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Return spillovers and dynamic conditional correlations among US, China, and Japanese stock markets: A comparison between the administration of Obama and Trump.

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ABSTRACT

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The global nature of the financial markets and the capital flows facilitate institutions and portfolio management firms to profit from diversifications. The opportunity to invest in lucrative financial opportunities can also expose investors to different risks. This master's thesis examines the return spillover effects and dynamic conditional correlations among the US, China, and Japanese stock markets. The goal is to understand and offer fresh perspectives to investors and portfolio managers to allocate decision making. The methodology of this work is based on the vector autoregressive (VAR) and dynamic conditional correlation-generalized autoregressive heteroskedasticity (DCC-GARCH) models to examine the return spillover effects and the dynamic conditional correlations among US, China, and Japan. During the Obama and Trump administrations, there were unidirectional return spillovers from US to Japan, but no return spillovers between US and China or between China and Japan. The DCC-GARCH model exhibits a lower short-term dynamic conditional correlation between US and China, but higher short-term dynamic conditional correlations between US and Japan and between China and Japan during the Trump presidency compared to that of Obama. The long-term dynamic conditional correlation between US and China was higher during the Trump presidency compared to the Obama administration. However, the long-term dynamic correlations were lower between US and Japan, and between China and Japan under the Trump administration.

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In Helsinki, October 17th, 2019

Frantz Desvallons

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LIST OF ABBREVIATIONS AND DEFINITIONS:

Abbreviations and definition:

ARCH = Autoregressive Conditional Heteroscedasticity.

CCC = Constant Conditional Correlation.

DCC = Dynamic Conditional Correlation.

DOD = degree of freedom.

GARCH = Generalized Autoregressive Conditional Heteroscedasticity.

GIF = generalized impulse function.

LLL = Log Likelihood.

MSCI = Morgan-Stanley Capital International.

Period 1 = Obama regime.

Period 2 = Trump regime.

VAR = Vector Autoregressive.

Std. = Standard.

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1. INTRODUCTION

The world's current political climates, ranging from the United States-China (US-China) trade war and the impending exit of United Kingdom (UK) from the European Union EU), have created a level of high uncertainty in the global financial markets. The Trump administration started to implement the America first policy by initiating a trade war with China. Between February and March 2018, Trump took the first steps in a show of force and announced global safeguard tariffs of 30 percent on solar panel imports and washing machines. In March 2018, the Trump regime imposed a 25 percent tariff on foreign made steel and 10 percent for aluminum, except for certain countries which are primarily US allies, but not for China (Harvey 2018). According to World Trade organization, 93.9 percent of China's total exports comprised of manufacturing products in 2017 and 77.8 percent of the US total imports were manufacturing products (WTO 2018). On April 2, 2018, China imposed tariffs on 128 US products, including imports of pork and certain fruits from the US as a response to president Trump's levies on Chinese steel and aluminum (Harvey 2018). China targeted the US agriculture products in retaliation because China imported 19 percent of the agriculture products that came from the US in 2018 (WTO, 2018). The ongoing trade war, however, comes with unintended consequences that are reflected in the global markets. On April 4, 2018, the Dow Jones Institutional News reported that the Financial Times Stock Exchanged (FTSE) 100 index was down by 3.5 percent (Dow jones Institutional News 2018).

During the summer of 2018, President Trump adhered to his campaign promise from May 2016 to confront China (if he had been elected president of the United States) to address the US trade deficit vis-à-vis China. President Trump imposed tariffs on $250 billion worth of Chinese products. The following month, on June 21, the global markets started to show signs of the trade war. The Dow Jones Industrial Average was down 0.7 percent, the Standard and Poor (S&P) fell 0.6 percent, and the Nasdaq Composite lost 0.8%. On a global scale, the FTSE fell 0.8%, the Shanghai Composite lost 1.4%, the Hang Seng went down by 1.3% (Live Briefs US 2018). China retaliated with its own levies on $113 billion worth of American products. President Trump further escalated the trade war in July 2018 by implementing a levy of 25 percent on 818 Chinese imports at its port of entry (Politi et al. 2018).

In September, as talk efforts were hindered, subsequent tariffs were implemented by the US, starting at 10 percent on 200 billion of Chinese goods important to the US starting in September 24, 2018. Trump stated that his action was justified since China had not addressed unfair policies and practices concerning US technology and intellectual property. As a result, China announced its own tariffs of 5 percent and 10 percent on a 60 billion of variety of US goods (including aircrafts, computers, textiles, chemicals, meat, clothing and agriculture) beginning that same day that US tariffs on China were intended to start. Consequently, the US West Texas Intermediate (WTI) crude futures CLc fell 0.5 percent at $68.57 a barrel on the fear that the trade war may negatively affect the global crude oil demands (Sanyal 2018). In the same September, the agriculture sector in the US was also concerned about trade between US and China that could negatively impact farmers in the US (Shearer 2018).

Meanwhile, 2 years before President Trump initiated the trade war, the UK conducted a referendum for the UK to leave the EU and the global markets reacted negatively. The result of the referendum, known as Brexit, a colloquial term for the EU's departure from the EU, has had an impact on the global market since the vote on June 23, 2016. Although the poll at the outset seemed to favor of the stay-camp, no one could have predicted the out. Nevertheless, it was clear that a divorce between the U.K. and the EU would not be easy. In fact, Simpson et al. (2018) indicated before the vote that the move for the U.K to leave EU will have lasting economic and political implications not just for the EU countries and the U.K. but also for the US assets and US wealth managers. The following day, June 24, the impact of the result in favor of Brexit was felt around Asia. The pounded fell from $1.50 on Thursday afternoon (June 23) to $1.34 in Asia by mid-Friday (June 24). On that same Friday, Tokyo's Nikkei 225 sank by almost 8 percent, Hong Kong's Hang Seng index dropped more than 4 percent, and Sydney's ASX 200 lost more than 3 percent. Moreover, the EU stocks and the markets in France, Britain, and Germany also dropped more than 8 percent. The US dollar dropped at least 4 percent against the Japanese yen, and the Euro lost 3 percent against the US dollar (Asia News Monitor 2016).

The purpose of this thesis is to study the return spillover effects and dynamic conditional correlations among US, China and Japanese stock markets and to compare the period under the presidency of President Barack Obama with that of President Donald J. Trump. Estimating spillover effects, conditional correlation, and covariance to hedge against potential risk is crucial for institutions such as hedge fund firms, investment firms, and multinational companies or for setting economic government policy. For example, investment banks and hedge fund companies may need to estimate and forecast spillover effects and the level of co-movements to which their investments are exposed in order to capture the benefit of diversification.

This work compares two different presidential administrations of the US government, taking into account the robustness of the US economy, in order to determine if there are return spillovers among the indices, understand the relationship of the US and Asian stock markets, and to comprehend how they change over time through the lenses of the dynamic conditional correlation and covariance process. There are many papers that focus on traditional risk-return analysis such as Capital Asset Pricing Model Theory (CAPM), which focuses on mean-variance-efficient, that is, "minimizing the variance of portfolio return and maximizing portfolio return, given the variance" (Fama and French 2004). Other literature looks at other factors that affect an asset such as those that cover Arbitrage Pricing Theory(APT), which focuses on the linear relationship between the expected return of an asset and its macroeconomic factors, such as interest rates, exchange rates, and inflation, to estimate the beta fof stock (Sharpe 1964). While the CAPM assumes that all investors are rational (Fama & French 2004), the APT theory addresses the investors' preferences (Sharpe 1964). Notwithstanding the important roles the aforementioned theories have played, they are not enough to explain the stock return spillover effects and time varying conditional correlation that may occur from one stock market to another due to sudden shocks from systematic risk.

1.1 Research questions

The research questions that will be addressed during this study are as follows,

1. Is there any linkage between the Asian major stock market indices' volatility clustering and the trade war between the US and China?

2. Does China's stock market movement also affects the Japanese stock market?

3. Are there significant dynamic conditional correlations among the stock market movements of the US, China, and Japan?

1.2 Objectives and motivations

The globalization of the financial markets, which facilitates the liberation of capital flows, has empowered international investors to expand the diversification of their portfolios across the globe and reap maximum returns on their investments. Nevertheless, the liberation of capital flows also comes with more exposure to various risks that may not be inherent to certain assets, but rather are a direct result from the spillover effects from one country's stock returns to another. Therefore, investors and multinational companies that seek to maximize their own wealth or on behalf of the shareholders need to take many approaches to consider risks that are associated with a country' stock market returns.

The recent trade war between the United States and China has caused shockwaves of uncertainty in the global markets. The choice of spontaneous trade policy adopted by President Trump, and the retaliatory measures by the Chinese leader, Xi, have caused down movements in the Asian stock market returns that seem to be more pronounced than those observed in the US major stock market indices. The reason for selecting this topic stems from the fact that government policies that may seem beneficial in the short-term to satisfy local producers and consumers, or for political purposes, may be detrimental in the long-term. Therefore, this work aims to show the implications of trade war and to what extent that the trade war policy has resulted in a more volatile atmosphere in the global financial markets. In addition, this work will be useful for financial institutions and fund managers to adopt new risk factors, and for government entities to create policies that may be more effective.

One of the objectives of this study is to determine the return spillovers and dynamic conditional correlations among the stock market index of the USA, China, and Japan. Another objective is to help multinational companies and fund managers to make informative decisions to portfolio asset allocation decision making. A pairwise comparison is conducted for all countries to determine whether there are return spillovers from one country to another and the dynamic relationship among them by comparing the periods during the Obama and Trump presidency.

1.3 Thesis's hypotheses

The hypotheses that are tested are primarily inspired by two previous studies. The first hypothesis, which addresses the spillover effects between the US and China was inspired by the work of Bilson (2002) which showed the existence of a negative relationship between political uncertainty and the stock returns in both emerging and developed markets. The second hypothesis takes into consideration the potential contagion of spillover effects between China and Japan due to the US-China trade war, follows the idea presented in Sarwar (2009) that the globalized markets pave way for spillover effects from one country to another. The evidence is clear that there are unusual fluctuations in the global market after each announcement of new tariffs imposed by the Trump administration or after retaliatory measures that are adopted by President Xi, given that the global markets are not in major recessions. Consequently, the following hypotheses that will be evaluated are as follows,

1. *The Trump administration's trade policy instigates more pronounced return spillover effects between the US and China compared to that adopted under the Obama administration.*

2. *The spillovers effects result from the trade war between the United States also affect the relationship of China and Japan.*

1.4 Structure of the thesis

This paper is organized into 7 sections and multiple sub-sections. Section 2 focuses on the theoretical framework relevant to the thesis's topic. Section 3 covers the information about the data and descriptive statistic analysis of key findings. Section 4 shows the methodology of the models that are applied in this research paper. Section 5 encompasses the analysis of the results. Section 6 provides information on limitations of this study and suggestions potential extensions. Section 7 contains the conclusion.

2. THEORETICAL FRAMEWORK

The focus of this section is on the history of the models that are used in this paper and similar model that was adopted in previous literature to determine spillover effects, which include return, shock, and volatility spillovers, and the dynamic conditional correlation. However, this study focuses on return spillover effects and the dynamic conditional correlations among the US, China, and Japanese stock markets. Additionally, a brief evolution of the GARCH model will be discussed. Moreover, a sub-section about volatility, spillover effects, and the contribution of this thesis to previous literature is also provided. It is crucial to explore certain factors that facilitate spillover effects, such the uncertainty that enables spillovers, whether it is resulted in from a government trade policy or from volatility contagions among the countries' indices.

2.1 Discussion of the ARCH/GARCH.

Researchers whose works focused on spillover effects have adopted non-linear models to properly model the financial data. Among those models is the autoregressive conditional heteroskedasticity (ARCH) model introduced by

Engle (1982). The ARCH model assumes that today's asset value depends on previous information and the zero mean is random. The traditional model, however, assumes a "constant one-period forecast variance" that does not depend on past information where the zero mean is assumed to be known (Engle 1982). Although the ARCH model is useful to estimate a one period forecast of the variance based on previous information, the generalized autoregressive heteroskedasticity (GARCH) model, an extension of the ARCH model introduced by Bollerslev (1986), is a more robust model that allows the conditional variance to be dependent on previous own lags (Brooks 2014, p. 428).

The GARCH model has proved to be useful to test theoretical economic theory, such the Capital Asset Pricing Model theory (CAPM), with real data. For example, Bollerslev et al. (1988) used the GARCH model to test the capital asset pricing theory (CAPM), which assumes that the distribution of portfolio covariance matrix is constant over time, using 6-month treasury bills, 20-year bonds, and stocks. Bollerslev and his associates found that the portfolio covariance matrix of the CAPM theory is rather time varying (Bollerslev et al. 1988). The GARCH model is also important because it is more robust than the ordinary least squared (OLS) type like model, to model non-linear aspects of financial time series. In addition, the GARCH model can better explain the following features in the financial time series than can the linear models:

- Leptokurtosis, that is returns distribution with fat tails and peak in the mean values.
- Volatility clustering, which is volatility in the market that appears bunches.
- Leverage effects, which are asymmetries between a higher volatility after high price dip and lower volatility for high price rise.

One of the extensions of the GARCH model is the DCC-GARCH model, which treats the conditional variance as time varying rather than constant. Mohammadi and Tan (2015) used the DCC-GARCH to study the return and volatility spillovers across the Mainland China, Hong Kong, and the United States. They found that the return spillovers were unidirectional from the US to China and from US to Hong Kong. Additionally, the dynamic conditional correlation among China, Hong Kong, and the US increased after the financial crisis in 2007 (Mohammadi & Tan 2015). Miyakoshi (2003) discovered also that the US has great influenced to Asian return spillovers. Miyakoshi (2003) used the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model and found that Asian market are affected by the influence of Japanese market and the US market, but the Japanese market has more influenced on volatility spillovers to other Asian countries.

Among other research that covers spillover effects include the work of Sarwar (2019). His work uses pre-crisis and post-crisis samples to determine the amount of return and volatility spillover effects and how those effects influence different Asian stock markets (Sarwar 2019). Another paper by Bilson (2002) focuses on government policy aspects and impacts on the spillover effects. Researches on spillover effects are important because the globalization of the stock markets, and the openness of major economies have given rise to substantial exposure to risk on assets, or a portfolio of assets.

The strong connectedness of the global stock markets requires investors to be more mindful of many risks in the form of spillover effects that may significantly undermine the concept of diversification in the global financial markets. Dimic (2005) established that political uncertainty, pertaining to government policy, negatively impacted developed and as well as emerging markets (Dimic 2005). As a result of uncertainty, global investors who want to invest in emerging markets and developed markets must be prepared to respond to changes in return spillovers, the dynamic correlations among different markets. Bilson (2002) also establishes that emerging markets exhibit a strong connection between stock returns and risk level that result from political uncertainty.

2.2. Discussion of spillover effects.

The model that is adopted to measure the spillover effects and the dynamic conditional correlation for this study is the VAR-DCC-GARCH model in the first order from the work of Engle (2002), suggesting that innovations to be modeled in DCC-GARCH and be derived from the univariate GARCH like model of the individual series(Engle 2002). The VAR-DCC-GARCH approach has been used in previous researched papers to estimate return, shock, and volatility spillovers among the series. Singhal (2016) and Carnero (2014), for example, use the VAR approach to estimate the return spillover and use the inferred residuals of the VAR model to estimate the coefficients of the DCC. Aggarwal (1999) adopts the DCC-GARCH model using Engle's proposition of using the GARCH model to infer residuals of the series that are in turn used in the multivariate GARCH model (Engle, 2002). Meanwhile, in the study of Yue et al. (2014), the VAR model is used for the purpose of conducting impulse response analysis between variables and to estimate the DCC coefficients.

Another relevant research that covered spillover effects is the work of Badshah (2018) using a multivariate generalized autoregressive conditional heteroskedasticity model (MGARCH) to study the index volatilities (VIX), the VXEFA, and the VXEEM. While the VIX focuses on US consumers' confidence level of the expected returns on their investments, the VXEFA and the VXEEM represent the volatility expectations for developed market and emerging market on cross-markets, respectively. The purpose of his study was to establish the spillover effects among the US and the developed markets and emerging markets. Badshah results show that volatility spillover usually starts from the U.S. and that spillovers influence both the developed and emerging markets' volatilities (Badshah 2018).

Sarwar (2019) adopted the vector autoregressive moving average with external variables, constant conditional correlation for covariance matrix, and quadratic generalized autoregressive conditional heteroscedasticity (VARMAX-CCC-QGARCH) and discovered that deviations in the VIX have negative effects on returns in all regional and emerging and foreign markets combined (Sarwar, 2019). Sarwar's results also point out that the more severe changes in the VIX occur during financial crisis (Sarwar 2019). Lien (2018) used a multiplicative error model (MEM) on his studies and found that volatility spillover originating from the United States affects many Asian stock markets. In addition, Lien's work discovered that the spillover among the Asian stock markets are mainly from the major players based on their economical hierarchy (Lien 2018).

Chittedi (2015) used the DCC-GARCH model to study the contagion that exists between the developed market and emerging market during and after a financial crisis. The result showed that stock markets' indices exhibit high and continuous correlation between USA and India (Chittedi 2015). Khalil (2018) used EGARCH model, using pre-crisis and post-crisis samples to study the return and volatility spillovers among the Asian emerging markets. He found that return and volatility spillovers increase during financial crisis (Khalil 2018). Jebran (2016) examined the stock market spillover effects among the Asian countries with a Multivariate GARCH model and found a bidirectional return spillover between China and Japan. Meanwhile, the volatility spillover was found to be unidirectional from China to Hong Kong (Jebran 2016).

Hamao (1987) used the moving average in the first order and the first order of the generalized autoregressive conditional heteroscedasticity (MA-GARCH) model to analyze major financial stock markets of New York, London, and Tokyo. The findings reveal that the return spillover was unidirectional from New York stock market to Tokyo, New York to London, and London to Tokyo (Hamao 1987).

Other models have been used by researchers to measure the dynamics between variables. Despite the robustness of the DCC model to streamline the time-varying conditional variance, the DCC has its limitations to capture the asymmetry dynamic conditional correlation among the variables. Accordingly, extensions of the DCC model include the asymmetric dynamic conditional correlation (ADCC) by Capiello (2006), which addresses the issue of asymmetry in the conditional correlation of equity and bonds, and the dynamic asymmetric capula (ADC) introduced by Christoffersen et al. (2012). The ADC has the purpose of capturing the long-run and short-run asymmetries and non-normal distribution in a multivariate setting (Christoffersen et al. 2012). Furthermore, Aielli (2013) contends that the DCC model is not consistent when it comes to large system. Therefore, he proposed a corrected-Dynamic conditional correlation version (cDCC) to compensate for the purported inconsistency in the DCC model (Aielli 2013).

2.3. Contribution to previous literature.

The cheap labor force that is available in many emerging countries, including some Asian countries, makes it more attractive for labor intense industries from the developed countries to tap into for the purpose of reducing cost of production and maximizing their profit margins. Consequently, the trading opportunities that are created by the demand for capital flows between major developed economies and emerging economies and the need to outsource production to countries where cheap labor exists, are among may reasons why portfolio diversifications have become more attractive for international investors. Therefore, it is crucial, as Cosset (1995) states, that investors take into consideration return and volatility spillover effects because of uncertainty from domestic and foreign government policies to measure the risk on their assets (Cosset 1995).

Although there is a vast number of papers that covered return and volatility spillover effects from the academic community, there is no current research that compared the presidency of Barack Obama and Donald J. Trump to determine to what extent the trade policies under those administrations affect the global stock markets. Therefore, this work will be a new addition to the existing literatures on return spillover effects and the relationship between the chosen variables under the mentioned administrations. Moreover, previous findings on return spillovers and dynamic conditional correlations will serve as the guide to research this topic.

3. METHODOLOGY

The returns for the US, China, and Japan are modeled using the bivariate vector autoregressive model (VAR) in the first order. Subsequently, the inferred variances from the VAR (1) model is used as input in the DCC-GARCH model to capture the return spillover effects and to estimate the dynamic conditional correlations between indices in a pairwise comparison. Although the VAR model, using MATLAB platform, was estimated separately to analyze the conditional returns, the VAR-DCC-GARCH model, using R programming language was also run to derive the ARCH and GARCH terms for the univariate series and the dynamic conditional correlation. In order to investigate the returns spillover between the stock market indices and dynamic conditional variance, the VAR-DCC-GARCH model is used.

The Generalized autoregressive conditional heteroscedasticity (GARCH) lets the conditional variance to be dependent of its previous own lags (Brooks 2014, p. 428). Meanwhile, the dynamic conditional correlation (DCC) aspect of the model allows the correlations to be time varying (Engle 2002). After reading the work of Engle and Sheppard (2001), it was determined that a first order of the GARCH model is sufficient to model the data in this research.

3.1 The VAR Model.

The VAR model process in the p-order is denoted as follows

$$r_t=\delta+\Phi_1 r_{t-1}+\cdots+\Phi_p r_{t-p}+\epsilon_t \quad (1)$$

where $\epsilon_t=(\epsilon_{1t},\ldots,\epsilon_{nt})'$ represents vector of serially uncorrelated innovations which follows the notion that $E(\epsilon_t)=0$, $E(\epsilon_t\epsilon_t')=\Sigma$, and $E(\epsilon_t\epsilon_s')=0$ for $t\neq s$; $\delta=(\delta_1,\ldots,\delta_n)'$; and Φi is a $N\times N$ matrix. In order to analyze and understand the dynamic relationship between the series, each series are paired in a bivariate setting. The bivariate VAR (1) is as follows

$r_{1t} = \delta_1 + \Phi_{11} r_{1,\,t-1} + \Phi_{12} r_{2,\,t-1} + \epsilon_{1t}$ (2)

$r_{2t} = \delta_2 + \Phi_{21} r_{1,\,t-1} + \Phi_{22} r_{2,\,t-1} + \epsilon_{2t}$ (3)

Where

The concurrent relationship between r_1 and r_2, the two independent variables in the equation 2 and 3, is represented by the elements of Σ. The parameters Φ_{ij} represents the (i, j) *th* element of Φ and Φ_{i0} is the ith element of Φ_0. E (ϵ_{it}) = 0 and E ($\epsilon_{1t}, \epsilon_{2t}$) = 0. Furthermore, each current return, r_{it} , depends on the previous information of variable r_{1t-1} and $r_{2t-1.}$ The residuals of the VAR is presented such that VAR ($\epsilon_t | r_{t-1}, \ldots r_1$) = ϵ_t. (Engle & Sheppard 2002; Brooks 2014, p290).

In equations 2 , Φ_{12} is the linear dependence of $r_{1,t}$ on $r_{2,\,t-1}$, given $r_{1,t-1}$, which is in other words the conditional effect of $r_{2,t-1}$ on $r_{1t.}$ Accordingly, if $\Phi_{12} = 0$, then $r_{1,t}$ depends only on its own past information. If $\Phi_{21} = 0$, that is equation 3, would show that $r_{2,\,t}$ does not depend on $r_{1,\,t-1}$ given $r_{2,\,t-1}$. In the case that $\Phi_{12} = 0$ and $\Phi_{21} \neq 0$, then there is a unidirectional relationship r_1 to r_2. If $\Phi_{12} = \Phi_{21} = 0$, that would entail equations (2) and (3) are coupled. Finally, if none of the aforesaid matrix parameters is equal to zero, then a feedback relationship exists (Tsay 2005, 309). In the equations 2 and 3, Φ_{11} and Φ_{22} are the autocorrelation of markets r_1 and r_2.

3.2 The DCC-GARCH Model

The DCC-GARCH model, which was introduced by Engle and Sheppard (2002) proposed a two-step process to parameterize the conditional correlations between two markets. The steps are to estimate the standardized residuals for each of the pairwise index using GARCH-type model and the second step is to derive the time-varying correlation estimates using the lagged values and covariance-matrices (Engle and Sheppard 2002). The DCC-GARCH model extends the constant conditional correlation (CCC)-GARCH model that was proposed by Bollerslev (1990) to study the behavior of different countries' exchange rates. Engle (2002) explained in his work that the difference between the CCC-GARCH model from the DCC-GARCH occurs where Rt is the time varying, whereas R in the CCC-GARCH model assumes a constant correlation, also known as a restricted DCC. The assumptions of Engle & Sheppard (2001) DCC-GARCH model that returns of k-assets, are assumed to be normally distributed with a mean of zero based on past information at time t-1.

The univariate GARCH process, based on the work of Bollerslev et al. (1988), is as follows,

$$\varepsilon_t \backslash \Psi_{t-1} \sim N(0, h_t), \tag{4}$$

$$h_t = \alpha_0 + \Sigma_{i=t}^{q} \alpha_i u_{t-i}^2 \Sigma_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{5}$$

where

Ψ_{t-1} in equation 4 is the past information at t-1 under the assumption that h_t follows a normal distribution process in which the following constraints must be met: $p \geq 0$, $q > 0$, $\alpha_0 > 0$, $\alpha_1 \geq 0$, $i = 1,\ldots,p$, and $\beta_j > 0$, $i = 1,\ldots,q$ (Shumway & Stoffer 2011, pp. 280-289).

In equation 5 the parameterization of the conditional variance is such that the conditional variance depends on p lags of the squared residuals and q lags of conditional variance(h_t). The interpretation of the GARCH model is as follows: α_0 represents the long-term mean value, α_1 is the ARCH term, the $\alpha_i u_{t-i}^2$ shows 1 lagged period and squared error term, which is the information of volatility of the previous period, and β_j is the GARCH term and σ_{t-j}^2 encompasses the fitted variance in the model for the previous period.

The estimators of the DCC are as follows:

$$H_t = D_t R_t D_t, \tag{6}$$

Where

H_t in equation 6 represents a N x N conditional covariance matrix, thus a 2 x 2 for the bivariate model. D_t is a diagonal matrix N x N that contains time-varying standard deviations, which are retrieved from a univariate GARCH model process where h_{it} is on the *i-th* diagonal and zero elsewhere with $i = 1,2 \ldots N$.

R_t is a matrix of time varying correlations ,$\rho_{ij,t}$,with ones on its main diagonal. Thus, the Ht matrix can be visualized as such,

$$H_t=\begin{pmatrix} h_{1,t}^2 & \cdots & h_{12,t} \\ \vdots & \ddots & \vdots \\ h_{21,t} & \cdots & h_{2,t}^2 \end{pmatrix}=$$

$$\begin{pmatrix} h_{1,t} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & h_{2,t} \end{pmatrix}\begin{pmatrix} 1 & \cdots & \rho_{12,t} \\ \vdots & \ddots & \vdots \\ \rho_{21,t} & \cdots & 1 \end{pmatrix}\begin{pmatrix} h_{1,t} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & h_{2,t} \end{pmatrix} \qquad (7)$$

The log likelihood function is used to estimate the parameters in Rt in the equation 7. Since the model calls for constraints for Rt in order for it to be definite positive for the sum all the parameters are to be less or equal to 1. That is, $\alpha + \beta \leq 1$ to conform to the notion that the stationarity of the variance is maintained and the convergence to a long-term average. (Engle and Sheppard, 2001). As stated in the DCC-GARCH model of Engle(2002), given that parameters D is noted as θ and R is denoted as ϕ, the log-likelihood functions that are used to estimate the volatility term and the correlation component are represented in equations(8) and (9), respectively and they are as follows:

$$L_v(\theta) = -\frac{1}{2}\sum_t (k(\log(2\pi + \log(|Dt|^2) + r_t{}'D_t^{-1}r_tD_t^{-2}r_t), \qquad (8)$$

$$L_c(\theta, \phi) = -\frac{1}{2}\sum_t (\log(|Rt|) + \varepsilon_t^{\prime R_t^{-1}\varepsilon_t} - \varepsilon_t'\varepsilon_t) \qquad (9)$$

As a consequence, the log-likelihood of (8) and (9) can be denoted as the sum of the parts of volatility and correlation that are shown in equation (10):

$$L(\theta, \phi) = L_v(\theta) + L_c(\theta, \phi). \qquad (10)$$

Where

$$\varepsilon_t = D_t^{-1}r_t, \qquad (11)$$

$$Rt = \operatorname{diag}\{Q_t\}^{-1} Qt \operatorname{diag}\{Q_t\}^{-1} \qquad (12)$$

$$Qt = (1-\alpha-\beta)\bar{Q} + \alpha\, \varepsilon_{t-1}\, \varepsilon'_{t-1} + \beta\, Q_{t-1} \qquad (13)$$

And also,

Rt is a N x N positive symmetric definite matrix,

Ɛt is an N×1 vector of standardized residuals;

Qt is the unconditional covariance between series i and j (in this case r1t and r2t) and follow a GARCH process,

Q is N x N unconditional covariance matrix of r_{1t} and r_{2t}, and α and β are scalar parameters that encompasses the dynamics of conditional quasicorrelations where α and β are non-negative scalar which ensure that 0≤ α + β < 1.

The correlation estimators are as follows,

$$p_{ij,\,t} = \frac{Q_{ij,t}}{\sqrt{Q_{ii,t},Q_{jj,t}}} \qquad (14)$$

Consequently, the bivariate dynamic conditional correlation (DCC) of the model of Engle (2002) can be represented as such:

$$p_{12t} = \frac{(1-\alpha-\beta)\bar{q}_{12}+\alpha\,\varepsilon 1{,}t-1\ \varepsilon 2{,}t-1+\beta_{12,t-1}}{\sqrt{((1-\alpha-\beta)\bar{q}_{11}+\alpha\,\varepsilon^2_{1,t-1}+\beta_{q11,t-1})((1-\alpha-\beta)\bar{q}_{22}+\alpha\,\varepsilon^2_{2,t-1}+\beta_{22,t-1})}} \qquad (15)$$

The diagnostic of the model includes Augmented Dickey-Fuller (ADF) test, Jarque-Bera test, and Engle’s LM test for ARCH effects. The diagnostic tests and the analysis for the ADF test, and Engle’s LM test are discussed in section 4.3. Jarque-Bera test and analysis is in section 5.4.2.

4. DATA DESCRIPTION AND ANALYSIS.

4.1 Data collection

The data included the total weekly returns using the standard Morgan-Stanley Capital International (MSCI) for the United States, China, and Japan retrieved from the Datastream. The period of January 21, 2013 to February 11, 2019 were chosen to cover two administrations under two US presidents. The MSCI was an ideal because MSCI takes into consideration the dividends paid to stockholders. Therefore, the need to control for the factor dividends is not necessary. The data was split into two sub-periods to investigate the return spillover effects and dynamic conditional correlations among US, China, and Japanese stock markets under the last four years of President Obama’s Administration(January 2013-

January 2017) and during the current administration of President Trump whose term started in January 2017. The first sub-period covered January 21, 2013 to January 16, 2017 and contains 210 weekly observations. The second sub-period has 109 weekly observations and it covers January 23, 2017 to February 11, 2019. The weekly returns are calculated with the logarithmic method that is shown below in equation 16.

$$R_t = \log (P_t/P_{t-1}), \tag{16}$$

Where,

P_t is the current day's observation

P_{t-1} is the previous day's observation.

Three different programs were used to manipulate the data. Microsoft Excel was used to organize and to derive the summary statistics results for the data. In addition, Microsoft Excel was used to create constant correlation and variance-covariance matrix tables. MATLAB was used to run the VAR model separately to get its conditional mean results, and to plot each index's return and other relevant figures and diagnostics for the series. Finally, R programming language was used to run the DCC-GARCH model to derive its estimates and plot the result of the dynamic conditional correlations and covariances.

For the purpose of simplicity, the terms first period, period 1, and Obama administration, Obama presidency or Obama regime will be used interchangeably for sub-period 1. Likewise, the terms second period, period 2, and Trump administration, Trump presidency or Trump regime will also be referred as a substitute for sub-period 2.

4.2 . Analysis of the time series plot analysis.

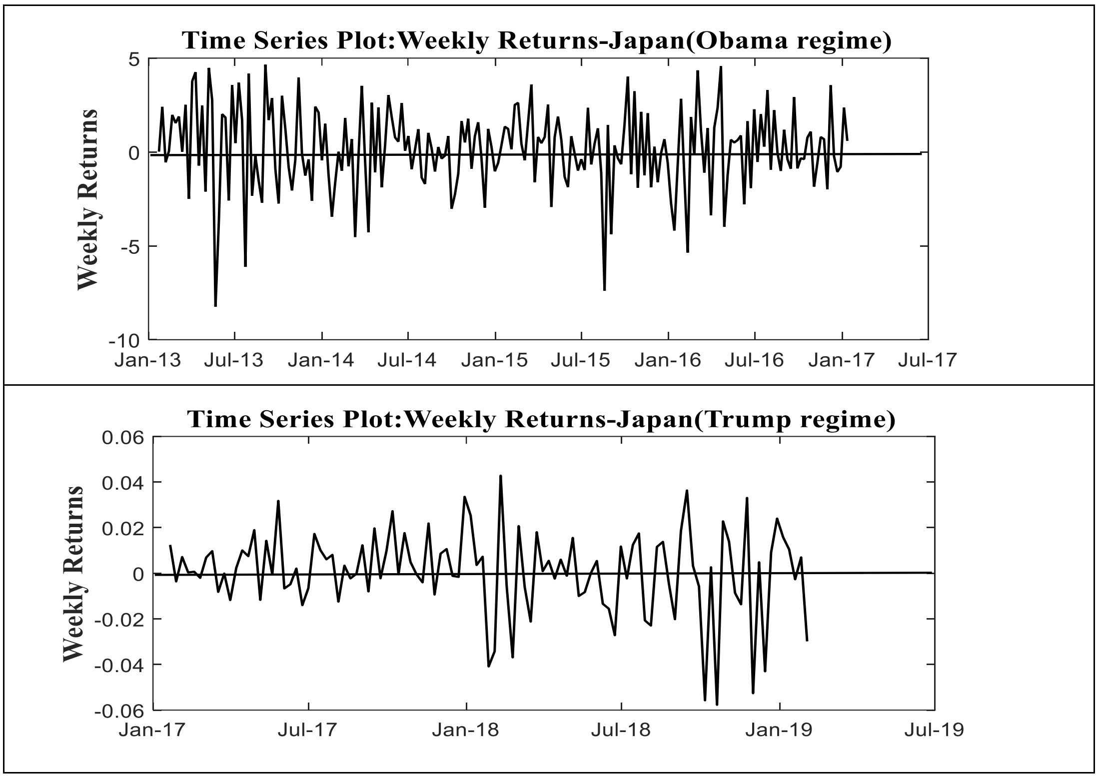

Figure 1. Japan returns for during the Obama administration and the Trump administration.

Figure 1 represents the weekly returns for Japan under the Obama administration and the Trump administration. Volatility clustering is exhibited around the mean during both periods. Looking at the top graph for period 1, it is noticeable that there are constant movements around the mean for Japan until the mid-2013 where there is major dip of approximately 8 percent. In additional, there appears to be volatility clustering in the mid-2015 and through 2016 during the Obama administration. During the Trump administration, Japan's returns are shown to fluctuate at a constant level around the mean until January 2018 and early 2019. Overall, Japan's returns exhibit volatility clustering at the beginning and toward the end of the Obama's first term in period 1, whereas major volatility clustering under the Trump administration seems to occur in January 2018 and early 2019. The major dips for Japan that occurred from 2013 to 2016 under the Obama administration may be resulted from the effects of the off-year election year in the United States for the US Congress in 2013 and the general election in 2016. The volatility clustering that occurred in period under the Trump administration may be a direct result from the trade war between US and China since the major sell offs of stocks occurred after each announcement of tariffs from the aforementioned countries.

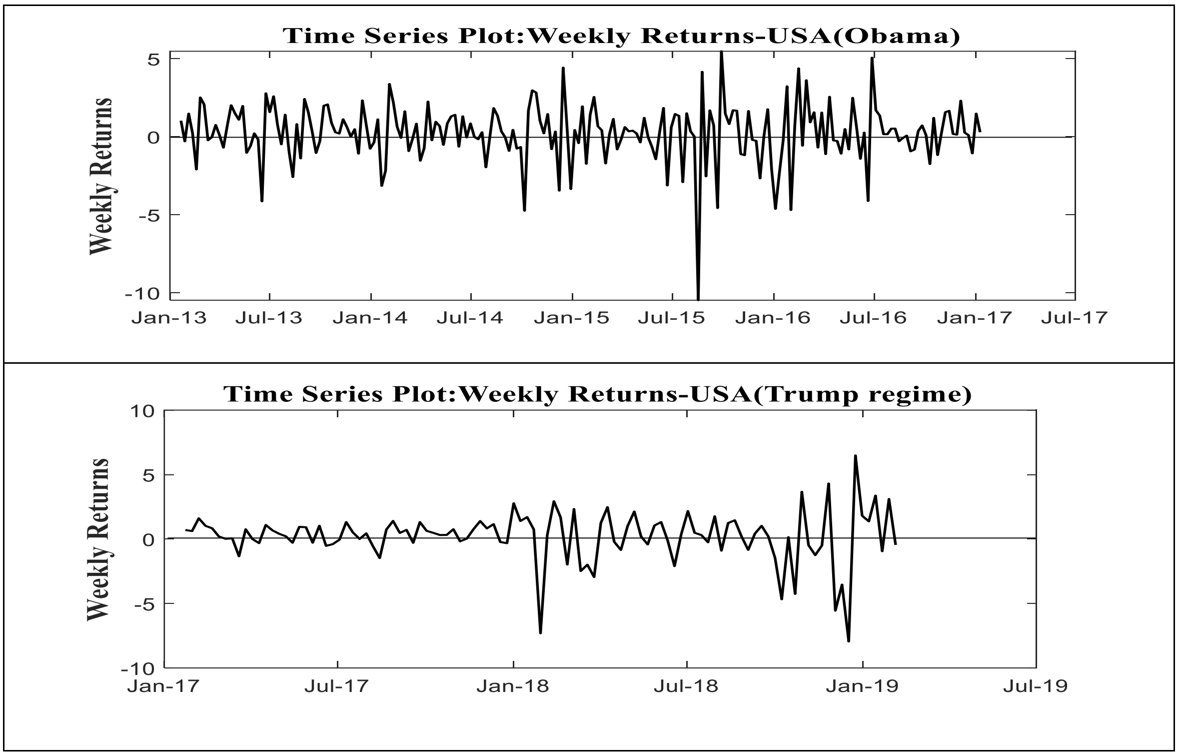

Figure 2. USA returns during the Obama administration and the Trump administration.

The US stock returns are presented in figure 2. The returns under the Obama administration appears to fluctuate tightly around the mean within +5 and -5 percent up until the middle of 2015 after which the major clustering occurs within the range of + 6 and -11 percent and stabilize thereafter. During the Trump administration, the major clustering occurred around January 2018 and early 2019 with major decline as low as -8 percent and as high as 6 percent. Higher volatility clustering in the US stock returns was between 2015 and 2016 (Figure 2). The US stock market uncertainty was more pronounced mainly in the mid-mid-2015. The volatility clustering in the data for the US stock returns during the Trump administration appears to correspond to the Trump's announcements of tariffs on aluminum and steel import in January 2018 and the subsequent tariffs on China henceforth.

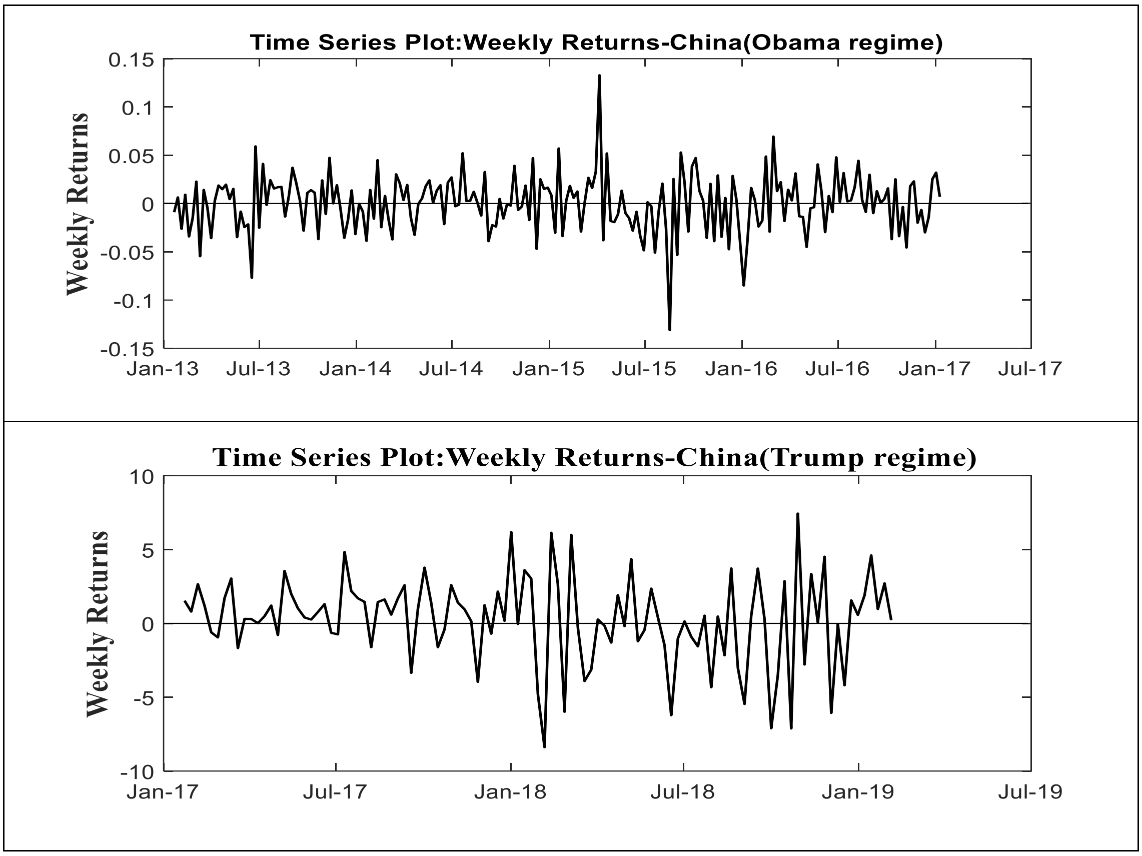

Figure 3. China returns during the Obama administration and the Trump administration.

China's returns are represented in figure 3. The returns for China during the Obama administration seem to move around the mean at a constant level until the beginning of 2013, which shows a decline of 7 percent. China's returns are shown to move around the mean within a margin of +5 and -5 percent until the middle of 2015 where China's returns reached a peak above 10 percent and a dipped below -10 percent by July of the same year. Moreover, China's returns seem to have constant level of movements around the mean under the Trump administration until January 2018 and early 2019 where wider movements are shown. Also, it is noticeable that China's returns also fluctuate during the first period within a range that is below -10 percent and above 10 percent. In the second period, China's index movement are mostly within -8 percent and +8 percent. Although China's returns experience much higher movement in terms of absolute value during the Obama period, the Chinese stock markets seem to experience more unstable period under Trump administration (figure 3).

4.3 Diagnostics of data.

This sub-section contains the diagnostics of the data using Augmented Dickey-Fuller test, and the ARCH test.

Table 1. ADF-test for the time series of Japan, USA, China.

ADF-Test Obama presidency: January 2013-January 2017		
Country	Statistics	P-value
Japan	-259.4276	0.0000
USA	-224.8231	0.0000
China	-144.0985	0.0000
ADF-Test Trump presidency: January 2017-February 2019		
Country	Test statistics	P-value
Japan	-249.5031	0.0000
USA	-178.6899	0.0010
China	-79.8874	0.0000

Augmented Dickey Fuller (ADF) test is crucial to determine the stationarity of the data for the GARCH model to be appropriate for the series. The ADF-test examines the null hypothesis (*H0*) which assumes that a unit root exists in the series sample (Dickey 1979). Table 1 shows that all indices exhibit highly statistical significance, 1% confidence level, for the 5 lags that were tested, indicating by the very low p-values for each of the series. Therefore, the H0 that states that there is unit root in the series is rejected in favor of the alternative hypothesis(H1) that the series for all the countries are stationary. The ARCH-test was also done to detect ARCH effect in order to model the residuals (table 2).

Table 2. ARCH test for the series of USA, China, and Japan.

Engle's ARCH-Test Obama presidency: January 2013-January 2017		
Country	Test statistics	P-value
Japan	20.141	0.0000
USA	28.513	0.0000
China	12.891	0.0244
Engle's ARCH-Test Trump presidency: January 2017-February 2019		
Country	Test statistics	P-value
Japan	15.792	0.0075
USA	15.792	0.0075
China	29.0984	0.0000

Table 2 shows the results for the Engle's ARCH LM-test for which the null hypothesis states that there is no ARCH effect in the residual or all the lags up to lag 5 are jointly uncorrelated (Brooks 2014, p.389). The evidence of the p-value in the first period indicates that the null hypothesis is rejected at 5 percent confidence level for all the countries and notably with a high significance for USA and Japan. Moreover, the second period shows the null hypothesis is also rejected at 5 percent confidence level and highly significant for all the countries' indices. Therefore, there are significant ARCH effects in all the series during both periods.

5. ANALYSIS OF RESULTS.

5.1. Summary of descriptive statistics

Table 3. Descriptive statistics for period 1 and period 2.

Descriptive Statistics	*Obama presidency: January 2013-January 2017*						
Country	Mean	Std Dev.	Kurtosis	Skewness	Min	Max	Jarque-Bera
Japan	0.0016	0.0217	4.0905	-0.5582	-0.0824	0.0465	21.4405***
USA	0.0024	0.0163	8.4494	-1.1234	-0.1048	0.0548	301.1184***
China	0.0002	0.0297	5.7257	-0.1144	-0.1312	0.1328	64.7034***
Descriptive Statistics	*Trump presidency: January 2017-February 2019*						
Country	Mean	Std Dev.	Kurtosis	Skewness	Min	Max	Jarque-Bera
Japan	0.0007	0.0184	4.4554	-0.8296	-0.0577	0.0428	21.7214***
USA	0.0021	0.0199	7.6319	-1.2049	-0.0795	0.0649	121.5412***
China	0.0027	0.0296	3.6339	-0.5261	-0.0839	0.0744	6.7269***

Note: ***, **, and * represent the level of significance of 1 percent, 5 percent, and 10 percent respectively.

Table 3 contains the descriptive statistics for both periods. It is noticeable that all the mean returns for all the countries' indices are positive. During the first period, USA had the highest mean return of 0.0024 followed by Japan, 0.0016, and China, 0.0002. China is the most volatile among the indices under the Obama administration, with a standard deviation of 0.0297 and USA is the safest index among all the indices with a standard deviation of 0.0163 for the same period. The mean return for China has improved during the Trump administration, from 0.0002 to 0.0027, but the mean returns for USA and Japan are much less during the Trump administration where USA incurred a mean return of 0.0021, and 0.007 for the Japan. China is also the most volatile index among the others under the Trump administration, but its standard deviation is less compared to that during the Obama administration (table 3). In addition, the Japan exhibits a lower standard deviation in the second period. Although USA has the lowest standard deviation, its standard deviation is much higher during the Trump regime. Kurtosis and Skewness show how the probability distribution is shaped (table 3). Positive skewness entails a long right tail in comparison to the left, and negative skewness is the opposite. Meanwhile, the kurtosis shows to the extent to which the data is merged to the center from the tails of the distribution (Ruppert & Matteson 2015).

Furthermore, Engle and Sheppard (2001) suggests that skewness that is negative for the series that experiences above normal kurtosis entails that they have extreme values in their left tails. The negative skewness that is shown in table 4 for all the countries in both periods indicates that all the indices data incur extreme values in the left tails. There are excess kurtoses for all the countries' indices during both periods, which are kurtoses that are above 3. The maximum and minimum values give an idea of how high and low each of the country's MSCI index has fluctuated for each period. China returns has the highest and lowest values during both periods whereas Japan has the smaller range of return's fluctuations during both periods. Jarque-Bera test was conducted in table 4 to assess the null hypothesis that states that a vector of the data with an unknown mean and variance are normally distributed (Jarque 1987). The p-values for all the series in each period show a high significance level at 1 percent. Other estimates and data fit for each series are summarized the tables and figures in the appendix (appendix I).

5.2 Correlation and covariance analysis

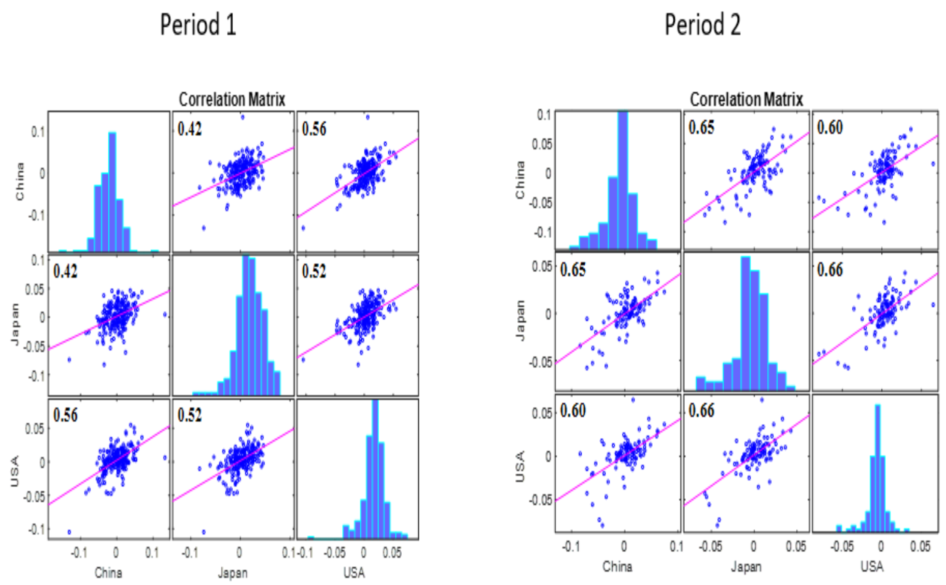

Figure 4. Correlation matrix for China, Japan, and USA for period 1 and 2.

The correlation matrix in figure 4 represents period 1(Obama administration) on the left and the period 2(Trump administration) on the right. The distribution histograms of the returns for each country are shown in the diagonal section, and the linear relationship in a pairwise comparison for each country and the correlation value between the countries are presented in the off-diagonal section of the graphs (figure 4). The distribution of the returns for each country does not appear to be normally distributed, there seem to be some outliers in all the tails of the data. Period 1 exhibits a distribution around the mean with thinner left tails as opposed to period 2 whereas the distribution appears to have fatter tails for all countries, except for USA whose distribution histogram seem to be consistent during both periods. The slopes in the pairwise comparison for all countries appear to be steeper in the second period, which supports the fact that the correlations among those countries are also much higher in the second period. Additionally, the charts in the off-diagonal section show that the data are more clustered around the center during period in period (figure 4). Therefore, period 2 seems to have more extreme values.

Table 4. Variance-covariance matrix for period 1 and period 2.

The diagonal values in bold represent each country's own variance and off-diagonal values are the covariance between each country and another.

Variance-Covariance matrix for Obama presidency: January 2013-January 2017			
Country	**Japan**	**USA**	**China**
Japan	**0.0005**	0.0002	0.0003
USA	0.0002	**0.0003**	0.0003
China	0.0003	0.0003	**0.0009**
Variance-Covariance matrix for Trump presidency: January 2017-February 2019			
Country	**Japan**	**USA**	**China**
Japan	**0.0003**	0.0002	0.0004
USA	0.0002	**0.0004**	0.0004
China	0.0004	0.0004	**0.0009**

Table 4 shows the variance-covariance matrix for period 1 and period 2. The diagonal values in table 5 are the own variance for each country and the off-diagonal values are the covariances between the countries in a pairwise comparison. The variance for Japan is shown to decline during the period 2, from 0.0005 in period 1 to 0.0003 in period 2. Meanwhile the variance for USA appears to increase in period 2, from 0.0003 in period 1 to 0.0004 in period 2. China's variances nevertheless remain unchanged and very high compared to the variances of USA and Japan. During period 2, the covariances between USA and China and between Japan and China have increased. Nevertheless, the covariances between USA and Japan remain the same for both periods. The high covariance between USA and China and China and Japan indices, in a pairwise comparison, indicates that they affect one another much more in the period 2. The unchanged covariance between USA and Japan suggests that they don't affect each as much.

5.3 Analysis of the models.

5.3.1 The VAR Analysis

This section covers the analysis of the results of the model. The VAR model is run separately to estimate the conditional return in order to determine the return spillover effects among the indices in a bivariate setting.

Table 5. Summary of the VAR (1) model results for period 1 and period 2.

	USA-China		**USA-Japan**		**China-Japan**	
Parameter	**Estimate**	**P-Value**	**Estimate**	**P-value**	**Estimate**	**P-value**
	Panel A	*VAR (1): January 2013-January 2017(Obama presidency)*				
δ_1	0.0028**	**0.0329**	0.0028**	**0.0315**	0.0004	0.8600
δ_2	0.0004	0.8453	0.0016	0.3052	0.0019	0.2017
ϕ_{11}	-0.1577*	**0.0607**	-0.1631**	**0.0447**	-0.1128	0.1411
ϕ_{12}	-0.0063	0.9045	-0.0003	0.9961	-0.0548	0.6001
ϕ_{21}	-0.0542	0.6884	0.1886**	**0.0470**	0.0766	0.1698
ϕ_{22}	-0.11042	0.1902	-0.2205***	**0.0066**	-0.1807**	**0.0183**
	Panel B	*VAR (1): January 2017-February 2019(Trump presidency)*				
Parameter	**Estimate**	**P-Value**	**Estimate**	**P-value**	**Estimate**	**P-value**
$\delta1$	0.0022	0.2657	0.0021	0.2899	0.0030	0.3127
$\delta2$	0.0027	0.3537	0.0004	0.8080	0.0007	0.6914
$\phi11$	0.0302	0.8056	0.0448	0.7325	-0.1514	0.2451
$\phi12$	-0.0893	0.2792	-0.1559	0.2782	0.0248	0.9069
$\phi21$	0.2465	0.1727	0.2394**	**0.0456**	0.0271	0.7374
$\phi22$	-0.2406**	**0.0487**	-0.2922**	**0.0262**	-0.1478	0.2636

***, **, and * denote the level of significance at 1 percent, 5 percent, and 10 percent, respectively.

Table 5 shows the parameters of the vector autoregressive model (VAR) in the first order that are used to model the conditional mean returns. The parameters are defined such that δ_1 and δ_2 are the constants for market 1 and market 2; Φ_{11}

and Φ_{22} represent the autocorrelation in returns for market 1 and 2 based on the information of their previous lag; and Φ_{12} and Φ_{21} encompass the return spillovers for market 1 and 2. Panel A, which represents the Obama presidency, shows statistical significance in the autocorrelation parameter for Φ_{11} , which is the effect of US own lagged returns on its current returns, but does not show significance for Φ_{22}, effect of China own lagged returns on it current returns. There is no statistical significance in the parameters Φ_{12} and Φ_{21} for the bivariate setting of the US and China (panel A). Consequently, there appears under the Obama administration that there were no cross-market return spillovers between the US and China. However, US previous own lagged returns impacted its current returns as revealed by the significance of parameter Φ_{11}. During the Trump presidency, which is shown in panel B, there seems to be no indication of return spillover between the US and China. The significance of parameter Φ_{22} reveals that China's current returns were impacted by its own returns from previous period (week) during the Trump presidency.

The return spillover between the US and Japan (panel A) appears to be a unidirectional from the US to Japan, given the significance of parameter Φ_{21}. Parameters Φ_{11} and Φ_{22}, which represent the autocorrelations for the US and Japan are significant at a 5 percent and 1 percent significance level indicating that during the Obama presidency, the US and Japanese stock current stock returns were impacted by their own previous weeks' information. During the Trump presidency the return spillover between the US and Japan was also one direction, from the US to Japan (panel B). Panel A shows during the Obama presidency that there were no return spillovers between China and Japan, but Japan own lagged returns affected its current returns. Panel B (Trump presidency) shows no statistical significance in the autocorrelation parameters, Φ_{11} and Φ_{22} or the cross-market spillover parameters, Φ_{12} and Φ_{21} for the pairwise China and Japan.

5.3.2 The DCC-GARCH (1,1) results.

The DCC-GARCH model contains the univariate GARCH results and the dynamic conditional correlation in a bivariate setting.

Table 6. Results for DCC-GARCH (1,1) model.

	Panel A		*DCC-GARCH (1,1)*		*Obama Presidency)*	
	USA-China		**USA-Japan**		**China-Japan**	
Parameters	**Estimate**	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**
α01	0.0000	0.1705	0.0000	0.1586***	0.0000	**0.0126**
α1	0.0000	0.9998	0.0000	0.9998	0.0000	0.9977
β1	0.9979***	**0.0000**	0.9979***	**0.0000**	0.9983***	**0.0000**
α02	0.0000***	**0.0158**	0.0000	0.2411	0.0000	0.2443
α2	0.0000	0.9977	0.0707	0.1553	0.0707	0.1560
β2	0.9983***	**0.0000**	0.8374***	**0.0000**	0.8374***	**0.0000**
Joint-DCCa1	0.0151	0.1614	0.0000	0.9989	0.0219	0.1427
Joint-DCCb1	0.9640***	**0.0000**	0.9040***	**0.0000**	0.9458***	**0.0000**
LLL	1017		1085		968.8	
	Panel B	*DCC-GARCH (1,1)*		*Trump presidency*		
Parameters	**Estimate**	**P-value**	**Estimate**	**P-value**	**Estimate**	**P-value**
α01	0.0000	0.3262	0.0000	0.9876	0.0001	0.4003
α1	0.4246***	**0.0098**	0.4246***	**0.0097**	0.1530*	**0.0728**
β1	0.5744***	**0.0001**	0.5744***	**0.0001**	0.7874	**0.0000**
α02	0.0001	0.4487	0.0000*	0.0683	0.0000*	**0.0658**
α2	0.1530*	**0.0753**	0.2407**	0.0242	0.2407**	**0.0222**
β2	0.7874***	**0.0000**	0.7050***	**0.0000**	0.7050***	**0.0000**
Joint-DCCa1	0.0069	0.7833	0.0332	0.4430	0.1191*	**0.0869**
Joint-DCCb2	0.9770***	**0.0000**	0.7560***	**0.0048**	0.7118***	**0.0000**
LLL	542.2		602.9		539.1	

***, **, and * denote the level of significance at 1 percent, 5 percent, and 10 percent, respectively.

Table 6 summarizes the results for the DCC-GARCH (1,1) model for period 1, panel A, and period 2, panel B, using R programming language. Selection information concerning the model is provided in appendix I (table H). The parameters α01 and α02 represent the constant terms for market index 1 and market index 2, respectively. Parameters α_1 and α_2 are the own conditional variance in the ARCH terms and the short-term persistence effect. β_1 and β_2 are the own conditional volatility in the GARCH terms and the long-term persistence of volatility. Joint-DCCa1 and joint-DCCb2 represent the dynamic correlations of the series where the former represents the short-term shock persistent between the conditional correlation of the market index 1 and 2, and the latter is the long-term persistent shock effect on the conditional correlation between market 1 and 2.

Panel A, which represents the period 1, shows that the ARCH terms (α_1 and α_2) are not statically significant for all indices. Nevertheless, the highly significance of the GARCH terms (β_1 and β_2) for all indices, indicating a long-term volatility persistency, entails that previous own volatility is predictive of the current volatility for the series. DCC1a (panel A) for all the indices were not statistically significant, that is no short-term persistence of shock between the pairwise compared indices in the dynamic conditional correlation. Meanwhile the DCCb1(Panel A) for each of the pairwise series is highly significant and close to 1, which implies that there is significant long-term persistence in the dynamic conditional correlation between USA and Japan, USA and China, and China and Japan.

The ARCH terms and the GARCH terms (β_1 and β_2) for period 2 for all the variables in panel B are statistically significant and even more so for the latter (table 6). Accordingly, there is a strong argument for short-term and long-term persistency for the all the indices and the previous own conditional variance. The own conditional volatility for each index affects its current ones. The result in panel B (table 6) reveals that DCC1a is not statistically significant for the pairwise USA and China and USA and Japan. However, DCC1a is weakly significant for China and Japan, which entails that there is a short-term persistence of shock in the dynamic conditional correlation between China and Japan. Finally, DCCb2 for all the bivariate series are all highly significant, thus, there is long-term persistence in the dynamic correlation between USA and China, USA and Japan, and China and Japan.

The coefficients for the short-term correlations (DCCa1) and the long-term correlations (DCCb1) seem to change from the Obama administration to Trump administration (table 6). The short-term correlations between the US and Japan and between China and Japan have increased during the Trump presidency. Meanwhile, the short-term correlation between US and China decreased during the Trump presidency. The long-term correlation between US and China is higher during the Trump administration, but lower between US and Japan and between China and Japan.

5.3.3 The DCC and covariance analysis

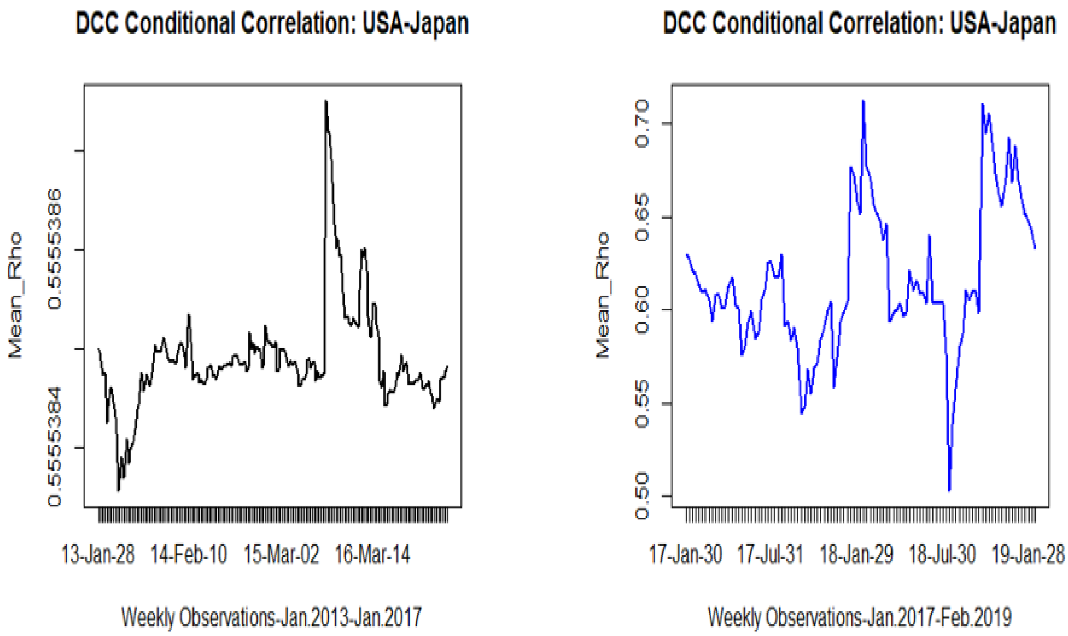

Figure 5. DCC graph between USA and Japan in period 1(Obama presidency) and period 2 (Trump presidency).

Figure 5 shows the dynamic conditional correlation between USA and Japan during the Obama administration on the left and the Trump administration that is on the right. In period 1 (Obama administration), the dynamic conditional correlation on average is shown to be dynamic, where it dips below 0.55, between 2013 and 2014, and takes a constant pattern at the beginning of 2014.

In 2016, the conditional correlation is dynamic again until late 2016 where it fluctuates constantly thereafter. Period 2 (Trump administration) shows a dynamic conditional correlation to fluctuate within 0.55 and 0.64 until the beginning of 2018 where the dynamic conditional correlation increases to 0.75. Around July 2018, the conditional correlation starts to decrease and reaches a correlation of 0.50. It is shown in period 2 that the conditional correlation suddenly increases up to 0.70 toward the end of 2018 and starts to decline thereafter. It is noticeable that the Trump administration has wider fluctuations in the dynamic conditional correlation between USA and Japan compared to the Obama administration.

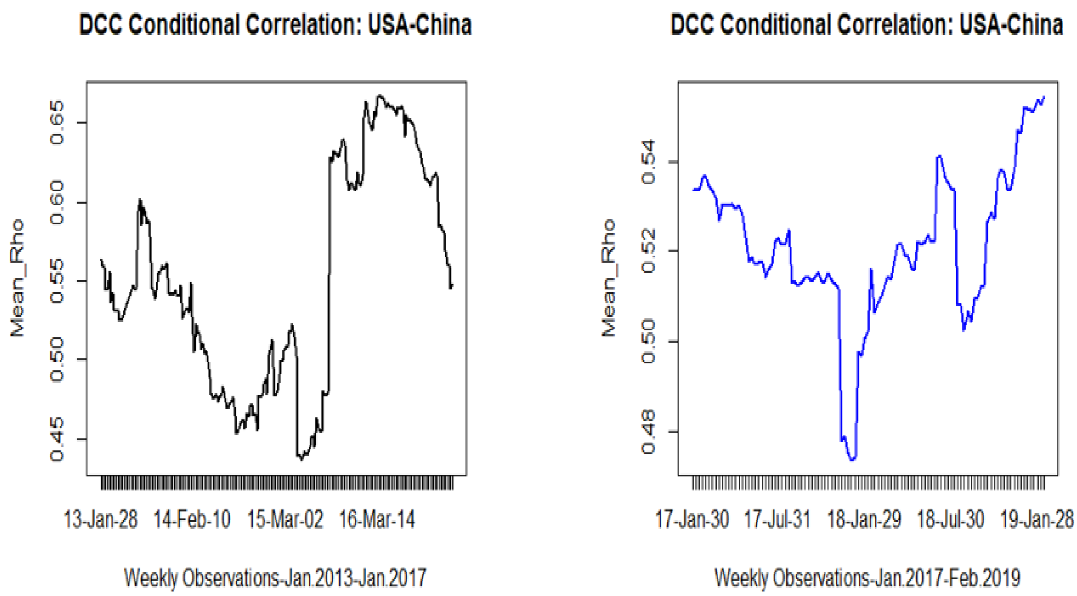

Figure 6. DCC graph between USA and China in period 1 (Obama presidency) and period 2 (Trump presidency).

The dynamic conditional correlation between USA and China for period 1 on the left and period 2 on the right is shown in figure 6. The plot on the left shows that the conditional correlation between USA and China fluctuates between 0.42 and 0.60 during the Obama administration until the end of 2014 where the conditional correlation increases to 0.68, and subsequently decreases toward the end the Obama administration. The plot on the right shows that by the time Donald Trump took office, the dynamic conditional correlation reaches 0.54 in declining, and by January 2018 the conditional correlation between USA and China reached approximately 0.47. Although the last observation in period 2 shows an uptrend for the conditional correlation, it is important to note that under the Trump administration the dynamic conditional correlation is more volatile compared to the that under the Obama administration for the relationship between USA and China.

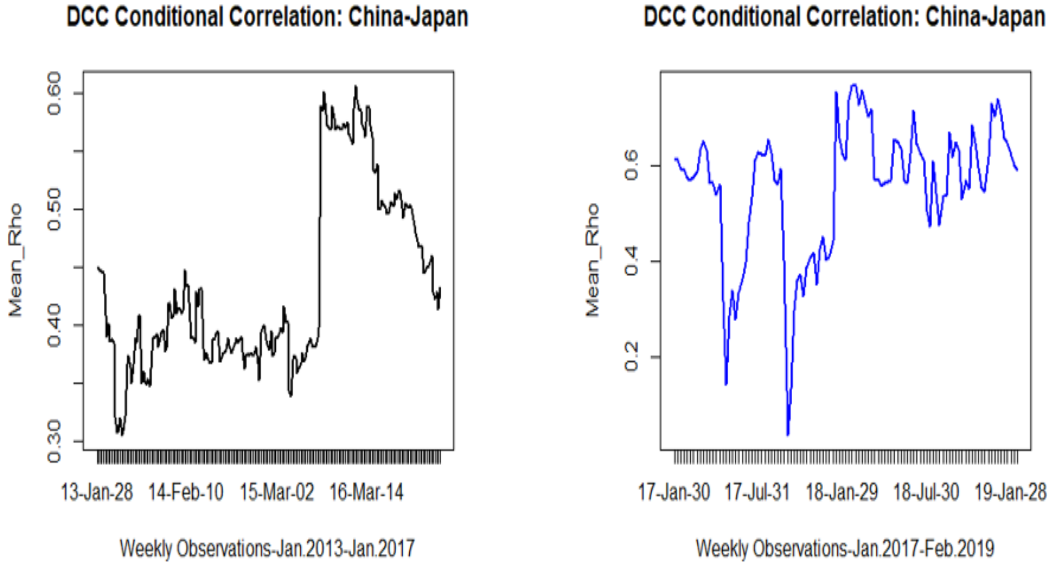

Figure 7. DCC graph between China and Japan in period 1(Obama presidency) and period 2 (Trump presidency).

Figure 7 illustrates the dynamic conditional correlation between China and Japan for period 1 and period 2. The dynamic conditional correlation between China and Japan was in decline during period 1 and reached its lowest point of 0.32 during the first few months of the year 2013. The DCC fluctuates within 0.35 and 0.45 until the middle of 2015 with a maximum value of 0.62 and was declining. The period 2, however, exhibits a fluctuation for the conditional correlation of 0.18 and 0.63 until January 2018 where the conditional correlation reaches its lowest point at approximately 0.10 and normalizes by the middle of 2018.

Period 2 shows much larger fluctuations in the dynamic correlation for all the indices in a pairwise comparison. Notably, January 2018 seems to have wider movements in the dynamic conditional correlation plots. Although the information on dynamic conditional correlations give investors opportunity to diversify their portfolios or seek opportunities elsewhere, the high frequency and large movements of conditional correlations that are shown during the Trump administration imply a more volatile stock market environment due to the sudden shift on trade policy adopted by the Trump administration. Figures 8, 9, and 10 represents the conditional covariance between USA and Japan, USA and China, and China and Japan for period 1(Obama administration) and period 2 (Trump administration), respectively.

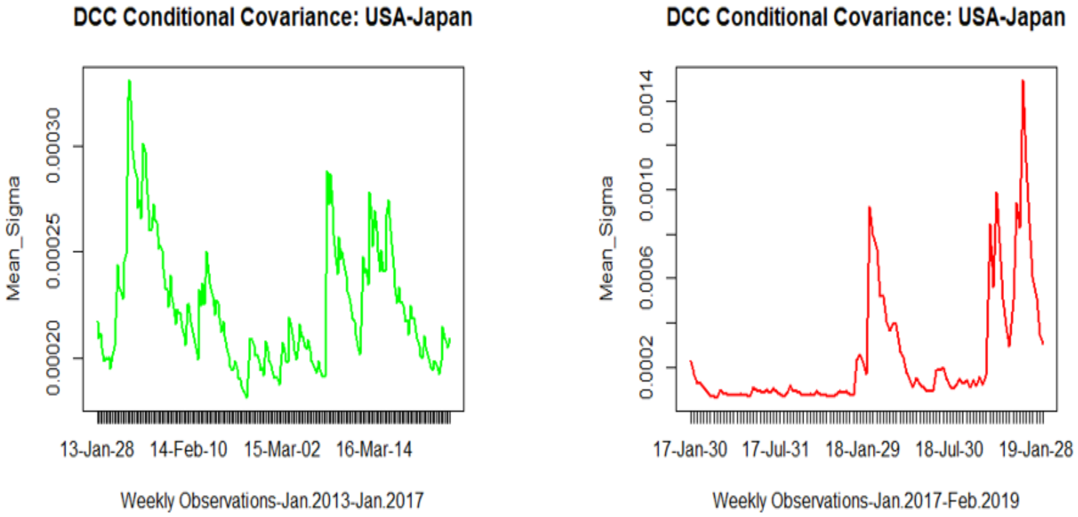

Figure 8. Pairwise conditional covariance between USA and Japan in period 1(Obama presidency) and period 2 (Trump presidency).

Figure 8 shows that the conditional covariance during the Obama administration fluctuates within 0.00020 and 0.0003, whereas the covariance during the Trump administration fluctuates between 0.00002 and 0.0014. Thus, the conditional covariance movements under the Trump regime are more pronounced. The high peaks of the conditional covariance between USA and Japan for period 1(Obama administration) are overserved in the mid-2013 and the middle of 2015, and the high peak for period 2(Trump regime) are in January 2018 and the end of 2018.

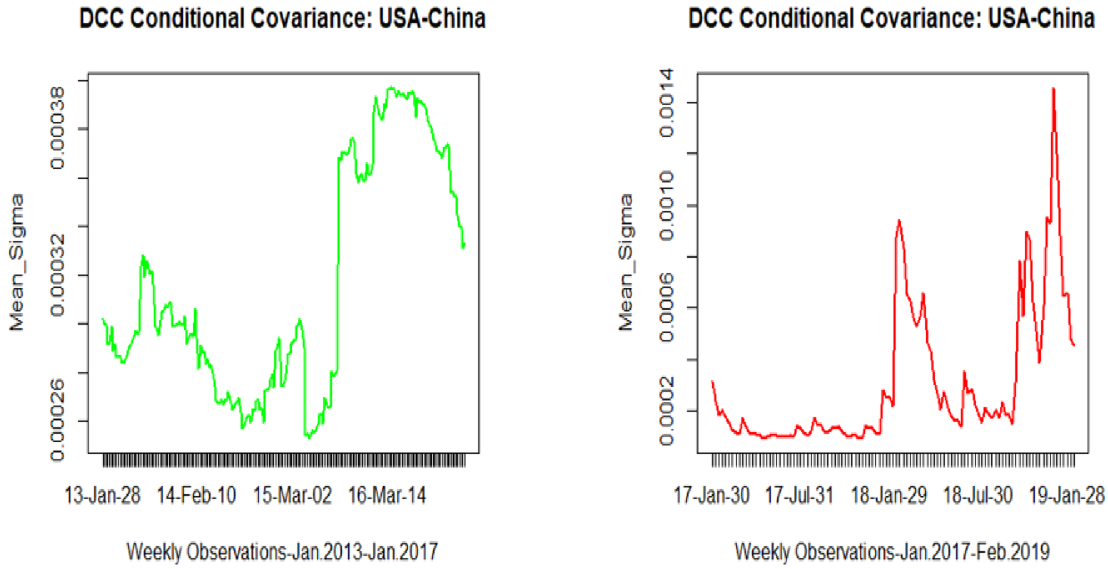

Figure 9. Pairwise conditional covariance between USA and China in period 1(Obama presidency) and period 2(Trump presidency).

The conditional covariances between USA and China in period 1 seem to fluctuate between 0.00026 and 0.0038, while the movements of the conditional covariance in period 2 are within 0.0002 and 0.0014 (figure 9). The highest peak of the conditional covariances in period 1 is noticeable at the beginning of 2016, while the highest peak for period 2 occurs toward the end of 2018 and the beginning of 2019. The conditional covariances in period 1 between USA and China indicated a much less fluctuation compared to the rest of that period. The conditional covariances for period seem to have more frequent high peaks indication a more volatile period under the Trump administration for the relationship between the US stock market and the Chinese stock market.

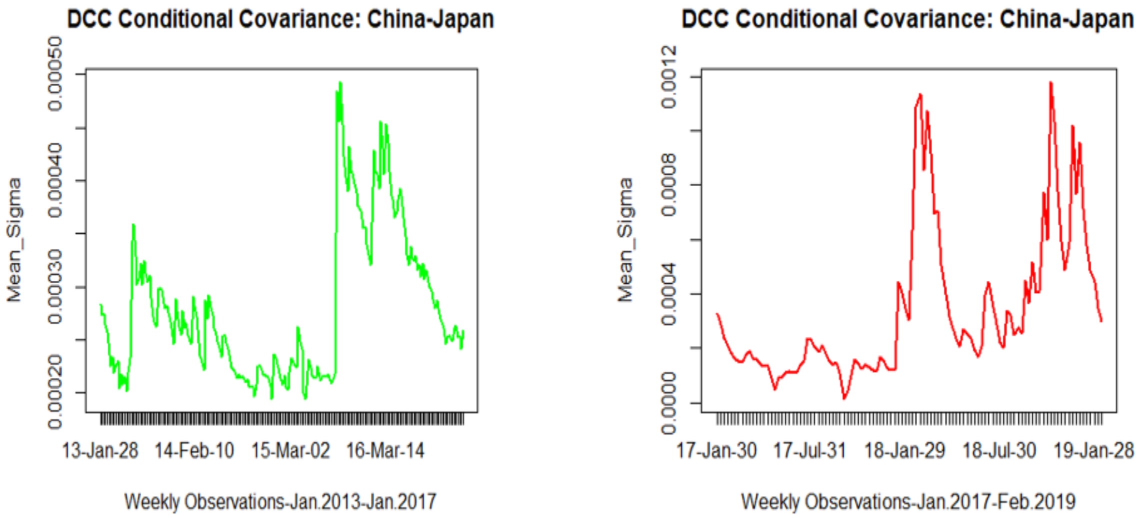

Figure 10. Pairwise conditional covariance between China and Japan in period 1(Obama presidency) and period 2 (Trump presidency).

The up movements and down movements of the conditional covariance between China and Japan, in figure 10, are within 0.00020 and 0.00050. On the other hand, period 2 exhibits covariance's movements that are within 0.0002 and 0.00012. The period 2 depicts a more volatile period for the conditional covariance between China and Japan. The highest peak of the conditional covariance in the period 1 is shown to be at the end of 2015, while the second period's highest peak is at the end of 2019.

The period 2 reveals patterns of similarity of the covariance movements for all the series in a pairwise comparison while period one shows different patterns of covariance movements for the indices. Moreover, the covariance movements between USA and Japan and USA and China are much higher compared to correlation between China and Japan in period 2.

6. LIMITATION AND EXTENSION

This paper is limited to the return spillover effects and dynamic conditional correlation between the USA and China, USA and Japan, and China and Japan during two distinct administration. Due to the scope of this thesis, two countries in the Asian stock markets were selected. As an extension to this study, more countries could be added in a bigger scale to analyze spillover effects for different Asian stock markets and see how the trade war between USA and China has affected those countries. Moreover, further research can be conducted to analyze the spillover effects between the aforesaid countries in the future with data covering the Trump presidency to capture the full effects of the trade war on the rest of the Asian stock markets and other countries across the globe. Further research will be beneficial to help financial managers and CEO's to be better equipped to prepare themselves for unforeseen volatility effects that can undermine the diversification process of their portfolios due to instability in government trade policy.

7. CONCLUSION.

The vector autoregressive (VAR) model reveals important information about the return spillover effects among the indices in a bivariate setting. The VAR model is used to capture the conditional mean and measure the return spillover effects among the relevant countries' stock returns (the US, China, and Japan). The (DCC-GARCH) model is used to determine the own previous conditional variance effects on each series current variance. The dynamic conditional correlation was conducted to analyze the relationship between those countries under the Obama and Trump presidency.

The results of the VAR (1) model shows that there is a unidirectional of return spillovers from US to Japan during the Obama administration and the Trump administration, but no return spillovers between US and China and between China and Japan during any of the administrations.

The dynamic conditional correlation graphs (figures 5, 6, and 7) show crucial features of the dynamics between the indices in bivariate settings. The time varying conditional correlation among the countries' indices are positive, which indicates a positive relationship between each pair of countries' indices. The short-term and long-term correlations reveals the persistence of changes in the dynamic correlations among the indices. The short-term correlations between the US and Japan and between China and Japan seem to be higher during the Trump presidency compared to the Obama presidency. Meanwhile, the short-term correlation between US and China appears to be lower during the Trump presidency. The long-term correlation between US and China is higher during the Trump administration. However, the long-term correlation seems to be lower between US and Japan and between China and Japan during the Trump administration.

The results of the dynamic conditional correlation (DCC) model in this study suggest that the Trump administration's trade policy affects the relationship of the US and China, US and Japan, and that of China and Japan. The hypothesis that the US-China trade war resulted in more pronounced return spillovers between the US and China during the Trump administration was not proven by the vector autoregressive (VAR) model results. It was not determined by the VAR model that return spillovers between US and China affect the relationship between China and Japanese stock markets, the other hypothesis.

The results of this work are important for portfolio managers to select the appropriate stock that will maximize their portfolio returns while appropriate the correct premium for the risk of holding a stock. In addition, the duration in terms of the horizon to hold a stock is crucial. Thus, knowing the short-term and long-term persistence in the dynamic correlation is important. A short horizon seems to be beneficial for investors who hold a combination of Chinese and US stocks in a portfolio during the Trump administration. Meanwhile, a long-term horizon would benefit the investors who hold a combination of US and Japanese stocks or Chinese and Japanese stocks in order to maximize their profits through diversifications.

LIST OF REFERENCES

Aggarwal, R. 1999. Volatility in Emerging Stock Markets. Journal of Financial and Quantitative Analysis, 34(1), pp. 33-55.

Aielli, G.P. 2013, "Dynamic Conditional Correlation: On Properties and Estimation", *Journal of Business & Economic Statistics,* vol. 31, no. 3, pp. 282.

Anonymous (2018). FTSE Down As Trade War Between U.S. and China Escalates. *Dow Jones Institutional News*.

Anonymous (2018). Stock Indexes Decline Early Thursday Amid Concerns About Ongoing Trade War Between US, China. *Live Briefs US*.

Badshah, I. 2018. Volatility Spillover from the Fear Index to Developed and Emerging Markets. Emerging Markets Finance and Trade, 54(1), pp. 27-40.

Bekaert, G. 2002. The dynamics of emerging market equity flows. Journal of International Money and Finance, 21(3), pp. 295-350.

Bilson, C. M. 2002. The explanatory power of political risk in emerging markets. International Review of Financial Analysis, 11(1), pp. 1-27.

Bollerslev, T. 1990. Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized Arch Model. The Review of Economics and Statistics, 72(3), pp. 498-505.

Bollerslev, T., Engle, R.F. & Wooldridge, J.M. 1988, "A Capital Asset Pricing Model with Time-Varying Covariances", *The Journal of Political Economy,* vol. 96, no. 1, pp. 116.

Bollerslev, T. 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), pp. 307-327.

Brooks, C. 2014. *Introductory econometrics for finance*. 3rd ed. Cambridge: Cambridge University Press.

Cappiello, L. 2006. Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns. *Journal of Financial Econometrics, 4*(4), p. 537.

Carnero, M. 2014. Estimating VAR-MGARCH models in multiple steps. *Studies in Nonlinear Dynamics and Econometrics*, *18*(3), p. 339.

Chittedi, K. 2015. Financial Crisis and Contagion Effects to Indian Stock Market: 'DCC–GARCH' Analysis. *Global Business Review, 16*(1), pp. 50-60.

Cosset, J. 1995. Political Risk and the Benefits of International Portfolio Diversification. *Journal of International Business Studies*, *26*(2), p. 301.

Christoffersen, P., Errunza, V., Jacobs, K. & Langlois, H. 2012, "Is the Potential for International Diversification Disappearing? A Dynamic Copula Approach", *The Review of Financial Studies,* vol. 5, no. 12, pp. 3711.

Dimic, N. 2015. The political risk factor in emerging, frontier, and developed stock markets. *Finance Research Letters, 15*, pp. 239-245.

Dickey, D. A. 1979. Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association, 74*(366), pp. 427-431.

Engle, R., and Sheppard, K. 2001. GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics. *The Journal of Economic Perspectives*, *15*(4), pp. 157- 168.

Engle, R. 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, *20*(3), pp. 339-350.

Engle, R. F. 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica, 50*(4), pp. 987-1007.

Fama, E. 2004. The Capital Asset Pricing Model: Theory and evidence. *Journal of Economic Perspectives, 18*(3), pp. 25-46.

Hamao, Y. 1990. CORRELATIONS IN PRICE CHANGES AND VOLATILITY ACROSS INTERNATIONAL STOCK MARKETS. *Review Of Financial Studies, 3*(2), pp. 281-307.

Jebran, K. 2016. Examining volatility spillover between Asian countries' stock markets. *China Finance and Economic Review, 4*(1), pp. 1-13.

Jarque, C. M. 1987. A Test for Normality of Observations and Regression Residuals. *International Statistical Review / Revue Internationale de Statistique, 55*(2), pp. 163-172.

Harvey, S. 2018. China imposes tariffs on 128 US products in retaliation to Trump's measures. *just - food global news*.

Khalil, J. 2018. Volatility spillover between stock and foreign exchange market of China: Evidence from subprime Asian financial crisis. *Journal of Asia Business Studies, 12*(2), pp. 220-232.

Lien, D. 2018. Volatility spillovers among the U.S. and Asian stock markets: A comparison between the periods of Asian currency crisis and subprime credit crisis. *North American Journal of Economics and Finance, 46*, pp. 187-201.

Miyakoshi, T. 2003. Spillovers of stock return volatility to Asian equity markets from Japan and the US. *Journal of International Financial Markets, Institutions & Money, 13*(4), pp. 383-399.

Mohammadi, H. & Tan, Y. 2015. Return and Volatility Spillovers across Equity Markets in Mainland China, Hong Kong and the United States. *Econometrics, 3*(2), pp. 215-232.

Politi, J., Fei, F. & Klasa, A. 2019, "Timeline: No end in sight for US-China trade war", *FT.com* .

Sharpe, W. F. 1964. CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK*. *Journal of Finance, 19*(3), pp. 425-442.

Sarwar, G. 2019. Interrelations of U.S. market fears and emerging markets returns: Global evidence. *International Journal of Finance & Economics, 24*(1), pp. 527-539.

Shearer, P. 2018. Trade war escalates between U.S. and China. *National Hog Farmer*.

Shumway, R. H. & Stoffer, D. S. 2011. *Time Series Analysis and Its Applications: With R Examples*. New York, NY: Springer New York.

Singhal, S. 2016. Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC- GARCH models. *Resources Policy, 50*, pp. 276-288.

Simpson, C., Finch, G. & Chellel, K. 2018. The Brexit Short. *Bloomberg Businessweek,* p. 36.

Sanyal, N. 2018. Market Movers: Trump imposes additional tariff on China; 3 PSU banks' merger & more [Stock in news]. *The Economic Times*.

Tsay, R. S. 2005. *Analysis of financial time series*. 2nd ed. Hoboken (NJ): Wiley.

Yue, Y. 2015. Price linkage between Chinese and international nonferrous metals commodity markets based on VAR-DCC-GARCH models. *Transactions of Nonferrous Metals Society of China, 25*(3), pp. 1020-1026.

Wishart, I. 2018, *Brexit*, Bloomberg Finance LP, New York. Retrieved from proquest [November 2019] 2016. World: Markets Open, Plunge Following Britain 'Leave' Vote. *Asia News Monitor*.

World Trade Organization (WTO) (2018), The United States of American and the WTO. Available from<https://www.wto.org/english/res_e/statis_e/daily_update_e/trade_profiles/CN_e.pdf . >Retrieved [22 November 2019].

World Trade Organization (WTO) (2018), The United States of American and the WTO. Available from https://www.wto.org/english/res_e/statis_e/daily_update_e/trade_profiles/US_e.pdf. Retrieved [22 November 2019].

APPENDIX I. Summary Diagnostics and model selection criteria.

The diagnostics summary of all the Japan, US, and China. The summary include the ordinary least squares estimates, Augmented Dickey-Fuller roots test, and the fit diagnostics for the model.

Japan, USA, and China during the Obama presidency.

Table A. Ordinary leasts estimates of Japan(Obama presidency).

Ordinary Least Squares Estimates			
SSE	0.09780364	**DFE**	207
MSE	0.0004725	**Root MSE**	0.02174
SBC	-998.14901	**AIC**	-1001.4865
MAE	0.01675963	**AICC**	-1001.4671
MAPE	104.509903	**HQC**	-1000.137
Durbin-Watson	2.2740	**Total RSquare**	0.0000

Table B. Augmented Dickey-Fuller Unit Root Tests of Japan(Obama presidency).

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**3**	-259.4276	<.0001	-7.4756	<.0001		_
Single Mean	**3**	-282.5590	<.0001	-7.5962	<.0001	28.8511	0.0010
Trend	**3**	-291.1517	<.0001	-7.6163	<.0001	29.0097	0.0010

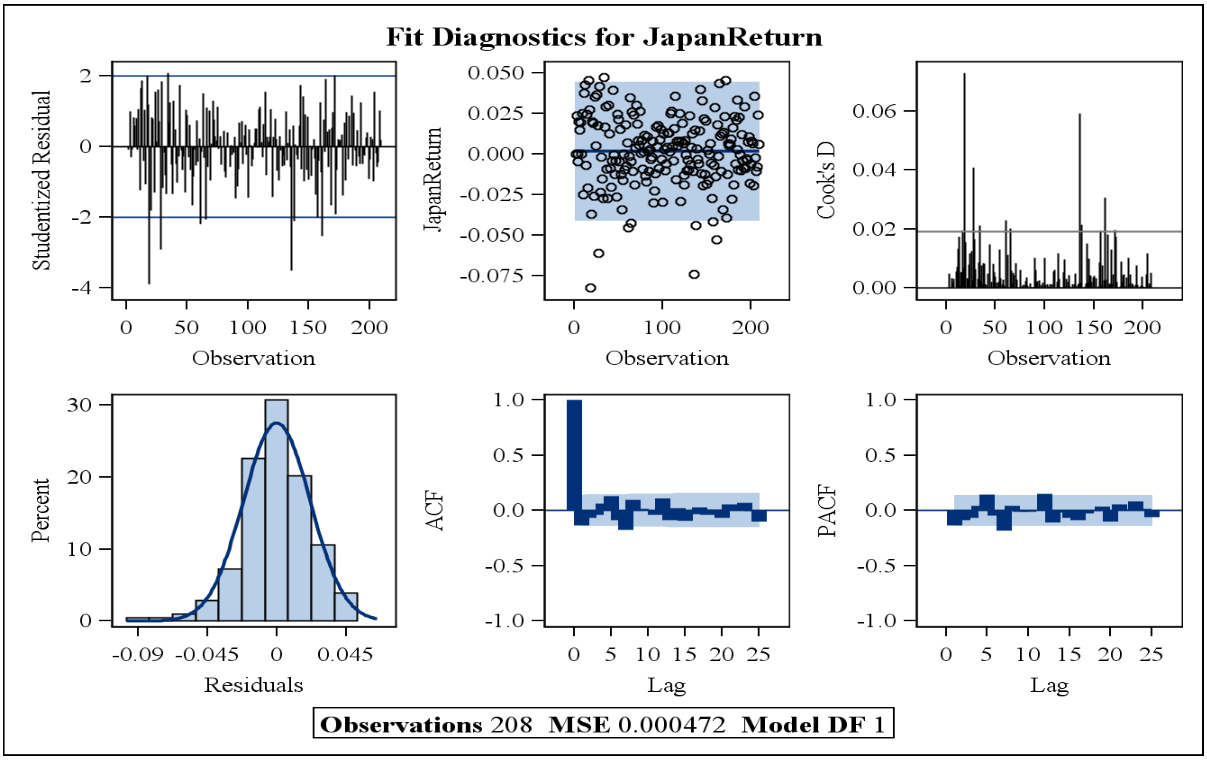

Figure 1. Diagnostics for Japan (Obama presidency).

Table C. OLS estimates for USA.

Ordinary Least Squares Estimates			
SSE	0.07091306	**DFE**	207
MSE	0.0003426	**Root MSE**	0.01851
SBC	-1065.0225	**AIC**	-1068.36
MAE	0.01284323	**AICC**	-1068.3406
MAPE	183.071404	**HQC**	-1067.0105
Durbin-Watson	2.3257	**Total R-Square**	0.0000

Table D. ADF test for USA.

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**3**	-224.8231	<.0001	-7.2525	<.0001		_
Single Mean	**3**	-292.3277	<.0001	-7.6605	<.0001	29.3422	0.0010
Trend	**3**	-302.6621	<.0001	-7.6892	<.0001	29.5652	0.0010

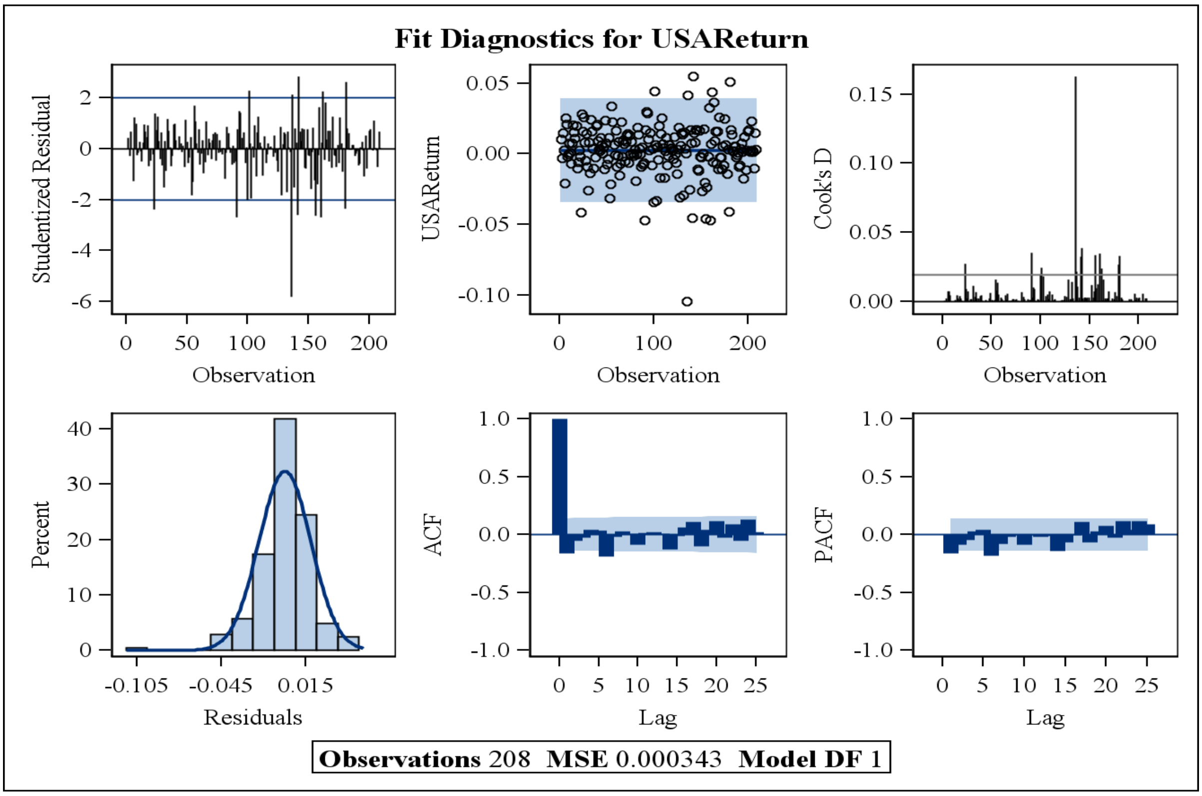

Figure 2. Diagnostics for USA.

Table D. OLS estimates for China.

Ordinary Least Squares Estimates			
SSE	0.18270692	**DFE**	207
MSE	0.0008826	**Root MSE**	0.02971
SBC	-868.16532	**AIC**	-871.50286
MAE	0.02255365	**AICC**	-871.48344
MAPE	99.8413925	**HQC**	-870.15333
Durbin-Watson	2.2581	**Total R-Square**	0.0000

Table E. ADF test for China.

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**3**	-144.0985	<.0001	-6.3940	<.0001		_
Single Mean	**3**	-144.1018	<.0001	-6.3791	<.0001	20.3560	0.0010
Trend	**3**	-144.0667	<.0001	-6.3625	<.0001	20.2483	0.0010

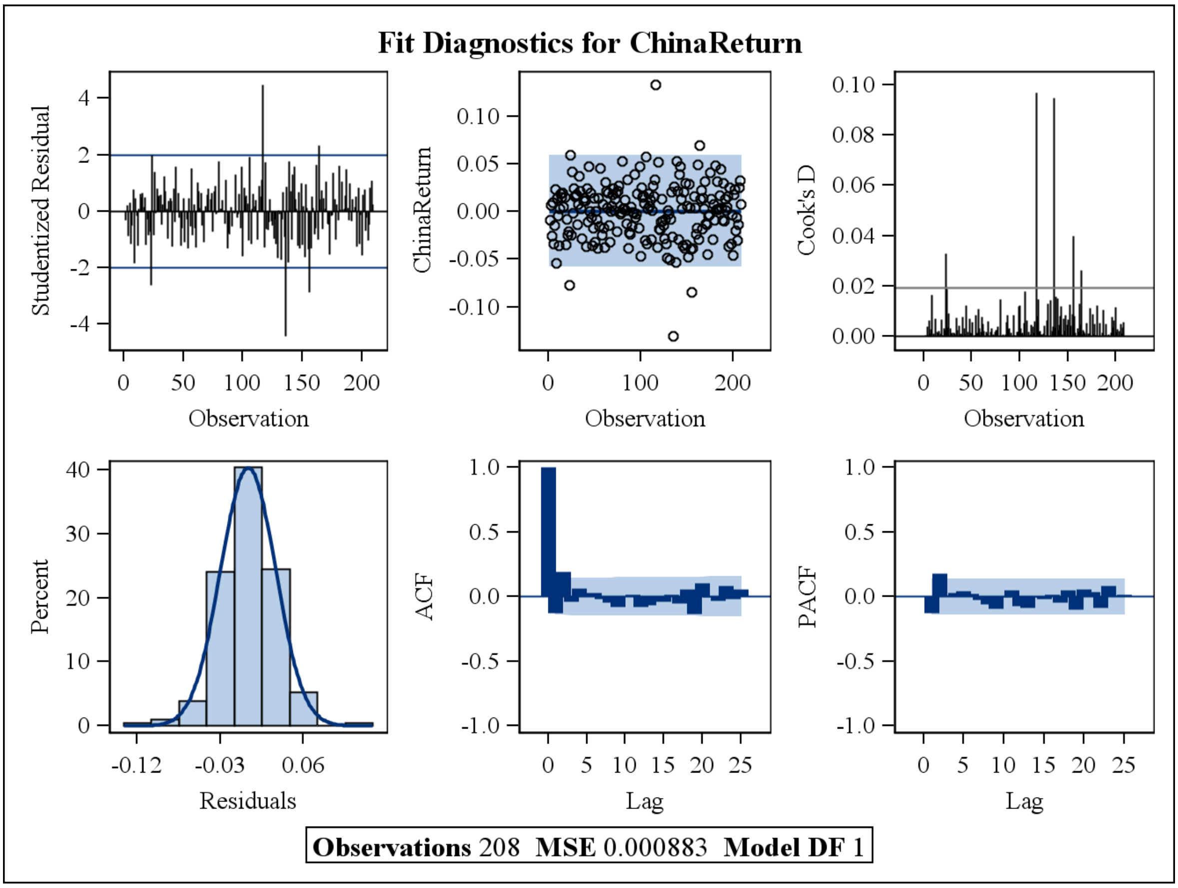

Figure 3. diagnostics for China.

Diagnostics summary Japan, USA, and China during the Trump presidency.

Table F. OLS for Japan.

Ordinary Least Squares Estimates			
SSE	0.03586204	**DFE**	106
MSE	0.0003383	**Root MSE**	0.01839
SBC	-547.77115	**AIC**	-550.44398
MAE	0.01332505	**AICC**	-550.40588
MAPE	113.861439	**HQC**	-549.36045
Durbin-Watson	2.2014	**Total R-Square**	0.0000

Table G. ADF test for Japan

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**3**	-249.5031	<.0001	-5.8781	<.0001		_
Single Mean	**3**	-260.7636	<.0001	-5.8742	<.0001	17.266	0.0010
Trend	**3**	-520.5927	<.0001	-6.3366	<.0001	20.094	0.0010

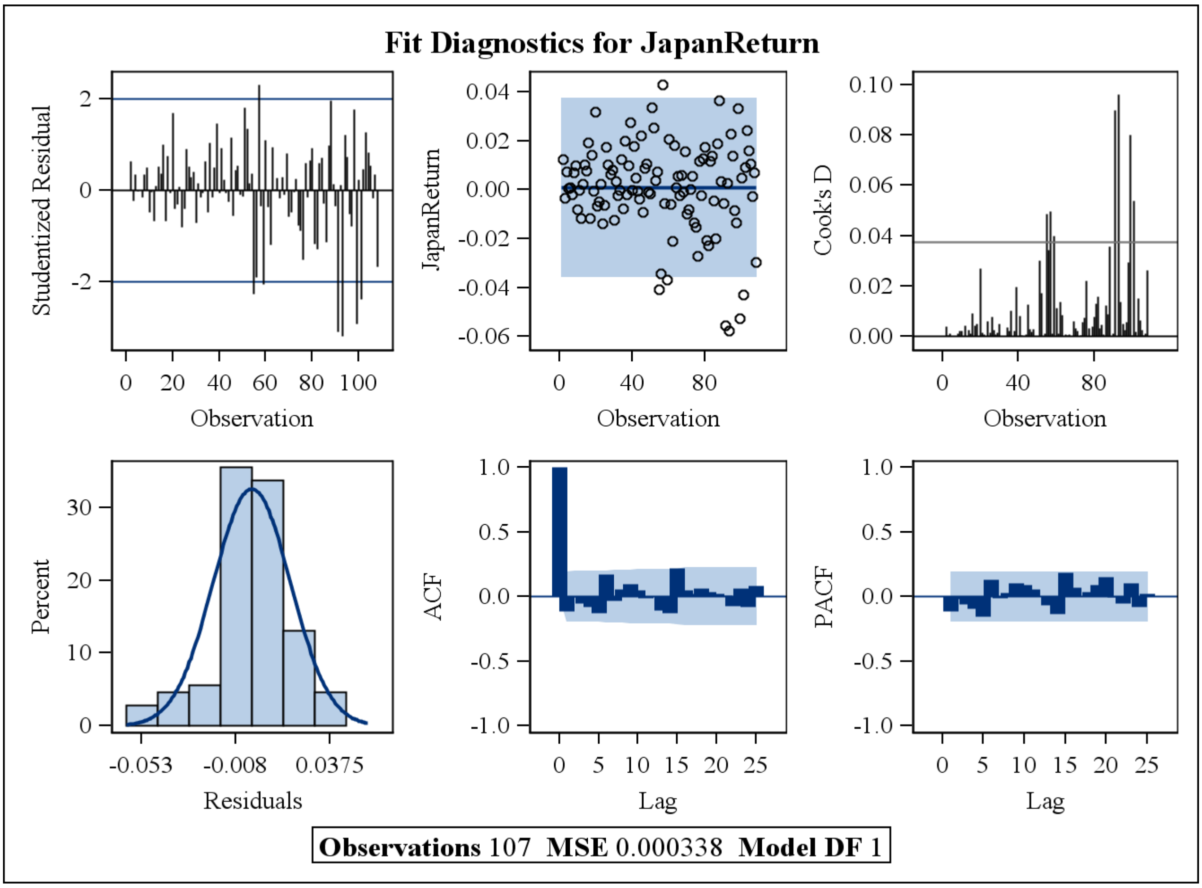

Figure 4. Disnotics for Japan(Trump presidency).

Table H. OLS for USA and ADF test (Trump presidency).

Ordinary Least Squares Estimates

SSE	0.0418963	**DFE**	106
MSE	0.0003952	**Root MSE**	0.01988
SBC	-531.13068	**AIC**	-533.80351
MAE	0.01278543	**AICC**	-533.76541
MAPE	285.970877	**HQC**	-532.71998
Durbin-Watson	2.0973	**Total R-Square**	0.0000

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**3**	-178.6899	<.0001	-5.5857	<.0001		_
Single Mean	**3**	-208.8930	<.0001	-5.7110	<.0001	16.3078	0.0010
Trend	**3**	-241.5062	<.0001	-5.7515	<.0001	16.6127	0.0010

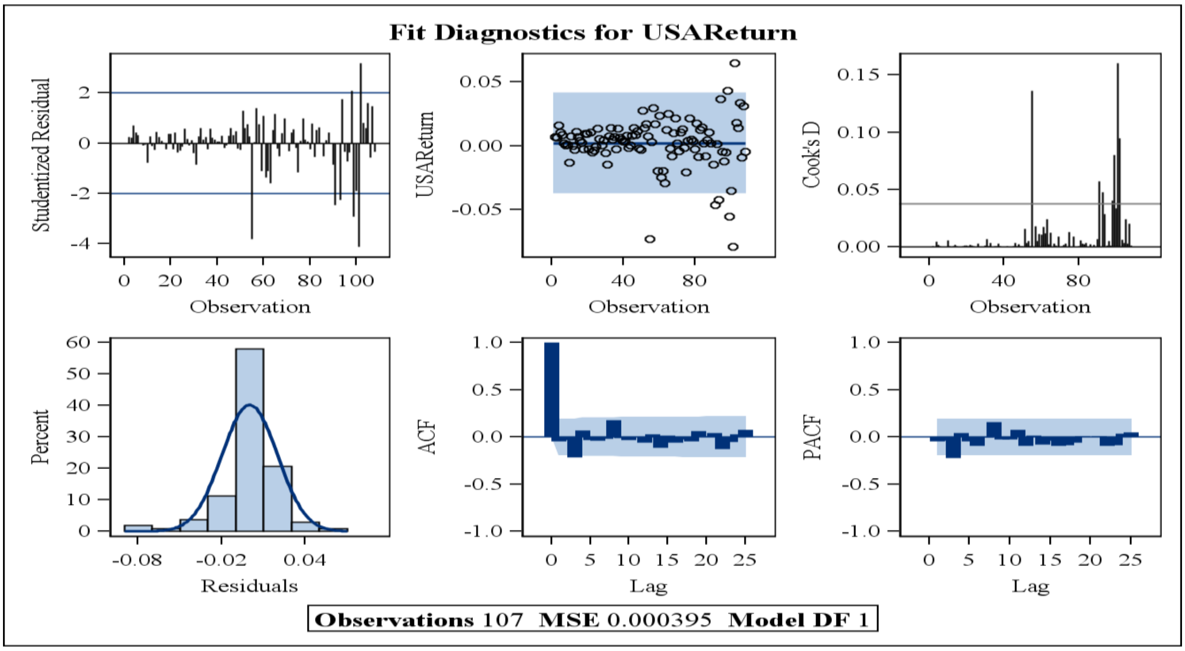

Figure 5. Disnostics US return(Trump presidency).

Table I. OLS for China(Trump presidency).

Ordinary Least Squares Estimates			
SSE	0.09270882	**DFE**	106
MSE	0.0008746	**Root MSE**	0.02957
SBC	-446.14422	**AIC**	-448.81705
MAE	0.02157915	**AICC**	-448.77896
MAPE	120.741084	**HQC**	-447.73352
Durbin-Watson	2.2811	**Total R-Square**	0.0000

Table J. ADF for China (Trump presidency).

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**3**	-79.8874	<.0001	-4.6275	<.0001		_
Single Mean	**3**	-85.2287	0.0010	-4.6897	0.0002	10.9965	0.0010
Trend	**3**	-117.4933	<.0001	-4.9175	0.0006	12.2099	0.0010

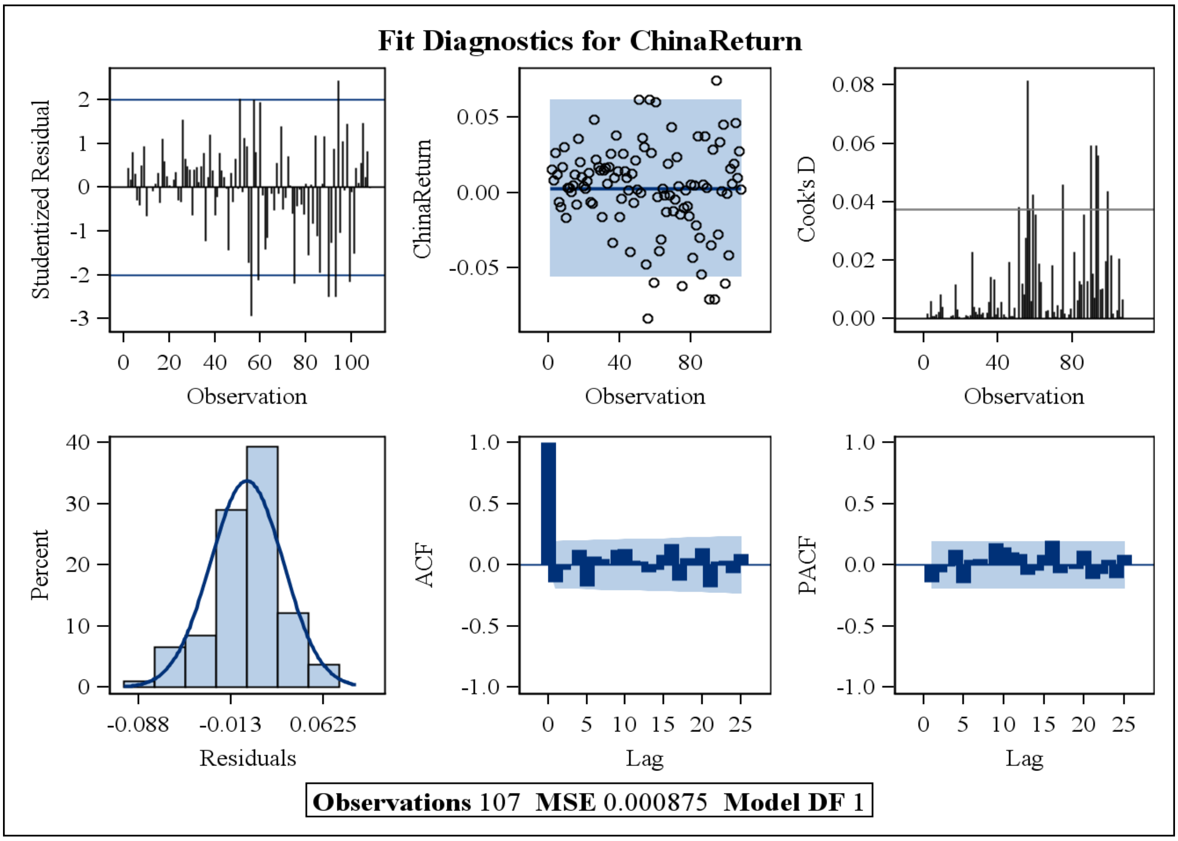

Figure 6. Diagnostics for China return (Trump presidency).

Table H. DCC-GARCH Model section criteria.

The DCC-GARCH model selection criteria for both periods.

US-China		**Period 1** **US-Japan**		**China-Japan**
Information Criteria --------------------- Akaike -9.6524 Bayes -9.4438 Shibata -9.6596 Hannan-Quinn -9.5680		Information Criteria --------------------- Akaike -10.304 Bayes -10.095 Shibata -10.311 Hannan-Quinn -10.219		Information Criteria --------------------- Akaike -9.1988 Bayes -8.9902 Shibata -9.2061 Hannan-Quinn -9.1145
		Period 2		
Information Criteria --------------------- Akaike -9.8908 Bayes -9.5661 Shibata -9.9163 Hannan-Quinn -9.7592		Information Criteria --------------------- Akaike -11.027 Bayes -10.702 Shibata -11.052 Hannan-Quinn -10.895		--------------------- Akaike -9.8344 Bayes -9.5097 Shibata -9.8599 Hannan-Quinn -9.7028