this paper has to compare the portfolio performance between fixed and actively adjusted weights of the asset investment as a whole of the sample period. Furthermore, this section has to emphasize that whether the cryptocurrency, in terms of coin and token, is appropriate to be a good asset in generating the investment opportunity or not.

Table 4.16 Average Quarterly Asset Returns

Assets	**3Q17**	**4Q17**	**1Q18**	**2Q18**	**3Q18**	**4Q18**	**1Q19**	**2Q19**	**3Q19**	**4Q19**	**Average quarterly returns**
TR	-0.258	0.848	-0.301	0.025	-0.075	-0.409	0.226	0.381	-0.099	-0.049	0.029
CR	0.326	1.397	-0.853	-0.033	-0.071	-0.517	0.032	0.964	-0.417	-0.146	0.068
WD	0.043	0.050	-0.018	0.011	0.044	-0.155	0.119	0.033	0.001	0.076	0.021
EM	0.068	0.069	0.009	-0.089	-0.020	-0.085	0.095	-0.003	-0.052	0.111	0.010
ACWI	0.046	0.052	-0.015	0.000	0.037	-0.147	0.116	0.029	-0.005	0.081	0.019
SP	0.039	0.059	-0.012	0.029	0.069	-0.159	0.131	0.037	0.012	0.079	0.028
DOW	0.048	0.098	-0.025	0.007	0.086	-0.137	0.117	0.026	0.012	0.056	0.029
ND	0.057	0.067	0.028	0.068	0.080	-0.194	0.160	0.039	0.010	0.117	0.043
DAX	0.040	0.007	-0.066	0.017	-0.005	-0.148	0.088	0.073	0.002	0.064	0.007
FTSE	0.008	0.042	-0.086	0.079	-0.017	-0.109	0.078	0.020	-0.002	0.024	0.004
NK	0.016	0.112	-0.073	0.053	0.078	-0.187	0.058	0.003	0.022	0.084	0.017
HSI	0.067	0.082	0.006	-0.039	-0.041	-0.086	0.130	-0.018	-0.090	0.082	0.009
BRT	0.183	0.150	0.050	0.123	0.040	-0.460	0.270	-0.027	-0.091	0.119	0.036
WTI	0.115	0.156	0.072	0.133	-0.012	-0.480	0.283	-0.028	-0.078	0.132	0.029
GD	0.044	0.008	-0.067	0.013	-0.183	0.111	0.084	0.137	0.050	0.089	0.029
CORP	0.013	0.011	-0.022	-0.009	0.009	-0.003	0.051	0.042	0.030	0.013	0.014
GOV	0.006	-0.002	-0.025	-0.006	-0.016	0.042	0.033	0.043	0.037	-0.016	0.010

During sample period, the coin return has offered the maximum average quarterly return as around 6.82 percent. Meanwhile, the FTSE 100 has offered minimum average of quarterly return as around 0.37 percent. After calculating the quarterly return, the static variance and covariance matrix has generated and shown as table 4.17. Meanwhile, the conditional variance and covariance matrix has calculated by DCC-GARCH (1,1), as mentioned before, and shown as table 4.18. Then, all portfolio performance in terms of static and dynamic portfolio have shown as table 4.21 – 4.26.

Nonetheless, this paper has to show the Sharpe Ratio of each asset to emphasize each asset's performance as table 4.19 – 4.20 before portfolio performance has been analyzed. It finds that the U.S. corporate bond offers the highest Sharpe Ratio in terms of the calculation from static and dynamic standard deviation. By the static standard deviation, the Sharpe Ratio has been generated as 0.34 percent. Meanwhile, the dynamic standard deviation calculated from DCC-GARCH (1,1) has generated the Sharpe Ratio as 1.60 percent. That is because of the lowest standard deviation in the U.S. corporate bond. Therefore, the portion of investment in the U.S. corporate bond might be higher than other assets.

Moreover, the standard deviation of cryptocurrency is the highest, comparing to the other traditional assets, which implies the highest risk as well. The quarterly static and conditional standard deviations of token are around 70.08 percent and 12.55 percent, respectively. Meanwhile, the quarterly static and conditional standard deviation of coin are around 84.20 percent and 16.89 percent, respectively. It shows that the coin has a higher risk rather than the token. The risk of token considering from static standard deviation is greater than the equity assets class, as around 5 – 8 times. It is more than the commodity assets class as around 3 – 4 times. Meanwhile, it is greater than the long-term government bond and corporate bond as around 14 times and 22 times, respectively. The risk of token considering from conditional standard deviation is more than equities as of 4 – 5 times. It is greater than commodities as around 2 – 3 times and is also greater than the long-term government bond and corporate bond as around 12 times and 18 times, respectively.

The risk of coin considering from static standard deviation is greater than equities as around 6 – 9 times. It is more than commodities as around 3 – 4 times, which is similar to the token's risk. It is also more than the long-term government bond and corporate bond as around 17 times and 26 times, respectively. Meanwhile, the risk of coin considering from conditional standard deviation is more than equities as about 6 – 7 times. It is greater than commodities as around 3- 4 times, which is also close to the token's risk. Furthermore, the coin's risk by conditional standard deviation has higher risk rather than the long-term government bond and corporate bond as around 16 times and 24 times, respectively. Therefore, the investment weight for coin and token in portfolio might be very low because their standard deviation is so high. It makes the Sharpe Ratio of coin and token is very low, comparing to other traditional assets.

As the results of the portfolio performance by applying the static and dynamic statistics as table 4.21 – 4.26, this paper finds that all dynamic portfolios have low value of standard deviation and portfolio return rather than static portfolio. The dynamic portfolios also offer the asset diversification more than the static portfolio. There are various assets more than the static portfolio. Furthermore, all dynamic portfolios have a higher Sharpe Ratio rather than the static portfolio, as around 4 – 6 times, because of the lower standard deviation. The static balanced portfolio has two assets, including S&P 500 and U.S. corporate bond, as around 13.15 percent and 86.85 percent, respectively. The dynamic balanced portfolio has three assets, including S&P 500 as of 14.01 percent, Nikkei 225 as of 3.63 percent, and U.S. corporate bond as of 82.35 percent. The Sharpe Ratio of static and dynamic balanced portfolio is around 0.67 and 3.57, respectively. Meanwhile, the fixed income portfolios in terms of static and dynamic portfolio recommend investing in the U.S. corporate bond only because the Sharpe Ratio of the U.S. corporate bond is higher than the long-term government bond.

The static equity portfolio has only one asset, which is S& P 500, while the dynamic equity portfolio has two assets, including S&P 500 as 80.28 percent and Nikkei 225 as 19.72 percent. The Sharpe ratio of static and dynamic equity portfolio is about 0.39 and 1.71, respectively. The weights of the static alternative portfolio with 100 percent of commodity assets are similar to the dynamic portfolio. However, the dynamic alternative portfolio with 100 percent of commodity has a higher Sharpe Ratio rather than the static portfolio as around 5 times. The static alternative portfolio with fixed income and commodity has two assets, which are WTI crude oil and U.S. corporate bond, as of 2.57 percent and 97.43 percent, respectively. Meanwhile, the dynamic alternative portfolio with fixed income and commodity has three assets, including WTI crude oil as around 4.33 percent, gold as around 0.13 percent, and U.S. corporate bond as around 95.54 percent. Its Sharpe Ratio is about 2.95, which is greater than the static portfolio as around 5 times.

The assets in a static alternative portfolio with equity and commodity include S&P 500 as around 74.71 percent and gold as around 25.29 percent. The assets in a dynamic alternative portfolio with equity and commodity include S&P 500 as of 52.29 percent, Nikkei 225 as of 17.63 percent, WTI crude oil as of 5.95 percent, and gold as of 24.13 percent. The Sharpe Ratio of the static and dynamic alternative portfolios with equity and commodity is around 0.45 and 2.03, respectively. The static alternative portfolio with all traditional asset classes has two assets, including S&P 500 as of 13.15 percent, and U.S. corporate bond as of 86.85 percent. Meanwhile, the dynamic alternative portfolio with all traditional asset classes has four assets, including S&P 500 as of 12.99 percent, Nikkei 225 as of 3.33 percent, WTI crude oil as of 1.94 percent, and U.S. corporate bond as of 81.73 percent. The Sharpe Ratio of static and dynamic alternative portfolios with all traditional asset classes is around 0.67 and 3.62, respectively.

The static and dynamic alternative portfolios with coin and token have only coin in there. Although the standard deviation of the coin is more than token as a bit, the coin return is higher than the token as around 2 times. So, the Sharpe Ratio of the coin is higher than the token for 2 times. The static alternative portfolio with equity and coin has two assets, including coin as of 4.85 percent and S&P 500 as of 95.15 percent. Meanwhile, the dynamic alternative portfolio with equity and coin includes three assets, which are coin as of 4.59 percent, S&P 500 as of 76.40 percent, and Nikkei 225 as of 19.00 percent. The Sharpe Ratio of static and dynamic alternative portfolios with equity and coin is 0.41 and 1.81, respectively. The weights of the static alternative portfolio with commodity and coin are similar to the dynamic portfolio, which diversifies to all assets – coin, WTI crude oil, and gold. However, the Sharpe Ratio of dynamic alternative portfolio with commodity and coin is greater than the static portfolio as around 4 times.

The weights of the static alternative portfolio with fixed income and coin are similar to the dynamic portfolio. Nonetheless, the weight of U.S. corporate bond is so high and close to 100 percent because the Sharpe Ratio of the U.S. corporate bond is quite high with the lowest value of the standard deviation. The static alternative portfolio with equity, commodity, and coin includes coin as of 2.75 percent, S&P 500 as of 74.53 percent, and gold as of 22.73 percent. The dynamic alternative portfolio with equity, commodity, and coin includes five assets, which are coin as of 3.27 percent, S&P 500 as of 50.32 percent, Nikkei 225 as of 17.15 percent, WTI crude oil as of 5.93 percent, and gold as of 23.33 percent. The Sharpe Ratio of the static and dynamic portfolios with equity, commodity, and coin is around 0.46 and 2.10, respectively.

The static alternative portfolio with fixed income, equity, commodity, and coin includes coin as of 0.20 percent, S&P 500 as of 13.34 percent, and U.S. corporate bond as of 86.47 percent. Meanwhile, the dynamic alternative portfolio with fixed income, equity, commodity, and coin includes coin as of 0.70 percent, S&P 500 as of 12.67 percent, Nikkei 225 as of 3.29 percent, WTI crude oil as of 1.94 percent, and U.S. corporate bond as of 81.40 percent. The Sharpe Ratio of the dynamic alternative portfolio with fixed income, equity, commodity, and coin is greater than the static portfolio as around 6 times. The static alternative portfolio with equity and token includes only S&P 500, while the dynamic portfolio includes token as of 1.85 percent, S&P 500 as of 79.14 percent, and Nikkei 225 as of 19.01 percent. The Sharpe Ratio of the static and dynamic alternative portfolios with equity and token is 0.39 and 1.73, respectively.

The static alternative portfolio with commodity and token includes WTI crude oil as of 35.30 percent and gold as of 64.70 percent. Meanwhile, the dynamic alternative portfolio with commodity and token includes token as of 3.73 percent, WTI crude oil as of 32.25 percent, and gold as of 64.02 percent. The Sharpe Ratio of the static and dynamic alternative portfolios with commodity and token is 0.28 and 1.29, respectively. The static alternative portfolio with fixed income and token includes the U.S. corporate bond only, while the dynamic portfolio includes token as of 0.51 percent and U.S. corporate bond as of 99.49 percent. The Sharpe Ratio of the static and dynamic alternative portfolio with fixed income and token is around 0.60 and 2.76, respectively. The static alternative portfolio with equity, commodity, and token includes S&P 500 as of 74.71 percent, and gold as of 25.29 percent. Meanwhile, the dynamic alternative portfolio with equity, commodity, and token includes token as of 0.73 percent, S&P 500 as of 52.11 percent, Nikkei 225 as of 17.36 percent, WTI crude oil as of 5.94 percent, and gold as of 23.86 percent. The Sharpe Ratio of the static and dynamic alternative portfolios with equity, commodity, and token is around 0.45 and 2.03, respectively.

The static alternative portfolio with fixed income, equity, commodity, and token includes S&P 500 as of 13.15 percent and U.S. corporate bond as of 86.85 percent, while the dynamic portfolio includes token as of 0.18 percent, S&P 500 as of 12.95 percent, Nikkei 225 as of 3.28 percent, WTI crude oil as of 1.93 percent, and U.S. corporate bond as of 81.65 percent. The Sharpe Ratio of the static and dynamic portfolio with fixed income, equity, commodity, and token is around 0.67 and 3.63, respectively. The static alternative portfolio with equity, coin, and token includes coin as of 4.85 percent, S&P 500 as of 95.15 percent. Meanwhile, the dynamic alternative portfolio includes coin as of 4.59 percent, S&P 500 as of 76.40 percent, and Nikkei 225 as of 19.01 percent. The Sharpe Ratio of the dynamic alternative portfolio with equity, coin, and token is greater than the static alternative portfolio as around 4 times.

The static alternative portfolio with commodity, coin, and token includes coin as of 6.61 percent, WTI crude oil as of 34.95 percent, and gold as of 58.45 percent. Meanwhile, the dynamic alternative portfolio with commodity, coin, and token includes coin as of 9.44 percent, WTI crude oil as of 30.41 percent, and gold as of 60.15 percent. The Sharpe Ratio of the static and dynamic alternative portfolios with commodity, coin, and token is around 0.29 and 1.43, respectively. The weights of the static portfolio with fixed income, coin, and token are similar to the dynamic portfolio. The weight of investment in the U.S. corporate bond is so high and close to 100 percent. Meanwhile, the Sharpe Ratio of the dynamic portfolio with fixed income, coin, and token is more than the static portfolio as around 5 times.

The static alternative portfolio with equity, commodity, coin, and token includes coin as of 2.75 percent, S&P 500 as of 74.53 percent, and gold as of 22.73 percent. Meanwhile, the dynamic alternative portfolio with equity, commodity, coin, and token includes coin 3.27 percent, S&P 500 as of 50.32 percent, Nikkei 225 as of 17.15 percent, WTI crude oil as of 5.93 percent, and gold as of 23.33 percent. The Sharpe Ratio of the static and dynamic portfolios with equity, commodity, coin, and token is around 0.46 and 2.10, respectively. Finally, the static alternative portfolio with all asset classes includes coin as of 0.20 percent, S&P 500 as of 13.34 percent, U.S. corporate bond as of 86.47 percent. The dynamic alternative portfolio with all asset classes includes coin as of 0.70 percent, S&P 500 as of 12.67 percent, Nikkei 225 as of 3.29 percent, WTI crude oil as of 1.94 percent, and U.S. corporate bond as of 81.40 percent.

The Sharpe Ratio of the static and dynamic portfolios with all asset classes is around 0.67 and 3.69, respectively.

Due to the analysis of the portfolio diversification benefits by investing in cryptocurrency, this paper finds that the cryptocurrency, especially coin, seems a good asset for the portfolio diversification. The portfolio with coin and various traditional assets provides the highest Sharp Ratio, comparing to other portfolios. However, the static and dynamic portfolios with both coin and token have no token for investment. It is consistent with a lower Sharpe Ratio of token and the moderate correlation between coin and token. Therefore, the coin is the better choice to invest rather than token during the sample period. Although the cryptocurrency, especially coin, seems a good asset to portfolio diversification, the weight of investment is quite low because the coin still has high volatility. Meanwhile, the weight of the U.S. corporate bond in portfolios is quite high for investment because it has higher return and lower volatility rather than other assets during the whole sample period. So, the Sharpe Ratio of the U.S. corporate bond offers the highest of all sample asset classes.

Table 4.17 Static Variance and Covariance Matrix (Quarterly)

	TR	CR	WD	EM	AC	SP	DOW	ND	DAX	FTSE	NK	HSI	BRT	WTI	GD	CORP	GOV
TR	0.1637	0.1355	0.0060	0.0079	0.0062	0.0051	0.0054	0.0049	0.0052	0.0082	0.0055	0.0096	0.0074	0.0091	0.0102	0.0009	-0.0007
CR	0.1355	0.2363	0.0007	0.0017	0.0008	-0.0007	0.0016	-0.0013	0.0038	0.0076	0.0036	0.0017	0.0056	0.0013	0.0112	0.0018	0.0013
WD	0.0060	0.0007	0.0039	0.0039	0.0039	0.0041	0.0040	0.0047	0.0034	0.0020	0.0040	0.0044	0.0052	0.0062	0.0006	0.0002	-0.0007
EM	0.0079	0.0017	0.0039	0.0057	0.0041	0.0038	0.0037	0.0045	0.0031	0.0021	0.0035	0.0063	0.0044	0.0055	0.0026	0.0003	-0.0006
AC	0.0062	0.0008	0.0039	0.0041	0.0039	0.0041	0.0040	0.0046	0.0033	0.0021	0.0039	0.0046	0.0051	0.0061	0.0008	0.0002	-0.0007
SP	0.0051	-0.0007	0.0041	0.0038	0.0041	0.0045	0.0044	0.0051	0.0034	0.0020	0.0042	0.0044	0.0053	0.0063	0.0001	0.0002	-0.0007
DOW	0.0054	0.0016	0.0040	0.0037	0.0040	0.0044	0.0045	0.0048	0.0033	0.0020	0.0042	0.0043	0.0050	0.0059	0.0001	0.0001	-0.0008
ND	0.0049	-0.0013	0.0047	0.0045	0.0046	0.0051	0.0048	0.0066	0.0036	0.0023	0.0047	0.0053	0.0067	0.0079	-0.0001	0.0002	-0.0007
DAX	0.0052	0.0038	0.0034	0.0031	0.0033	0.0034	0.0033	0.0036	0.0042	0.0022	0.0040	0.0033	0.0046	0.0051	0.0000	0.0002	-0.0007
FTSE	0.0082	0.0076	0.0020	0.0021	0.0021	0.0020	0.0020	0.0023	0.0022	0.0027	0.0024	0.0025	0.0040	0.0042	0.0011	0.0001	-0.0005
NK	0.0055	0.0036	0.0040	0.0035	0.0039	0.0042	0.0042	0.0047	0.0040	0.0024	0.0059	0.0042	0.0055	0.0063	-0.0014	-0.0001	-0.0012
HSI	0.0096	0.0017	0.0044	0.0063	0.0046	0.0044	0.0043	0.0053	0.0033	0.0025	0.0042	0.0075	0.0053	0.0064	0.0027	0.0002	-0.0007
BRT	0.0074	0.0056	0.0052	0.0044	0.0051	0.0053	0.0050	0.0067	0.0046	0.0040	0.0055	0.0053	0.0197	0.0204	-0.0003	0.0002	-0.0015
WTI	0.0091	0.0013	0.0062	0.0055	0.0061	0.0063	0.0059	0.0079	0.0051	0.0042	0.0063	0.0064	0.0204	0.0235	0.0015	0.0002	-0.0017
GD	0.0102	0.0112	0.0006	0.0026	0.0008	0.0001	0.0001	-0.0001	0.0000	0.0011	-0.0014	0.0027	-0.0003	0.0015	0.0132	0.0011	0.0014
CORP	0.0009	0.0018	0.0002	0.0003	0.0002	0.0002	0.0001	0.0002	0.0002	0.0001	-0.0001	0.0002	0.0002	0.0002	0.0011	0.0003	0.0004
GOV	-0.0007	0.0013	-0.0007	-0.0006	-0.0007	-0.0007	-0.0008	-0.0007	-0.0007	-0.0005	-0.0012	-0.0007	-0.0015	-0.0017	0.0014	0.0004	0.0008

Table 4.18 Conditional Variance and Covariance Metrix (Quarterly)

	TR	CR	WD	EM	AC	SP	DOW	ND	DAX	FTSE	NK	HSI	BRT	WTI	GD	CORP	GOV
TR	0.00742	0.00503	0.00007	0.00005	0.00007	0.00007	0.00006	0.00004	0.00008	0.00001	0.00010	0.00006	0.00009	0.00008	0.00018	0.00000	-0.00001
CR	0.00503	0.00986	0.00008	0.00005	0.00008	0.00007	0.00007	0.00011	0.00010	0.00009	0.00002	0.00002	0.00002	0.00001	0.00006	-0.00002	-0.00003
WD	0.00007	0.00008	0.00015	0.00011	0.00014	0.00017	0.00016	0.00020	0.00012	0.00009	0.00008	0.00009	0.00010	0.00010	0.00003	-0.00001	-0.00002
EM	0.00005	0.00005	0.00011	0.00023	0.00012	0.00010	0.00010	0.00013	0.00013	0.00010	0.00014	0.00024	0.00009	0.00011	0.00005	0.00000	-0.00002
AC	0.00007	0.00008	0.00014	0.00012	0.00014	0.00016	0.00016	0.00019	0.00012	0.00009	0.00009	0.00011	0.00010	0.00010	0.00003	-0.00001	-0.00002
SP	0.00007	0.00007	0.00017	0.00010	0.00016	0.00024	0.00022	0.00027	0.00012	0.00008	0.00007	0.00009	0.00011	0.00011	0.00002	-0.00001	-0.00003
DOW	0.00006	0.00007	0.00016	0.00010	0.00016	0.00022	0.00025	0.00024	0.00013	0.00009	0.00006	0.00008	0.00011	0.00011	0.00002	-0.00001	-0.00003
ND	0.00004	0.00011	0.00020	0.00013	0.00019	0.00027	0.00024	0.00042	0.00015	0.00009	0.00008	0.00011	0.00012	0.00012	0.00003	-0.00001	-0.00003
DAX	0.00008	0.00010	0.00012	0.00013	0.00012	0.00012	0.00013	0.00015	0.00026	0.00015	0.00009	0.00011	0.00010	0.00010	-0.00003	-0.00001	-0.00003
FTSE	0.00001	0.00009	0.00009	0.00010	0.00009	0.00008	0.00009	0.00009	0.00015	0.00018	0.00007	0.00011	0.00012	0.00012	0.00000	0.00000	-0.00002
NK	0.00010	0.00002	0.00008	0.00014	0.00009	0.00007	0.00006	0.00008	0.00009	0.00007	0.00031	0.00018	0.00006	0.00006	-0.00004	-0.00001	-0.00002
HSI	0.00006	0.00002	0.00009	0.00024	0.00011	0.00009	0.00008	0.00011	0.00011	0.00011	0.00018	0.00036	0.00008	0.00009	0.00002	-0.00001	-0.00002
BRT	0.00009	0.00002	0.00010	0.00009	0.00010	0.00011	0.00011	0.00012	0.00010	0.00012	0.00006	0.00008	0.00102	0.00097	0.00007	-0.00001	-0.00003
WTI	0.00008	0.00001	0.00010	0.00011	0.00010	0.00011	0.00011	0.00012	0.00010	0.00012	0.00006	0.00009	0.00097	0.00112	0.00009	-0.00001	-0.00003
GD	0.00018	0.00006	0.00003	0.00005	0.00003	0.00002	0.00002	0.00003	-0.00003	0.00000	-0.00004	0.00002	0.00007	0.00009	0.00059	0.00003	0.00005
CORP	0.00000	-0.00002	-0.00001	0.00000	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	0.00000	-0.00001	-0.00001	-0.00001	-0.00001	0.00003	0.00002	0.00002
GOV	-0.00001	-0.00003	-0.00002	-0.00002	-0.00002	-0.00003	-0.00003	-0.00003	-0.00003	-0.00002	-0.00002	-0.00002	-0.00003	-0.00003	0.00005	0.00002	0.00004

Table 4.19 Sharpe Ratio of Each Asset (Calculated by Static Standard Deviation)

	TR	CR	SP	FTSE	NK	HSI	WTI	GD	CORP	GOV
Quarterly Return	2.8908%	6.8201%	2.8461%	0.3683%	1.6624%	0.9455%	2.9245%	2.8694%	1.3631%	0.9657%
Quarterly S.D.	70.0849%	84.2047%	11.6176%	9.0829%	13.3494%	15.0299%	26.5572%	19.9210%	3.2143%	4.8846%
Sharpe Ratio	0.0376	0.0780	0.2230	0.0124	0.1054	0.0459	0.1005	0.1312	0.3445	0.1454
Risk free rate	0.2557%									

Note: The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.20 Sharpe Ratio of Each Asset (Calculated by Conditional Standard Deviation)

	TR	CR	SP	FTSE	NK	HSI	WTI	GD	CORP	GOV
Quarterly Return	2.8908%	6.8201%	2.8461%	0.3683%	1.6624%	0.9455%	2.9245%	2.8694%	1.3631%	0.9657%
Quarterly S.D.	12.5527%	16.8940%	2.4567%	2.2858%	2.9648%	3.2600%	5.7499%	4.1767%	0.6926%	1.0334%
Sharpe Ratio	0.2099	0.3886	1.0544	0.0493	0.4745	0.2116	0.4642	0.6258	1.5990	0.6871
Risk free rate	0.2557%									

Note: The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.21 Static and Dynamic Portfolio Performance

Assets	**Fixed Income Portfolio**		**Balanced Portfolio**		**Equity Portfolio**		**Alternative Portfolio (Commodity 100%)**	
	Static	**DCC**	**Static**	**DCC**	**Static**	**DCC**	**Static**	**DCC**
TR								
CR								
SP			13.15%	14.01%	100.00%	80.28%		
FTSE			0.00%	0.00%	0.00%	0.00%		
NK			0.00%	3.63%	0.00%	19.72%		
HSI			0.00%	0.00%	0.00%	0.00%		
WTI							35.30%	33.24%
GD							64.70%	66.76%
CORP	100.00%	100.00%	86.85%	82.35%				
GOV	0.00%	0.00%	0.00%	0.00%				
Sum Weights	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
Quarterly Return	**1.36%**	**1.36%**	**1.56%**	**1.58%**	**2.85%**	**2.61%**	**2.89%**	**2.89%**
S.D.	**1.86%**	**0.40%**	**1.95%**	**0.37%**	**6.71%**	**1.38%**	**9.58%**	**2.06%**
Sharpe Ratio	**0.597**	**2.746**	**0.667**	**3.568**	**0.386**	**1.713**	**0.275**	**1.278**

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The static portfolio is generated by static correlation, variance, and covariance. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.22 Static and Dynamic Portfolio Performance (Cont.)

Assets	**Alternative Portfolio (Fixed Income and Commodity)**		**Alternative Portfolio (Equity and Commodity)**		**Alternative Portfolio (Fixed Income, Equity, and Commodity)**		**Alternative Portfolio (Coin and Token)**	
	Static	**DCC**	**Static**	**DCC**	**Static**	**DCC**	**Static**	**DCC**
TR							0.00%	0.00%
CR							100.00%	100.00%
SP			74.71%	52.29%	13.15%	12.99%		
FTSE			0.00%	0.00%	0.00%	0.00%		
NK			0.00%	17.63%	0.00%	3.33%		
HSI			0.00%	0.00%	0.00%	0.00%		
WTI	2.57%	4.33%	0.00%	5.95%	0.00%	1.94%		
GD	0.00%	0.13%	25.29%	24.13%	0.00%	0.00%		
CORP	97.43%	95.54%			86.85%	81.73%		
GOV	0.00%	0.00%			0.00%	0.00%		
Sum Weights	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
Quarterly Return	**1.40%**	**1.43%**	**2.85%**	**2.65%**	**1.56%**	**1.60%**	**6.82%**	**6.82%**
S.D.	**1.88%**	**0.40%**	**5.82%**	**1.18%**	**1.95%**	**0.37%**	**48.62%**	**9.93%**
Sharpe Ratio	**0.610**	**2.947**	**0.446**	**2.026**	**0.667**	**3.622**	**0.135**	**0.661**

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The static portfolio is generated by static correlation, variance, and covariance. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.23 Static and Dynamic Portfolio Performance (Cont.)

Assets	Alternative Portfolio (Equity and Coin)		Alternative Portfolio (Commodity and Coin)		Alternative Portfolio (Fixed Income and Coin)		Alternative Portfolio (Equity, Commodity, and Coin)	
	Static	**DCC**	**Static**	**DCC**	**Static**	**DCC**	**Static**	**DCC**
TR								
CR	4.85%	4.59%	6.61%	9.44%	0.10%	1.11%	2.75%	3.27%
SP	95.15%	76.40%					74.53%	50.32%
FTSE	0.00%	0.00%					0.00%	0.00%
NK	0.00%	19.00%					0.00%	17.15%
HSI	0.00%	0.00%					0.00%	0.00%
WTI			34.95%	30.42%			0.00%	5.93%
GD			58.45%	60.15%			22.73%	23.33%
CORP					99.90%	98.89%		
GOV					0.00%	0.00%		
Sum Weights	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
Quarterly Return	**3.04%**	**2.80%**	**3.15%**	**3.26%**	**1.37%**	**1.42%**	**2.96%**	**2.78%**
S.D.	**6.75%**	**1.41%**	**9.99%**	**2.10%**	**1.86%**	**0.41%**	**5.92%**	**1.20%**
Sharpe Ratio	**0.412**	**1.811**	**0.290**	**1.427**	**0.597**	**2.852**	**0.457**	**2.104**

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The static portfolio is generated by static correlation, variance, and covariance. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.24 Static and Dynamic Portfolio Performance (Cont.)

Assets	Alternative Portfolio (Fixed Income, Equity, Commodity, and Coin)		Alternative Portfolio (Equity and Token)		Alternative Portfolio (Commodity and Token)		Alternative Portfolio (Fixed Income and Token)	
	Static	**DCC**	**Static**	**DCC**	**Static**	**DCC**	**Static**	**DCC**
TR			0.00%	1.85%	0.00%	3.73%	0.00%	0.51%
CR	0.20%	0.70%						
SP	13.34%	12.67%	100.00%	79.14%				
FTSE	0.00%	0.00%	0.00%	0.00%				
NK	0.00%	3.29%	0.00%	19.01%				
HSI	0.00%	0.00%	0.00%	0.00%				
WTI	0.00%	1.94%			35.30%	32.25%		
GD	0.00%	0.00%			64.70%	64.02%		
CORP	86.47%	81.40%					100.00%	99.49%
GOV	0.00%	0.00%					0.00%	0.00%
Sum Weights	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
Quarterly Return	**1.57%**	**1.63%**	**2.85%**	**2.62%**	**2.89%**	**2.89%**	**1.36%**	**1.37%**
S.D.	**1.97%**	**0.37%**	**6.71%**	**1.37%**	**9.58%**	**2.03%**	**1.86%**	**0.40%**
Sharpe Ratio	**0.668**	**3.687**	**0.386**	**1.725**	**0.275**	**1.294**	**0.597**	**2.763**

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The static portfolio is generated by static correlation, variance, and covariance. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.25 Static and Dynamic Portfolio Performance (Cont.)

Assets	**Alternative Portfolio (Equity, Commodity, and Token)**		**Alternative Portfolio (Fixed Income, Equity, Commodity, and Token)**		**Alternative Portfolio (Equity, Coin, and Token)**		**Alternative Portfolio (Commodity, Coin, and Token)**	
	Static	**DCC**	**Static**	**DCC**	**Static**	**DCC**	**Static**	**DCC**
TR	0.00%	0.73%	0.00%	0.18%	0.00%	0.00%	0.00%	0.00%
CR					4.85%	4.59%	6.61%	9.44%
SP	74.71%	52.11%	13.15%	12.95%	95.15%	76.40%		
FTSE	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%		
NK	0.00%	17.36%	0.00%	3.28%	0.00%	19.01%		
HSI	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%		
WTI	0.00%	5.94%	0.00%	1.93%			34.95%	30.41%
GD	25.29%	23.86%	0.00%	0.00%			58.45%	60.15%
CORP			86.85%	81.65%				
GOV			0.00%	0.00%				
Sum Weights	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
Quarterly Return	**2.85%**	**2.65%**	**1.56%**	**1.60%**	**3.04%**	**2.80%**	**3.15%**	**3.26%**
S.D.	**5.82%**	**1.18%**	**1.95%**	**0.37%**	**6.75%**	**1.41%**	**9.99%**	**2.10%**
Sharpe Ratio	**0.446**	**2.029**	**0.667**	**3.625**	**0.412**	**1.811**	**0.290**	**1.427**

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The static portfolio is generated by static correlation, variance, and covariance. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.26 Static and Dynamic Portfolio Performance (Cont.)

Assets	Alternative Portfolio (Fixed Income, Coin, and Token)		Alternative Portfolio (Equity, Commodity, Coin, and Token)		Alternative Portfolio (Fixed Income, Equity, Commodity, Coin, and Token)	
	Static	**DCC**	**Static**	**DCC**	**Static**	**DCC**
TR	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
CR	0.10%	1.11%	2.75%	3.27%	0.20%	0.70%
SP			74.53%	50.32%	13.34%	12.67%
FTSE			0.00%	0.00%	0.00%	0.00%
NK			0.00%	17.15%	0.00%	3.29%
HSI			0.00%	0.00%	0.00%	0.00%
WTI			0.00%	5.93%	0.00%	1.94%
GD			22.73%	23.33%	0.00%	0.00%
CORP	99.90%	98.89%			86.47%	81.40%
GOV	0.00%	0.00%			0.00%	0.00%
Sum Weights	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**
Quarterly Return	**1.37%**	**1.42%**	**2.96%**	**2.78%**	**1.57%**	**1.63%**
S.D.	**1.86%**	**0.41%**	**5.92%**	**1.20%**	**1.97%**	**0.37%**
Sharpe Ratio	**0.597**	**2.852**	**0.457**	**2.104**	**0.668**	**3.687**

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The static portfolio is generated by static correlation, variance, and covariance. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.27 Fixed Income Portfolio by Actively Adjusted Weights of Investment

Assets	**Fixed Income Portfolio**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
CORP	100.0000%	0.0000%	0.0000%	100.0000%	0.0000%	100.0000%	100.0000%	100.0000%	100.0000%
GOV	0.0000%	100.0000%	100.0000%	0.0000%	100.0000%	0.0000%	0.0000%	0.0000%	0.0000%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**1.1115%**	**-2.4904%**	**-0.5603%**	**0.9438%**	**4.1996%**	**5.1129%**	**4.2433%**	**3.0450%**	**1.2685%**
S.D.	**0.3714%**	**0.5464%**	**0.5658%**	**0.4020%**	**0.5555%**	**0.3773%**	**0.3671%**	**0.3770%**	**0.4474%**
Sharpe Ratio	**2.3042**	**- 5.0259**	**- 1.4421**	**1.7116**	**7.0994**	**12.8720**	**10.8613**	**7.3988**	**2.2639**
Compound Annual Growth Rate = 8.3239%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.28 Fixed Income Portfolio by Fixed Weights of Investment

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
CORP	**100.0000%**	1.1115%	-2.2217%	-0.9475%	0.9438%	-0.2734%	5.1129%	4.2433%	3.0450%	1.2685%
GOV	**0.0000%**	-0.2091%	-2.4904%	-0.5603%	-1.5559%	4.1996%	3.2589%	4.3195%	3.7163%	-1.6310%
Sum Weights	**100.0000%**									
Quarterly Returns	**1.3489%**	**1.1115%**	**-2.2217%**	**-0.9475%**	**0.9438%**	**-0.2734%**	**5.1129%**	**4.2433%**	**3.0450%**	**1.2685%**
S.D.	**0.3714%**	**0.3714%**	**0.3675%**	**0.3959%**	**0.4020%**	**0.3743%**	**0.3773%**	**0.3671%**	**0.3770%**	**0.4474%**
Sharpe Ratio	**2.9432**	**2.3042**	**-6.7418**	**-3.0386**	**1.7116**	**-1.4134**	**12.8720**	**10.8613**	**7.3988**	**2.2639**
		Compound Annual Growth Rate = 6.0323%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.29 Balanced Portfolio by Actively Adjusted Weights of Investment

Assets	**Balanced Portfolio**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
SP	19.1577%	0.0000%	0.0000%	22.8104%	0.0000%	5.2995%	8.5537%	7.1915%	18.8078%
FTSE	0.0000%	0.0000%	92.5381%	0.0000%	0.0000%	4.0027%	1.1425%	0.0000%	0.0000%
NK	28.6712%	0.0000%	7.4619%	17.7011%	0.0000%	0.0000%	0.0000%	3.5113%	14.6150%
HSI	1.3205%	100.0000%	0.0000%	0.0000%	0.0000%	3.2933%	0.0000%	0.0000%	4.8548%
CORP	50.8506%	0.0000%	0.0000%	59.4885%	0.0000%	87.4045%	90.3038%	89.2971%	61.7224%
GOV	0.0000%	0.0000%	0.0000%	0.0000%	100.0000%	0.0000%	0.0000%	0.0000%	0.0000%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**5.0188%**	**0.5806%**	**7.7068%**	**3.5316%**	**4.1996%**	**5.9050%**	**4.1726%**	**2.8824%**	**3.8897%**
S.D.	**0.4804%**	**1.6108%**	**1.3141%**	**0.5450%**	**0.5555%**	**0.3634%**	**0.3323%**	**0.3296%**	**0.4915%**
Sharpe Ratio	**9.9158**	**0.2018**	**5.6703**	**6.0112**	**7.0994**	**15.5448**	**11.7867**	**7.9702**	**7.3941**
	Compound Annual Growth Rate = 18.9174%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.30 Balanced Portfolio by Fixed Weights of Investment

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
SP	17.8834%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	17.2428%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
CORP	64.8738%	1.1115%	-2.2217%	-0.9475%	0.9438%	-0.2734%	5.1129%	4.2433%	3.0450%	1.2685%
GOV	0.0000%	-0.2091%	-2.4904%	-0.5603%	-1.5559%	4.1996%	3.2589%	4.3195%	3.7163%	-1.6310%
Sum Weights	**100.0000%**									
Quarterly Returns	**2.7275%**	**3.2036%**	**-1.5616%**	**-0.7622%**	**1.1458%**	**-4.4990%**	**7.9097%**	**3.1130%**	**0.6391%**	**3.6472%**
S.D.	**0.3924%**	**0.3924%**	**0.3985%**	**0.6312%**	**0.5432%**	**0.4610%**	**0.7015%**	**0.5003%**	**0.4627%**	**0.5101%**
Sharpe Ratio	**6.2996**	**7.5130**	**-4.5599**	**-1.6126**	**1.6387**	**-10.3137**	**10.9114**	**5.7107**	**0.8285**	**6.6485**
		Compound Annual Growth Rate = 6.1709%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.31 Equity Portfolio by Actively Adjusted Weights of Investment

Assets	**Equity Portfolio**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
SP	35.1381%	0.0000%	0.0000%	55.2260%	0.0000%	31.7940%	79.0992%	33.4809%	42.4886%
FTSE	0.0000%	0.0000%	92.5381%	0.0000%	0.0000%	40.5808%	20.9008%	0.0000%	0.0000%
NK	61.8925%	0.0000%	7.4619%	44.7740%	0.0000%	0.0000%	0.0000%	66.5191%	44.2650%
HSI	2.9694%	100.0000%	0.0000%	0.0000%	100.0000%	27.6252%	0.0000%	0.0000%	13.2463%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**9.2542%**	**0.5806%**	**7.7068%**	**7.3412%**	**-8.5780%**	**10.9302%**	**3.3571%**	**1.8795%**	**8.1473%**
S.D.	**0.9833%**	**1.6108%**	**1.3141%**	**1.3077%**	**1.9037%**	**1.5513%**	**1.2852%**	**1.3110%**	**1.2638%**
Sharpe Ratio	**9.1514**	**0.2018**	**5.6703**	**5.4184**	**-4.6402**	**6.8810**	**2.4132**	**1.2386**	**6.2442**
Compound Annual Growth Rate = 19.6364%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.32 Equity Portfolio by Fixed Weights of Investment

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	**1Q18**	**2Q18**	**3Q18**	**4Q18**	**1Q19**	**2Q19**	**3Q19**	**4Q19**
SP	44.6497%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	55.3503%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
Sum Weights	**100.0000%**									
Quarterly Returns	**5.4509%**	**7.2109%**	**-0.2288%**	**-0.8427%**	**0.8264%**	**-11.8450%**	**13.0686%**	**0.6821%**	**-4.4405%**	**8.0589%**
S.D.	**1.0327%**	**1.0327%**	**1.0772%**	**1.7354%**	**1.4950%**	**1.2866%**	**1.9801%**	**1.3924%**	**1.2936%**	**1.4481%**
Sharpe Ratio	**5.0308**	**6.7350**	**-0.4498**	**-0.6329**	**0.3817**	**-9.4053**	**6.4708**	**0.3063**	**-3.6304**	**5.3885**
				Compound Annual Growth Rate = 5.1700%						

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.33 Alternative Portfolio by Actively Adjusted Weights of Investment (Commodity 100%)

Assets	**Alternative Portfolio (Commodity 100%)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
WTI	100.0000%	100.0000%	100.0000%	100.0000%	0.0000%	68.6774%	0.0000%	0.0000%	39.6875%
GD	0.0000%	0.0000%	0.0000%	0.0000%	100.0000%	31.3226%	100.0000%	100.0000%	60.3125%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**15.6443%**	**7.2144%**	**13.2626%**	**-1.2212%**	**11.0908%**	**22.0600%**	**13.7000%**	**5.0399%**	**10.6068%**
S.D.	**3.1610%**	**2.9714%**	**2.8439%**	**2.9727%**	**2.3658%**	**2.6728%**	**2.4875%**	**2.3840%**	**2.3199%**
Sharpe Ratio	**4.8682**	**2.3419**	**4.5736**	**-0.4968**	**4.5798**	**8.1580**	**5.4047**	**2.0068**	**4.4618**
	Compound Annual Growth Rate = 48.1975%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.34 Alternative Portfolio by Fixed Weights of Investment (Commodity 100%)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	**1Q18**	**2Q18**	**3Q18**	**4Q18**	**1Q19**	**2Q19**	**3Q19**	**4Q19**
WTI	63.9784%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	36.0216%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
Sum Weights	100.0000%									
Quarterly Returns	8.9482%	**10.3059%**	**2.1951%**	**8.9525%**	**-7.3563%**	**-26.7088%**	**21.1283%**	**3.1332%**	**-3.1899%**	**11.6383%**
S.D.	2.2623%	**2.2623%**	**2.1293%**	**2.1555%**	**2.1459%**	**2.3012%**	**2.5640%**	**2.6774%**	**2.3621%**	**2.7744%**
Sharpe Ratio	3.8423	**4.4425**	**0.9108**	**4.0347**	**-3.5472**	**-11.7173**	**8.1406**	**1.0747**	**-1.4587**	**4.1027**
		Compound Annual Growth Rate = 5.9748%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.35 Alternative Portfolio by Actively Adjusted Weights of Investment (Fixed Income and Commodity)

Assets	Alternative Portfolio (Fixed Income and Commodity)								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
WTI	17.5188%	100.0000%	100.0000%	0.0000%	0.0000%	6.2323%	0.0000%	0.0000%	15.0955%
GD	0.0000%	0.0000%	0.0000%	0.0000%	12.9635%	0.0000%	4.3635%	0.0000%	16.1738%
CORP	82.4812%	0.0000%	0.0000%	100.0000%	0.0000%	93.7677%	95.6365%	100.0000%	68.7307%
GOV	0.0000%	0.0000%	0.0000%	0.0000%	87.0365%	0.0000%	0.0000%	0.0000%	0.0000%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**3.6575%**	**7.2144%**	**13.2626%**	**0.9438%**	**5.0929%**	**6.5561%**	**4.6559%**	**3.0450%**	**4.3026%**
S.D.	**0.6032%**	**2.9714%**	**2.8439%**	**0.4020%**	**0.5773%**	**0.4090%**	**0.3899%**	**0.3770%**	**0.8590%**
Sharpe Ratio	**5.6401**	**2.3419**	**4.5736**	**1.7116**	**8.3792**	**15.4060**	**11.2847**	**7.3988**	**4.7111**
Compound Annual Growth Rate = 24.2210%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.36 Alternative Portfolio by Fixed Weights of Investment (Fixed Income and Commodity)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
WTI	12.0640%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	0.0000%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
CORP	87.9360%	1.1115%	-2.2217%	-0.9475%	0.9438%	-0.2734%	5.1129%	4.2433%	3.0450%	1.2685%
GOV	0.0000%	-0.2091%	-2.4904%	-0.5603%	-1.5559%	4.1996%	3.2589%	4.3195%	3.7163%	-1.6310%
Sum Weights	**100.0000%**									
Quarterly Returns	**2.5779%**	**2.8648%**	**-1.0834%**	**0.7668%**	**0.6826%**	**-6.0300%**	**7.9066%**	**3.3916%**	**1.7338%**	**2.7041%**
S.D.	**0.4745%**	**0.4745%**	**0.4668%**	**0.4670%**	**0.4735%**	**0.4826%**	**0.5332%**	**0.5320%**	**0.4860%**	**0.5818%**
Sharpe Ratio	**4.8942**	**5.4987**	**-2.8683**	**1.0945**	**0.9016**	**-13.0253**	**14.3498**	**5.8947**	**3.0412**	**4.2083**
Compound Annual Growth Rate = 6.1935%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.37 Alternative Portfolio by Actively Adjusted Weights of Investment (Equity and Commodity)

Assets	Alternative Portfolio (Equity and Commodity)								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
SP	27.9270%	0.0000%	0.0000%	55.2260%	0.0000%	18.9174%	26.0180%	13.1210%	27.9168%
FTSE	0.0000%	0.0000%	70.2545%	0.0000%	0.0000%	11.0381%	17.5792%	0.0000%	0.0000%
NK	56.1867%	0.0000%	5.2586%	44.7740%	0.0000%	0.0000%	0.0000%	40.1919%	36.9497%
HSI	1.2464%	0.0000%	0.0000%	0.0000%	0.0000%	22.3558%	0.0000%	0.0000%	7.8291%
WTI	10.4725%	100.0000%	24.4869%	0.0000%	0.0000%	31.0969%	0.0000%	0.0000%	6.6670%
GD	4.1674%	0.0000%	0.0000%	0.0000%	100.0000%	16.5918%	56.4029%	46.6871%	20.6374%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**9.7184%**	**7.2144%**	**9.0771%**	**7.3412%**	**11.0908%**	**16.4458%**	**9.0446%**	**3.4046%**	**8.6594%**
S.D.	**0.9637%**	**2.9714%**	**1.3457%**	**1.3077%**	**2.3658%**	**1.6992%**	**1.5326%**	**1.2800%**	**1.1246%**
Sharpe Ratio	**9.8189**	**2.3419**	**6.5554**	**5.4184**	**4.5798**	**9.5279**	**5.7345**	**2.4600**	**7.4729**
	Compound Annual Growth Rate = 41.0022%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.38 Alternative Portfolio by Fixed Weights of Investment (Equity and Commodity)

Assets	**Weights of DCC-3Q17**	**Quarterly Returns**								
		4Q17	**1Q18**	**2Q18**	**3Q18**	**4Q18**	**1Q19**	**2Q19**	**3Q19**	**4Q19**
SP	31.8440%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	42.0806%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
WTI	13.4628%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	12.6126%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
Sum Weights	**100.0000%**									
Quarterly Returns	**6.1644%**	**7.5674%**	**-0.0243%**	**1.2477%**	**-1.9843%**	**-13.7334%**	**14.5306%**	**1.7893%**	**-3.8183%**	**8.8590%**
S.D.	**0.9845%**	**0.9845%**	**1.0206%**	**1.5529%**	**1.3284%**	**1.2436%**	**1.6928%**	**1.3178%**	**1.2015%**	**1.3362%**
Sharpe Ratio	**6.0015**	**7.4265**	**-0.2744**	**0.6388**	**-1.6862**	**-11.2487**	**8.4325**	**1.1638**	**-3.3908**	**6.4387**
Compound Annual Growth Rate = 5.8773%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.39 Alternative Portfolio by Actively Adjusted Weights of Investment (Fixed Income, Equity, and Commodity)

Assets	Alternative Portfolio (Fixed Income, Equity, and Commodity)								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
SP	15.7451%	0.0000%	0.0000%	22.8106%	0.0000%	4.6945%	7.7550%	7.1915%	17.1588%
FTSE	0.0000%	0.0000%	63.9442%	0.0000%	0.0000%	0.5857%	1.4063%	0.0000%	0.0000%
NK	26.5246%	0.0000%	5.1453%	17.7011%	0.0000%	0.0000%	0.3339%	3.5113%	16.6414%
HSI	0.7295%	0.0000%	0.0000%	0.0000%	0.0000%	3.2773%	0.0000%	0.0000%	4.4219%
WTI	5.4995%	100.0000%	22.2885%	0.0000%	0.0000%	4.3977%	0.0000%	0.0000%	3.7009%
GD	0.0000%	0.0000%	0.0000%	0.0000%	12.9635%	0.0000%	2.8951%	0.0000%	6.0325%
CORP	51.5014%	0.0000%	0.0000%	59.4883%	0.0000%	87.0448%	87.6098%	89.2971%	52.0445%
GOV	0.0000%	0.0000%	8.6219%	0.0000%	87.0365%	0.0000%	0.0000%	0.0000%	0.0000%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0001%**
Quarterly Returns	**5.3948%**	**7.2144%**	**8.2326%**	**3.5317%**	**5.0929%**	**6.7823%**	**4.4316%**	**2.8824%**	**4.7966%**
S.D.	**0.4855%**	**2.9714%**	**1.2159%**	**0.5450%**	**0.5773%**	**0.3876%**	**0.3473%**	**0.3296%**	**0.5694%**
Sharpe Ratio	**10.5854**	**2.3419**	**6.5602**	**6.0112**	**8.3792**	**16.8405**	**12.0235**	**7.9702**	**7.9744**
	Compound Annual Growth Rate = 24.2013%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.40 Alternative Portfolio by Fixed Weights of Investment (Fixed Income, Equity, and Commodity)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
SP	14.2584%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	15.3659%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
WTI	5.7498%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	0.0000%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
CORP	64.6259%	1.1115%	-2.2217%	-0.9475%	0.9438%	-0.2734%	5.1129%	4.2433%	3.0450%	1.2685%
GOV	0.0000%	-0.2091%	-2.4904%	-0.5603%	-1.5559%	4.1996%	3.2589%	4.3195%	3.7163%	-1.6310%
Sum Weights	**100.0000%**									
Quarterly Returns	**3.1207%**	**3.7304%**	**-1.1075%**	**-0.0298%**	**0.8986%**	**-6.5205%**	**8.8023%**	**2.8389%**	**0.3073%**	**3.9613%**
S.D.	**0.4097%**	**0.4097%**	**0.4171%**	**0.5973%**	**0.5270%**	**0.4717%**	**0.6722%**	**0.5177%**	**0.4795%**	**0.5266%**
Sharpe Ratio	**6.9922**	**8.4803**	**-3.2678**	**-0.4779**	**1.2200**	**-14.3654**	**12.7141**	**4.9902**	**0.1077**	**7.0371**
Compound Annual Growth Rate = 6.0950%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.41 Alternative Portfolio by Actively Adjusted Weights of Investment (Token and Coin)

Assets	Alternative Portfolio (Token and Coin)								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
TR	0.0000%	100.0000%	100.0000%	0.0000%	0.0000%	100.0000%	46.1805%	100.0000%	0.0000%
CR	100.0000%	0.0000%	0.0000%	100.0000%	100.0000%	0.0000%	53.8196%	0.0000%	100.0000%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**139.6500%**	**-30.0964%**	**2.5220%**	**-7.0610%**	**-51.6883%**	**22.5869%**	**69.4954%**	**-9.9486%**	**-14.6281%**
S.D.	**10.9966%**	**11.9519%**	**13.5994%**	**9.8699%**	**9.1961%**	**4.9576%**	**5.9502%**	**3.2463%**	**10.2764%**
Sharpe Ratio	**12.6761**	**-2.5395**	**0.1667**	**-0.7413**	**-5.6485**	**4.5044**	**11.6366**	**-3.1434**	**-1.4484**
Compound Annual Growth Rate = 10.5622%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.42 Alternative Portfolio by Fixed Weights of Investment (Token and Coin)

Assets	**Weights of DCC-3Q17**	**Quarterly Returns**								
		4Q17	**1Q18**	**2Q18**	**3Q18**	**4Q18**	**1Q19**	**2Q19**	**3Q19**	**4Q19**
TR	0.0000%	84.8322%	-30.0964%	2.5220%	-7.5329%	-40.8987%	22.5869%	38.1454%	-9.9486%	-4.9451%
CR	100.0000%	139.6500%	-85.3068%	-3.2632%	-7.0610%	-51.6883%	3.1823%	96.3956%	-41.7006%	-14.6281%
Sum Weights	**100.0000%**									
Quarterly Returns	**32.6208%**	**139.650%**	**-85.3068%**	**-3.2632%**	**-7.0610%**	**-51.6883%**	**3.1823%**	**96.3956%**	**-41.7006%**	**-14.6281%**
S.D.	**10.9966%**	**10.9966%**	**9.7643%**	**11.8897%**	**9.8699%**	**9.1961%**	**9.8309%**	**8.4743%**	**9.8609%**	**10.2764%**
Sharpe Ratio	**2.94320**	**12.6761**	**-8.7628**	**-0.2960**	**-0.7413**	**-5.6485**	**0.2977**	**11.3449**	**-4.2548**	**-1.4484**
Compound Annual Growth Rate = -83.3412%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.43 Alternative Portfolio by Actively Adjusted Weights of Investment (Equity and Coin)

Assets	**Alternative Portfolio (Equity and Coin)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
CR	11.5671%	0.0000%	0.0000%	0.0000%	100.0000%	0.0097%	47.9112%	0.0000%	0.0000%
SP	24.7445%	0.0000%	0.0000%	55.2260%	0.0000%	31.7875%	52.0888%	33.4809%	42.4887%
FTSE	0.0000%	0.0000%	92.5381%	0.0000%	0.0000%	40.5701%	0.0000%	0.0000%	0.0000%
NK	59.7875%	0.0000%	7.4619%	44.7740%	0.0000%	0.0000%	0.0000%	66.5191%	44.2649%
HSI	3.9010%	100.0000%	0.0000%	0.0000%	0.0000%	27.6328%	0.0000%	0.0000%	13.2464%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**24.6312%**	**0.5806%**	**7.7068%**	**7.3412%**	**-51.6883%**	**10.9298%**	**48.1209%**	**1.8795%**	**8.1473%**
S.D.	**1.5725%**	**1.6108%**	**1.3141%**	**1.3077%**	**9.1961%**	**1.5512%**	**4.1471%**	**1.3110%**	**1.2638%**
Sharpe Ratio	**15.5015**	**0.2018**	**5.6703**	**5.4184**	**-5.6485**	**6.8811**	**11.5418**	**1.2386**	**6.2442**
Compound Annual Growth Rate = 12.0323%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.44 Alternative Portfolio by Fixed Weights of Investment (Equity and Coin)

Assets	**Weights of DCC-3Q17**	**Quarterly Returns**								
		4Q17	**1Q18**	**2Q18**	**3Q18**	**4Q18**	**1Q19**	**2Q19**	**3Q19**	**4Q19**
CR	5.1246%	139.6500%	-85.3068%	-3.2632%	-7.0610%	-51.6883%	3.1823%	96.3956%	-41.7006%	-14.6281%
SP	39.9843%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	54.8911%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
Sum Weights	**100.0000%**									
Quarterly Returns	**6.9106%**	**14.0523%**	**-4.5456%**	**-1.1272%**	**0.1592%**	**-13.7129%**	**12.5595%**	**5.4567%**	**-6.5914%**	**6.9033%**
S.D.	**1.1557%**	**1.1557%**	**1.1788%**	**1.8179%**	**1.5196%**	**1.3351%**	**1.9703%**	**1.4085%**	**1.3352%**	**1.4899%**
Sharpe Ratio	**5.7584**	**11.9380**	**-4.0729**	**-0.7607**	**-0.0635**	**-10.4626**	**6.2446**	**3.6926**	**-5.1283**	**4.4619**
Compound Annual Growth Rate = 4.9170%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.45 Alternative Portfolio by Actively Adjusted Weights of Investment (Commodity and Coin)

Assets	**Alternative Portfolio (Commodity and Coin)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
CR	41.5920%	0.0000%	0.0000%	100.0000%	0.0000%	0.0000%	36.9082%	0.0000%	0.0000%
WTI	58.4080%	100.0000%	100.0000%	0.0000%	0.0000%	68.6774%	0.0000%	0.0000%	39.6875%
GD	0.0000%	0.0000%	0.0000%	0.0000%	100.0000%	31.3226%	63.0918%	100.0000%	60.3125%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**67.2207%**	**7.2144%**	**13.2626%**	**-7.0610%**	**11.0908%**	**22.0600%**	**44.2214%**	**5.0399%**	**10.6068%**
S.D.	**4.8924%**	**2.9714%**	**2.8439%**	**9.8699%**	**2.3658%**	**2.6728%**	**3.4523%**	**2.3840%**	**2.3199%**
Sharpe Ratio	**13.6877**	**2.3419**	**4.5736**	**-0.7413**	**4.5798**	**8.1580**	**12.7352**	**2.0068**	**4.4618**
Compound Annual Growth Rate = 79.8335%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.46 Alternative Portfolio by Fixed Weights of Investment (Commodity and Coin)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	**1Q18**	**2Q18**	**3Q18**	**4Q18**	**1Q19**	**2Q19**	**3Q19**	**4Q19**
CR	14.2686%	139.6500%	-85.3068%	-3.2632%	-7.0610%	-51.6883%	3.1823%	96.3956%	-41.7006%	-14.6281%
WTI	60.4490%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	25.2823%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
Sum Weights	**100.0000%**									
Quarterly Returns	**12.7283%**	**29.5914%**	**-9.5100%**	**7.8795%**	**-6.3605%**	**-33.5812%**	**19.6779%**	**15.5157%**	**-9.4051%**	**8.1282%**
S.D.	**2.5970%**	**2.5970%**	**2.4085%**	**2.5564%**	**2.4245%**	**2.4617%**	**2.7885%**	**2.7163%**	**2.5742%**	**2.8993%**
Sharpe Ratio	**4.8028**	**11.2962**	**-4.0547**	**2.9822**	**-2.7289**	**-13.7456**	**6.9650**	**5.6180**	**-3.7529**	**2.7153**
Compound Annual Growth Rate = 3.1860%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.47 Alternative Portfolio by Actively Adjusted Weights of Investment (Fixed Income and Coin)

Assets	**Alternative Portfolio (Fixed Income and Coin)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
CR	13.7094%	100.0000%	100.0000%	0.0000%	0.0000%	0.2593%	4.3123%	0.0000%	0.0000%
CORP	86.2906%	0.0000%	0.0000%	100.0000%	0.0000%	99.7407%	95.6877%	100.0000%	100.0000%
GOV	0.0000%	0.0000%	0.0000%	0.0000%	100.0000%	0.0000%	0.0000%	0.0000%	0.0000%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**20.1043%**	**-85.3068%**	**-3.2632%**	**0.9438%**	**4.1996%**	**5.1079%**	**8.2172%**	**3.0450%**	**1.2685%**
S.D.	**1.5312%**	**9.7643%**	**11.8897%**	**0.4020%**	**0.5555%**	**0.3761%**	**0.4942%**	**0.3770%**	**0.4474%**
Sharpe Ratio	**12.9630**	**-8.7628**	**-0.2960**	**1.7116**	**7.0994**	**12.9017**	**16.1100**	**7.3988**	**2.2639**
Compound Annual Growth Rate = -70.2835%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.48 Alternative Portfolio by Fixed Weights of Investment (Fixed Income and Coin)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
CR	3.2673%	139.6500%	-85.3068%	-3.2632%	-7.0610%	-51.6883%	3.1823%	96.3956%	-41.7006%	-14.6281%
CORP	96.7327%	1.1115%	-2.2217%	-0.9475%	0.9438%	-0.2734%	5.1129%	4.2433%	3.0450%	1.2685%
GOV	0.0000%	-0.2091%	-2.4904%	-0.5603%	-1.5559%	4.1996%	3.2589%	4.3195%	3.7163%	-1.6310%
Sum Weights	**100.0000%**									
Quarterly Returns	**2.3706%**	**5.6381%**	**-4.9364%**	**-1.0231%**	**0.6822%**	**-1.9533%**	**5.0498%**	**7.2542%**	**1.5830%**	**0.7491%**
S.D.	**0.4999%**	**0.4999%**	**0.4663%**	**0.5333%**	**0.5012%**	**0.4615%**	**0.4753%**	**0.4394%**	**0.4722%**	**0.5355%**
Sharpe Ratio	**4.2307**	**10.7667**	**-11.1358**	**-2.3977**	**0.8511**	**-4.7864**	**10.0859**	**15.9289**	**2.8109**	**0.9215**
Compound Annual Growth Rate = 6.2218%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.49 Alternative Portfolio by Actively Adjusted Weights of Investment (Equity, Commodity, and Coin)

Assets	**Alternative Portfolio (Equity, Commodity, and Coin)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
CR	11.2432%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	28.9396%	0.0000%	0.0000%
SP	17.9641%	0.0000%	0.0000%	55.2260%	0.0000%	18.9174%	20.3436%	13.6094%	27.9168%
FTSE	0.0000%	0.0000%	70.2545%	0.0000%	0.0000%	11.0382%	1.5155%	0.0000%	0.0000%
NK	56.0513%	0.0000%	5.2586%	44.7740%	0.0000%	0.0000%	0.8941%	39.7606%	36.9497%
HSI	2.6194%	0.0000%	0.0000%	0.0000%	0.0000%	22.3558%	0.0000%	0.0000%	7.8292%
WTI	12.1220%	100.0000%	24.4869%	0.0000%	0.0000%	31.0968%	0.0000%	0.0000%	6.6670%
GD	0.0000%	0.0000%	0.0000%	0.0000%	100.0000%	16.5918%	48.3072%	46.6300%	20.6374%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**25.1490%**	**7.2144%**	**9.0771%**	**7.3412%**	**11.0908%**	**16.4458%**	**35.3040%**	**3.3979%**	**8.6594%**
S.D.	**1.5586%**	**2.9714%**	**1.3457%**	**1.3077%**	**2.3658%**	**1.6992%**	**2.7344%**	**1.2773%**	**1.1246%**
Sharpe Ratio	**15.9714**	**2.3419**	**6.5554**	**5.4184**	**4.5798**	**9.5279**	**12.8173**	**2.4600**	**7.4729**
	Compound Annual Growth Rate = 60.5683%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.50 Alternative Portfolio by Fixed Weights of Investment (Equity, Commodity, and Coin)

Assets	**Weights of DCC-3Q17**	**Quarterly Returns**								
		4Q17	**1Q18**	**2Q18**	**3Q18**	**4Q18**	**1Q19**	**2Q19**	**3Q19**	**4Q19**
CR	4.1024%	139.6500%	-85.3068%	-3.2632%	-7.0610%	-51.6883%	3.1823%	96.3956%	-41.7006%	-14.6281%
SP	28.3232%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	42.9881%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
WTI	14.2860%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	10.3002%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
Sum Weights	**100.0000%**									
Quarterly Returns	**7.4213%**	**13.2717%**	**-3.2606%**	**1.0562%**	**-2.1440%**	**-16.0236%**	**14.3547%**	**5.2569%**	**-5.8331%**	**7.9573%**
S.D.	**1.0891%**	**1.0891%**	**1.1106%**	**1.6094%**	**1.3664%**	**1.2834%**	**1.7214%**	**1.3425%**	**1.2506%**	**1.3790%**
Sharpe Ratio	**6.5797**	**11.9516**	**-3.1661**	**0.4974**	**-1.7562**	**-12.6847**	**8.1905**	**3.7254**	**-4.8685**	**5.5851**
Compound Annual Growth Rate = 5.4114%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.51 Alternative Portfolio by Actively Adjusted Weights of Investment (Fixed Income, Equity, Commodity, and Coin)

Assets	**Alternative Portfolio (Fixed Income, Equity, Commodity, and Coin)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
CR	4.9833%	0.0000%	0.0000%	0.0000%	0.0000%	0.0788%	3.7969%	0.0000%	0.0000%
SP	11.0323%	0.0000%	0.0000%	22.8104%	0.0000%	4.6488%	7.2782%	7.1914%	17.1590%
FTSE	0.0000%	0.0000%	63.9446%	0.0000%	0.0000%	0.6099%	0.0000%	0.0000%	0.0000%
NK	25.3723%	0.0000%	5.1455%	17.7011%	0.0000%	0.0000%	0.4400%	3.5114%	16.6415%
HSI	1.0949%	0.0000%	0.0000%	0.0000%	0.0000%	3.2758%	0.0000%	0.0000%	4.4224%
WTI	5.7691%	100.0000%	22.2886%	0.0000%	0.0000%	4.3841%	0.0000%	0.0000%	3.7014%
GD	0.0000%	0.0000%	0.0000%	0.0000%	12.9635%	0.0000%	3.0119%	0.0000%	6.0328%
CORP	51.7482%	0.0000%	0.0000%	59.4885%	0.0000%	87.0026%	85.4731%	89.2972%	52.0429%
GOV	0.0000%	0.0000%	8.6213%	0.0000%	87.0365%	0.0000%	0.0000%	0.0000%	0.0000%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**12.0201%**	**7.2144%**	**8.2326%**	**3.5316%**	**5.0929%**	**6.7745%**	**7.9715%**	**2.8824%**	**4.7967%**
S.D.	**0.7104%**	**2.9714%**	**1.2160%**	**0.5450%**	**0.5773%**	**0.3870%**	**0.4563%**	**0.3296%**	**0.5695%**
Sharpe Ratio	**16.5597**	**2.3419**	**6.5602**	**6.0112**	**8.3792**	**16.8438**	**16.9109**	**7.9702**	**7.9744**
	Compound Annual Growth Rate = 29.2273%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.52 Alternative Portfolio by Fixed Weights of Investment (Fixed Income, Equity, Commodity, and Coin)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
CR	1.5679%	139.6500%	-85.3068%	-3.2632%	-7.0610%	-51.6883%	3.1823%	96.3956%	-41.7006%	-14.6281%
SP	12.8360%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	15.2825%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
WTI	5.8374%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	0.0000%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
CORP	64.4762%	1.1115%	-2.2217%	-0.9475%	0.9438%	-0.2734%	5.1129%	4.2433%	3.0450%	1.2685%
GOV	0.0000%	-0.2091%	-2.4904%	-0.5603%	-1.5559%	4.1996%	3.2589%	4.3195%	3.7163%	-1.6310%
Sum Weights	**100.0000%**									
Quarterly Returns	**3.5794%**	**5.8406%**	**-2.4183%**	**-0.1058%**	**0.6900%**	**-7.1393%**	**8.6718%**	**4.2901%**	**-0.3673%**	**3.6224%**
S.D.	**0.4370%**	**0.4370%**	**0.4400%**	**0.6195%**	**0.5341%**	**0.4828%**	**0.6710%**	**0.5213%**	**0.4885%**	**0.5376%**
Sharpe Ratio	**7.6053**	**12.7795**	**-6.0774**	**-0.5836**	**0.8132**	**-15.3164**	**12.5425**	**7.7394**	**-1.2753**	**6.2621**
Compound Annual Growth Rate = 6.1012%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.53 Alternative Portfolio by Actively Adjusted Weights of Investment (Equity and Token)

Assets	Alternative Portfolio (Equity and Token)								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
TR	3.1688%	0.0000%	0.0835%	0.0000%	100.0000%	16.2198%	61.8045%	0.0000%	0.0000%
SP	33.4966%	0.0000%	0.0000%	55.2260%	0.0000%	24.2860%	26.4609%	33.4809%	42.4887%
FTSE	0.0000%	0.0000%	92.5159%	0.0000%	0.0000%	37.6377%	11.7346%	0.0000%	0.0000%
NK	59.9543%	0.0000%	7.4006%	44.7740%	0.0000%	0.0000%	0.0000%	66.5191%	44.2649%
HSI	3.3802%	100.0000%	0.0000%	0.0000%	0.0000%	21.8565%	0.0000%	0.0000%	13.2464%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**11.6619%**	**0.5806%**	**7.7039%**	**7.3412%**	**-40.8987%**	**12.6278%**	**24.7930%**	**1.8795%**	**8.1473%**
S.D.	**1.1164%**	**1.6108%**	**1.3135%**	**1.3077%**	**5.7229%**	**1.5329%**	**2.4993%**	**1.3110%**	**1.2638%**
Sharpe Ratio	**10.2168**	**0.2018**	**5.6705**	**5.4184**	**-7.1911**	**8.0708**	**9.8178**	**1.2386**	**6.2442**
Compound Annual Growth Rate = 8.7231%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.54 Alternative Portfolio by Fixed Weights of Investment (Equity and Token)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
TR	0.0000%	84.8322%	-30.0964%	2.5220%	-7.5329%	-40.8987%	22.5869%	38.1454%	-9.9486%	-4.9451%
SP	44.6497%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	55.3503%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
Sum Weights	**100.0000%**									
Quarterly Returns	**5.4509%**	**7.2109%**	**-0.2288%**	**-0.8427%**	**0.8264%**	**-11.8450%**	**13.0686%**	**0.6821%**	**-4.4405%**	**8.0589%**
S.D.	**1.0327%**	**1.0327%**	**1.0772%**	**1.7354%**	**1.4950%**	**1.2866%**	**1.9801%**	**1.3924%**	**1.2936%**	**1.4481%**
Sharpe Ratio	**5.0308**	**6.7350**	**-0.4498**	**-0.6329**	**0.3817**	**-9.4053**	**6.4708**	**0.3063**	**-3.6304**	**5.3885**
Compound Annual Growth Rate = 5.1700%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.55 Alternative Portfolio by Actively Adjusted Weights of Investment (Commodity and Token)

Assets	Alternative Portfolio (Commodity and Token)								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
TR	18.1262%	0.0000%	0.0000%	100.0000%	0.0000%	20.9313%	55.0124%	0.0000%	0.0000%
WTI	81.8738%	100.0000%	100.0000%	0.0000%	0.0000%	55.7415%	0.0000%	0.0000%	39.6875%
GD	0.0000%	0.0000%	0.0000%	0.0000%	100.0000%	23.3272%	44.9876%	100.0000%	60.3125%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**28.1855%**	**7.2144%**	**13.2626%**	**-7.5329%**	**11.0908%**	**22.4556%**	**27.1480%**	**5.0399%**	**10.6068%**
S.D.	**3.8322%**	**2.9714%**	**2.8439%**	**8.1315%**	**2.3658%**	**2.4732%**	**2.4924%**	**2.3840%**	**2.3199%**
Sharpe Ratio	**7.2881**	**2.3419**	**4.5736**	**-0.9578**	**4.5798**	**8.9762**	**10.7899**	**2.0068**	**4.4618**
Compound Annual Growth Rate = 56.7919%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.56 Alternative Portfolio by Fixed Weights of Investment (Commodity and Token)

Assets	**Weights of DCC-3Q17**	**Quarterly Returns**								
		4Q17	**1Q18**	**2Q18**	**3Q18**	**4Q18**	**1Q19**	**2Q19**	**3Q19**	**4Q19**
TR	0.0000%	84.8322%	-30.0964%	2.5220%	-7.5329%	-40.8987%	22.5869%	38.1454%	-9.9486%	-4.9451%
WTI	63.9784%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	36.0216%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
Sum Weights	**100.0000%**									
Quarterly Returns	**8.9482%**	**10.3059%**	**2.1951%**	**8.9525%**	**-7.3563%**	**-26.7088%**	**21.1283%**	**3.1332%**	**-3.1899%**	**11.6383%**
S.D.	**2.2623%**	**2.2623%**	**2.1293%**	**2.1555%**	**2.1459%**	**2.3012%**	**2.5640%**	**2.6774%**	**2.3621%**	**2.7744%**
Sharpe Ratio	**3.8423**	**4.4425**	**0.9108**	**4.0347**	**-3.5472**	**-11.7173**	**8.1406**	**1.0747**	**-1.4587**	**4.1027**
Compound Annual Growth Rate = 5.9748%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.57 Alternative Portfolio by Actively Adjusted Weights of Investment (Fixed Income and Token)

Assets	**Alternative Portfolio (Fixed Income and Token)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
TR	5.1334%	100.0000%	100.0000%	0.0000%	0.0000%	2.7014%	7.6649%	0.0000%	0.0000%
CORP	94.8666%	0.0000%	0.0000%	100.0000%	0.0000%	97.2986%	92.3351%	100.0000%	100.0000%
GOV	0.0000%	0.0000%	0.0000%	0.0000%	100.0000%	0.0000%	0.0000%	0.0000%	0.0000%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**5.4093%**	**-30.0964%**	**2.5220%**	**0.9438%**	**4.1996%**	**5.5849%**	**6.8418%**	**3.0450%**	**1.2685%**
S.D.	**0.8782%**	**11.9519%**	**13.5994%**	**0.4020%**	**0.5555%**	**0.3887%**	**0.4533%**	**0.3770%**	**0.4474%**
Sharpe Ratio	**5.8683**	**-2.5395**	**0.1667**	**1.7116**	**7.0994**	**13.7115**	**14.5307**	**7.3988**	**2.2639**
Compound Annual Growth Rate = -3.3265%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.58 Alternative Portfolio by Fixed Weights of Investment (Fixed Income and Token)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
TR	0.0000%	84.8322%	-30.0964%	2.5220%	-7.5329%	-40.8987%	22.5869%	38.1454%	-9.9486%	-4.9451%
CORP	100.0000%	1.1115%	-2.2217%	-0.9475%	0.9438%	-0.2734%	5.1129%	4.2433%	3.0450%	1.2685%
GOV	0.0000%	-0.2091%	-2.4904%	-0.5603%	-1.5559%	4.1996%	3.2589%	4.3195%	3.7163%	-1.6310%
Sum Weights	**100.0000%**									
Quarterly Returns	**1.3489%**	**1.1115%**	**-2.2217%**	**-0.9475%**	**0.9438%**	**-0.2734%**	**5.1129%**	**4.2433%**	**3.0450%**	**1.2685%**
S.D.	**0.3714%**	**0.3714%**	**0.3675%**	**0.3959%**	**0.4020%**	**0.3743%**	**0.3773%**	**0.3671%**	**0.3770%**	**0.4474%**
Sharpe Ratio	**2.9432**	**2.3042**	**-6.7418**	**-3.0386**	**1.7116**	**-1.4134**	**12.8720**	**10.8613**	**7.3988**	**2.2639**
Compound Annual Growth Rate = 6.0323%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.59 Alternative Portfolio by Actively Adjusted Weights of Investment (Equity, Commodity, and Token)

Assets	**Alternative Portfolio (Equity, Commodity, and Token)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
TR	3.0383%	0.0000%	0.0000%	0.0000%	0.0000%	11.7397%	42.4918%	0.0000%	0.0000%
SP	26.3874%	0.0000%	0.0000%	55.2260%	0.0000%	15.6441%	10.5446%	13.1210%	27.9168%
FTSE	0.0000%	0.0000%	70.2545%	0.0000%	0.0000%	13.1985%	12.5733%	0.0000%	0.0000%
NK	55.6351%	0.0000%	5.2586%	44.7740%	0.0000%	0.0000%	0.0000%	40.1919%	36.9497%
HSI	1.9572%	0.0000%	0.0000%	0.0000%	0.0000%	19.1250%	0.0000%	0.0000%	7.8291%
WTI	11.7409%	100.0000%	24.4869%	0.0000%	0.0000%	26.8020%	0.0000%	0.0000%	6.6669%
GD	1.2412%	0.0000%	0.0000%	0.0000%	100.0000%	13.4907%	34.3903%	46.6871%	20.6374%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**12.3755%**	**7.2144%**	**9.0771%**	**7.3412%**	**11.0908%**	**16.9392%**	**21.5626%**	**3.4046%**	**8.6594%**
S.D.	**1.1204%**	**2.9714%**	**1.3457%**	**1.3077%**	**2.3658%**	**1.6391%**	**1.9566%**	**1.2800%**	**1.1246%**
Sharpe Ratio	**10.8176**	**2.3419**	**6.5554**	**5.4184**	**4.5798**	**10.1785**	**10.8900**	**2.4600**	**7.4729**
	Compound Annual Growth Rate = 48.6098%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.60 Alternative Portfolio by Fixed Weights of Investment (Equity, Commodity, and Token)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
TR	0.0000%	84.8322%	-30.0964%	2.5220%	-7.5329%	-40.8987%	22.5869%	38.1454%	-9.9486%	-4.9451%
SP	31.8440%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	42.0806%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
WTI	13.4628%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	12.6126%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
Sum Weights	**100.0000%**									
Quarterly Returns	**6.1644%**	**7.5674%**	**-0.0243%**	**1.2477%**	**-1.9843%**	**-13.7334%**	**14.5306%**	**1.7893%**	**-3.8183%**	**8.8590%**
S.D.	**0.9845%**	**0.9845%**	**1.0206%**	**1.5529%**	**1.3284%**	**1.2436%**	**1.6928%**	**1.3178%**	**1.2015%**	**1.3362%**
Sharpe Ratio	**6.0015**	**7.4265**	**-0.2744**	**0.6388**	**-1.6862**	**-11.2487**	**8.4325**	**1.1638**	**-3.3908**	**6.4387**
				Compound Annual Growth Rate = 5.8773%						

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.61 Alternative Portfolio by Actively Adjusted Weights of Investment (Fixed Income, Equity, Commodity, and Token)

Assets	Alternative Portfolio (Fixed Income, Equity, Commodity, and Token)								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
TR	1.3671%	0.0000%	0.0000%	0.0000%	0.0000%	1.7438%	6.5049%	0.0000%	0.0000%
SP	14.8140%	0.0000%	0.0000%	22.8104%	0.0000%	4.3717%	6.3877%	7.1912%	17.1596%
FTSE	0.0000%	0.0000%	63.9446%	0.0000%	0.0000%	1.1004%	1.5690%	0.0000%	0.0000%
NK	25.4809%	0.0000%	5.1455%	17.7011%	0.0000%	0.0000%	0.0000%	3.5114%	16.6430%
HSI	0.8925%	0.0000%	0.0000%	0.0000%	0.0000%	3.0657%	0.0000%	0.0000%	4.4217%
WTI	5.7375%	100.0000%	22.2886%	0.0000%	0.0000%	4.1156%	0.0000%	0.0000%	3.6992%
GD	0.0000%	0.0000%	0.0000%	0.0000%	12.9635%	0.0000%	2.1804%	0.0000%	6.0312%
CORP	51.7080%	0.0000%	0.0000%	59.4884%	0.0000%	85.6028%	83.3579%	89.2974%	52.0453%
GOV	0.0000%	0.0000%	8.6213%	0.0000%	87.0365%	0.0000%	0.0000%	0.0000%	0.0000%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**6.4355%**	**7.2144%**	**8.2326%**	**3.5316%**	**5.0929%**	**6.9929%**	**6.5859%**	**2.8824%**	**4.7964%**
S.D.	**0.5351%**	**2.9714%**	**1.2160%**	**0.5450%**	**0.5773%**	**0.3903%**	**0.4170%**	**0.3296%**	**0.5694%**
Sharpe Ratio	**11.5479**	**2.3419**	**6.5602**	**6.0112**	**8.3792**	**17.2633**	**15.1799**	**7.9702**	**7.9744**
	Compound Annual Growth Rate = 25.9128%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.62 Alternative Portfolio by Fixed Weights of Investment (Fixed Income, Equity, Commodity, and Token)

Assets	**Weights of DCC-3Q17**	**Quarterly Returns**								
		4Q17	**1Q18**	**2Q18**	**3Q18**	**4Q18**	**1Q19**	**2Q19**	**3Q19**	**4Q19**
TR	0.0000%	84.8322%	-30.0964%	2.5220%	-7.5329%	-40.8987%	22.5869%	38.1454%	-9.9486%	-4.9451%
SP	14.2633%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	15.4034%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
WTI	5.7553%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	0.0000%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
CORP	64.5780%	1.1115%	-2.2217%	-0.9475%	0.9438%	-0.2734%	5.1129%	4.2433%	3.0450%	1.2685%
GOV	0.0000%	-0.2091%	-2.4904%	-0.5603%	-1.5559%	4.1996%	3.2589%	4.3195%	3.7163%	-1.6310%
Sum Weights	**100.0000%**									
Quarterly Returns	**3.1233%**	**3.7341%**	**-1.1059%**	**-0.0299%**	**0.8969%**	**-6.5270%**	**8.8070%**	**2.8363%**	**0.3021%**	**3.9649%**
S.D.	**0.4101%**	**0.4101%**	**0.4176%**	**0.5979%**	**0.5276%**	**0.4723%**	**0.6730%**	**0.5183%**	**0.4801%**	**0.5272%**
Sharpe Ratio	**6.9922**	**8.4814**	**-3.2605**	**-0.4776**	**1.2154**	**-14.3618**	**12.7056**	**4.9794**	**0.0967**	**7.0362**
					Compound Annual Growth Rate = 6.0931%					

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.63 Alternative Portfolio by Actively Adjusted Weights of Investment (Equity, Coin, and Token)

Assets	**Alternative Portfolio (Equity, Coin, and Token)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
TR	0.0000%	0.0000%	0.0837%	0.0000%	0.0000%	16.2198%	26.3195%	0.0000%	0.0000%
CR	11.5670%	0.0000%	0.0000%	0.0000%	100.0000%	0.0000%	32.6723%	0.0000%	0.0000%
SP	24.7442%	0.0000%	0.0000%	55.2260%	0.0000%	24.2860%	41.0082%	33.4809%	42.4887%
FTSE	0.0000%	0.0000%	92.5278%	0.0000%	0.0000%	37.6381%	0.0000%	0.0000%	0.0000%
NK	59.7878%	0.0000%	7.3884%	44.7740%	0.0000%	0.0000%	0.0000%	66.5191%	44.2649%
HSI	3.9009%	100.0000%	0.0000%	0.0000%	0.0000%	21.8561%	0.0000%	0.0000%	13.2464%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**24.6312%**	**0.5806%**	**7.7042%**	**7.3412%**	**-51.6883%**	**12.6278%**	**43.0589%**	**1.8795%**	**8.1473%**
S.D.	**1.5725%**	**1.6108%**	**1.3136%**	**1.3077%**	**9.1961%**	**1.5329%**	**3.6278%**	**1.3110%**	**1.2638%**
Sharpe Ratio	**15.5015**	**0.2018**	**5.6705**	**5.4184**	**-5.6485**	**8.0708**	**11.7986**	**1.2386**	**6.2442**
Compound Annual Growth Rate = 11.0238%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.64 Alternative Portfolio by Fixed Weights of Investment (Equity, Coin, and Token)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
TR	0.0000%	84.8322%	-30.0964%	2.5220%	-7.5329%	-40.8987%	22.5869%	38.1454%	-9.9486%	-4.9451%
CR	5.1113%	139.6500%	-85.3068%	-3.2632%	-7.0610%	-51.6883%	3.1823%	96.3956%	-41.7006%	-14.6281%
SP	40.3296%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	54.5591%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
Sum Weights	**100.0000%**									
Quarterly Returns	**6.8974%**	**14.0270%**	**-4.5405%**	**-1.1040%**	**0.1978%**	**-13.7325%**	**12.5612%**	**5.4626%**	**-6.5520%**	**6.9053%**
S.D.	**1.1534%**	**1.1534%**	**1.1754%**	**1.8169%**	**1.5168%**	**1.3312%**	**1.9694%**	**1.4064%**	**1.3327%**	**1.4875%**
Sharpe Ratio	**5.7584**	**11.9397**	**-4.0806**	**-0.7483**	**-0.0382**	**-10.5080**	**6.2485**	**3.7023**	**-5.1081**	**4.4704**
		Compound Annual Growth Rate = 4.9543%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.65 Alternative Portfolio by Actively Adjusted Weights of Investment (Commodity, Coin, and Token)

Assets	**Alternative Portfolio (Commodity, Coin, and Token)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
TR	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	20.9314%	16.8051%	0.0000%	0.0000%
CR	41.5920%	0.0000%	0.0000%	100.0000%	0.0000%	0.0000%	28.1430%	0.0000%	0.0000%
WTI	58.4080%	100.0000%	100.0000%	0.0000%	0.0000%	55.7414%	0.0000%	0.0000%	39.6875%
GD	0.0000%	0.0000%	0.0000%	0.0000%	100.0000%	23.3271%	55.0520%	100.0000%	60.3125%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**67.2208%**	**7.2144%**	**13.2626%**	**-7.0610%**	**11.0908%**	**22.4556%**	**41.0810%**	**5.0399%**	**10.6068%**
S.D.	**4.8924%**	**2.9714%**	**2.8439%**	**9.8699%**	**2.3658%**	**2.4732%**	**3.1689%**	**2.3840%**	**2.3199%**
Sharpe Ratio	**13.6877**	**2.3419**	**4.5736**	**-0.7413**	**4.5798**	**8.9762**	**12.8831**	**2.0068**	**4.4618**
Compound Annual Growth Rate = 78.7085%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.66 Alternative Portfolio by Fixed Weights of Investment (Commodity, Coin, and Token)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
TR	0.0000%	84.8322%	-30.0964%	2.5220%	-7.5329%	-40.8987%	22.5869%	38.1454%	-9.9486%	-4.9451%
CR	14.2687%	139.6500%	-85.3068%	-3.2632%	-7.0610%	-51.6883%	3.1823%	96.3956%	-41.7006%	-14.6281%
WTI	60.4480%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	25.2833%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
Sum Weights	**100.0000%**									
Quarterly Returns	**12.7283%**	**29.5914%**	**-9.5102%**	**7.8794%**	**-6.3606%**	**-33.5807%**	**19.6777%**	**15.5159%**	**-9.4050%**	**8.1282%**
S.D.	**2.5970%**	**2.5970%**	**2.4084%**	**2.5564%**	**2.4244%**	**2.4616%**	**2.7885%**	**2.7163%**	**2.5742%**	**2.8993%**
Sharpe Ratio	**4.8028**	**11.2962**	**-4.0549**	**2.9822**	**-2.7290**	**-13.7454**	**6.9650**	**5.6181**	**-3.7529**	**2.7153**
		Compound Annual Growth Rate = 3.1861%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.67 Alternative Portfolio by Actively Adjusted Weights of Investment (Fixed Income, Coin, and Token)

Assets	**Alternative Portfolio (Fixed Income, Coin, and Token)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
TR	0.0000%	100.0000%	100.0000%	0.0000%	0.0000%	2.7014%	2.2010%	0.0000%	0.0000%
CR	13.7094%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	3.5822%	0.0000%	0.0000%
CORP	86.2906%	0.0000%	0.0000%	100.0000%	0.0000%	97.2986%	94.2168%	100.0000%	100.0000%
GOV	0.0000%	0.0000%	0.0000%	0.0000%	100.0000%	0.0000%	0.0000%	0.0000%	0.0000%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**20.1043%**	**-30.0964%**	**2.5220%**	**0.9438%**	**4.1996%**	**5.5849%**	**8.2905%**	**3.0450%**	**1.2685%**
S.D.	**1.5312%**	**11.9519%**	**13.5994%**	**0.4020%**	**0.5555%**	**0.3887%**	**0.4947%**	**0.3770%**	**0.4474%**
Sharpe Ratio	**12.9630**	**-2.5395**	**0.1667**	**1.7116**	**7.0994**	**13.7115**	**16.2424**	**7.3988**	**2.2639**
	Compound Annual Growth Rate = 3.8772%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.68 Alternative Portfolio by Fixed Weights of Investment (Fixed Income, Coin, and Token)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
TR	0.0000%	84.8322%	-30.0964%	2.5220%	-7.5329%	-40.8987%	22.5869%	38.1454%	-9.9486%	-4.9451%
CR	3.2673%	139.6500%	-85.3068%	-3.2632%	-7.0610%	-51.6883%	3.1823%	96.3956%	-41.7006%	-14.6281%
CORP	96.7327%	1.1115%	-2.2217%	-0.9475%	0.9438%	-0.2734%	5.1129%	4.2433%	3.0450%	1.2685%
GOV	0.0000%	-0.2091%	-2.4904%	-0.5603%	-1.5559%	4.1996%	3.2589%	4.3195%	3.7163%	-1.6310%
Sum Weights	**100.0000%**									
Quarterly Returns	**2.3706%**	**5.6381%**	**-4.9364%**	**-1.0231%**	**0.6822%**	**-1.9533%**	**5.0498%**	**7.2542%**	**1.5830%**	**0.7491%**
S.D.	**0.4999%**	**0.4999%**	**0.4663%**	**0.5333%**	**0.5012%**	**0.4615%**	**0.4753%**	**0.4394%**	**0.4722%**	**0.5355%**
Sharpe Ratio	**4.2307**	**10.7667**	**-11.1358**	**-2.3977**	**0.8511**	**-4.7864**	**10.0860**	**15.9288**	**2.8109**	**0.9215**
					Compound Annual Growth Rate = 6.2218%					

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.69 Alternative Portfolio by Actively Adjusted Weights of Investment (Equity, Commodity, Coin, and Token)

Assets	**Alternative Portfolio (Equity, Commodity, Coin, and Token)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
TR	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	11.7396%	13.1545%	0.0000%	0.0000%
CR	11.2432%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	22.7523%	0.0000%	0.0000%
SP	17.9641%	0.0000%	0.0000%	55.2260%	0.0000%	15.6441%	17.0188%	13.4060%	27.9169%
FTSE	0.0000%	0.0000%	70.2551%	0.0000%	0.0000%	13.1992%	3.7221%	0.0000%	0.0000%
NK	56.0512%	0.0000%	5.2581%	44.7740%	0.0000%	0.0000%	0.0000%	39.9217%	36.9496%
HSI	2.6195%	0.0000%	0.0000%	0.0000%	0.0000%	19.1244%	0.0000%	0.0000%	7.8291%
WTI	12.1220%	100.0000%	24.4867%	0.0000%	0.0000%	26.8020%	0.0000%	0.0000%	6.6671%
GD	0.0000%	0.0000%	0.0000%	0.0000%	100.0000%	13.4907%	43.3523%	46.6723%	20.6373%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**25.1491%**	**7.2144%**	**9.0771%**	**7.3412%**	**11.0908%**	**16.9392%**	**33.5961%**	**3.4012%**	**8.6594%**
S.D.	**1.5586%**	**2.9714%**	**1.3457%**	**1.3077%**	**2.3658%**	**1.6391%**	**2.5737%**	**1.2787%**	**1.1246%**
Sharpe Ratio	**15.9714**	**2.3419**	**6.5554**	**5.4184**	**4.5798**	**10.1785**	**12.9541**	**2.4600**	**7.4729**
	Compound Annual Growth Rate = 60.0825%								

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.70 Alternative Portfolio by Fixed Weights of Investment (Equity, Commodity, Coin, and Token)

Assets	Weights of DCC-3Q17	Quarterly Returns								
		4Q17	1Q18	2Q18	3Q18	4Q18	1Q19	2Q19	3Q19	4Q19
TR	0.0000%	84.8322%	-30.0964%	2.5220%	-7.5329%	-40.8987%	22.5869%	38.1454%	-9.9486%	-4.9451%
CR	4.1024%	139.6500%	-85.3068%	-3.2632%	-7.0610%	-51.6883%	3.1823%	96.3956%	-41.7006%	-14.6281%
SP	28.3232%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	42.9881%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
WTI	14.2860%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	10.3002%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
Sum Weights	**100.0000%**									
Quarterly Returns	**7.4213%**	**13.2717%**	**-3.2606%**	**1.0562%**	**-2.1440%**	**-16.0236%**	**14.3547%**	**5.2569%**	**-5.8331%**	**7.9573%**
S.D.	**1.0891%**	**1.0891%**	**1.1106%**	**1.6094%**	**1.3664%**	**1.2834%**	**1.7214%**	**1.3425%**	**1.2506%**	**1.3790%**
Sharpe Ratio	**6.5797**	**11.9516**	**-3.1661**	**0.4974**	**-1.7562**	**-12.6847**	**8.1905**	**3.7254**	**-4.8685**	**5.5851**
Compound Annual Growth Rate = 5.4114%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.71 Alternative Portfolio by Actively Adjusted Weights of Investment (Fixed Income, Equity, Commodity, Coin, and Token)

Assets	**Alternative Portfolio (Fixed Income, Equity, Commodity, Coin, and Token)**								
	DCC-4Q17	**DCC-1Q18**	**DCC-2Q18**	**DCC-3Q18**	**DCC-4Q18**	**DCC-1Q19**	**DCC-2Q19**	**DCC-3Q19**	**DCC-4Q19**
TR	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	1.7438%	1.3910%	0.0000%	0.0000%
CR	4.9832%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	3.3506%	0.0000%	0.0000%
SP	11.0323%	0.0000%	0.0000%	22.8104%	0.0000%	4.3716%	7.1458%	7.1914%	17.1588%
FTSE	0.0000%	0.0000%	63.9446%	0.0000%	0.0000%	1.1004%	0.0000%	0.0000%	0.0000%
NK	25.3721%	0.0000%	5.1455%	17.7011%	0.0000%	0.0000%	0.2926%	3.5114%	16.6417%
HSI	1.0949%	0.0000%	0.0000%	0.0000%	0.0000%	3.0657%	0.0000%	0.0000%	4.4218%
WTI	5.7692%	100.0000%	22.2886%	0.0000%	0.0000%	4.1156%	0.0000%	0.0000%	3.7009%
GD	0.0000%	0.0000%	0.0000%	0.0000%	12.9635%	0.0000%	2.8343%	0.0000%	6.0326%
CORP	51.7483%	0.0000%	0.0000%	59.4885%	0.0000%	85.6029%	84.9856%	89.2971%	52.0443%
GOV	0.0000%	0.0000%	8.6213%	0.0000%	87.0365%	0.0000%	0.0000%	0.0000%	0.0000%
Sum Weights	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**	**100.0000%**
Quarterly Returns	**12.0200%**	**7.2144%**	**8.2326%**	**3.5316%**	**5.0929%**	**6.9929%**	**8.0215%**	**2.8824%**	**4.7966%**
S.D.	**0.7104%**	**2.9714%**	**1.2160%**	**0.5450%**	**0.5773%**	**0.3903%**	**0.4575%**	**0.3296%**	**0.5694%**
Sharpe Ratio	**16.5597**	**2.3419**	**6.5602**	**6.0112**	**8.3792**	**17.2633**	**16.9742**	**7.9702**	**7.9744**
Compound Annual Growth Rate = 29.3617%									

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill. The DCC portfolio is generated by dynamic conditional correlation, variance, and covariance.

Table 4.72 Alternative Portfolio by Fixed Weights of Investment (Fixed Income, Equity, Commodity, Coin, and Token)

Assets	**Weights of DCC-3Q17**	**Quarterly Returns**								
		4Q17	**1Q18**	**2Q18**	**3Q18**	**4Q18**	**1Q19**	**2Q19**	**3Q19**	**4Q19**
TR	0.0000%	84.8322%	-30.0964%	2.5220%	-7.5329%	-40.8987%	22.5869%	38.1454%	-9.9486%	-4.9451%
CR	1.5679%	139.6500%	-85.3068%	-3.2632%	-7.0610%	-51.6883%	3.1823%	96.3956%	-41.7006%	-14.6281%
SP	12.8359%	5.9425%	-1.2323%	2.8926%	6.9487%	-15.8951%	13.1262%	3.7178%	1.1820%	7.8955%
FTSE	0.0000%	4.1839%	-8.5666%	7.9031%	-1.6734%	-10.9097%	7.7855%	1.9918%	-0.2349%	2.3854%
NK	0.0000%	11.1832%	-7.3153%	5.2720%	7.8254%	-18.6573%	5.7805%	0.3301%	2.2306%	8.3761%
HSI	15.2825%	8.2340%	0.5806%	-3.8559%	-4.1124%	-8.5780%	13.0222%	-1.7667%	-8.9759%	8.1908%
WTI	5.8374%	15.6443%	7.2144%	13.2626%	-1.2212%	-47.9909%	28.2706%	-2.8161%	-7.8234%	13.1680%
GD	0.0000%	0.8244%	-6.7197%	1.2972%	-18.2529%	11.0908%	8.4427%	13.7000%	5.0399%	8.9214%
CORP	64.4763%	1.1115%	-2.2217%	-0.9475%	0.9438%	-0.2734%	5.1129%	4.2433%	3.0450%	1.2685%
GOV	0.0000%	-0.2091%	-2.4904%	-0.5603%	-1.5559%	4.1996%	3.2589%	4.3195%	3.7163%	-1.6310%
Sum Weights	**100.0000%**									
Quarterly Returns	**3.5794%**	**5.8406%**	**-2.4183%**	**-0.1059%**	**0.6900%**	**-7.1393%**	**8.6717%**	**4.2901%**	**-0.3673%**	**3.6224%**
S.D.	**0.4370%**	**0.4370%**	**0.4400%**	**0.6195%**	**0.5341%**	**0.4828%**	**0.6710%**	**0.5213%**	**0.4885%**	**0.5376%**
Sharpe Ratio	**7.6053**	**12.7795**	**-6.0774**	**-0.5836**	**0.8132**	**-15.3163**	**12.5425**	**7.7394**	**-1.2753**	**6.2621**
Compound Annual Growth Rate = 6.1012%										

Note: The expected return and optimal weights of investment base on maximize Sharpe Ratio assumption. The risk-free rate is equal to 0.26 percent calculated by the U.S. 3-year treasury bill.

Table 4.73 All Dynamic Portfolio Performance Comparison

	Fixed Income Portfolio		Balanced Portfolio		Equity Portfolio		Alternative Portfolio (Commodity 100%)		Alternative Portfolio (Fixed Income and Commodity)		Alternative Portfolio (Equity and Commodity)	
	Active	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**
Average annual return	7.50%	5.46%	16.84%	5.70%	18.05%	5.55%	43.29%	8.93%	21.66%	5.75%	36.44%	6.41%
Average annual S.D.	1.78%	1.55%	2.68%	2.04%	5.57%	5.66%	10.75%	9.50%	4.19%	2.00%	6.48%	5.19%
Sharpe Ratio	3.63	2.87	5.91	2.29	3.06	0.80	3.93	0.83	4.92	2.36	5.46	1.04
Compound Annual Growth Rate	8.32%	6.03%	18.92%	6.17%	19.64%	5.17%	48.20%	5.97%	24.22%	6.19%	41.00%	5.88%

Note: The fixed portfolio has fixed the weights of asset investment during a whole of the sample period. Meanwhile, the active portfolio has actively adjusted the weights of asset investment in every three months.

Table 4.74 All Dynamic Portfolio Performance Comparison (Cont.)

	Alternative Portfolio (Fixed Income, Equity, and Commodity)		Alternative Portfolio (Coin and Token)		Alternative Portfolio (Equity and Coin)		Alternative Portfolio (Commodity and Coin)		Alternative Portfolio (Fixed Income and Coin)		Alternative Portfolio (Equity, Commodity, and Coin)	
	Active	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**
Average annual return	21.49%	5.72%	53.70%	15.81%	25.62%	5.85%	77.18%	9.75%	-20.30%	5.80%	54.97%	6.50%
Average annual S.D.	3.30%	2.05%	35.58%	40.07%	10.34%	5.87%	15.01%	10.41%	11.48%	1.95%	7.28%	5.40%
Sharpe Ratio	6.20	2.29	1.48	0.37	2.38	0.82	5.07	0.84	-1.86	2.45	7.41	1.02
Compound Annual Growth Rate	24.20%	6.10%	10.56%	-83.34%	12.03%	4.92%	79.83%	3.19%	-70.28%	6.22%	60.57%	5.41%

Note: The fixed portfolio has fixed the weights of asset investment during a whole of the sample period. Meanwhile, the active portfolio has actively adjusted the weights of asset investment in every three months.

Table 4.75 All Dynamic Portfolio Performance Comparison (Cont.)

	Alternative Portfolio (Fixed Income, Equity, Commodity, and Coin)		Alternative Portfolio (Equity and Token)		Alternative Portfolio (Commodity and Token)		Alternative Portfolio (Fixed Income and Token)		Alternative Portfolio (Equity, Commodity, and Token)		Alternative Portfolio (Fixed Income, Equity, Commodity, and Token)	
	Active	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**
Average annual return	26.01%	5.82%	15.04%	5.55%	52.21%	8.93%	-0.13%	5.46%	43.41%	6.41%	23.01%	5.72%
Average annual S.D.	3.45%	2.10%	7.86%	5.66%	13.25%	9.50%	12.91%	1.55%	6.72%	5.19%	3.36%	2.06%
Sharpe Ratio	7.24	2.28	1.78	0.80	3.86	0.83	-0.09	2.87%	6.31	1.04	6.55	2.29
Compound Annual Growth Rate	29.23%	6.10%	8.72%	5.17%	56.79%	5.97%	-3.33%	6.03%	48.61%	5.88%	25.91%	6.09%

Note: The fixed portfolio has fixed the weights of asset investment during a whole of the sample period. Meanwhile, the active portfolio has actively adjusted the weights of asset investment in every three months.

Table 4.76 All Dynamic Portfolio Performance Comparison (Cont.)

	Alternative Portfolio (Equity, Coin, and Token)		Alternative Portfolio (Commodity, Coin, and Token)		Alternative Portfolio (Fixed Income, Coin, and Token)		Alternative Portfolio (Equity, Commodity, Coin, Token)		Alternative Portfolio (Fixed Income, Equity, Commodity, Coin, Token)	
	Active	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**	**Active**	**Fixed**
Average annual return	24.13%	5.88%	75.96%	9.75%	7.05%	5.80%	54.43%	6.50%	26.13%	5.82%
Average annual S.D.	10.10%	5.86%	14.80%	10.41%	13.22%	1.95%	7.18%	5.40%	3.45%	2.10%
Sharpe Ratio	2.29	0.83	5.07	0.84	0.46	2.45	7.43	1.02	7.27	2.28
Compound Annual Growth Rate	11.02%	4.95%	78.71%	3.19%	3.88%	6.22%	60.08%	5.41%	29.36%	6.10%

Note: The fixed portfolio has fixed the weights of asset investment during a whole of the sample period. Meanwhile, the active portfolio has actively adjusted the weights of asset investment in every three months.

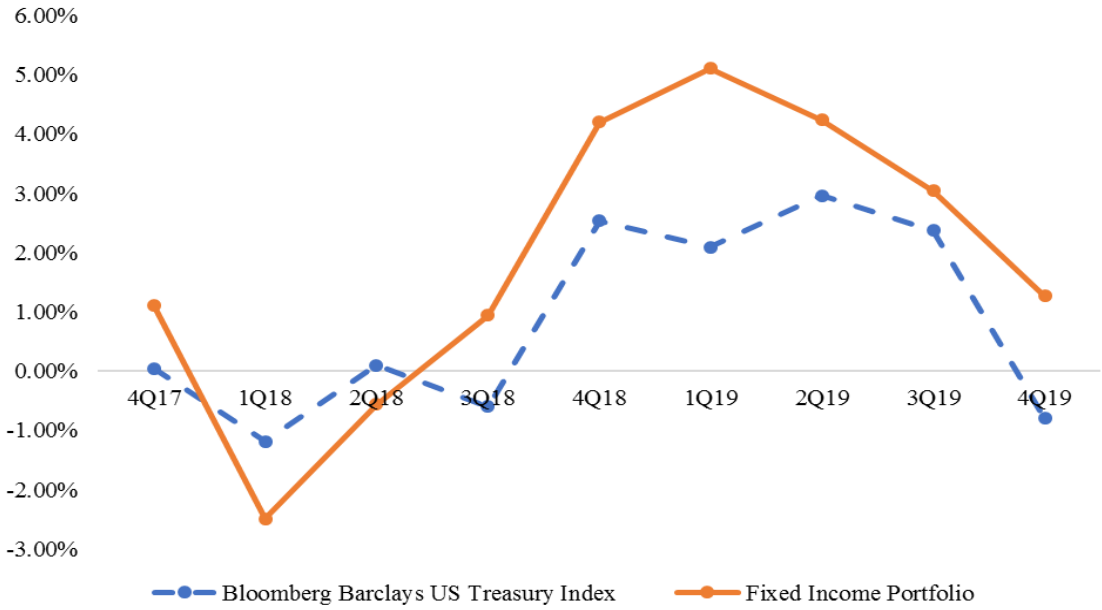

Figure 4.10 Portfolio Performance between Fixed Income Portfolio and Benchmark

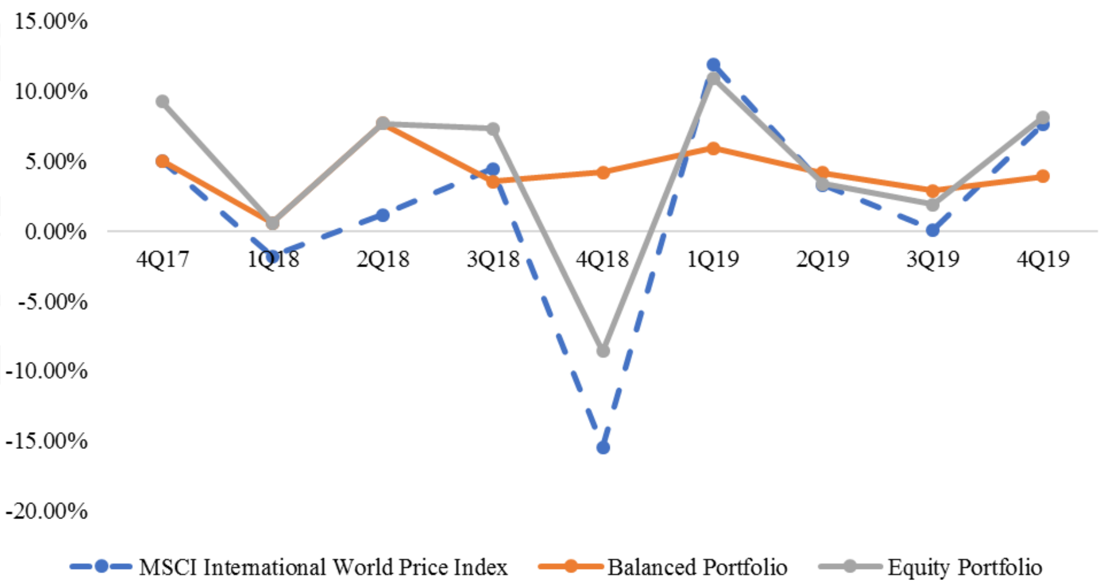

Figure 4.11 Portfolio Performance among Balanced Portfolio, Equity Portfolio, and Benchmark

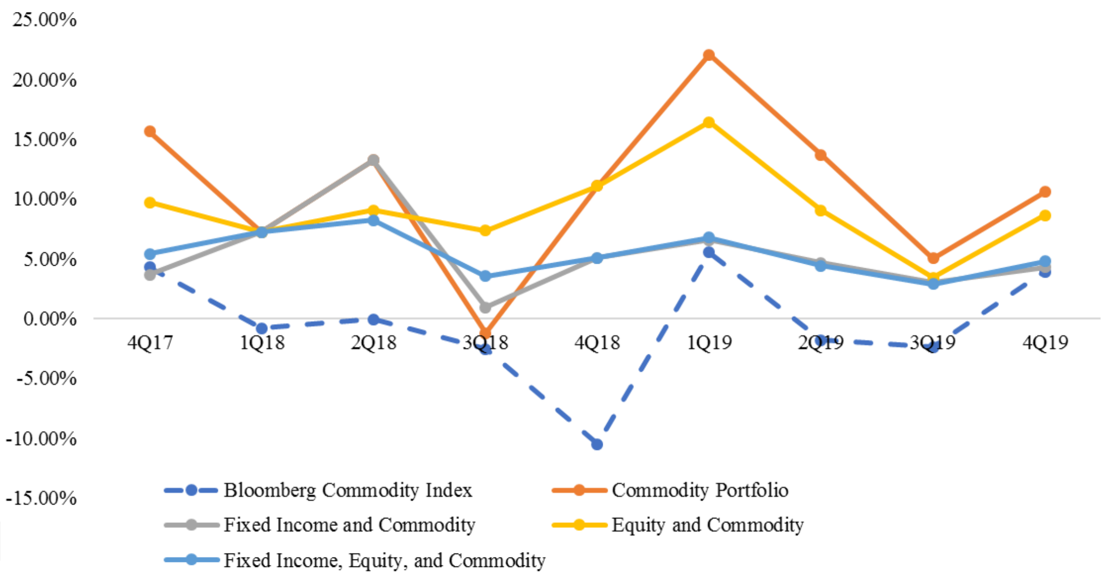

Figure 4.12 Portfolio Performance among Commodity Portfolio, Fixed Income and Commodity Portfolio, Equity and Commodity Portfolio, Fixed Income-equity-commodity, and Benchmark

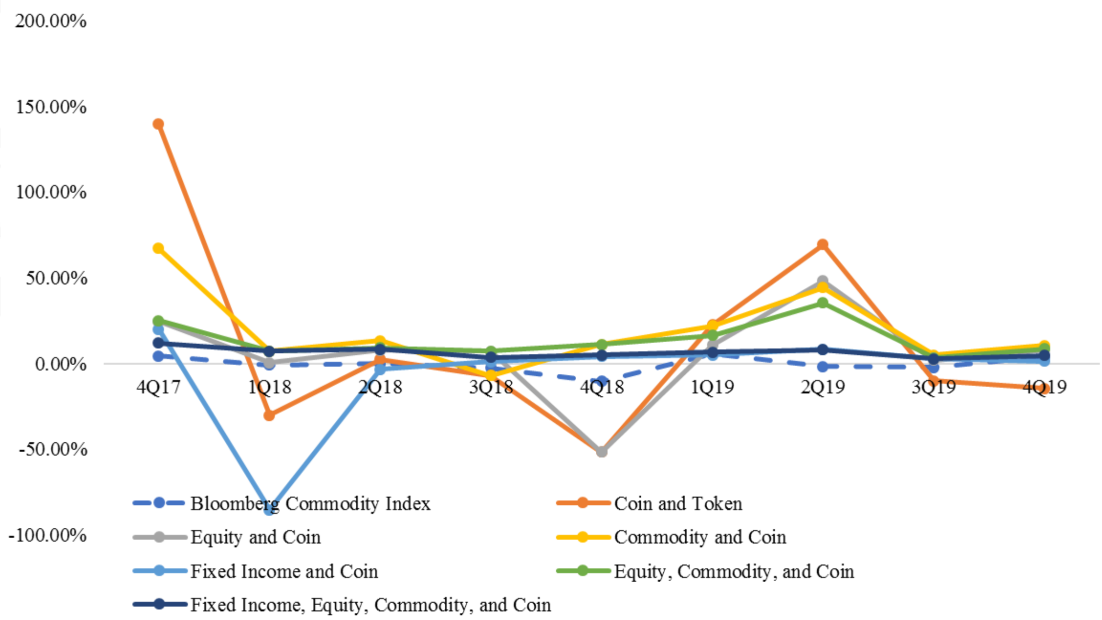

Figure 4.13 Portfolio Performance among Coin Mixed Portfolio and Benchmark

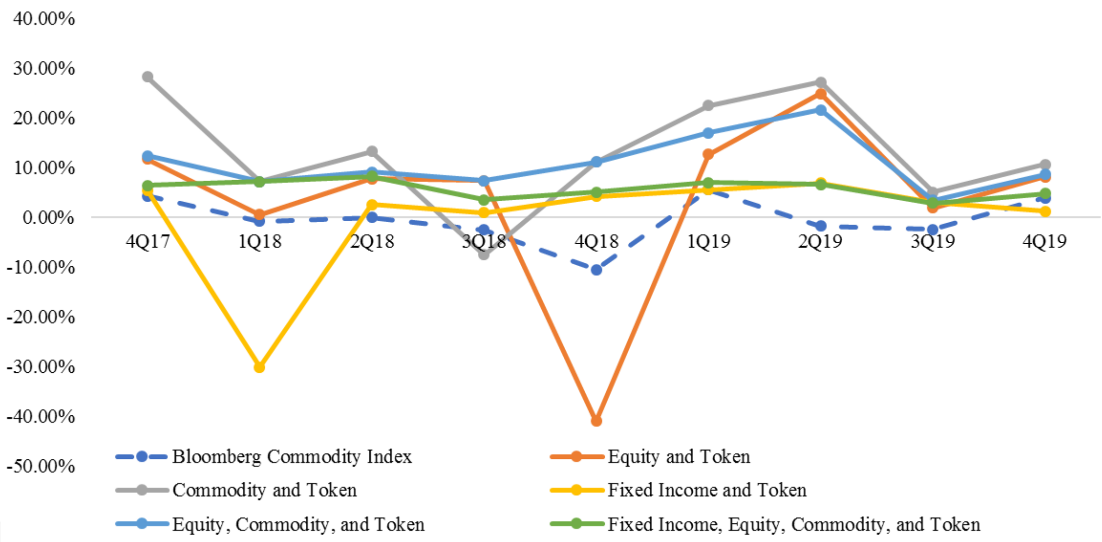

Figure 4.14 Portfolio Performance among Token Mixed Portfolio and Benchmark

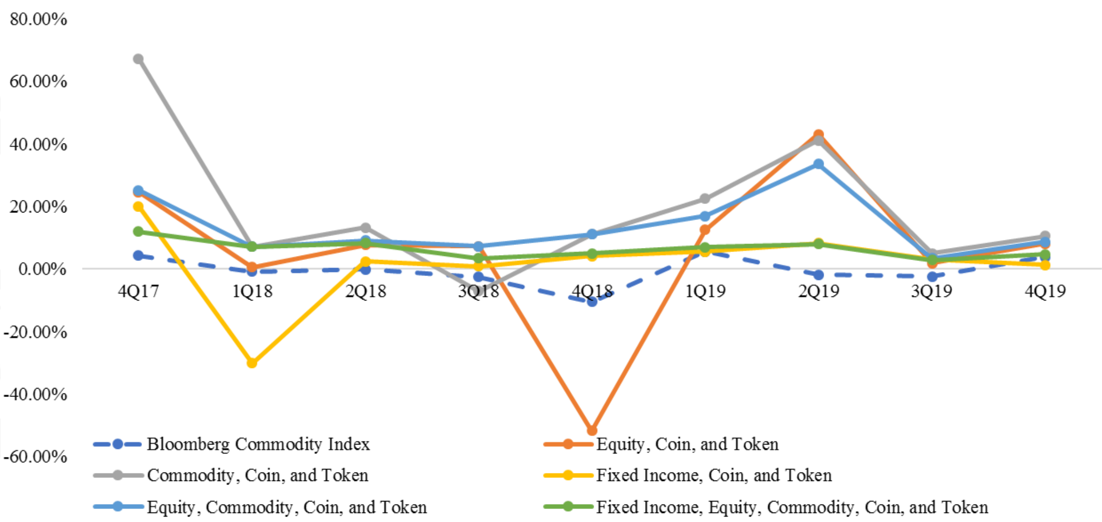

Figure 4.15 Portfolio Performance among Token and Coin Mixed Portfolio and Benchmark

As the previous results, this paper finds that the dynamic portfolios considering by dynamic conditional correlation, variance, and covariance, have better Sharpe Ratio than static portfolio. That is because of a lower standard deviation. Therefore, this paper has applied the DCC-GARCH (1,1) model to analyze the all-portfolio performance through asset allocation technique. Due to portfolio performance analysis through asset allocation technique, this paper finds that the actively adjusted weight portfolios offer higher risk and average annual return. The higher risk is tiny when comparing to the huge increase of the average return. The Sharpe Ratio of actively adjusted weight portfolios then is better than the fixed weight portfolio.

The top 5 best portfolio performance represented in terms of average annual return, Sharpe Ratio, and Compound Annual Growth Rate (CAGR) always have either coin or token in there. Therefore, most of the portfolio performance, which includes either coin or token, has a higher plotted performance rather than the benchmark. The top 5 best average annual return comprises the commodity and coin portfolio as around 77.18 percent per annum, the commodity – coin – token portfolio as around 75.96 percent per annum, the equity – commodity – coin portfolio as around 54.97 percent per annum, the equity – commodity – coin – token portfolio as around 54.43 percent per annum, and the coin and token portfolio as around 53.70 percent per annum. The top 5 best Sharpe Ratio includes equity – commodity – coin – token as around 7.43, equity – commodity – coin portfolio as around 7.41, fixed income - equity – commodity – coin – token as around 7.27, fixed income – equity – commodity – coin as around 7.24, and fixed income – equity – commodity – token as around 6.55.

The top 5 best Compound Annual Growth Rate (CAGR) comprises commodity and coin portfolio as around 79.89 percent per annum, commodity – coin – token portfolio as around 78.71 percent per annum, equity – commodity – coin portfolio as around 60.57 percent per annum, equity – commodity – coin – token portfolio as around 60.08 percent per annum, as well as commodity and token portfolio as around 56.79 percent per annum. Nonetheless, although coin and token seem a good diversified and offer better performance rather than others, the portfolios which add either coin or token have higher risk represented by the standard deviation rather than others as well. The top 5 worst standard deviation portfolios include coin and token portfolio as around 35.58 percent per annum, commodity and coin as around 15.01 percent per annum, commodity – coin – token as around 14.80 percent per annum, commodity and token as around 13.25 percent per annum, and fixed income – coin – token as around 13.22 percent per annum.

It implies that even though coin and token could be good assets to create an investment opportunity, the investors should actively adjust the investment weights. In other words, the investors have always monitored their portfolio performance and re-consider the weights of investment in coin and token. However, as the results, the optimal weights of coin and token are quite low because both are high risk assets with high standard deviation.

CHAPTER 5

CONCLUSION

Due to the high volatility and unpredictable intrinsic value of the cryptocurrency, this paper has to study the fundamental movement by cointegration and the dynamic linkages between cryptocurrencies, including coin and token, to examine the long-term and short-term relationship among those assets firstly. As the empirical results as previous section, this paper conclude that coin and token are positively long-term related to each other. The developed stock market also has a negative long-term relationship with coin, while it has a positive long-term relationship with token. The fixed income asset has a positive long-term relationship with coin and token. Meanwhile, the commodity asset has a positive long-term relationship with token. It emphasizes that coin and token prices could adjust fast during high volatility period. Therefore, the cryptocurrencies, including coin and token, might have some fundamental movement characteristics. The fundamental movement of the developed stock, fixed income, and commodity markets could indicate the coin and token fundamental movement in the long-term period.

In terms of short-term dynamic spillover, coin return can cause token return. It implies that the expected return of coin could transfer to the token return. Furthermore, there is some causality between cryptocurrencies and main traditional assets; for instance, coin return and developed stock market return, coin return and gold return, as well as token return and developed stock market return. The coin return can cause the developed stock market return and gold returns. Meanwhile, the developed stock market return can cause token return. It implies that the expectation, especially expected return on investment, could transmit from the coin market to developed stock and gold markets, as well as from the developed stock market to token market.

This paper also shows that coin return and token return have immediately positive responded from their own shock by the first period. They are quite high positively responded from the shock of each other by the first period as well, and then back to the equilibrium within three to four periods. It means that the cryptocurrency returns are rapidly adaptable when the shock occurs. Meanwhile, the impulse response functions of coin return and token return from the shock of main traditional markets are not significant. It implies that the shock of traditional asset market does not affect the movement of cryptocurrency return.

In cases of the short-term volatility spillover between cryptocurrencies and other traditional assets, there is variance spillover between coin and token. It implies that the volatility of coin return and token return can influence to each other. The token market can transmit the investment risks to the coin market, while the coin market can transmit the investment risks to the token market as well. Meanwhile, the shock of all main traditional asset market does not affect to the cryptocurrency volatility. It is consistent with the empirical results of the impulse response function as mentioned above.

Due to the long-term cointegration relationship and some short-term dynamic spillover among coin, token, and developed stock market through MSCI international world price market, so this paper has taken the WORLD, as representing the developed stock market, and TOKEN to be exogenous variables into an ARIMA and VAR model for forecasting coin price. Furthermore, this paper has also taken the WORLD and COIN to be exogenous variables into an ARIMA and VAR model for forecasting token price. Finally, this paper finds that the ARIMA with the WORLD as an exogenous variable, or ARIMAX model, and the VAR model depended on lagged WORLD variable are quite reliable rather than RW and ARIMA models in terms of out-of-sample forecasting coin and token prices over 20 days horizon ahead.

It implies that the ARIMA with WORLD as an exogenous variable and VAR depended on lagged WORLD variable could forecast coin and token prices in the long forecasting horizon because of the lowest average RMSE over 20 days forecasts ahead. This paper can conclude that the MSCI international world price index could be a significant indicator to improve coin and token forecast accuracy in the forecasting long horizon. Moreover, as the out-of-sample forecasting trends, the cryptocurrency prices, including coin and token, still increase continuously for 20 days ahead. Nonetheless, the longer forecasting horizon of coin and token has provided higher RMSE. Therefore, the forecasting ability of cryptocurrency would be effective in the short-term period. It is because of high volatility of the cryptocurrency price.

The forecasting trends from the appropriate forecasting model would be useful for investors and speculators who interested in cryptocurrency to do trading strategy. Furthermore, due to the dynamic spillover results through the causality direction, the movement return of the coin market might be applied to be short-term indicators for trading strategy in the developed stock and gold markets as well. Although the cryptocurrency returns are very volatile rather than other asset classes, they are rapidly adaptive to the shock of each other, and they also do not respond to other asset shocks. Therefore, the cryptocurrencies, including coin and token, might be the benefit to the investors for portfolio diversification. However, in the short-term period, the investors should avoid investing in assets which have volatility linkages simultaneously, especially token and coin.

Then, this paper has focused on the discussion of the portfolio optimization and diversification benefits by investment in coin and token. This paper has divided the portfolios into 4 types with 23 various portfolios. The static correlation and dynamic conditional correlation have been applied to form portfolio optimization. The dynamic conditional correlation has been calculated from DCC-GARCH (1,1) model. Meanwhile, the static correlation has been generated by a simple moving average correlation. As the results of the static and dynamic conditional correlations, this paper finds that coin and token are moderately positive correlated with each other. Meanwhile, they have extremely low correlations with the other traditional assets. This result is consistent with many previous papers, i.e., Bruniske & White (2017), Sontakke & Ghaisas (2017), Chen et al. (2017). Those papers also found that the cryptocurrencies, especially Bitcoin and Ethereum, have exceedingly correlations with other asset classes. Some of them implied that there is no any correlation between cryptocurrencies and other traditional assets. Therefore, the cryptocurrency might be an alternative asset class to benefit for portfolio diversification.

This paper has then proved the optimal portfolio performance when adding coin and token to the portfolio. Finally, this paper finds that the optimal portfolios formed by the dynamic conditional correlation, conditional variance, and conditional covariance have provided a greater Sharpe Ratio rather than the static portfolios, formed by the static correlation, variance, and covariance. However, the purpose of the investment are the maximized returns of investment as a whole investment period. The investors have always generated an investment opportunity from the market trend. This paper has then proved the portfolio performance by actively adjusted weights of investment. All portfolios, including traditional portfolio, coin portfolio, token portfolio, and crypto portfolio, have applied the dynamic conditional correlation, conditional variance, and conditional covariance. Finally, this paper finds that the actively adjusted weight portfolios provide a huge average annual return and higher standard deviation rather than fixed weights of the investment portfolio. The higher standard deviation is tiny when comparing to the huge increase of the average return. The Sharpe Ratio of actively adjusted weight portfolios then is better than the fixed weight portfolio.

The portfolios performed well, which presented in terms of average annual return, Sharpe Ratio, and Compound Annual Growth Rate (CAGR), always have either coin or token in there. Therefore, most of the portfolio performance, which includes either coin or token, has a higher plotted performance rather than the benchmark. It implies that the investment in coin and token could be an alternative asset class to benefit for portfolio optimization and diversification. It is consistent with many recent papers that conclude cryptocurrencies, especially Bitcoin, are an alternative asset class to generate the investment opportunity; i.e. Andrianto & Diputra (2017), Chuen et al. (2017), Bruniske & White (2017), Sontakke & Ghaisas (2017), Y.Liu & Tsyvinski (2021). Nonetheless, the optimal weights of coin and token are tiny. Furthermore, when coin and token have invested in the same portfolio, the optimal weight of token is close to zero. It is consistent with the moderate correlation between coin and token, as well as the long-term cointegration and volatility spillover between coin and token. It emphasized that the coin and token should not simultaneously invest.

Nonetheless, due to the high-risk level of cryptocurrencies, including coin and token, the investors should be careful to invest. They should have always re-considered about the weights of investment in either coin or token. The optimal weights of investment in coin and token of each period should be quite low rather than other traditional assets, which are well-known about fundamental movement. Furthermore, the investors should monitor the news related to the cryptocurrency, private digital currencies, as well as the Central Bank Digital Currency (CBDC) because they might impact to the investment in the existing cryptocurrencies. All empirical results of this paper could be benefits for investors to do trading strategy and form portfolio optimization to generate the investment opportunity during the increasing market trend and high volatility.

BIBLIOGRAPHY

Alam, S. (2017). Testing the weak form of efficient market in cryptocurrency. *Journal of Engineering and Applied Sciences, 12*(9), 2285-2288.

Amsden, R., & Schweizer, D. (2018). Are blockchain crowdsales the new 'gold rush'? Success determinants of initial coin offerings. doi:10.2139/ssrn.3163849

Andrianto, Y., & Diputra, Y. (2017). The effect of cryptocurrency on investment portfolio effectiveness. *Journal of Finance and Accounting, 5*(6), 229-238. doi:10.11648/j.jfa.20170506.14

Bakar, N. A., & Rosbi, S. (2017). Autoregressive integrated moving average (ARIMA) model for forecasting cryptocurrency exchange rate in high volatility environment: A new insight of bitcoin transaction. *International Journal of Advanced Engineering Research and Science, 4*(11), 130-137. doi:10.22161/ijaers.4.11.20

Bali, T. G., & Engle, R. F. (2010). The intertemporal capital asset pricing model with dynamic conditional correlations. *Journal of Monetary Economics, 57*(4), 377-390. doi:10.1016/j.jmoneco.2010.03.002

Bank of Thailand. (2019). *Digitalization on financial services and implications for monetary policy in Thailand*. Bank of Thailand. Retrieved from https://www.bot.or.th/Thai/MonetaryPolicy/EconomicConditions/AAA/DigitalizationonFinancialServicesandMPinThailand_EN_final2.pdf?fbclid=IwAR2CkffhWYEuWt7cAePeTCga456hf3-p-_VxM5EU84rcFZL5jFHN8Z2Jh7c

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money, 54*, 177-189. doi:10.1016/j.intfin.2017.12.004

Bessler, W., Opfer, H., & Wolff, D. (2017). Multi-asset portfolio optimization and out-of-sample performance: An evaluation of Black–Litterman, mean-variance, and naïve diversification approaches. *The European Journal of Finance, 23*(1), 1-30. doi:10.1080/1351847X.2014.953699

Bianchi, D. (2020). Cryptocurrencies as an Asset Class? An empirical assessment. *The Journal of Alternative Investments, 23*(2), 162-179. doi:10.3905/jai.2020.1.105

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? *Finance Research Letters*, *20*, 192-198. doi:10.1016/j.frl.2016.09.025

Briere, M., Oosterlinck, K., & Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management*, *16*(6), 365-373.

Burniske, C., & White, A. (2016). *Bitcoin: Ringing the bell for a new asset class*. Retrieved from https://j2-capital.com/wp-content/uploads/2017/11/ARK_Coinbase-Bitcoin-New-Asset-Class.pdf

Chang, T., Fang, W., & Wen, L.-F. (2001). Energy consumption, employment, output, and temporal causality: Evidence from Taiwan based on cointegration and error-correction modelling techniques. *Applied Economics*, *33*(8), 1045-1056. doi:10.1080/00036840122484

Chatziantoniou, I., Degiannakis, S., Delis, P., & Filis, G. (2019). Can spillover effects provide forecasting gains? The case of oil price volatility. *Munich Personal RePEc Archive*, *96266*, 1-9. Retrieved from https://mpra.ub.uni-muenchen.de/id/eprint/96266

Chen, C. Y. H., Härdle, W. K., Hou, A. J., & Wang, W. (2018). Pricing cryptocurrency options: The case of CRIX and bitcoin. *2018-004*, 1-33. Retrieved from http://hdl.handle.net/10419/230715

Chevallier, J. (2010). EUAs and CERs: Vector autoregression, impulse response function and cointegration analysis. *Economics Bulletin*, *30*(1), 558-576.

Christiansen, C. (2007). Volatility-spillover effects in European bond markets. *European Financial Management*, *13*(5), 923-948. doi:10.1111/j.1468-036X.2007.00403.x

Chuen, D. L. K., Guo, L., & Wang, Y. (2017). Cryptocurrency: A new investment opportunity? *The Journal of Alternative Investments*, *20*(3), 16-40. Retrieved from https://ink.library.smu.edu.sg/lkcsb_research

Conrad, C., Custovic, A., & Ghysels, E. (2018). Long-and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. *Journal of Risk and Financial Management*, *11*(2), 23-34. doi:10.3390/jrfm11020023

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters, 165*(C), 28-34. doi:10.1016/j.econlet.2018.01.004

Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics*, *13*(3), 253-265.

Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters*, *16*, 139-144. doi:10.1016/j.frl.2015.10.025

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics, 20*(3), 339-350. Retrieved from https://www.jstor.org/stable/1392121

Ericsson, N. R., & MacKinnon, J. G. (2002). Distributions of error correction tests for cointegration. *The Econometrics Journal*, *5*(2), 285-318. doi:10.1111/1368-423X.00085

Fisher, K. L., & Statman, M. (1997). The mean–variance-optimization puzzle: Security portfolios and food portfolios. *Financial Analysts Journal, 53*(4), 41-50. doi:10.2469/faj.v53.n4.2098

Georgoula, I., Pournarakis, D., Bilanakos, C., Sotiropoulos, D., & Giaglis, G. M. (2015). Using time-series and sentiment analysis to detect the determinants of bitcoin prices. doi:10.2139/ssrn.2607167

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M., & Siering, M. (2014). Bitcoin-asset or currency? revealing users' hidden intentions. *Twenty Second European Conference on Information Systems*, 1-14. Retrieved from https://ssrn.com/abstract=2425247

Gökgöz, F., & Atmaca, M. E. (2012). Financial optimization in the Turkish electricity market: Markowitz's mean-variance approach. *Renewable and Sustainable Energy Reviews*, *16*(1), 357-368. doi:10.1016/j.rser.2011.06.018

Gorman, L. R., & Jorgensen, B. (2002). Domestic versus international portfolio selection: A statistical examination of the home bias. *Multinational Finance Journal*, *6*(3/4), 131-166. Retrieved from https://ssrn.com/abstract=2627563

Granger, C. W., Huangb, B.-N., & Yang, C.-W. (2000). A bivariate causality between stock prices and exchange rates: Evidence from recent Asianflu. *The Quarterly Review of Economics and Finance, 40*(3), 337-354. doi:10.1016/S1062-9769(00)00042-9

Harvey, A. C., & Todd, P. (1983). Forecasting economic time series with structural and Box-Jenkins models: A case study. *Journal of Business & Economic Statistics, 1*(4), 299-307. Retrieved from https://www.jstor.org/stable/1391661

Hiemstra, C., & Jones, J. D. (1994). Testing for linear and nonlinear granger causality in the stock price-volume relation. *The Journal of Finance, 49*(5), 1639-1664. doi:10.1111/j.1540-6261.1994.tb04776.x

Howell, S. T., Niessner, M., & Yermack, D. (2020). Initial coin offerings: Financing growth with cryptocurrency token sales. *The Review of Financial Studies 33,* 3925-3974. doi:10.1093/rfs/hhz131

Ji, Q., & Fan, Y. (2012). How does oil price volatility affect non-energy commodity markets? *Applied Energy, 89*(1), 273-280. doi:10.1016/j.apenergy.2011.07.038

Konno, H., & Kobayashi, K. (1997). An integrated stock-bond portfolio optimization model. *Journal of Economic Dynamics and Control, 21*(8-9), 1427-1444. doi:10.1016/S0165-1889(97)00033-X

Korkie, B., Sivakumar, R., & Turtle, H. J. (2006). Variance spillover and skewness in financial asset returns. *The Financial Review, 41*(1), 139-156. doi:10.1111/j.1540-6288.2006.00135.x

Lee, J. (2006). The comovement between output and prices: Evidence from a dynamic conditional correlation GARCH model. *Economics Letters, 91*(1), 110-116. doi:10.1016/j.econlet.2005.11.006

Liu, M.-H., & Shrestha, K. M. (2008). Analysis of the long-term relationship between macro-economic variables and the Chinese stock market using heteroscedastic cointegration. *Managerial Finance, 34*(11), 744-755. doi:10.1108/03074350810900479

Liu, W. (2019). Portfolio diversification across cryptocurrencies. *Finance Research Letters, 29*, 200-205. doi:10.1016/j.frl.2018.07.010

Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies, 34*, 2689-2727. doi:10.1093/rfs/hhaa113

Lyócsa, Š., Výrost, T., & Baumöhl, E. (2012). Stock market networks: The dynamic conditional correlation approach. *Physica A: Statistical Mechanics and its Applications*, *391*(16), 4147-4158. doi:10.1016/j.physa.2012.03.038

Maghyereh, A., & Al-Kandari, A. (2007). Oil prices and stock markets in GCC countries: New evidence from nonlinear cointegration analysis. *Managerial Finance*, *33*(7), 449-460. doi:10.1108/03074350710753735

Maysami, R. C., Howe, L. C., & Rahmat, M. A. (2004). Relationship between macroeconomic variables and stock market indices: Cointegration evidence from stock exchange of Singapore's All-S sector indices. *Jurnal Pengurusan 24*, 47-77.

Meyler, A., Kenny, G., & Quinn, T. (1998). Forecasting Irish inflation using ARIMA models. *Central Bank and Financial Services Authority of Ireland Technical Paper Series*, *1998*(3/RT/98), 1-48. Retrieved from https://mpra.ub.uni-muenchen.de/11359/

Ng, A. (2000). Volatility spillover effects from Japan and the US to the Pacific–Basin. *Journal of international money and finance*, *19*(2), 207-233. doi:10.1016/S0261-5606(00)00006-1

Nieh, C.-C., & Lee, C.-F. (2001). Dynamic relationship between stock prices and exchange rates for G-7 countries. *The Quarterly Review of Economics and Finance*, *41*(4), 477-490. doi:10.1016/S1062-9769(01)00085-0

Paul, S., & Bhattacharya, R. N. (2004). Causality between energy consumption and economic growth in India: A note on conflicting results. *Energy Economics*, *26*(6), 977-983. doi:10.1016/j.eneco.2004.07.002

Platanakis, E., & Urquhart, A. (2018). Should investors include bitcoin in their portfolios? A portfolio theory approach. *British Accounting Review*, *52*(4), 1-42. doi:10.1016/j.bar.2019.100837

Rose, C. (2015). The evolution of digital currencies: Bitcoin, A cryptocurrency causing A monetary revolution. *International Business & Economics Research Journal* *14*(4), 617-622. doi:10.19030/iber.v14i4.9353

Skintzi, V. D., & Refenes, A. N. (2006). Volatility spillovers and dynamic correlation in European bond markets. *Journal of International Financial Markets, Institutions and Money, 16*(1), 23-40. doi:10.1016/j.intfin.2004.12.003

Sontakke, K. A., & Ghaisas, A. (2017). Cryptocurrencies: A developing asset class. *International Journal of Business Insights & Transformation, 10*(2), 10-17. doi:10.1080/1540496X.2016.1193002

Steinbach, M. C. (2001). Markowitz revisited: Mean-variance models in financial portfolio analysis. *Society for Industrial and Applied Mathematics, 43*(1), 31-85. doi:10.1137/S0036144500376650

Sudarchan, A., & Manu, K. S. (2019). Forecasting bitcoin prices: ARIMA and seasonal decomposition approach. *JETIR June 2019, 6*(6), 118-127.

Syed Zwick, H., & Syed, S. A. S. (2019). Bitcoin and gold prices: A fledging long-term relationship. *Munich Personal RePEc Archive*(92512), 1-12. Retrieved from https://mpra.ub.uni-muenchen.de/92512/

Trimborn, S., & Härdle, W. K. (2018). CRIX an Index for blockchain based currencies. *Journal of Empirical Finance, 49*, 107-122.

Trimborn, S., Li, M., & Härdle, W. K. (2018). Investing with cryptocurrencies-A liquidity constrained investment approach. *Journal of Financial Econometrics, 18*(2), 280-306. doi:10.1093/jjfinec/nbz016

Van Wijk, D. (2013). *What can be expected from the BitCoin.* Erasmus Universiteit Rotterdam, Rotterdam, Netherlands, (345986)

Virtanen, I., & Yli-Olli, P. (1987). Forecasting stock market prices in a thin security market. *Omega, 15*(2), 145-155. doi:10.1016/0305-0483(87)90029-6

Wang, P., & Moore, T. (2008). Stock market integration for the transition economies: time-varying conditional correlation approach. *The Manchester School, 76*(s 1), 116-133. doi:10.1111/j.1467-9957.2008.01083.x

Wang, P., Zhang, W., Li, X., & Shen, D. (2019). Is cryptocurrency a hedge or a safe haven for international indices? A comprehensive and dynamic perspective. *Finance Research Letters, 31*, 1-18. doi:10.1016/j.frl.2019.04.031

Wu, K., Wheatley, S., & Sornette, D. (2018). Classification of cryptocurrency coins and tokens by the dynamics of their market capitalisations. *Royal Society Open Science, 5*(9), 1-10. doi:10.1098/rsos.180381

Yi, S., Xu, Z., & Wang, G.-J. (2018). Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? *International Review of Financial Analysis, 60*, 98-114. doi:10.1016/j.irfa.2018.08.012

Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing, 50*, 159-175. doi:10.1016/S0925-2312(01)00702-0

BIOGRAPHY

Name-Surname	Miss Watcharaporn Kantaphayao
Academic Background	- Master's Degree in Business Administration (Finance), Kasetsart University, Bangkok, Thailand in 2012 - Bachelor of Economics (English Program), Mae Fah Luang University, Chiangrai, 2008 - Princess Chulabhorn's College Chiangrai, Chiangrai, 2004
Experience	- Senior Researcher, Research Group Kasikorn Research Center Company Limited in July 2020 - Present - Researcher, Project of In-depth Database Development for the Life Sciences Industry (Medical and Healthcare Services), School of Development Economics, National Institute of Development Administration in January 2019 – December 2019 - Research Assistant, Project of Life Sciences Industry Index Development of Thailand, School of Development Economics, National Institute of Development Administration in January 2019 – December 2019 - Senior Researcher, Research Group Kasikorn Research Center Company Limited in June 2013 – May 2018 - Assistant Manager, Investment Banking Finansia Syrus Securities Public Company Limited in February 2012 – February 2013 - Assistant Analyst, Derivatives Product Department Asia Plus Securities Public Company Limited in November 2011 – February 2012 - Financial Analyst, Bond Registration and Information Service Department The Thai Bond Market Association (ThaiBMA) in May 2008 – November 2011