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EMPIRICAL ANALYSIS OF DEPENDENCE STRUCTURES AND SPILLOVER EFFECTS ACROSS STOCK MARKETS: A STUDY OF RELATIONSHIP BETWEEN VIETNAM AND ITS MAJOR TRADING PARTNERS

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ABSTRACT

This thesis studies dependence structures and spillover effects between the Vietnamese stock market and the American, Japanese, and European equity markets over the period from 2005 to 2020. For this purpose, I use copula-based models to investigate the dependence structure and asymmetric VAR-BEKK-GARCH frameworks to further define spillover effects. I find evidence of substantial influences of the United States (US) and Japanese markets on the Vietnamese market. In addition, the results also show that the Vietnamese stock market is more likely to experience extreme events jointly with the Japanese market. It is also noteworthy that the dependence structure between the markets varies over time and increases during crises. The results with VAR-BEKK-GARCH models indicate the existence of unidirectional return spillovers from the US and European markets to the Vietnamese market and no return linkage between Vietnamese and Japanese markets. In addition, by conducting the second-order Granger-type causality test, I find evidence for bi-directional volatility spillovers between Vietnamese and American markets, whereas for the other markets, I note one-way volatility transmissions from the advanced market to Vietnam's market.

Keywords: stock markets, dependence structure, spillover effect, copula model, VAR-BEKK-GARCH model.

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1. Introduction

Due to the increased level of integration of the world economy, co-movements among international financial markets have become a popular subject in previous literature (e.g., Hamao et al., 1990; Hu, 2006; Bekaert et al., 2014). The relatively free flow of goods and capital, as well as technological advancements are considered as the main factors facilitating this phenomenon. A better understanding of interdependency across national markets is, therefore, crucial not only for investors, but also for policymakers. Although numerous studies have documented the linkages among international stock markets (e.g., Li et al., 2015), the issue is very much unsettled since different studied periods and sample countries may result in different findings. As such, the topic is still relevant today and requires further consideration. This thesis contributes to the ongoing literature on co-movement patterns in financial markets by investigating the dependence between the Vietnamese stock market and the equity markets in the US, Japan, and European countries (European Union and the United Kingdom, hereafter called EU28).

This study chooses the Vietnamese equity market as the subject of interest as despite the country's potential and strong momentum,[1] little has been done in research on the dependence between the stock markets of Vietnam and its major trading partners. To the best of my knowledge, this paper is the first study that comprehensively evaluates the interaction between the Vietnamese stock market and other equity markets by investigating both the dependence structure as well as the direction of the linkages (i.e., spillover effects). In addition, there are two reasons for me to investigate the relationship between Vietnam and the US, Japan, and EU28. First, these countries/areas are Vietnam's largest trading partners in recent years.[2] Previous literature has documented a positive correlation between trade and stock market integration (e.g., Chen et al., 1997; Forbes et al., 2004; Balli et al., 2014). Indeed, when two countries have a strong trading relationship, bad performance in the larger country's market could lead to a reduction in demand for goods and services from the smaller country. That would result in a decline of returns in the smaller country's market. Thus, countries with strong trading ties tend to have financial markets that move together. Second, the US, Japanese, and European stock markets are classified as developed markets (MSIC, 2020) which are expected to have considerable influences on various

[1] Vietnam's average GDP growth rate for the period from 2015 to 2019 was 6.8% (World Bank, 2020).

[2] Top 6 largest trading partners of Vietnam in 2020 were China, the US, South Korea, Association of Southeast Asian Nations (ASEAN), EU28, and Japan (General Department of Vietnam Customs, 2021).

markets in the region as well as all over the world. Therefore, by examining the relationship between the Vietnamese stock market and the considered advanced markets, I can evaluate the degree of integration of the Vietnamese market into the world and regional markets.

For the purpose of this thesis, the strength of dependence structure is measured by the non-linear correlation coefficient estimated from bivariate copula-based models. Meanwhile, the spillover effect is defined as a situation when changes of returns and/or volatililies in one market drive changes of returns and/or volatilities in a different market. In other words, this thesis assumes that spillover effects can occur across both returns (return spillovers) and volatilities (volatility spillovers). The spillover effect is modelled though a bivariate vector autoregressive (VAR) model in conjunction with an asymmetric multivariate GARCH model (i.e., BEKK-GARCH specification by Kroner et al., 1998). It is noteworthy that the copula model and the VAR-BEKK-GARCH specification are two alternative approaches in analyzing dependence of financial time series. However, they are, to some extent, suitable for different purposes. Copula-based models which simultaneously account for asymmetric, nonlinear, and tail dependence have proved to be a better fit for modelling dependence of financial time series (e.g., Embrechts et al., 2003; Patton, 2004; Hu, 2006). Despite this, copulas are not well established to ascertain the direction of dependence. Moreover, Patton (2007) notes that when the analysis is primarily concentrated on the conditional mean and/or variance of a vector of variables, copulas may not be the "right tool for the job". Instead, he suggests that a standard VAR model and/or a multivariate GARCH model may be more appropriate. Therefore, I use the VAR-BEKK-GARCH specification to investigate the direction of return and volatility spillovers.

By employing the two mentioned approaches, the thesis aims to bring a more complete picture of the relationship between the Vietnamese stock market and the US, Japanese, and European markets. First, I intend to quantify dependence structures between the markets using both constant and time-varying copulas. In addition to that, I also investigate the probability of joint extreme events in the relationships by evaluating the tail dependence coefficient with the Student's t copula. Second, I provide insights on stock return and volatility transmissions between Vietnam's market and the other countries' markets. I also evaluate the ability of using foreign information from the developed markets to forecast returns and volatilities in the Vietnamese equity market.

This thesis is motivated by a vast number of previous articles and research which can be divided into two main groups: (i) copula-based models used to investigate the dependence structure between financial markets, and (ii) VAR-BEKK-GARCH models used to examine the spillover effect. The first of primary sources is the work of Patton (2004; 2006a; 2006b and 2013) which cover the application of copula-based models in multivariate analyses on financial time series. This approach allows modeling the marginal distributions separately from the dependence structure (the copula) which links these distributions to form the joint distribution. This framework has become popular in recent years (e.g., Opschoor et al., 2020) due to its great degree of flexibility in specifying the model. Indeed, with a copula function, the researcher is able to incorporate many different aspects into one specification. Patton (2006a) introduces the notion of time-varying copulas and Creal et al. (2013) propose a new mechanism to update the copula parameters over time, referred to as Generalized Autoregressive Score (GAS) models. The second source of motivation are the papers that document spillover effects using multivariate GARCH (MGARCH) models. An example is the study by Li et al. (2015). The authors employ an asymmetric BEKK-GARCH model to investigate volatility spillovers across the US, Japan and several emerging stock markets.[3]

This thesis also contributes to the growing literature on interdependency between the Vietnamese and developed equity markets by taking into account the following aspects. First, I take the perspective of a USD investor. Therefore, I adjust the stock returns to reflect changes in the exchange rate of each country's currency against the US dollar. Mohammadi et al. (2015) claim that this is a useful exercise for an international investor who is concerned with portfolio diversification.

Second, my study employs both daily close-to-close (CC) and close-to-open (CO) returns in exploring the interaction between Vietnamese and Japanese markets. According to King et al. (1990), when the markets have overlapping trading hours, it is necessary to also examine changes in prices between the close of trading on one day and the opening of trading on the following day.

Third, I employ the GAS specification to let the copula parameter change over time. This approach, as demonstrated by Creal et al. (2013), provides a better performance than the method of Patton (2006a). Moreover, accounting for the existing significant skewness in financial data, I

[3] including China, India, Indonesia, Malaysia, the Philippines, and Thailand

use the asymmetric Student's t (skewed t) distribution of Hansen (1994) as the marginal distribution.

Furthermore, I follow Kroner et al. (1998) and use an asymmetric MGARCH model to estimate the volatility transmission. This framework can capture the asymmetric effect in the conditional variance as well as covariance. Therefore, it helps determine the spillovers of past negative return shocks (unexpected price drops) from a market to a different market. In addition, I estimate the MGARCH model under different distribution assumptions of the error terms: (i) the error terms jointly have a normal distribution; or (ii) the error terms jointly have a Student's t distribution. It is useful as financial data are well-known to have heavy tails.

Another contribution of my thesis is that I conduct Granger-causality tests for the mean as well as second-order Granger-type causality tests for the variance in order to ascertain the direction of the dependence. Since interpreting the results from the BEKK-GARCH specification is not straightforward, I also visualize the volatility spillover effect through news impact surfaces, a 3D extension of news impact curves proposed by Kroner et al. (1998).

Finally, I include the European stock market into the study. To the best of my knowledge, there is a very limited amount of papers which investigate the stock linkage between Vietnamese and European markets, although the EU28 are currently the second largest importers of Vietnamese goods and services.

I examine the relationship between the Vietnamese stock market and American, Japanese, and European equity markets over the period from 2005 to 2020. With copula models, I find evidence of substantial influences of the US and Japanese markets on the Vietnamese market. In addition, the results also show that the Vietnamese stock market is more likely to experience extreme events jointly with the Japanese market. It is also noteworthy that the dependence structure between the markets varies over time and increases during crises. The results with VAR-BEKK-GARCH models indicate the existence of unidirectional return spillovers from the US and European markets to the Vietnamese market and no return linkages between Vietnamese and Japanese markets. In addition, by conducting the second-order Granger-type causality test, I find evidence for bi-directional volatility spillovers between Vietnamese and American markets, whereas for the other markets, I note one-way volatility transmissions from the advanced market to Vietnam's market.

The thesis is organized as follows. Section 2 contains a literature review. Section 3 explains the methods used in this study. Section 4 presents the characteristics of studied markets as well as data and some descriptive statistics. Section 5 contains the empirical results. Finally, in Section 6, I conclude and with remarks and implications for future research.

2. Literature review

2.1. Empirical findings on dependence structures and spillover effects across stock markets

Dependence across financial markets has been the subject of much attention in recent years. Indeed, for portfolio diversification purposes, this field of study has interested both academics and practitioners as high co-movements of different markets limit the possible gains from diversification. For a long time period, the standard method of estimating dependence has been Pearson's correlation coefficient, which is appropriate for jointly normally distributed data. However, multivariate financial time series are usually nonlinear, non-normally distributed (e.g., Hamao et al., 1990; Erb et al., 1994; Longin et al., 2001). Therefore, to examine the interdependency in financial data, a different measure is needed. Copula-based models which simultaneously account for asymmetric, nonlinear, and tail dependence have proved to be a better fit for modelling dependence of financial time series (e.g., Embrechts et al., 2003; Patton, 2004; Hu, 2006).

A copula is a function that connects univariate marginal distributions to produce a multivariate distribution. This method has been long popular in the statistics literature. The first paper employing copulas in finance is that of Embrechts et al. (1999), in which the authors use a static copula to capture the dependence structure of different equities in risk management. Since then, the number of papers using copulas in finance has grown massively. For instance, Costinot et al. (2000) propose an application of copulas to the analysis of the Asian 1997–1998 crisis and conclude that there was an increase in the dependence of the exchange rate returns between the crisis period and the "normal" one. The authors consider it as evidence of contagion. By using a semiparametric mixed copula model, Hu (2006) measures the structure of dependence across four markets[4] over the period from 1970 to 2003 and finds that the dependence is asymmetric and

[4] including the US, the UK, Japan, and Hong Kong.

stronger in the left tail, implying that the markets are more likely to crash together than to boom together.

Until Patton (2006a), copulas were valuable in modelling dependence but neglected the dynamic behavior of dependence. Patton (2006a) introduces the notion of time-varying copulas and uses them to evaluate the asymmetry of dependence structure between the Deutsche mark and the yen against the US dollar. He then finds evidence that the mark–dollar and yen–dollar exchange rates are more correlated when they are depreciating against the dollar than when they are appreciating. More recently, Creal et al. (2013) propose a new mechanism to let the copula parameter change over time. This approach is referred to as Generalized Autoregressive Score (GAS) models. By using both simulation and empirical analyses, the authors find evidence that their method captures the true dependence pattern more closely than the approach employed by Patton (2006a). My thesis, therefore, uses the GAS specification to construct the dynamic copula model.

Despite these advantages, copulas are not well established to ascertain the direction of dependence. Patton (2007) notes that when the analysis is primarily focused on the multivariate conditional mean and/or variance, copulas may not be the "right tool for the job". Instead, he suggests that a standard VAR model and/or a multivariate GARCH model may be more appropriate. Indeed, this classical specification is quite commonly used in literature to investigate the return and volatility spillovers across financial markets. Earlier studies have concentrated on the relationships among developed markets (e.g., Hamao et al., 1990; Lin et al., 1994). More recently, the interest has shifted to focus on spillover effects from developed markets to emerging markets as well as stock linkages among emerging markets. By using a bivariate EGARCH model, Miyakoshi (2003) examines the extent of return and volatility transmissions from Japan and the US to seven Asian equity markets[5] over the period from 1998 to 2000. The results indicate that the return spillover from the US to the Asian markets is substantial, while the volatilities of these markets are influenced more by the Japanese market than by the US. Moreover, Miyakoshi (2003) also finds that there exist some adverse volatility spillovers from the considered Asian markets to the Japanese market. Similarly, Li et al. (2015) use asymmetric VAR-BEKK-GARCH models to evaluate the interdependency between the global leading stock markets (i.e., the US, Japan) and

[5] including the markets in South Korea, Taiwan, Singapore, Thailand, Indonesia, Malaysia, Hong Kong

six Asian developing markets[6] over the period between 1993 and 2012. The authors find the existence of significant one-way volatility transmissions from the American market to both the Japanese and the Asian emerging markets. However, they also note that during the Asian financial crisis, the linkages became not only stronger, but also bidirectional. In addition, the influence of the Japanese market on the Asian emerging markets became more important in the last five years of the sample period. Therefore, previous literature suggests significant spillovers of both returns and volatilities from the US stock market to the Asian emerging markets. Meanwhile, in the relationship between the Japanese market and the other Asian markets, volatility transmissions are more obvious than return linkages. In addition, it is noteworthy that empirical results indicate that volatility spillovers change from normal to turbulent periods. The considered stock markets became more integrated during crises.

2.2. Empirical findings on Vietnamese Stock Market relevant to the studied subject

There are a few papers which examine the relationship between Vietnam's equity market and other markets in the world. However, these papers typically provide information about only one or two aspects of the relationships. For instance, Tran et al. (2016) and Duong et al. (2020) investigate the dependence structure among emerging stock markets, including the Vietnamese market. In contrast, Ngo (2018) and Vo et al. (2018) examine the spillover effects across stock markets from other countries to Vietnam.

Tran et al. (2016) employ constant copulas to daily stock index returns over the period from 2006 to 2015 and conclude that there exists financial contagion from both developed and emerging stock markets[7] to Vietnam's equity market. They also confirm the leading role of US and Japanese markets on the considered Asian emerging markets. More recently, Duong et al. (2020) investigate the tail dependence in the Association of Southeast Asian Nations (ASEAN) stock markets during the period from 2001 to 2017. The authors use various copula functions in their empirical analysis and conclude that the time-varying Student's t copula by Patton (2006a) is the most appropriate way to explain co-movements in the sample data. They also find that the Vietnamese stock market has the weakest dependence with other ASEAN markets and there exists

[6] including China, India, Indonesia, Malaysia, the Philippines and Thailand
[7] The considered emerging markets include Indonesia, Taiwan, the Philippines, Malaysia, Hong Kong, Brazil, Bulgaria, Croatia, Mexico, Russia, Turkey, South Korea, Singapore, Australia, Shanghai, India and Vietnam. The considered developed markets include France, Germany, the UK, the US, Japan, the Netherlands, and Italia.

tail dependence in each pair of markets. My study contributes to Duong et al. (2020) by using the dynamic Student's t copula with a GAS specification (see Creal et al., 2013). The GAS specification has been more successful in capturing time-varying dependencies as it accounts for more characteristics of the copula function via the score function.

On the subject of mean and volatility transmissions from other stock markets to the Vietnamese market, a few studies can be listed. Ngo (2018) and Vo et al. (2018) use a bivariate VAR model in conjunction with a BEKK-GARCH framework to analyze the spillover effects across stock markets. Ngo studies the interdependence in stock prices between China and four countries in Southeast Asia[8] during the period from 2000 to 2018. Vo et al. (2018) examine the relationship between the Vietnamese stock market and the US, Hong Kong and Japanese markets over the sample period between 2000 and 2015. Both papers find evidence of statistically significant return and volatility spillovers between the Vietnamese market and the afore-mentioned markets. Moreover, in both studies the conclusion is that during and after the 2008 global financial crisis, the stock markets became more interrelated.

3. Methodology

3.1. Copula-based models with marginal skewed t distributed innovations

3.1.1. Copula theory

The dependence between random variables $X_1, X_2, \ldots, X_k$ is completely described by their joint distribution function.

$$F(x_1, x_2, \ldots, x_k) = \Pr[X_1 \leq x_1, X_2 \leq x_2, \ldots, X_k \leq x_k].$$

A copula is a function that connects univariate marginal distributions to produce a multivariate distribution. Copula theory is based on Sklar (1959) who states that if F is an k-dimensional distribution function with continuous margins F_1, F_2, …, F_k, then F has a unique dependence function, or copula:

$$F(x_1, x_2, \ldots, x_k) = C\big(F_1(x_1), F_2(x_2), \ldots, F_k(x_k)\big). \tag{1}$$

The so-called Sklar's theorem allows to decompose any multivariate distribution into its k univariate marginal distributions and a k-dimensional copula, which fully captures the dependence

[8] Vietnam, Thailand, Singapore and Malaysia

structure. Furthermore, if I define $U_i \equiv F_i(x_i)$ ("probability integral transformation" of X_i, PIT) then U_i is distributed uniformly on (0,1). It follows that the copula, C, can be interpreted as the joint distribution of the series of probability integral transforms, $U \equiv [U_1, U_2, \dots, U_k]'$.

$$F(x_1, x_2, \dots, x_k) = C\big(F_1(x_1), F_2(x_2), \dots, F_k(x_k)\big)$$

$$= C(u_1, u_2, \dots, u_k) = \Pr[U_1 \le u_1, U_2 \le u_2, \dots, U_k \le u_k],$$

$$\Leftrightarrow C(u_1, u_2, \dots, u_k) = F\Big(F_1^{-1}(u_1), F_2^{-1}(u_2), \dots, F_k^{-1}(u_k)\Big). \tag{2}$$

It is clear from equation (2) that the copula is a map from $[0,1]^k$ to $[0,1]$. When the densities f_i exist,[9] the above representation of the joint cumulative density function (CDF) implies the following representation for the joint probability density function (PDF):

$$f(x_1, x_2, \dots, x_k) = \frac{\partial^k F(x_1, x_2, \dots, x_k)}{\partial X_1 \partial X_2 \dots \partial X_k} = \frac{\partial^k C\big(F_1(x_1), F_2(x_2), \dots, F_k(x_k)\big)}{\partial F_1(x_1)\, \partial F_2(x_2) \dots \partial F_k(x_k)} \times \prod_{i=1}^{k} f_i(x_i) =$$

$$= \frac{\partial^k C(u_1, u_2, \dots, u_k)}{\partial U_1 \partial U_2 \ \dots \partial U_k} \times \prod_{i=1}^{k} f_i(x_i) = c(u_1, u_2, \dots, u_k) \times \prod_{i=1}^{k} f_i(x_i), \tag{3}$$

where:

$$c(u_1, u_2, \dots, u_k) = \frac{\partial^k C(u_1, u_2, \dots, u_k)}{\partial U_1 \partial U_2 \ \dots \partial U_k}.$$

One of the applications of this theorem in econometric modelling is in the construction of flexible multivariate distributions (Patton, 2006b). We may combine a mix of k different marginal distributions with any copula to form a valid multivariate distribution. For example, in the bivariate context, one might link a Gaussian distributed variable with an exponentially distributed variable by a Student's t copula to obtain a valid bivariate distribution. This ability allows the researcher to employ the large body of previous literature on modeling univariate time series, leaving only the task of modelling the dependence structure.

Equation (3) implies the following formula for the log-likelihood function L of a random sample of (i.i.d.) vectors $x^{(t)}$, $x^{(t)} = \Big(x_1^{(t)}, x_2^{(t)}, \dots, x_k^{(t)}\Big), t = 1, 2, \dots, n$ (observations):

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[9] Here I use lowercase letters (e.g., f_i) to denote the probability density function (PDF) and uppercase letters (e.g., F_i) to represent the cumulative density function (CDF).

$$L = \sum_{t=1}^{n} \log f\left(x_1^{(t)}, x_2^{(t)}, \dots, x_k^{(t)}\right)$$

$$= \sum_{t=1}^{n} \log c\left(u_1^{(t)}, u_2^{(t)}, \dots, u_k^{(t)}\right) + \sum_{i=1}^{k}\sum_{t=1}^{n} \log f_i\left(x_i^{(t)}\right)$$

$$= \underbrace{L_c}_{dependence} + \underbrace{\textstyle\sum_{i=1}^{k} L_i}_{marginals}, \tag{4}$$

where: $u_i^{(t)} = F_i\left(x_i^{(t)}\right)$; $L_c = \sum_{t=1}^{n} \log c\left(u_1^{(t)}, u_2^{(t)}, \dots, u_k^{(t)}\right)$; $L_i = \sum_{t=1}^{n} \log f_i\left(x_i^{(t)}\right)$.

Thus, L can be decomposed into two parts: (i) the log-likelihood contribution from dependence structure in the data represented through the copula C, and (ii) the log-likelihood contributions from each margin. Note that when the k variables are independent from one another, the first part in equation (4) equals zero.

Suppose that for fully parametric models the density of the copula C is determined by the vector of parameters κ, $c(u_1, u_2, \dots, u_k; \kappa)$ and the margins F_i and the corresponding univariate densities f_i are identified by (vector) parameters Ψ_i, i.e., $F_i = F_i(x_i; \Psi_i)$ and $f_i = f_i(x_i; \Psi_i)$. The vector of parameters for the whole specification, $\Theta = (\Psi_1, \Psi_2, \dots, \Psi_k, \kappa)$, can be estimated by the maximum likelihood (ML) estimation. There are two ways to conduct the estimation procedure: (i) simultaneous maximization of the log-likelihood L in equation (4), and (ii) multi-stage ML estimation (sometimes called “inference functions for margins” method).

The multi-stage ML procedure can be considered as the ML estimation of the dependence structure given the estimated margins. First, the parameters Ψ_i for each margin are estimated separately through the ML method:

$$\widehat{\Psi}_i^{MSML} = argmax_{\Psi_i} L_i(\Psi_i) = argmax_{\Psi_i} \textstyle\sum_{t=1}^{n} \log f_i\left(x_i^{(t)}; \Psi_i\right).$$

Second, the parameters κ of the copula C are then estimated by maximizing the copula likelihood contribution L_c conditional on $\Psi_i = \widehat{\Psi}_i^{MSML}$:

$$\hat{\kappa}^{MSML} = argmax_{\kappa} L_c\left(\widehat{\Psi}_1^{MSML}, \widehat{\Psi}_2^{MSML}, \dots, \widehat{\Psi}_k^{MSML}, \kappa\right)$$

$$= argmax_{\kappa} \textstyle\sum_{t=1}^{n} \log c\left(F_1\left(x_1^{(t)}; \widehat{\Psi}_1^{MSML}\right), F_2\left(x_2^{(t)}; \widehat{\Psi}_2^{MSML}\right), \dots, F_k\left(x_k^{(t)}; \widehat{\Psi}_k^{MSML}\right); \kappa\right).$$

The multi-stage ML estimation has the benefit of being considerably easier to implement, at the cost of an efficiency loss. However, simulation studies done by Patton (2006b) indicate that this loss is not great in many cases.

Similar to the ML estimator, the multi-stage ML estimator is consistent and asymptotically normal under the usual regularity conditions (see Patton, 2006b) for the multivariate model and for each of its margins. The robust estimator of the asymptotic multi-stage ML covariance matrix is given by:

$$\hat{V}_{MSML} = \hat{A}_n^{-1}\hat{B}_n\left(\hat{A}_n^{-1}\right)',$$

where:

$\hat{B}_n = \frac{1}{n}\sum_{t=1}^{n} \hat{s}_t\hat{s}_t'$ (the covariance matrix of the scores),

$\hat{s}_t \equiv (\hat{s}_{1t}', \hat{s}_{2t}', \dots, \hat{s}_{kt}', \hat{s}_{ct}')'$,

$\hat{s}_{it} = \frac{\partial}{\partial\Psi_i}\log f_{it}\left(x_i^{(t)}; \hat{\Psi}_i^{MSML}\right), i = 1, 2, \dots, k,$

$\hat{s}_{ct} = \frac{\partial}{\partial\kappa}\log c_t\left(F_{1t}\left(x_1^{(t)}; \hat{\Psi}_1^{MSML}\right), F_{2t}\left(x_2^{(t)}; \hat{\Psi}_2^{MSML}\right), \dots, F_{kt}\left(x_k^{(t)}; \hat{\Psi}_k^{MSML}\right); \hat{\kappa}^{MSML}\right),$

$\hat{A}_n = \frac{1}{n}\sum_{t=1}^{n} \hat{H}_t$ (the hessian),

$$\hat{H}_t = \begin{bmatrix} \nabla^2_{11,t} & 0 & \cdots & 0 & 0 \\ 0 & \nabla^2_{22,t} & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & \nabla^2_{kk,t} & 0 \\ \nabla^2_{1c,t} & \nabla^2_{2c,t} & \cdots & \nabla^2_{kc,t} & \nabla^2_{cc,t} \end{bmatrix},$$

$\nabla^2_{ii,t} = \frac{\partial^2}{\partial\Psi_i\partial\Psi_i'}\log f_{it}\left(x_i^{(t)}; \hat{\Psi}_i^{MSML}\right), i = 1, 2, \dots, k,$

$\nabla^2_{ic,t} = \frac{\partial^2}{\partial\kappa\partial\Psi_i'}\log c_t\left(F_{1t}\left(x_1^{(t)}; \hat{\Psi}_1^{MSML}\right), F_{2t}\left(x_2^{(t)}; \hat{\Psi}_2^{MSML}\right), \dots, F_{kt}\left(x_k^{(t)}; \hat{\Psi}_k^{MSML}\right); \hat{\kappa}^{MSML}\right),$

$\nabla^2_{cc,t} = \frac{\partial^2}{\partial\kappa\partial\kappa'}\log c_t\left(F_{1t}\left(x_1^{(t)}; \hat{\Psi}_1^{MSML}\right), F_{2t}\left(x_2^{(t)}; \hat{\Psi}_2^{MSML}\right), \dots, F_{kt}\left(x_k^{(t)}; \hat{\Psi}_k^{MSML}\right); \hat{\kappa}^{MSML}\right).$

As there are no closed forms for any of the above scores nor for the hessian, the estimator of the covariance matrix, $\hat{V}_{MSML}$, is quite tedious to obtain. For simplicity, I use central finite differences as the approximation of derivatives. I also compute $\hat{V}_{MSML}$ using the Newey-West heteroskedasticity-autocorrelation-consistent (HAC) estimator of the variance-covariance matrix to account for the possibility of autocorrelation in the error terms.

3.1.2. Marginal models

Prior to fitting the copula function, I need to specify an appropriate model for the marginal densities. As documented by many empirical studies, financial asset returns share some stylized facts such as: fat tails, volatility clustering, and leverage effect. Therefore, employing autoregressive moving average (ARMA) models for the conditional means as well as asymmetric generalized autoregressive conditional heteroskedasticity models (i.e., GJR-GARCH) for the conditional variances is a common choice of many researchers while modelling univariate time series (e.g., Patton, 2013). The GJR-GARCH(p, o, q) model is proposed by Glosten et al. (1993). It extends the standard GARCH model of Bollerslev (1986) to capture the leverage effect, an important phenomenon in the conditional variance of stock returns. The whole specification is represented as follows:

$$r_{it} = \delta + \sum_{j=1}^{p} \varphi_j r_{it-j} + \sum_{j=1}^{q} \theta_j \varepsilon_{it-j} + \varepsilon_{it} = \mu_{it} + \varepsilon_{it} \quad \text{for } i = 1,2, \tag{5}$$

$$\varepsilon_{it} = \sigma_{it} z_{it}, z_{it} \sim i.i.d. F_i(0,1), \tag{6}$$

$$\sigma_{it}^2 = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{it-j}^2 + \sum_{j=1}^{o} \gamma_j \varepsilon_{it-j}^2 I_{[\varepsilon_{it-j}<0]} + \sum_{j=1}^{q} \beta_j \sigma_{it-j}^2, \tag{7}$$

where: $I_{[\varepsilon_{it-j}<0]}$ is an indicator function that takes the value 1 if $\varepsilon_{it-j} < 0$ and 0 otherwise; r_{it} is the continuously compounded return of the stock index i at time t; ε_{it} is interpreted as the shocks from the stochastic process at time t; δ is the constant term in the conditional mean equation; φ_j is the coefficient on the AR term at lag j; θ_j is the coefficient on the MA term at lag j; μ_{it} is the conditional mean at time t given the time $t-1$ information set, $\mathcal{F}_{t-1}$; z_{it} (standardized residuals) is an unobservable random variable belonging to an i.i.d. process; σ_{it}^2 is the variance of ε_{it} conditional on $\mathcal{F}_{t-1}$; ω is the constant term in the conditional variance equation; α_j measures the impact of past shocks on the conditional variance; γ_j represents the sensitivity of the conditional variance to negative shocks; β_j measures the persistence of the conditional variance.

In this study, for simplicity, I fit an ARMA(p,q) combined with a GJR-GARCH(1,1,1) for each time series. Thus, equation (7) becomes:

$$\sigma_{it}^2 = \omega + \alpha\varepsilon_{it-1}^2 + \gamma\varepsilon_{it-1}^2 I_{[\varepsilon_{it-1}<0]} + \beta\sigma_{it-1}^2 \tag{8}$$

The parameters of the GJR-GARCH must be restricted to ensure that the inferred variances are always positive. The restrictions are $\omega > 0$, $\alpha \geq 0$, $\alpha + \gamma \geq 0$, $\beta \geq 0$, and for covariance stationarity: $\alpha + 0.5 \times \gamma + \beta < 1$.

In order to choose the optimal orders of p and q for the conditional mean equation, I use information criteria, i.e., the Akaike and the Bayesian Information Criteria (AIC, BIC) and consider ARMA models with both p and q in the interval [0,3].

It is well known that the standardized residuals ($z_{it} = \varepsilon_{it}/\sigma_{it}$) obtained from a GARCH model are generally non-normal (e.g., Bollerslev, 1987). This observation has led to the introduction of heavy-tailed distributions for innovations. For instance, Bollerslev (1987) uses a t-GARCH model to investigate the dynamic changes in prices of foreign exchange rates and stock indices. Hansen (1994) extends the t-GARCH model to account for the skewness of financial data. He builds a new density, referred to as the skewed Student's t distribution, with which he models the GARCH innovations. This thesis follows the work of Hansen (1994) in modelling the margin. Thus, the marginal distribution $F_i(0,1)$ in equation (6) is assumed to be a skewed Student's t distribution.

A random variable, Z_{it}, which has a skewed Student's t distribution with ν degrees of freedom and λ skewness parameter, denoted as $Z_{it} \sim SkewT(\nu, \lambda)$, has the following density function:

$$f(Z_{it}|\nu,\lambda) = \begin{cases} bc\left(1 + \dfrac{1}{\nu - 2}\left(\dfrac{bZ_{it} + a}{1 - \lambda}\right)^2\right)^{-\frac{\nu+1}{2}}, & Z_{it} < -\dfrac{a}{b} \\ bc\left(1 + \dfrac{1}{\nu - 2}\left(\dfrac{bZ_{it} + a}{1 + \lambda}\right)^2\right)^{-\frac{\nu+1}{2}}, & Z_{it} \geq -\dfrac{a}{b} \end{cases},$$

where ν and λ are the two shape parameters of the distribution: $2 < \nu < \infty$, and $-1 < \lambda < 1$; the degrees of freedom, ν, which controls the thickness of the tails, and the skewness parameter, λ, which controls the level of asymmetry. The constants a, b, and c are given by:

$$a = \frac{4\lambda c(\nu - 2)}{\nu - 1},$$

$$b^2 = 1 + 3\lambda^2 - a^2,$$

$$c = \frac{\Gamma\left(\frac{\nu + 1}{2}\right)}{\sqrt{\pi(\nu - 2)}\Gamma\left(\frac{\nu}{2}\right)}.$$

When λ = 0 the skewed Student's t distribution collapses to the standard Student's t distribution. As $\nu \to \infty$ it is reduced to an asymmetric Normal distribution, and when $\nu \to \infty$ and λ = 0 it collapses to the standard normal distribution N(0,1). I also assume that the parameters ν and λ are constant over time.

In this thesis, for simplicity, I follow the empirical work done by Patton (2013) and estimate the univariate conditional mean and variance models with Gaussian quasi-maximum likelihood. After that, I fit the skewed Student's t distribution to the inferred standardized residuals from the previous step, and use the ML method to estimate the parameters ν and λ. It is noteworthy that other researchers conduct the estimation of marginal densities differently. For instance, Jondeau et al., 2006 estimate the conditional mean and variance models as a whole using the assumed marginal distribution (i.e., the Hansen's skewed Student's t distribution). However, in the interest of time I decide to follow the method of Patton (2013) as it is easier to implement.

3.1.3. Copula-based models

In this study, the interdependence between the Vietnamese stock market and the markets of the US, Japan, and the EU28 are investigated in pairs. Thus, I use bivariate copulas and equation (1) can be rewritten as follows:

$$F(z_1, z_2) = \Pr[Z_1 \leq z_1, Z_2 \leq z_2] = C\big(F_1(z_1), F_2(z_2)\big).$$

This is equivalent to:

$$C(u_1, u_2) = F\big(F_1^{-1}(u_1), F_2^{-1}(u_2)\big),$$

where U_i is the PIT of the marginal standardized residuals Z_i using the estimated skewed t distribution function obtained from the previous subsection, $U_i \equiv F_{SkewT(\hat{\nu},\hat{\lambda})}(z_i)$. Let $i = 1$ denote the Vietnamese market and $i = 2$ represent one of the other markets (i.e., US, Japan, or the

EU28). In other words, the thesis refers to Vietnam as the first market and one of the other countries/areas as the second market.

For comparison purposes, I consider two copulas: the Gaussian copula and the Student's t copula. These two copula functions have different characteristics in terms of tail dependence. The Gaussian copula has no tail dependence, while the Student's t copula has symmetric non-zero tail dependence. By comparing these two copulas, I can show the importance of investigating tail dependence in risk management. The normal copula is the copula associated with the bivariate normal distribution, while the Student's t copula is the dependence function which has the form of a bivariate Student's t distribution. Patton (2006b) provides the functional forms of these two copulas' densities.

The Gaussian copula is defined by the densities C_N (CDF) and c_N (PDF) with correlation matrix Σ and correlation coefficient ρ:

$$C_N(u_1, u_2; \Sigma) = \Phi_\Sigma\left(\Phi^{-1}(u_1), \Phi^{-1}(u_2)\right),$$

$$c_N(u_1, u_2; \Sigma) = \frac{1}{\sqrt{\det(\Sigma)}} \exp\left(-\frac{\left(\Phi^{-1}(u_1), \Phi^{-1}(u_2)\right)(\Sigma^{-1} - I_2)\left(\Phi^{-1}(u_1), \Phi^{-1}(u_2)\right)'}{2}\right) \Leftrightarrow$$

$$c_N(u_1, u_2; \rho) = \frac{1}{\sqrt{1-\rho^2}} \exp\left(-\frac{\rho^2\left(\Phi^{-1}(u_1)^2 + \Phi^{-1}(u_2)^2\right) - 2\rho\Phi^{-1}(u_1)\Phi^{-1}(u_2)}{2(1-\rho^2)}\right), \qquad (9)$$

where: $\rho \in (-1,1)$, Φ_Σ is the bivariate normal distribution with correlation matrix Σ, and Φ^{-1} is the inverse CDF of a N(0,1) random variable. The correlation coefficient, ρ, represents the strength of the dependence between the two markets in each pair.

Similarly, the Student's t copula is defined by the densities C_T (CDF) and c_T (PDF) with a degrees-of-freedom parameter $\nu > 2$ and a correlation matrix Σ with correlation coefficient ρ:

$$C_T(u_1, u_2; \Sigma, \nu) = T_{\Sigma,\nu}\left(T_\nu^{-1}(u_1), T_\nu^{-1}(u_2)\right),$$

$$c_T(u_1, u_2; \Sigma, \nu) = \frac{\Gamma\left(\frac{\nu+2}{2}\right)\Gamma\left(\frac{\nu}{2}\right)\left(1 + \frac{\left(T_\nu^{-1}(u_1), T_\nu^{-1}(u_2)\right)\ \Sigma^{-1}\left(T_\nu^{-1}(u_1), T_\nu^{-1}(u_2)\right)'}{\nu}\right)^{-\frac{\nu+2}{2}}}{\det(\Sigma)^{\frac{1}{2}}\ \Gamma\left(\frac{\nu+1}{2}\right)^2 \prod_{i=1}^{2}\left(1 + \frac{T_\nu^{-1}(u_i)^2}{\nu}\right)^{-\frac{\nu+1}{2}}},$$

which is equivalent to:

$$c_T(u_1,u_2;\rho,\nu) = \frac{\Gamma\left(\frac{\nu+2}{2}\right)\left(1+\frac{T_\nu^{-1}(u_1)^2+T_\nu^{-1}(u_2)^2+2\,\rho\,T_\nu^{-1}(u_1)T_\nu^{-1}(u_2)}{\nu(1-\rho^2)}\right)^{-\frac{\nu+2}{2}}}{\Gamma\left(\frac{\nu}{2}\right)\nu\pi\sqrt{1-\rho^2}\;\,t_\nu\left(T_\nu^{-1}(u_1)\right)\;t_\nu\left(T_\nu^{-1}(u_2)\right)}, \quad (10)$$

where: $\rho \in (-1,1)$ and $\nu \in (2,\infty)$, $T_{\Sigma,\nu}$ is the bivariate standardized Student's t distribution with correlation matrix Σ and degrees of freedom ν, T_ν^{-1} is the inverse CDF of a standard Student's t random variable with ν degrees of freedom, t_ν is the PDF of a standard Student's t random variable with ν degrees of freedom.

As previously mentioned, one advantage of the Student's t copula over the Gaussian is that it allows for non-zero dependence in the extreme tails. Understanding the tail behavior between return series in different market conditions is crucial not only for asset and risk management, but also for market supervision. Tail dependence is measured by the probability that two random variables are jointly dependent in their tails. Joe (1997) and Coles et al. (1999) define the upper tail dependence, τ^u, and the lower tail dependence, τ^l, as follows:

$$\tau^u = \lim_{q\to 1^-} \Pr\left(X_2 > F_2^{-1}(q) \,|\, X_1 > F_1^{-1}(q)\right) = \lim_{q\to 1^-} \Pr(U_2 > q | U_1 > q)$$

$$= \lim_{q\to 1^-} \frac{1-2q+C(q,q)}{1-q},$$

$$\tau^l = \lim_{q\to 0^+} \Pr\left(X_2 \le F_2^{-1}(q) \,|\, X_1 \le F_1^{-1}(q)\right) = \lim_{q\to 0^+} \Pr(U_2 \le q | U_1 \le q)$$

$$= \lim_{q\to 0^+} \frac{C(q,q)}{q},$$

where τ^u and $\tau^l \in [0,1]$. If the tail dependence coefficients, τ^u and τ^l, are both larger than zero, the two markets' returns tend to be upper (right) or lower (left) tail dependent respectively. Thus, the parameters τ^u and τ^l capture the behavior of the random variables during extreme events. For example, $\tau^l > 0$ implies a non-zero probability of observing extremely large losses of both markets at the same time.

The tail dependence coefficients implied by the Student's t copula are symmetric and computed as follows (Demarta et al., 2005):

$$\tau^u = \tau^l = 2\, T_{\nu+1}\left(-\sqrt{\nu+1}\sqrt{\frac{1-\rho}{1+\rho}}\right), \tag{11}$$

where $T_{\nu+1}$ is the CDF of a standard Student's t random variable with $\nu + 1$ degrees of freedom.

3.1.4. Time-varying Student's t-GAS copula model

3.1.4.1. Testing for presence of time-varying dependence

It is well known that correlation is often higher in high-volatility regimes than in low-volatility regimes (e.g., Hamao et al., 1990; Longin et al., 1995). Therefore, it is natural to assume that the dependence structure can evolve over time. However, to provide more information, I also follow Patton (2013) and employ three types of tests for time-varying dependence. The null hypotheses in all of Patton's tests are in favor of a constant conditional copula. The first test considers a structural break in rank correlation at a specified point in the sample, t^*. The test has the null hypothesis that the rank correlation coefficient before and after day t^* is the same, i.e., H_0: $\rho_1 = \rho_2$ against H_1: $\rho_1 \neq \rho_2$, where:

$$\rho_t = \begin{cases} \rho_1, & t \leq t^* \\ \rho_2, & t > t^* \end{cases},$$

and ρ_t is the rank correlation measure at time t.

The second test is exactly like the first one, except that it allows for a change-point at an unknown date. I here assume that the break (if any) did not occur near the edges of the sample period. Thus, I have sufficient observations to estimate the pre- and post-break parameters. A common choice is to search for change-points in the interval $[0.15n, 0.85n]$, where n is the sample size.

The third type is a test for autocorrelation in the dependence measure. The test considers the following regression:

$$u_{1t}u_{2t} = \vartheta_0 + \frac{\vartheta_1}{p}\sum_{j=1}^{p} u_{1t-j}u_{2t-j} + \epsilon_t\,, \tag{12}$$

where u_{it} is the PIT of the standardized residuals using the empirical distribution function $u_{it} = F_i^{edf}(\mathcal{E})$:

$$F_i^{edf}(\mathcal{E}) = \frac{1}{n+1}\sum_{t=1}^{n} 1\{z_{it} \leq \mathcal{E}\},$$

where $1\{z_{it} \leq \mathcal{E}\}$ is an indicator function assuming the value 1 if $z_{it} \leq \mathcal{E}$ and 0 otherwise. Under the null of a constant copula, ϑ_1 should be equal to zero, thus I test for the significance of ϑ_1 in equation (12) through a simple t-test.

Significance levels for all three test statistics can be obtained using the i.i.d. bootstrap method of Remillard, 2017 and Patton, 2013. The process can be described as follows: (i) I randomly draw rows, with replacement, from the matrix of PIT of the fitted standardized residuals until I get a bootstrapped sample of length n, and (ii) I calculate the t-statistic of the test for the bootstrapped sample, and (iii) I repeat the two previous steps 10,000 times, and (iv) an approximate p-value for the test is then given by the proportion of simulations that generate a test statistic greater than the one observed in the data.

3.1.4.2. Generalized autoregressive score (GAS) specification

Patton (2006a) introduces the notion of dynamic copulas and use them to model the dependence path of different currency exchange rates. More recently, Creal et al. (2013) present a new framework to model the time-variation in copulas, named Generalized Autoregressive Score (GAS) models. For both simulated and empirical data, the GAS specification tends to be more successful in capturing time-varying dependencies as it accounts for more characteristics of the copula function via the score function. My study employs the GAS framework combined with a Student's t copula to model the dynamic process of dependence over time, assuming the degrees of freedom is constant.

Let the copula parameter ρ_t evolve through time following a function of its lagged values and a "forcing variable" that is related to the score of the copula log-likelihood. As the copula parameter ρ_t is forced to take values in the interval (-1,1), I need to transform it to guarantee this restriction and then model the evolution of the transformed parameter, denoted f_t, by a GAS process. The whole course is given by:

$$\rho_t = \frac{1-\exp(-f_t)}{1+\exp(-f_t)} \Leftrightarrow f_t = \log\left(\frac{1+\rho_t}{1-\rho_t}\right), \tag{13}$$

$$f_{t+1} = w + bf_t + a\tilde{I}_t^{-1/2}\tilde{s}_t \ , \tag{14}$$

$$\tilde{s}_t = \frac{\partial}{\partial f} \log c(u_{1t}, u_{2t}; \rho_t) = \left(\frac{\partial \rho_t}{\partial f}\right)^{-1} \frac{\partial}{\partial \rho} \log c(u_{1t}, u_{2t}; \rho_t) = \left(\dot{h}_t\right)^{-1} . s_t \ ,$$

$$\dot{h}_t = \frac{\partial \rho_t}{\partial f} = \frac{2\exp(-f_t)}{1+\exp(-f_t)^2} \ ,$$

$$s_t = \frac{\partial}{\partial \rho} \log c(u_{1t}, u_{2t}; \rho_t) \ ,$$

$$\tilde{I}_t = E_{t-1}[\tilde{s}_t \, \tilde{s}_t'] = \left(\dot{h}_t\right)^{-1} I_t \left(\dot{h}_t'\right)^{-1},$$

$$I_t = E_{t-1}[s_t \, s_t'] \ .$$

Therefore, the future value of the transformed parameter is a function of a constant, its current value, and the scaled score of the conditional copula-likelihood. The information matrices in this case are computed numerically (see Appendix of Creal et al. 2013).

3.2. Bivariate VAR-GJR-BEKK-GARCH model

As mentioned in the introduction section, the dependence structure and the spillover effect are indeed relevant. Both expressions are used to illustrate the interaction between different markets. However, with the spillover effect, one can see the direction of the dependence. In other words, one can examine not only whether shocks in a market can trigger changes of returns and/or volatilities in a different market, but also whether the relationship is unidirectional or bidirectional. Therefore, investigating both the dependence structure and the spillover effect is necessary. This thesis employs a bivariate VAR-GJR-BEKK-GARCH model to explore return and volatility transmissions between the markets.

However, it is noteworthy that copula-based models can be used to investigate the spillover effect as well. For example, since the US market opens only after the Vietnamese market closes, I can employ the copula to model dependence between returns on day t in the Vietnamese market and those on day $t-1$ in the American market. Based on that result, I can draw the conclusion on the return spillover from the US market to the Vietnamese market. On the other hand, to examine whether return spillovers between the two markets can go in the opposite direction, I can pair returns on day t in the Vietnamese market with those on the same day in the American market. In addition to that, I can fit a copula to the squared standardized residuals in order to investigate the volatility spillover between the markets. Although using copulas to explore return and volatility transmissions between markets is feasible and interesting, it is also time-consuming. Therefore, in this paper, I use bivariate VAR-GJR-BEKK-GARCH models which are easier and faster to implement.

3.2.1. Unit root and stationarity tests

Both the copula-based model and the VAR-GJR-BEKK-GARCH framework require the return time series to be stationary. I therefore use the augmented Dickey-Fuller (ADF) test by Dickey (1984) as well as the KPSS test by Kwiatkowski et al. (1992) to check for the stationarity of the data. The ADF test verifies the null hypothesis that a time series y_t is I(1), i.e., it is a unit root process, against the alternative that it is stationary, i.e., it is I(0). The test assumes that the dynamics in the data have an ARMA specification. The ADF test is based on estimating the test regression:

$$y_t = \zeta' D_t + \phi y_{t-1} + \sum_{j=1}^{p} \gamma_j \nabla y_{t-j} + \epsilon_t \ ,$$

where: D_t is a vector of deterministic terms (constant, trend, etc.); the terms ∇y_{t-j} are the lagged difference terms. The number of lags included in the regression is set so that the error ϵ_t is serially uncorrelated. Under the null hypothesis, y_t is I(1) which implies that $\phi = 1$. The ADF t-statistic is given by:

$$ADF = \frac{\hat{\phi} - 1}{SE\ (\hat{\phi})}.$$

The lag length p is chosen according to the rule of thumb suggested by Schwert (1989):

$$p_{max} = 12\left(\frac{n}{100}\right)^{1/4},$$

where n is the sample size.

Beside the ADF test, I also use the KPSS test to confirm the results. The KPSS test verifies the null that y_t is I(0). The specification used in the test is given by:

$$y_t = \zeta' D_t + \mu_t + u_t \ ,$$

$$\mu_t = \mu_{t-1} + \epsilon_t, \epsilon_t \sim WN\ (0, \sigma_\epsilon^2),$$

where: D_t are deterministic components; u_t is I(0); μ_t is a random walk process with innovation variance σ_ϵ^2. The null hypothesis is H_0: $\sigma_\epsilon^2 = 0$ while the alternative is H_1: $\sigma_\epsilon^2 > 0$. The KPSS test statistic is given by:

$$KPSS = \frac{n^{-2}\sum_{t=1}^{n}\hat{S}_t^2}{\hat{s}^2},$$

where: n is the sample size; $\hat{s}^2$ is the Newey-West estimate of the long-run variance; $\hat{S}_t = \sum_{j=1}^{t}\hat{u}_j$; $\hat{u}_j$ is the residual of the regression of y_t on D_t. I follow Kwiatkowski et al. (1992) and choose $\sqrt{n}$ as the lag length.

3.2.2. Bivariate VAR(p)-GJR-BEKK-GARCH(1,1,1) model

I use a bivariate stable and stationary vector autoregressive VAR(p) framework to model the conditional mean of the system of two time series. Let $\mathcal{F}_{t-1}$ denote the set of past information available at time t, thus the regression for the mean given $\mathcal{F}_{t-1}$ is a bivariate VAR(p) model:

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \varphi_{11}^1 & \varphi_{12}^1 \\ \varphi_{21}^1 & \varphi_{22}^1 \end{bmatrix} \begin{bmatrix} r_{1,t-1} \\ r_{2,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \varphi_{11}^p & \varphi_{12}^p \\ \varphi_{21}^p & \varphi_{22}^p \end{bmatrix} \begin{bmatrix} r_{1,t-p} \\ r_{2,t-p} \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix}, \tag{15}$$

where r_1 stands for log-returns of the first market's index and r_2 denotes log-returns of the second market's index. The vector $u_t = \left(u_{1,t}, u_{2,t}\right)'$ is a white noise, i.e., E(u_t) = 0, E($u_t u_t{}'$) = Σ_t and E($u_t u_s{}'$) = 0 for s≠t. The innovations u_t can be considered as shocks from the process. Σ_t is a 2 by 2 matrix representing the conditional variance-covariance matrix of innovations, i.e., $\Sigma_t = E(u_t u_t{}' | \mathcal{F}_{t-1})$. Thus, u_t are conditionally distributed with mean 0 and variance Σ_t:

$$u_t | \mathcal{F}_{t-1} \sim \mathrm{F}\,(0, \Sigma_t)\,.$$

More specifically, the mean equation for each market can be written as follows:

$$r_{1,t} = \mu_1 + \varphi_{11}^1 r_{1,t-1} + \varphi_{12}^1 r_{2,t-1} + \cdots + \varphi_{11}^p r_{1,t-P} + \varphi_{12}^p r_{2,t-P} + u_{1,t}\,, \tag{16}$$

$$r_{2,t} = \mu_2 + \varphi_{21}^1 r_{1,t-1} + \varphi_{22}^1 r_{2,t-1} + \cdots + \varphi_{21}^p r_{1,t-P} + \varphi_{22}^p r_{2,t-P} + u_{2,t}\,. \tag{17}$$

Thus, it is clear that the return on each market is a linear function of its own past as well as past returns in the other market. The possibility of spillovers in returns from Market i to Market j can be examined by testing the joint hypotheses that $\varphi_{ij}^1 = \varphi_{ij}^2 = \cdots = \varphi_{ij}^p = 0$.

Based on the residuals from equation (15), the conditional variance-covariance matrix of innovations, Σ_t, is assumed to follow a GJR-BEKK-GARCH(1,1,1) specification (Kroner et al., 1998). This framework is a multivariate extension of a univariate GJR-GARCH model in which:

$$\Sigma_t = OO' + A'\,u_{t-1}u_{t-1}'A + G'\eta_{t-1}\eta_{t-1}'G + B'\Sigma_{t-1}B, \tag{18}$$

where: O is a 2 by 2 lower triangular matrix; A, B and G are 2 by 2 parameter matrices; and the term $\eta_{t-1} = u_{t-1} \odot I_{[u_{t-1}<0]}$ where $I_{[u_{t-1}<0]}$ is a 2 by 1 vector of indicator variables so that the i^{th} position is 1 if $u_{i,t-1} < 0$.

The model in matrix notation is given by:

$$\begin{bmatrix} \sigma_{11,t} & \sigma_{12,t} \\ \sigma_{12,t} & \sigma_{22,t} \end{bmatrix} = \begin{bmatrix} o_{11} & 0 \\ o_{21} & o_{22} \end{bmatrix} \begin{bmatrix} o_{11} & 0 \\ o_{21} & o_{22} \end{bmatrix}'$$
$$+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} u_{1,t-1}^2 & u_{1,t-1}\, u_{2,t-1} \\ u_{1,t-1}\, u_{2,t-1} & u_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' \begin{bmatrix} \eta_{1,t-1}^2 & \eta_{1,t-1}\, \eta_{2,t-1} \\ \eta_{1,t-1}\, \eta_{2,t-1} & \eta_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} \sigma_{11,t-1} & \sigma_{12,t-1} \\ \sigma_{21,t-1} & \sigma_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}.$$

Matrix A shows how conditional variances are correlated with past shocks. Matrix G captures the asymmetric response of the markets to past negative shocks. Matrix B illustrates the volatility persistence of the markets. Moreover, the diagonal elements of the matrices measure the own effect, while the off-diagonal elements capture the cross-market effect. For instance, the diagonal elements of matrix A (a_{ii}) measure the effect of own past shocks on a market's current volatility. Meanwhile, the off-diagonal elements of the matrix A (a_{ij}) capture the effect of country i's past shock on country j's current volatility.

More specifically, the variance of the first market's returns can be written as follows:

$$\begin{aligned} \sigma_{11,t} = {} & o_{11}^2 + a_{11}^2 u_{1,t-1}^2 + 2a_{11}a_{21}\, u_{1,t-1}\, u_{2,t-1} + a_{21}^2 u_{2,t-1}^2 + \\ & g_{11}^2 \eta_{1,t-1}^2 + 2g_{11}g_{21}\, \eta_{1,t-1}\, \eta_{2,t-1} + g_{21}^2 \eta_{2,t-1}^2 + \\ & b_{11}^2 \sigma_{11,t-1} + 2b_{11}b_{21}\sigma_{12,t-1} + b_{21}^2 \sigma_{22,t-1} . \end{aligned} \tag{19}$$

In addition, the variance of the second market's returns is given by:

$$\begin{aligned} \sigma_{22,t} = {} & o_{21}^2 + o_{22}^2 + a_{12}^2 u_{1,t-1}^2 + 2a_{12}a_{22}\, u_{1,t-1}\, u_{2,t-1} + a_{22}^2 u_{2,t-1}^2 + \\ & g_{12}^2 \eta_{1,t-1}^2 + 2g_{12}g_{22}\, \eta_{1,t-1}\, \eta_{2,t-1} + g_{22}^2 \eta_{2,t-1}^2 + \\ & b_{12}^2 \sigma_{11,t-1} + 2b_{12}b_{22}\sigma_{12,t-1} + b_{22}^2 \sigma_{22,t-1} . \end{aligned} \tag{20}$$

Moreover, the covariance between the two markets' returns is given by:

$$\sigma_{12,t} = o_{11}o_{21} + a_{11}a_{12}u_{1,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})\, u_{1,t-1}\, u_{2,t-1} + a_{21}a_{22}u_{2,t-1}^2 + g_{11}g_{12}\eta_{1,t-1}^2 + (g_{12}g_{21} + g_{11}g_{22})\, \eta_{1,t-1}\, \eta_{2,t-1} + g_{21}g_{22}\eta_{2,t-1}^2 + b_{11}b_{12}\sigma_{11,t-1} + (b_{12}b_{21} + b_{11}b_{22})\, \sigma_{12,t-1} + b_{21}b_{22}\sigma_{22,t-1}\,. \tag{21}$$

The whole specification is estimated simultaneously by (quasi) ML method. For comparison purposes, I assume two different distributions for the error terms u_t: the Gaussian distribution and the Student's t distribution.

When u_t are bivariate normally distributed, the log-likelihood function of the whole framework for a sample u_t $(t = 1, \dots, n)$ is given by:

$$\ln l\,(\Theta\,) = \sum_{t=1}^{n} \ln l_t(\Theta\,)\,, \tag{22}$$

$$\ln l_t(\Theta) = -\frac{K}{2}\ln 2\pi - \frac{1}{2}\ln|\Sigma_t| - \frac{1}{2}u_t'\Sigma_t^{-1}u_t\,, \tag{23}$$

where: $\Theta = (\,\Phi_1, \Phi_2, vech(O)', vec(A)', vec(G)', vec(B)')'$ is the vector of parameters for the whole model.[10] Of which, Φ_i is the parameter vector for market i's mean equation, and the rest are for the BEKK specification. $|\Sigma_t|$ is the determinant of Σ_t. K is the number of time series.

In addition, when u_t follow a bivariate Student's t distribution with unknown (but constant) degrees of freedom, denoted ν $(2 < \nu < \infty)$, the log-likelihood function is as follows:

$$\ln l\,(\Theta\,) = \sum_{t=1}^{n} \ln l_t(\Theta\,), \tag{24}$$

$$\ln l_t(\Theta) = \ln\Gamma\left(\frac{\nu+K}{2}\right) - \ln\Gamma\left(\frac{\nu}{2}\right) - \frac{K}{2}\ln\pi - \frac{K}{2}\ln(\nu-2) - \frac{\nu+K}{2}\ln\left(1 + \frac{u_t'\Sigma_t^{-1}u_t}{\nu-2}\right) - \frac{1}{2}\ln|\Sigma_t|. \tag{25}$$

3.2.3. News Impact Surfaces

[10] $vec(H)$ denotes the vectorization of a m by n matrix H, that is, the mn by 1 column vector obtained by stacking the columns of the matrix H on top of one another.
$vech(H)$ denotes the half-vectorization of a squared n by n matrix H, that is, the $n(n+1)/2$ by 1 column vector obtained by vectorizing only the lower triangular part of H.

One drawback of the BEKK specification is that various estimated parameters are hard to interpret, especially with the squared terms of innovations. Therefore, I follow Kroner et al. (1998) and use news impact surfaces (NIS) to interpret the results. News impact curves/surfaces show the impact of past return shocks (news) on the current conditional volatility at estimated values of the static parameters. Particularly, NIS graph the conditional variance and covariance as functions of the shocks using the estimated parameters from the BEKK specification, holding the past conditional variances and covariances constant at their unconditional sample mean levels. NIS is defined as:

$$NIS(z_{t-1}) = \Sigma_t(z_{t-1}|\Sigma_{t-1} = \bar{\Sigma}) - \Sigma_t(0|\Sigma_{t-1} = \bar{\Sigma}), \quad (26)$$

where $z_{t-1} = (z_{1t-1}, z_{2t-1})'$ denotes the standardized past return shocks, $\bar{\Sigma}$ is the unconditional variance-covariance matrix. The equations (19), (20), (21) imply the functional forms for NIS. Thus, NIS for the variance of the first market's returns is given by:

$$NIS_{11} = a_{11}^2 u_{1,t-1}^2 + 2a_{11}a_{21}\, u_{1,t-1}\, u_{2,t-1} + a_{21}^2 u_{2,t-1}^2 + g_{11}^2 \eta_{1,t-1}^2 + 2g_{11}g_{21}\, \eta_{1,t-1}\, \eta_{2,t-1} + g_{21}^2 \eta_{2,t-1}^2\,, \quad (27)$$

while NIS for the variance of the second market's returns is given by:

$$NIS_{22} = a_{12}^2 u_{1,t-1}^2 + 2a_{12}a_{22}\, u_{1,t-1}\, u_{2,t-1} + a_{22}^2 u_{2,t-1}^2 + g_{12}^2 \eta_{1,t-1}^2 + 2g_{12}g_{22}\, \eta_{1,t-1}\, \eta_{2,t-1} + g_{22}^2 \eta_{2,t-1}^2\,, \quad (28)$$

lastly, NIS for the covariance between the two markets' returns is as follows:

$$NIS_{12} = a_{11}a_{12} u_{1,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})\, u_{1,t-1}\, u_{2,t-1} + a_{21}a_{22} u_{2,t-1}^2 + g_{11}g_{12} \eta_{1,t-1}^2 + (g_{12}g_{21} + g_{11}g_{22})\, \eta_{1,t-1}\, \eta_{2,t-1} + g_{21}g_{22} \eta_{2,t-1}^2\,, \quad (29)$$

where: $u_{t-1} = \bar{\Sigma}^{1/2} z_{t-1}$; $z_{1t-1} = [-4{:}\, 0.1{:}\, 4]$; and $z_{2t-1} = [-4{:}\, 0.1{:}\, 4]$.

3.2.4. Hypothesis tests

3.2.4.1. Granger causality test

In order to know if there is any return linkage between the markets, I employ the Granger (1969) causality test. This test is often used following estimation of a VAR model to investigate how much of the first variable's current value (in a bivariate framework) can be explained by the second variable's past values, and vice versa. Time series y_2 is said to Granger-cause time series y_1 if y_2

helps in the prediction of y_1, that is, if the coefficients of y_2's lags are statistically significant in a regression of y_1 on y_2. My study examines the following hypotheses:

(i) There is no Granger causality in the relationship between market 1 and market 2

$$H_0 : \varphi_{12}^1 = \varphi_{21}^1 = \varphi_{12}^2 = \varphi_{21}^2 = \cdots = \varphi_{12}^p = \varphi_{21}^p = 0$$

(ii) Market 2 does not Granger-cause market 1

$$H_0 : \varphi_{12}^1 = \varphi_{12}^2 = \cdots = \varphi_{12}^p = 0$$

(iii) Market 1 does not Granger-cause market 2

$$H_0 : \varphi_{21}^1 = \varphi_{21}^2 = \cdots = \varphi_{21}^p = 0$$

The above hypotheses are tested using a Wald statistic. Suppose that there are J independent linear restrictions that need to be tested, i.e., $H_0 : R\Phi = c$, against the alternative hypothesis, $H_1 : R\Phi \neq c$ where R is a matrix of rank J, with J rows and $2 \times (1 + 2 \times p)$ columns, and c is a J by 1 vector of zeros, and $\Phi = (\Phi_1, \Phi_2)'$ is the parameter vector of the VAR model. Thus, the Wald statistic is computed by:

$$W = \left(R\hat{\Phi}\right)' \left[R\widehat{\mathrm{Var}}\left[\hat{\Phi}\right] R'\right]^{-1} \left(R\hat{\Phi}\right),$$

where $\hat{\Phi}$ and $\widehat{\mathrm{Var}}\left[\hat{\Phi}\right]$ are the estimators of Φ and $\mathrm{Var}\left[\hat{\Phi}\right]$. Here I use the Newey-West HAC estimator to compute $\widehat{\mathrm{Var}}\left[\hat{\Phi}\right]$. The Wald statistic W is asymptotically distributed as $\chi^2(J)$ under the null hypothesis.

3.2.4.2. Hypothesis tests for spillover effects in variances

The idea of Granger causality in the conditional mean which is presented in the previous subsection can also be generalized to apply to the conditional variance. Comte et al. (2000) provide sufficient conditions for second-order Granger-type noncausality in the multivariate GARCH specification. Let $Var[u_t|\mathcal{F}_{t-1}] = \Sigma_t$, where $u_t = \left(u_{1,t}, u_{2,t}\right)'$ and Σ_t is the conditional variance-covariance matrix of the vector u_t given the $t-1$ information set, $\mathcal{F}_{t-1}$. Then, the condition for no second-order causality from y_2 onto y_1, denoted by $y_2 \nrightarrow y_1$, is:

$$y_2 \nrightarrow y_1 \Leftrightarrow E\left(\sigma_{11,t+1}|\mathcal{F}_{1,t}\right) = \sigma_{11,t+1} ,$$

where $\mathcal{F}_{1,t}$ is the information set available at the end of time t of only the series y_1. Thus, it means that y_2 does not help predict the conditional variance of y_1. In the BEKK framework, the condition is specifically given by: $a_{21} = g_{21} = b_{21} = 0$.

By symmetry, the condition for no second-order causality from y_1 onto y_2, denoted by $y_1 \nrightarrow y_2$, is as follows:

$$y_1 \nrightarrow y_2 \Leftrightarrow E\left(\sigma_{22,t+1} | \mathcal{F}_{2,t}\right) = \sigma_{22,t+1} \Leftrightarrow a_{12} = g_{12} = b_{12} = 0 \, .$$

The hypothesis tests are conducted using the Wald test and use the asymptotic χ^2 distribution of the Wald statistic as an approximation.

Modelling and programming is done in MATLAB combined with Andrew Patton's Copula toolbox; Kevin Sheppard's Oxford MFE Toolbox and James LeSage's Econometrics Toolbox.[11] I use the MATLAB packages built by Patton and LeSage for the empirical work with copula-based models. Meanwhile, the Oxford MFE Toolbox is used in the analysis with the VAR-BEKK-GARCH framework.

4. Markets and Data

4.1. Overview of trading relationships between Vietnam and the US, Japan, and EU28

Ever since Vietnam initiated Doi Moi (Renovation)[12] in 1986, the country has been gradually opening up the economy to foreign trade and investment. Vo et al. (2019) note that Vietnam's integration into the world's economy had four milestones: (i) joining ASEAN in 1995 and the ASEAN Free Trade Area in 1996; (ii) negotiating and signing the Vietnam-US bilateral trade agreement in 2000; (iii) becoming a member of the World Trade Organization in 2007, and (iv) focusing on bilateral and plurilateral free trade agreements since 2008. Therefore, as a result, the interdependency between the Vietnamese market and the other considered markets is expected to have increased over time.

According to Vietnam's Ministry of Industry and Trade (VMIT), despite facing numerous difficulties throughout 2020, the country's total import-export turnover grew by 5.4% to USD545.4

[11] These MATLAB toolboxes are available on their developers' websites.
[12] Doi Moi is a reform programme launched by Vietnam's government since 1986. The main objectives of Doi Moi are (i) to rectify the inefficiencies of the state industrial sector, (ii) to restructure the non-state agricultural sector, (iii) to free the economy to respond to market forces (Forbes et al., 1991).

billion compared with 2019 (VMIT, 2021). As of early 2021, Vietnam has commerce relationships with more than 200 countries all over the world. Of which, US, Japan and EU28 are Vietnam's most important partners.

The trading relationship between Vietnam and the US started to grow significantly after the United States granted Vietnam conditional "normal trade relations" in 2001. After 25 years from the reestablishment of diplomatic relations, bilateral trade between the two countries has expanded over 250-fold, from only USD300 million in 1995 to USD75.7 billion in 2019 (General Statistics Office of Vietnam, 2021). In 2020, the United States became Vietnam's second largest trading partner with a bilateral volume of USD90.8 billion, accounting for 16.65% of the total import and export turnover (VMIT, 2021). Meanwhile, according to the Office of the US Trade Representative, Vietnam was the US's thirteenth largest trading partner. As the trade tensions between China and the US escalated, bilateral trade of Vietnam-US increased with growth of nearly 20% in 2020 alone. At the same time, US trade deficit with Vietnam rose to approximately USD63.4 billion, an increase of 13% over 2019.

Japan has always been in the group of largest trading partners of Vietnam. In 2020, Japan was the sixth largest trading partner of Vietnam. Bilateral trade between the two countries amounted to USD39.6 billion, a decrease of 0.6% over 2019 (VMIT, 2021). The relationship between the two countries has been boosted significantly from various cooperation agreements. Moreover, Japan has been consistently among the largest sources of corporate investment in Vietnam. It ranks second in cumulative investment in Vietnam and topped the annual list in 2017 and 2018 based on the data reported by Vietnam's Ministry of Planning and Investment.

The diplomatic relations between Vietnam and the European Economic Community (i.e., the principal component of EU) officially started in 1990 and in 1995 Vietnam and the EU signed their first framework cooperation agreement. Over the following 25 years, the relationship has improved dramatically. In 2020 the EU was Vietnam's fifth largest trading partner as well as second largest export market, while Vietnam is the EU's seventeenth trade partner in goods. The import-export turnover between Vietnam and the EU reached over USD49.8 billion in 2020, decreased by 0.1% compared to 2019 (VMIT, 2021). The EU-Vietnam free trade agreements which took effect on August 1, 2020 is expected to create new opportunities for growth and development on both sides.

In summary, Vietnam has long-standing trading relationships with the US, Japan and European countries, which is predicted to lead to a high degree of economic integration between Vietnam and those countries. That, in turn, may link the stock markets of these nations together.

4.2. Overview of Vietnamese Stock Market

Right from the early 1990s, Vietnam's government has aimed to establish and develop the domestic stock market to create a new fund-raising channel for investment. The State Securities Commission of Vietnam (SSC) was set up in 1996 as a governmental agency charged with the mission of organizing and regulating the operations in the field of securities and securities market.

On July 28, 2000–4 years from the establishment of SSC–the very first stock exchange of Vietnam, Ho Chi Minh Securities Trading Center (HOSTC), opened its first trading session with only two publicly traded firms, coded REE and SAM. Five years later, on 14 July 2005, Vietnam's second stock exchange, Hanoi Securities Trading Center (HASTC), was launched in Vietnam's capital. In 2007 and 2009, HOSTC and HASTC were renamed to Ho Chi Minh stock exchange (HOSE) and Hanoi Stock Exchange (HNX) respectively.

In 2006, the government of Vietnam promulgated the Securities law, which set up the very first legal framework for transactions on the domestic stock exchange. Foreign investors were initially restricted to a maximum of 20% ownership of Vietnamese companies' equities. However, this restriction had been relaxed gradually to 30% in 2005 and 49% in 2007. Vietnam's government conducted its 2001–2007 divestment plan from thousands of state-own enterprises, which boosted stock market capitalization. The fraction of stock market capitalization as a percent of the country's GDP increased from only 1% in 2005 to 23% in 2006, and 43% in 2007 (SSC, 2021). In addition, the trading platform on the HOSE was upgraded many times during the period of 2006–2009. Those improvements facilitated e-transactions and reduced waiting time for investors. All the mentioned changes contributed to the deeper integration of Vietnam's stock market into the world's capital market.

According to statistics from SSC, by the end of 2020, the total market capitalization of the Vietnamese stock market was approximately USD240 billion. At the time this was equivalent to about 88% GDP of Vietnam, which was relatively lower than its neighboring countries (e.g., Thailand with 105% in 2019; Malaysia with 111% in 2019, World Bank (2020)). In the early 2021, HOSE was the largest stock exchange of the country with 392 stocks being traded on it; and with approximately 2.8 million investor accounts and market capitalization of over USD185 billion (SSC, 2021).

The number of foreign investors who are active on the Vietnamese stock markets has been continuously growing by an average of 10% annually between 2015 and 2020. As of the end of 2020, there were over 35,000 international investor accounts on the Vietnamese stock market, which held approximately 20% of total market capitalization (SSC, 2021). A high level of market participation of international investors is expected to increase dependency between the domestic market and the world market. On the other hand, foreign investors' participation could enhance the market transparency. The trading participation of international investors in the Vietnamese stock exchange is relatively lower compared to Thailand's market with 28.7% at the end of 2020 (Stock Exchange of Thailand, 2021). Currently, Vietnam's authorities allow foreign investors to buy, without limits, government and corporate bonds as well as listed stocks that are not on the conditional businesses list.[13]

VN-index (VNI) is the market index of HOSE and usually used as the proxy for the Vietnamese stock market's performance (e.g., Duong et al., 2020). VNI is a capitalization-weighted index of all the companies listed on HOSE. Over the period 2010–2019, despite the remarkable development of the country,[14] VNI was displaying a relatively poor performance,[15] only increased by about 94%, equal to 6.9% compound annual growth rate. However, in 2020 Vietnam's GDP increased by 2.9%, a success for Vietnam with the growth rate among the highest in the world (General Statistics Office of Vietnam, 2021) and the benchmark VN-Index increased by 14.87% compared to the end of 2019.

4.3. Data and preliminary analysis

I use the following indices as benchmarks for the four chosen countries/area: Vietnam VN-Index (VNI) for Vietnam; S&P 500 Index (SPX) for the US; Nikkei 225 Index (N225) for Japan and STOXX Europe 600 Index (SXXP) for European countries. All four indices capture the overall performance of large-capitalized companies in the respective markets. In this paper, I take the perspective of a USD investor. Thus, the index prices are adjusted for exchange rate risk. I

[13] As defined in the Decree 60/2015/ND-CP promulgated by Vietnam's government on June 26, 2015.
[14] e.g., Vietnam's average annual GDP growth rate for the period from 2010 to 2019 is 6.3% (World Bank, 2020).
[15] e.g., compared to the average annual VND deposit interest rate of over 7.5% for the period from 2010–2019 (State Bank of Vietnam, Annual reports from 2010 – 2019)

therefore use data on the following cross exchange rates: USD/VND; USD/JPY and USD/EUR. The data are obtained from Thomson Reuters. For convenience, I use each country's abbreviation to represent its stock market index: VNM for Vietnam VN-Index; US for S&P 500 Index; JPN for Nikkei 225 Index and EU for STOXX Europe 600.

The data contains 4,174 observations and it covers the period from 2005 to 2020. The period includes several international events which could affect dependence between the considered stock markets, e.g., the global financial crisis of 2007–2008, the European sovereign debt crisis of 2010–2012, the Chinese stock market turbulence of 2015, the gradual opening up of Vietnam, and most recently the Covid-19 recession.

The trading hours for each market are presented in Table A.1 (see Appendix A). The American market opens when the Vietnamese market has closed. Meanwhile, the European market starts trading when Vietnam's market has only half an hour before closing. Thus, American and European markets are roughly non-overlapping markets with Vietnam. In contrast, the equity trading in Japan and Vietnam almost completely overlaps with a gap of less than two hours. According to King et al. (1990), when the markets do not have overlapping trading hours, it is convenient to examine changes in prices over the 24-hour period from the close of trading on one day to the close of trading on the next. On the other hand, when the markets have overlapping trading hours, the authors state that it is necessary to examine also changes in price between the close of trading on one day and the opening of trading on the following day. More specifically, suppose I investigate the relationship between two overlapping markets, where market 1 opens first. The opening price in market 1 will reflect its reaction to the previous day's change in market 2 after market 1 had closed. Meanwhile, the opening price in market 2 will also include its reaction to market 1's opening price that will have occurred earlier in the day. However, that is only the case when market 2 is a mature one with high efficiency. Otherwise, in case market 2 is a developing market (like the Vietnamese market), there could be a delay in the price adjustment to new information, and thus, the opening price in that market will reflect its reaction to the previous day's closing price in market 1. Therefore, the close-to-open return would be more informative in case of overlapping markets. To account for both possibilities, I use both the daily close-to-close (CC) and close-to-open (CO) return to explore the interaction between Vietnamese and Japanese markets. Meanwhile, only the daily CC return is employed to analyze the relationship between the Vietnamese stock market and the American as well as European markets.

Furthermore, due to the non-overlapping trading, a shock on day t in the stock markets of the US or European countries will not be reflected in the Vietnamese market until day $t+1$. Therefore, the appropriate pairing is time $t-1$ for the US or European markets and time t for Vietnam's. I assume here that possible contagion effects go from the larger to the smaller markets.

In addition to different trading hours, the countries have different trading days due to holidays. The non-trading days of each market range from 77 to 256 days out of the total 4,174 days, equivalently from 1.8% to 6.1% of the whole sample. I synchronize the data by filling prices on non-trading days with the linear interpolation method, which helps eliminate spurious correlation.

All index prices (except S&P 500) are converted into USD before computing the return by using the local opening and closing exchange rates accordingly. The daily continuously compounded returns for each stock market are calculated as follows:

$$R_t^{CC} = 100 \times \log\left(\frac{P_t^{Closing}}{P_{t-1}^{Closing}}\right),$$

$$R_t^{CO} = 100 \times \log\left(\frac{P_t^{Opening}}{P_{t-1}^{Closing}}\right).$$

Figure B.1 (see Appendix B) describes changes of the closing price in the Vietnamese stock market, compared to the other countries' markets over the sample period. There are signs of co-movements in prices for each pair of markets. In addition, it seems that the correlation became more obvious since the end of 2008. Visually, the Vietnamese stock market is more associated with American and Japanese markets.

The series of close-to-close log-returns are plotted in Figure B.2 (see Appendix B). Based on the figure, there are no apparent trends in any of the series, which suggests they are stationary. The stationarity of the data is required to employ both copula-based and VAR models. Furthermore, all of the series display volatility clustering (i.e., prolonged periods of high volatility are followed by those of low volatility and so on) and there are also some unusually large or small observations (i.e., outliers). Thus, the data are likely to exhibit heteroscedasticity and ARCH or GARCH models may be used to capture the volatility dynamics. In addition, the series apparently share some moments in which the volatilities are dramatically higher, i.e., end of 2008 or beginning of 2020. This fact, seemingly, confirms the idea of interdependency across markets.

The time series of exchange-rate returns are described in Figure B.3 (see Appendix B). As can be seen from the figure, the cross-currency rate of USD/VND is stable compared to those of USD/JPY or USD/EUR. The main reason for that is the State Bank of Vietnam has been managing the VND through a soft peg to the US dollar. Indeed, the International Monetary Fund (IMF) has classified Vietnam's exchange rate arrangement as a "stabilized arrangement" (IMF, 2020). A stabilized arrangement involves a spot market exchange rate that remains within a margin of 2% for six months or more.

Before going into any further analysis, I examine the normality of the data as well as general correlation between the VNM series and the other series. Table A.2 provides some summary statistics for the data.

Table A.2: Descriptive Statistics for index return series

This table reports summary statistics on daily stock index returns. The first column lists the reported statistics, that is, the sample mean; standard deviation; skewness; kurtosis; linear correlation; and rank correlation. The table also reports the hypothesis decision of Jarque-Bera test and Kolmogorov-Smirnov test. Jarque-Bera test verifies the null of normality of data. Kolmogorov-Smirnov test has the null that the two time-series are from the same continuous distribution. I report hypothesis test results at 5% significance level.

	VNM(CC)	VNM(CO)	US(CC)	JPN(CC)	JPN(CO)	EU(CC)
Mean	0.028	0.085	0.027	0.020	0.048	0.009
Std. Dev.	1.395	0.992	1.217	1.400	0.756	1.353
Skewness	-0.367	-0.347	-0.574	-0.631	-0.134	-0.441
Kurtosis	5.418	8.820	18.019	11.276	3.951	13.200
Linear correlation	1	1	0.247	0.205	0.202	0.231
Rank correlation	1	1	0.196	0.168	0.215	0.175
Jarque-Bera test	reject	reject	reject	reject	reject	reject
Kolmogorov-Smirnov test			reject	fail to reject	reject	fail to reject

The average daily returns are positive but negligibly small compared to the sample standard deviation. On average, the Vietnamese stock market, like other developing markets, has higher returns than the developed markets. It also has a considerably high volatility, although its volatility is not the highest among all of the studied markets. The data exhibit negative skewness and excess kurtosis which indicates that the returns are not normally distributed. In addition, the Jarque-Bera statistics reject the null hypothesis of normality at 5% significance level. In fact, with negative skewness and heavy tailed behavior, there is a greater probability of extremely small values being realized in all of the series.

This thesis assumes the same type of conditional distribution for all the considered series. I therefore employ the two-sample Kolmogorov-Smirnov test to check whether the series are from the same continuous distribution. The results show that for CC return series, at 5% significance level, I fail to reject the null for Japanese and European markets, while for the American market I reject it. It means that CC returns in Vietnamese and American markets are not from the same distribution. Looking at the data on CO returns, at the same significance level, the VNM and JPN series are also not from the same continuous distribution. However, it is noteworthy that this test compares the unconditional distributions of two random samples, while my study analyzes the conditional distributions. Thus, the results might be different.

As a first step in the analysis of interdependency between markets, sample linear and rank correlations are evaluated. Of all three advanced markets, correlation between the US and Vietnamese markets is the highest with linear and rank correlation coefficients of 0.247 and 0.196 respectively. It is also notable that in the pair VNM-JPN the close-to-open returns exhibit a higher rank correlation than the close-to-close returns, which implies the necessity of using overnight returns in examining the interaction between Vietnamese and Japanese markets. Indeed, a higher rank correlation indicates a higher degree of dependence. Thus, in the pair VNM-JPN, CO returns bring more information on the dependency.

To be more certain about the stationarity of the data, I use both the ADF test and the KPSS test. The results of these tests are presented in Tables A.3 and A.4 (see Appendix A). At 5% significance level, I reject the unit-root null with the ADF test and fail to reject the stationarity null with the KPSS test. Therefore, I have evidence for the stationarity characteristic of the return time series.

Moreover, I examine the sample (partial) autocorrelation function (ACF and PACF) as well as the cross-correlation function (CCF) in order to determine appropriate orders of the ARMA models of marginals. The ACF and PACF for each series are plotted in Figures B.4–9 (see Appendix B), indicating that autocorrelation exists in all of the return series, except for the cases of EU and JPN(CO). Generally, the ACF and PACF drop significantly after lag one, which suggests that the lagged orders are not quite high. In addition, I do not observe any significant trends in the ACF plots. Thus, it suggests the stationarity of the series.

For the squared-returns series, the ACF & PACF (see Appendix B, Figures B.10–15) show significant serial dependence, which indicates that the series are conditionally heteroscedastic. Therefore, I use the GARCH specification to model the conditional variance for each series.

Furthermore, I also plot the CCF for each pair of markets (see Appendix B, Figure B.16). The graph suggests that the VNM series is significantly correlated with US and EU series at lag one, while it is well associated with the JPN series at lag zero. Therefore, this finding supports my assumption that possible contagion effects go from the larger to the smaller markets.

5. Research results

5.1. Conditional dependence structure

5.1.1. Marginal models

After carefully conducting the order selection for each series, the optimal models are chosen based on the information criteria (AIC and BIC). The chosen models are listed in Table A.5. The estimation results for the marginal mean and variance models are presented in Table A.6 (see Appendix A).

Table A.5: Chosen models for each series of returns

This table reports the chosen models for each return series based on the information criteria (i.e., AIC and BIC). I consider up to the order (3,3) for ARMA models of marginals.

Return series	**Chosen model**
VNM (CC)	ARMA(1,2) – GJR (1,1,1)
VNM (CO)	ARMA(1,2) – GJR (1,1,1)
US	ARMA(1,0) – GJR (1,1,1)
JPN (CC)	ARMA(0,1) – GJR (1,1,1)
JPN (CO)	ARMA(0,0) – GJR (1,1,1)
EU	ARMA(0,0) – GJR (1,1,1)

Before estimating the marginal distributions, I test the goodness of fit of the inferred standardized residuals to verify whether they are i.i.d. distributed. Firstly, I plot the ACF for the standardized residuals (see Appendix B, Figures B.17–20). If the mean model is correctly specified, I should expect the ACF values fall inside of the two-standard-error bands for white noise. The results indicate that in general the ACF values lie between the bounds. Secondly, I use the Ljung-Box Q-test on the standardized residual and their squared values. The Ljung-Box Q-test assesses the null hypothesis that a series of (squared) residuals exhibits no autocorrelation for a fixed number of lags, against the alternative that there is some non-zero autocorrelation. Thus, if the mean and variance equations are correctly specified, all Q-statistics should be insignificant. The p-values of the Ljung-Box test are reported in Table A.7 (see Appendix A). I choose to report the test results at maximum lags of 20, 25, and 30 where the choice of maximum lag is based on Box et al. (1994). These statistics indicate that at 5% significance level I cannot reject the null hypotheses in any of the cases, with the exception of VNM (CC)'s standardized-residual series at lag 20. However, the p-value for this case is just under 0.05. Thus, there might exist a "false positive" (i.e., type I error). I, therefore, conclude that the specifications for marginal mean and variance models are reasonable.

Table A.8 (see Appendix A) presents the estimation results for the fitted skewed t distribution of each standardized-residual series. As can be seen from the table, all of the series exhibit negative skewness and heavy-tails behavior. Q-Q plots show that in general the skewed t distribution fits all of the series, except some extreme values in the tails (see Appendix B, Figures B.21–24).

5.1.2. Testing for time-varying dependence

During the period from 2005 to 2020, the world's economy has gone through several big events that may influence the interconnectedness of cross-nation financial markets. Table A.9 presents the list of several important international events. Based on these dates, I test for the break of rank correlation in each pair of indices.

The p-values of these tests are displayed in Table A.10 (see Appendix A). The results show that at 5% significance level, there are evident change-points on Sep 16, 2008 and Feb 24, 2020 in rank correlation in the pairs of VNM-US and VNM-JPN. These points mark the global financial crisis of 2007–2008 and the ongoing Covid-19 epidemic. Thus, it indicates that these events affected the relationship between the Vietnamese market and the US or Japanese market. In addition, at the same significance level, I find evidence of non-zero autocorrelation in rank correlation for the pairs of VNM-EU and VNM-JPN, which suggests the "autoregressive" type of the dependence. In summary, the test results imply a rejection of the constant-correlation null for all of the pairs. Therefore, there is evidence in favor of time-varying copulas.

Table A.9: Considered dates for time-varying dependence tests

This table presents the dates considered for the structural break test in rank correlation. These events are chosen based on my own interest in their potentials of triggering a contagion. I follow Mishkin (2011) and Lane (2012) to choose the dates representing the global financial crisis of 2007–2008 and European sovereign debt crisis of 2010–2012 respectively.

Date	Event
16-Sep-2008	Global financial crisis of 2007–2008 Government bailout of American International Group (AIG)
27-Apr-2010	European sovereign debt crisis of 2010–2012 Standard and Poor's (S&P) downgraded Greece and Portuguese debt ratings.
12-Jun-2015	Chinese stock market turbulence of 2015–2016 Popping of the Chinese stock market bubble
22-Mar-2018	US-China trade war of 2017–2020 D. Trump signed the "Presidential Memorandum Targeting China's Economic Aggression".
24-Feb-2020	Covid-19 pandemic recession of 2020–present

5.1.3. Constant copulas

For comparison purposes, I examine both the static Gaussian and Student's t copulas. Table A.11 presents the estimation results of these copulas. As the Student's t copula collapses to the normal copula when $\nu \to \infty$ (i.e., the models are nested), I can compare these two models via an upper-tailed t test on the significance of the inverse of ν. The results show that the inverse of the degrees of freedom (ν^{-1}) is statistically larger than zero at 5% level in all of the pairs. Therefore, the Student's t copula fits the data better than the Gaussian one. In addition, the log-likelihood values with the Student's t copula are greater than those with the Gaussian copula, which also suggests the appropriateness of the Student's t copula.

In addition, the degrees of freedom for the pairs of VNM-US (i.e., 27) and VNM-EU (i.e., 28.6) are considerably larger than those for the pairs of VNM-JPN (i.e., 16.4 and 9.2). That implies more substantial joint fat tails in the bivariate density of Vietnamese and Japanese stock returns. Thus, there is a greater chance of observing the indices VNI and N225 surge or plunge together.

Table A.11: Estimation results for Constant copula models

Here I report the multi-stage ML estimates, with asymptotic multi-stage ML standard errors in parentheses, of the parameters of the constant copula models. I also present the log-likelihood value at the estimated parameters. (*) indicates a rejection of the null hypothesis of insignificance at the 5% level. I reports the results for two copulas: the Gaussian and the Student's t. The coefficient $\bar{\rho}$ represents the overall strength of the dependence. ν^{-1} denotes the inverse of the degrees of freedom. τ^u and τ^l represent the tail dependence coefficients.

VNM-US Pair					
Copula model	$\bar{\rho}$	ν^{-1}	**Log-likelihood**	τ^u	τ^l
Normal	$0.208^{(*)}$ (0.017)		92.339	0.00000	0.00000
Student's t	$0.208^{(*)}$ (0.017)	$0.037^{(*)}$ (0.013)	94.864	0.00020	0.00020
VNM-JPN Pair (CC returns)					
Copula model	$\bar{\rho}$	ν^{-1}	**Log-likelihood**	τ^u	τ^l
Normal	$0.177^{(*)}$ (0.018)		66.059	0.00000	0.00000
Student's t	$0.179^{(*)}$ (0.018)	$0.061^{(*)}$ (0.018)	72.960	0.00283	0.00283
VNM-JPN Pair (CO returns)					
Copula model	$\bar{\rho}$	ν^{-1}	**Log-likelihood**	τ^u	τ^l
Normal	$0.237^{(*)}$ (0.019)		120.983	0.00000	0.00000
Student's t	$0.237^{(*)}$ (0.019)	$0.109^{(*)}$ (0.019)	142.359	0.03097	0.03097
VNM-EU Pair					
Copula model	$\bar{\rho}$	ν^{-1}	**Log-likelihood**	τ^u	τ^l
Normal	$0.162^{(*)}$ (0.017)		55.708	0.00000	0.00000
Student's t	$0.163^{(*)}$ (0.017)	$0.035^{(*)}$ (0.017)	57.770	0.00007	0.00007

The correlation coefficient, $\bar{\rho}$, represents the overall strength of dependency over time. This parameter takes positive values in all of the pairs, which indicates that the returns in the considered markets move up and down together. Moreover, it is likely that the Vietnamese stock market is influenced the most by the US and Japanese markets, as the values of $\bar{\rho}$ for the pairs of VNM-US and VNM-JPN are the largest at over 0.2. In addition, $\bar{\rho}$ for the VNM-JPN pair takes a larger value with CO returns (i.e., 0.24) than with CC returns (i.e., 0.18). This suggests a higher probability of observing CO returns in the pair VNM-JPN move together. Thus, one can predict the behavior of CO returns in Vietnam's market by looking at the same-day CO return in the Japanese market. This fact is consistent with findings in King et al. (1990) that for the markets with overlapping trading hours, the close-to-open returns provide more information. It is reasonable as the opening prices in overlapping markets reflect the reactions of those markets towards the previous day's information that have not been incorporated yet.

As previously mentioned, copula-based models can provide information on the joint tail behavior of random variables which is important in risk management. The Student's t copula allows for symmetric non-zero tail dependence coefficients (i.e., $\tau^u = \tau^l$). Table A.11 also reports these estimated parameters. The implied tail dependence coefficients estimated for the pairs of VNM-US (i.e., 0.0002) and VNM-EU (i.e., 0.0001) are dramatically smaller than those for the pairs of VNM-JPN (i.e., 0.0028 for CC returns and 0.0310 for CO returns). It indicates that in comparison with the other markets, the Vietnamese stock market is more likely to experience extreme events together with the Japanese market. For example, when the overnight return on N225 takes an unusually small (large) value, there is approximately a 3.1% probability for the CO return on VNI to also take an extremely small (large) value.

5.1.4. Dynamic copulas

The structural break analysis conducted in the subsection 5.1.2 indicates that there exist evident change-points in correlation between the markets. For example, the rank correlation between Vietnamese and American markets is not the same for the periods before and after the US government's bailout of AIG. Therefore, I use a dynamic Student's t GAS copula framework to model the dependence path over time. The estimation results are displayed in Table A.12 (see Appendix A).

I first note that the parameter b representing the persistence in the GAS framework is dramatically greater than the coefficient a on the scaled score of copula log-likelihood. This fact suggests a high degree of persistence in the dependence structure. Secondly, the estimated degrees of freedom for the dynamic Student's t copula are larger than those for the constant Student's t copula in three out of four pairs, indicating that some joint extreme events are generated by time-varying correlations rather than by joint fat tails.

I plot the dynamic path of correlation coefficients for each pair of markets in Figures B.25–28, while changes in the tail dependence parameter are described in Figures B.29–32. The plots for the pair VNM-US are presented here as an example and the rest are displayed in Appendix B.

Figure B.25: Time-varying correlation coefficient for VNM-US Pair

The figure illustrates the time-varying process of the correlation coefficient estimated from the Student's t-GAS copula. The blue dots represent the "big" events listed in Table A.9.

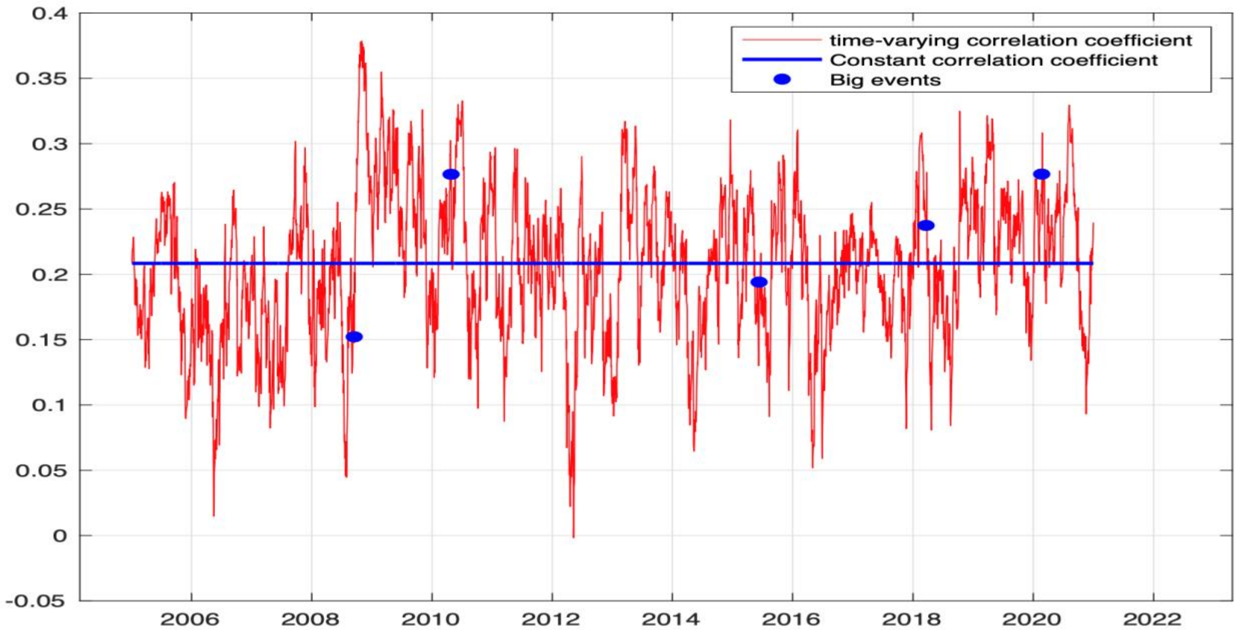
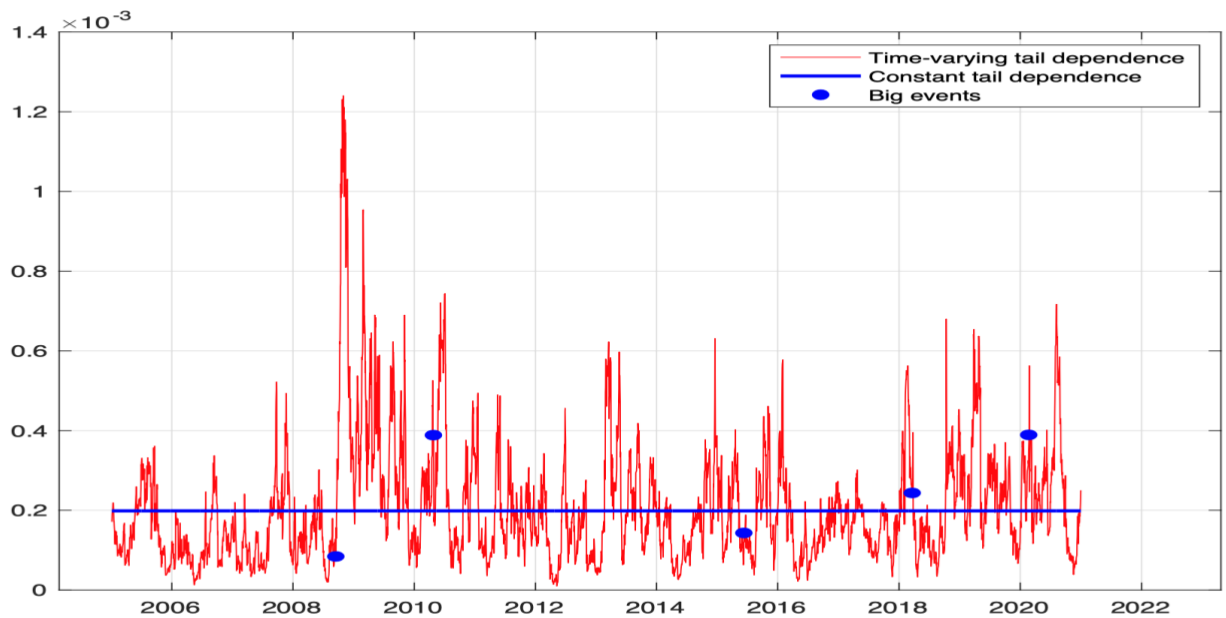


Figure B.29: Time-varying tail dependence coefficient for VNM-US Pair

The figure describes the time path of the tail dependence coefficient estimated from the Student's t-GAS copula. The blue dots represent the "big" events listed in Table A.9.



For most of the sample period, there exists a positive correlation between the markets in each pair, which means that returns in the Vietnamese stock market move up and down together with those in the other markets. In addition, it seems that the interaction between the Vietnamese stock market and the other developed markets was less important at the beginning of the sample period (i.e., in 2005–2006). One reason for that could be the low openness level of the Vietnamese equity market during that time. For example, foreigners' ownership of Vietnamese firms' equities was limited to only 30% over that period. Liu et al. (1997) examine the impact of market openness level on spillover effects across stock markets and note that the market openness is an important channel for the cross-nation transmissions of returns and volatilities.

The blue dots in those figures represent the "big" events listed in Table A.9. It is noteworthy that the correlation coefficient as well as the tail dependence parameter in all of the considered pairs increase significantly after the first blue dot (which represents the bailout of AIG). Therefore, my study is consistent with findings in previous empirical analyses that dependency between stock markets increased after the 2008 global financial crisis. The second blue dot represents the 2010 European sovereign debt crisis. It is notable that the dependence between the markets in each pair augmented after this event as well. It means that the European sovereign debt crisis also affected the interaction between the Vietnamese market and the other considered markets. The third and fourth blue dots denote the crash of the Chinese stock market in 2015 and the US-China trade war in 2018 respectively. These two events, seemingly, did not have a clear effect on dependence between Vietnam's market and the other markets. The fifth blue dot represents the start of the ongoing Covid-19 pandemic. Compared to the VNM-EU pair, the pandemic had greater impacts on the relationships of VNM-US and VNM-JPN. It is noteworthy that these findings are consistent with the results from the structural break tests conducted previously.

Moreover, the dynamic correlation and tail dependence parameters vary quite substantially from their static levels. For example, in the pair VNM-US the correlation coefficient ranges from zero to above 0.35, while its fixed level stands at 0.21. Deviations of the dynamic tail dependence parameter from its static level are even larger. The tail dependence coefficient ranges from just above zero to 0.0012 (i.e., at the first blue dot), compared to its fixed level of 0.0002. It indicates that the probability of Vietnamese and American markets crashing together increased 6-fold during the global financial crisis. Therefore, using a constant copula might not be sufficient in analyzing co-movements across markets as dependency increases during periods of turmoil.

In summary, firstly, with constant copula-based models, I find positive dependence in each pair of markets, which indicates that returns in the Vietnamese market move up and down together with those in the other considered markets. However, influences of the US and Japanese markets on the Vietnamese market are the most substantial. In addition, in comparison with the other markets, the Vietnamese stock market is more likely to experience extreme events jointly with the Japanese market. Secondly, with the time-varying Student's t-GAS copula, I note that the interaction between the Vietnamese stock market and the other developed markets was less important in the beginning of the sample period (i.e., in 2005–2006) and increased significantly after the 2008 global financial crisis. There could be two reasons for this fact: (i) improvements in the openness level of the Vietnamese stock market, and (ii) contagion during market crashes.

5.2. Spillover effects

5.2.1. Model selection

The second main goal of my thesis is to examine the spillover effects between the Vietnamese stock market and the considered advanced markets. As previously mentioned, the ADF and KPSS tests indicate that the sample data are stationary. I therefore can use the VAR specification to model the mean equations directly. Table A.13 presents the selected models for each pair of markets based on the information criteria (i.e., AIC and BIC) as well as the likelihood ratio test.

Table A.13: Chosen VAR-BEKK-GARCH models for each pair of markets

The table reports the optimal VAR-BEKK-GARCH models for each pair of markets. The models are selected based on the information criteria (i.e., BIC and AIC) and the likelihood ratio test. Due to difficulties in estimating the complex VAR-BEKK-GARCH model as well as concerns about "overfitting" issue, I narrow the order-selection process: I consider the VAR model up to order four in conjunction with the BEKK-GARCH specification of order one.

Pair	Chosen model
VNM - US	Bivariate VAR(1) -BEKK-GARCH(1,1,1)
VNM – JPN (CC)	Bivariate VAR(1) -BEKK-GARCH(1,1,1)
VNM – JPN (CO)	Bivariate VAR(4) -BEKK-GARCH(1,1,1)
VNM – EU	Bivariate VAR(1) -BEKK-GARCH(1,1,1)

For comparison purposes, I assume two different densities for the residuals: the Gaussian distribution and the Student's t distribution. A likelihood ratio test is conducted for each pair to evaluate the goodness-of-fit of the proposed specifications. The p-values of these tests are close to zero, indicating that the Student's t distribution fits the data better than the Gaussian distribution.

I perform a residual-based diagnostic analysis to verify whether the residuals are white noise. Figures B.33–36 (see Appendix B) illustrate the series of standardized residuals estimated from the VAR-BEKK-t-GARCH model for each pair of markets. Each graph shows a rectangular band of scatter around the zero level with no remarkable trends over time, which indicates the model adequacy. I also plot the ACF and cross-correlation function (CCF) for each pair of data in Figures B.41–44 (see Appendix B). It seems that there still exist significant autocorrelation and cross-correlation at some lags, especially for the series of CO returns. Therefore, as a precaution, I use the HAC standard errors to make inferences.

5.2.2. Return spillover effects

The estimation results of VAR-BEKK-t-GARCH for each pair of data are presented in Table A.15 (see Appendix A). This section presents my findings on return linkages between the considered developed stock markets and the Vietnamese equity market.

Firstly, the Vietnamese stock market does have past return linkages with the US and EU markets. However, the association is stronger towards the US. The coefficients φ_{12}^{l} represent the past return linkages from market 2 (i.e., one of the developed markets) to market 1 (i.e., Vietnam) at lag l. The estimates of φ_{12}^{1} in the pairs of VNM-US and VNM-EU are statistically significant at 5% level with the magnitudes of 0.22 and 0.14 respectively. It indicates that on average, a one percentage point (pp) increase of the return in the US or EU market is, *ceteris paribus*, associated with an increase of 0.22pp or 0.14pp respectively in the return on the following trading day in the Vietnamese stock market. In contrast, the coefficients φ_{21}^{l} representing the past return transmissions from market 1 to market 2 are insignificant at 5% level in all of the pairs.

In addition, the p-values of the Granger-causality test conducted for each pair of markets (see Table A.16 in Appendix A) indicate that there exist unidirectional past return spillovers from the US and EU markets to the Vietnamese market, while there is no past return linkages between Vietnamese and Japanese markets.[16] My conclusion for the VNM-JPN pair is inconsistent with

[16] Taking the multiple hypothesis problem into account, the decisions are made in comparison with the ratio of 0.05/k (where k is the number of simultaneous tests) (Bonferroni correction).

findings in Vo et al. (2018). However, there are several differences between my study and their analysis: different sample periods, different choices of models, and different treatments of currency risk. I use an asymmetric multivariate GARCH model, whereas Vo et al. (2018) use a symmetric framework. My study accounts for changes in the local currencies against the US dollar, while their paper does not.

It is also noteworthy that my results here are consistent with the outcomes I obtain from the copula-based model. That is, there exists positive dependence between returns on day t in the Vietnamese market and those on day $t-1$ in American and European markets. The difference is that with the VAR-BEKK-GARCH specification I can simultaneously examine the direction of this relationship. For example, I can conclude that there is no past return spillovers from the Vietnamese market to the US and EU markets.

One natural implication of these findings is to use past returns in American and European markets to predict returns in the Vietnamese market. However, a side effect of this is the reduction of diversification benefits. For example, a risk-adverse investor would hold both American and Vietnamese equities in her portfolio for diversification purposes. However, due to return linkages between the two markets, her Vietnamese equities can move together in the same direction with her US stocks, which diminishes the diversification benefits. Moreover, stock return linkages might lead to contagion during crises. For instance, if there is a steep fall in the US market, international investors, with knowledge about the interdependency among stock markets, would try to sell off their equities in emerging markets (e.g., Vietnam's market) as a concern about the lower liquidity of these markets. The selling pressure from international investors would, in turn, push the Vietnamese market down. The herding behavior could even aggravate the situation. Domestic market participants would imitate the actions of foreign investors (i.e., they would also sell off their stocks) and as a consequence, returns in the Vietnamese stock market would decline sharply and volatilities would increase. That is reasonable as my findings with copulas indicate that tail dependence augments during market crashes.

5.2.3. Volatility spillover effects

In my BEKK-GARCH models, the matrices A, G, and B control the evolution of the conditional variance of the markets. Matrix A shows how the conditional variance is correlated with past squared errors (shocks or "news"), while matrix G captures the asymmetric response of the markets to past negative shocks or "bad news". Moreover, matrix B indicates the degree of volatility persistence among the markets. The diagonal elements of the matrices represent own effects, whereas the off-diagonal elements indicate the spillovers.

Firstly, I analyze the estimation results of matrix A. The parameter a_{21} is significantly different from zero at 5% level in the pair of VNM-US. Therefore, in general an unexpected past fall or increase of S&P 500 index's returns is associated with an increase of VN Index's return volatility. One possible reason for this phenomenon is that investors consider past shocks in the US market as new information and try to reassess the vulnerability of their portfolios and then take reactions, which spreads the shocks from the US market to other markets (including the Vietnamese market). However, based on my findings with copulas, the probability of joint extreme events between the Vietnamese and American markets is not substantial. Therefore, it is unlikely that the two markets would crash together. In addition, in all of the pairs, the magnitude of a_{11} is significantly larger than that of a_{22}, which suggests that the own-past-shocks effects are more pronounced for the Vietnamese stock market than for the developed markets. This is consistent with the finding of Li et al. (2015): past shocks play a greater role in the volatility of the emerging markets than those in the volatility of the developed markets. One possible explanation for this fact is the lower efficiency of developing markets relative to developed markets. Therefore, stock prices in developing markets adjust to new information slower than those in developed markets. That results in the more significant effect of past shocks on the current volatility of developing markets, relative to advanced markets.

Secondly, there exist "bad news" spillovers between the Vietnamese stock market and the US and Japanese markets. In the VNM-US pair, there are bi-directional transmissions of past "bad news" between the two markets: the coefficients g_{21} and g_{12} are both significantly different from zero with the size of the former double that of the latter. Therefore, I can conclude that past negative shocks from the US market are associated with an increase in volatilities of the Vietnamese market and vice versa. However, this correlation should not be interpreted as a causal relationship as the bivariate VAR-BEKK-GARCH model cannot control for other common factors that could affect both markets (e.g., shared important markets like Japanese and European markets). That is considered a limitation of this thesis. In the VNM-JPN pair, when using CO returns, g_{21} is statistically significant at 5% level. However, with CC returns I obtain the opposite outcome, i.e., g_{12} is statistically significant. As previously mentioned, in case of overlapping trading the overnight return tends to be more informative. Therefore, I conclude that there exist unidirectional past negative-shock transmissions from the Japanese market to the Vietnamese market. It means that an unexpected fall of overnight returns in the Japanese market is associated with an increase of the Vietnamese market's opening-prices volatility.

Looking at matrix B which measures the volatility persistence of the considered markets, its two off-diagonal elements are insignificant at 5% level in the pairs of VNM-US and VNM-JPN. Meanwhile, they are statistically significant but estimated to be small at 0.0062 in the pair of VNM-EU. Thus, it suggests that there is no strong evidence for past volatility-persistence transmissions between the Vietnamese stock market and the considered developed markets. Moreover, the diagonal elements of matrix B are significantly different from zero at 5% level. b_{22} are closer to one than b_{11}, which indicates a higher degree of volatility persistence for the considered developed markets, compared to the Vietnamese market.

One drawback of the BEKK specification is that various estimated parameters are hard to interpret, especially with the squared terms of innovations. Therefore, the news impact surface (NIS) is useful for interpretation purposes. This method shows the impact of past return shocks (news)[17] on the current conditional volatility. The NIS for each pair of markets are plotted in Figures B. 45–47 (see Appendix B). I plot on the top the variances of market 1 (VNM) and 2 (US/JPN/EU) respectively and at the bottom the covariance between the two markets. Firstly, in all of the pairs, the Vietnamese stock market is not affected by the sign of its own shocks. In contrast, the US, JPN, and EU markets are very sensitive to their own "bad news". Secondly, in the VNM-US pair, the variance NIS for the Vietnamese market shows an increase in the +/- and -/+ quadrants. It means that the Vietnamese stock market is the most unstable when it declines whereas the US market performs well and vice versa. From the variance NIS for the US market, I can observe an asymmetry in responses to joint bad and joint good news: the variance of the US market augments in the -/- quadrant, whereas it stays unchanged in the +/+ quadrant. Moreover, the covariance NIS indicates that the two markets become the most integrated when the US market declines, while the VNM market is stable. That is a good signal for investors as it is unlikely that the two markets experience their extreme events jointly. Thirdly, for the pair of VNM-JPN, it is worth noting that

[17] For the purpose of interpretation with NIS, shocks (news) are defined as standardized residuals, $z_{it} = [-4,4]$.

the variance NIS for the Vietnamese market indicates an increase in the -/- quadrant, which suggests that Vietnam's stock market becomes the most volatile when it receives "bad news" from both markets. Moreover, the covariance NIS for this pair also exhibits an increase in the -/- quadrant, indicating that the two markets become more interacted during crashes. Thus, it appears that the VNM and JPN markets would decline together. This is consistent with what I find with copula-based models. Lastly, in the VNM-EU pair, the variance NIS for Vietnam's market shows that the market neglects shocks from the European market. It implies that shock spillovers between the two markets are not significant.

In order to verify whether information from the considered advanced markets helps predict the conditional variance of the Vietnamese stock market, I conduct the second-order Granger-type causality test. The p-values of the test are reported in Table A.17 (see Appendix A). The results indicate that at 5% significance level, there exists a bi-directional second-order causality between Vietnamese and American markets. Meanwhile, in the pairs of VNM-JPN and VNM-EU, I record one-way second-order causalities from the advanced market to the Vietnamese market.[18] My conclusions here are consistent with findings in the previous literature.

Overall, by employing VAR-BEKK-t-GARCH models, I find the existence of unidirectional past return spillovers from the US and EU markets to the Vietnamese market, while there is no past return linkage between Vietnamese and Japanese markets. In addition, I also find evidence for bi-directional volatility spillovers between Vietnamese and American markets. Meanwhile, the results for the pairs of VNM-JPN and VNM-EU show one-way second-order causalities from the developed market to Vietnam's market.

6. Conclusions

With the globalization of the world economy as well as the liberalization of capital flows, the interdependency between financial markets becomes more apparent than before. My thesis investigates the conditional dependence structure and spillover effects between the Vietnamese stock market and the American, Japanese, and European markets. The empirical analysis is conducted based on daily close-to-close (CC) and close-to-open (CO) returns on market indices for the period from 2005 to 2020. Some interesting findings are summarized here.

[18] Taking the multiple hypothesis problem into account, the decisions are made in comparison with the ratio of $0.05/k$ (where k is the number of simultaneous tests) (Bonferroni correction).

Firstly, with constant copula-based models, I find positive dependence in each pair of markets, which indicates that returns in the Vietnamese market move up and down together with those in the other considered markets. However, influences of the US and Japanese markets on the Vietnamese market are the most substantial. In addition, the implied tail dependence coefficients estimated for the pairs of VNM-US and VNM-EU are dramatically smaller than those for the pairs of VNM-JPN, suggesting that in comparison with the other markets, the Vietnamese stock market is more likely to experience extreme events jointly with the Japanese market.

Secondly, with the time-varying Student's t-GAS copula, I investigate the evolution of dependence over the sample period. It is notable that the interaction between the Vietnamese stock market and the other developed markets was less important in the beginning of the sample period (i.e., in 2005–2006) and increased significantly after the 2008 global financial crisis. There could be two reasons for this fact: (i) improvements in the openness level of the Vietnamese stock market, and (ii) contagion during market crashes.

Thirdly, by employing VAR-BEKK-t-GARCH models for each pair of markets, I find the existence of unidirectional past return spillovers from the US and EU markets to the Vietnamese market, while there is no past return linkage between Vietnamese and Japanese markets. One natural implication of these findings is to use past returns in American and European markets to predict current returns in the Vietnamese market. However, the return transmissions can limit the benefits of diversification, or even cause contagion during crises.

Eventually, by conducting the second-order Granger-type causality test, I find evidence for bi-directional volatility spillovers between Vietnamese and American markets at 5% significance level. Meanwhile, in the pairs of VNM-JPN and VNM-EU, the results show one-way second-order causalities from the developed market to Vietnam's market.

The findings in my study have several implications for international investors as well as policymakers. Understanding the interaction between Vietnam's stock market and the global leading markets helps international portfolio managers, who own Vietnamese equities, create better trading strategies. The results presented in my thesis enable investors to forecast the behavior of returns and volatilities of Vietnamese stock market towards foreign shocks. The findings are of importance in risk management as they can be used, for instance, in computing the value-at-risk (VaR). On the other hand, Vietnamese policymakers can use my findings to better understand the domestic market and consequently make informed decisions in planning their economic and financial policies.

Although my thesis employs reliable methodologies, there are certain limitations that need to be considered. The first limitation is related to the low-dimensional models used in the study. As previously discussed, bivariate models cannot control for other common factors that could affect both markets (e.g., shared important markets). In addition, it is likely that international investors would hold securities from more than two countries' markets in their portfolios. Therefore, an increase of model dimensions is needed. For copulas, this could be achieved either via Oh et al. (2017) or Opschoor et al. (2020). The second limitation is relevant to the standard errors used in making inferences for copula-based models. For convenience purposes, I estimate the asymptotic multi-stage ML covariance matrix numerically by using central finite differences as the approximation of derivatives. However, a block bootstrapped estimate of the multi-stage ML covariance matrix should be considered (Patton, 2013). Another limitation is related to the assumption that all of the return series are conditionally drawn from the same type of distribution. As this assumption might not hold for the sample data, it would be interesting to consider copula models with mixed marginal distributions. The last limitation is relevant to the data used in this thesis. Compared to daily data, high frequency data seem to provide more insights into the dependency between overlapping markets. For example, high frequency data can capture the spillovers between the Japanese and Vietnamese markets during the two-hours gap in their trading time. These limitations can be potentially addressed in future research.

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APPENDIX A

Table A.1: Trading Hours for the studied stock markets

This table reports the trading hours of the considered stock markets. As the United States and Europe are located in many different time zones, I here choose the US Eastern time (i.e., New York time) and London time to represent the time zones for the American and European markets as New York and London stock exchanges are the largest bourses in these country/areas.

Country/Area	Time-zone	Local trading hours	GMT trading hours
Vietnam	GMT+07:00	9:15 to 14:30	02:15 to 07:30
US	GMT-04:00	9:30 to 16:00	13:30 to 20:00
Japan	GMT+09:00	9:00 to 15:00	00:00 to 06:00
EU	GMT+01:00	8:00 to 16:30	07:00 to 15:30

Table A.2: Descriptive Statistics for index return series

This table reports summary statistics on daily stock index returns. The first column lists the reported statistics, that is, the sample mean; standard deviation; skewness; kurtosis; linear correlation; and rank correlation. The table also reports the hypothesis decision of Jarque-Bera test and Kolmogorov-Smirnov test. Jarque-Bera test verifies the null of normality of data. Kolmogorov-Smirnov test has the null that the two time-series are from the same continuous distribution. I report hypothesis test results at 5% significance level.

	VNM(CC)	VNM(CO)	US(CC)	JPN(CC)	JPN(CO)	EU(CC)
Mean	0.028	0.085	0.027	0.020	0.048	0.009
Std. Dev.	1.395	0.992	1.217	1.400	0.756	1.353
Skewness	-0.367	-0.347	-0.574	-0.631	-0.134	-0.441
Kurtosis	5.418	8.820	18.019	11.276	3.951	13.200
Linear correlation	1	1	0.247	0.205	0.202	0.231
Rank correlation	1	1	0.196	0.168	0.215	0.175
Jarque-Bera test	reject	reject	reject	reject	reject	reject
Kolmogorov-Smirnov test			reject	fail to reject	reject	fail to reject

Table A.3: Results of ADF test for unit root

This table reports the results of the ADF test for the sample return time series. The ADF test verifies the null that a time series is a unit root process, i.e., I(1). I report hypothesis test results at 5% significance level. The chosen lag length $p = 12 \times \left(\frac{n}{100}\right)^{1/4}$, where n is the sample size.

Series	I(1)	Statistics	Critical value
VNM(CC)	reject	-9.51	-2.86
VNM(CO)	reject	-8.66	-2.86
US	reject	-11.56	-2.86
JPN(CC)	reject	-11.30	-2.86
JPN(CO)	reject	-11.34	-2.86
EU	reject	-10.86	-2.86

Table A.4: Results of KPSS test for stationarity

This table reports the results of the KPSS test for the sample return time series. The KPSS test verifies the null that a time series is stationary, i.e., I(0). I report hypothesis test results at 5% significance level. The chosen lag length $p = \sqrt{n}$, where n is the sample size.

Series	I(0)	Statistic	Critical value
VNM(CC)	fail to reject	0.08	0.46
VNM(CO)	fail to reject	0.31	0.46
US	fail to reject	0.20	0.46
JPN(CC)	fail to reject	0.13	0.46
JPN(CO)	fail to reject	0.18	0.46
EU	fail to reject	0.04	0.46

Table A.5: Chosen models for each series of returns

This table reports the chosen models for each return series based on the information criteria (i.e., AIC and BIC). I consider the ARMA model up to the order (3,3).

	Chosen model
VNM (CC)	ARMA(1,2) – GJR (1,1,1)
VNM (CO)	ARMA(1,2) – GJR (1,1,1)
US	ARMA(1,0) – GJR (1,1,1)
JPN (CC)	ARMA(0,1) – GJR (1,1,1)
JPN (CO)	ARMA(0,0) – GJR (1,1,1)
EU	ARMA(0,0) – GJR (1,1,1)

Table A.6: Estimation results for marginal mean and variance models

This table reports the ML estimates, standard errors and t-statistics for each marginal mean and variance model.

	VNM (CC)			VNM (CO)			US			JPN (CC)			JPN (CO)			EU		
	Coefficient	S.E.	t-stat	Coefficient	S.E.	t-stat	Coefficient	S.E.	t-stat	Coefficient	S.E.	t-stat	Coefficient	S.E.	t-stat	Coefficient	S.E.	t-stat
δ	0.002	0.003	0.71	0.003	0.001	2.43	0.038	0.012	3.18	0.024	0.014	1.65	0.049	0.010	4.72	0.012	0.014	0.86
AR{1}	0.872	0.060	14.53	0.961	0.010	94.30	-0.051	0.016	-3.13									
MA{1}	-0.708	0.063	-11.16	-0.758	0.018	-41.59				-0.158	0.016	-9.78						
MA{2}	-0.102	0.023	-4.42	-0.126	0.018	-7.05												
ω	0.032	0.004	8.92	0.006	0.001	11.98	0.025	0.002	14.33	0.060	0.007	9.05	0.018	0.003	5.63	0.025	0.003	9.98
β	0.847	0.007	128.79	0.865	0.003	248.34	0.855	0.008	110.36	0.855	0.010	86.82	0.877	0.014	63.99	0.885	0.007	119.08
α	0.114	0.009	12.50	0.116	0.006	20.18	0.026	0.004	5.96	0.041	0.008	5.25	0.046	0.010	4.66	0.025	0.006	4.02
γ	0.057	0.013	4.34	0.039	0.009	4.43	0.186	0.013	14.87	0.134	0.011	11.86	0.087	0.016	5.40	0.150	0.011	13.28

Table A.7: p-values of the Ljung–Box Q-test to fitted standardized residuals from marginal mean and variance models

This table reports p-values of the Ljung-Box Q-test to fitted standardized residuals from marginal mean and variance models. Q(P) and $Q^2(P)$ denote the Ljung-Box Q-test of order P to the standardized residuals and their squared values respectively.

	Q(20)	**Q(25)**	**Q(30)**	**Q^2(20)**	**Q^2(25)**	**Q^2(30)**
VNM (CC)	0.04	0.10	0.20	0.26	0.40	0.35
VNM (CO)	0.33	0.46	0.60	0.63	0.76	0.88
US	0.27	0.44	0.42	0.58	0.69	0.77
JPN (CC)	0.37	0.44	0.41	0.17	0.21	0.36
JPN(CO)	0.58	0.73	0.81	0.98	0.99	0.99
EU	0.45	0.68	0.84	0.91	0.87	0.95

Figure A.8: Estimation results for the marginal distribution

The table reports the estimated parameters of the fitted skewed Student's t distribution for each standardized-residual series. The parameter ν represents the degrees of freedom. The parameter λ denotes the skewness level.

Parameter	**VNM (CC)**	**VNM (CO)**	**US**	**JPN (CC)**	**JPN (CO)**	**EU**
Degrees of freedom ν	6.56	4.30	5.68	8.43	63.33	7.37
Skewness parameter λ	-0.07	-0.05	-0.15	-0.13	-0.09	-0.11

Table A.9: Considered dates for time-varying dependence tests

This table presents the considered dates for the structural break test in rank correlation. These events are chosen based on my own interest in their potentials of triggering a contagion. I follow Mishkin (2011) and Lane (2012) to choose the dates representing the global financial crisis of 2007–2008 and European sovereign debt crisis of 2010–2012 respectively.

Date	**Event**
16-Sep-2008	Global financial crisis of 2007–2008 Government bailout of American International Group (AIG)
27-Apr-2010	European sovereign debt crisis of 2010–2012 Standard and Poor's (S&P) downgraded Greece and Portuguese debt ratings.
12-Jun-2015	Chinese stock market turbulence of 2015–2016 Popping of the Chinese stock market bubble
22-Mar-2018	US-China trade war of 2017–2020 D. Trump signed the "Presidential Memorandum Targeting China's Economic Aggression".
24-Feb-2020	Covid-19 pandemic recession of 2020–present

Table A.10: p-values of time-varying dependence tests

This table reports the p-values of the structural break test for time-varying dependence. The null hypothesis is in favor of a constant copula. I run the test for the five specific dates listed in table A.9. In addition to that, I also test for a change-point at an unknown date within the interval $[0.15n, 0.85n]$, where n is the sample size. Lastly, I test for autocorrelation in rank correlation based on an autoregressive (AR) model. I consider the test for lags 1, 5, 10. The p-values for the tests are calculated using the i.i.d. bootstrap method presented in subsection 3.1.4.1. The number of simulations is 10,000. The symbol (*) indicates a rejection of the null hypothesis at the 5% level.

Pair	**VNM-US**	**VNM-JPN (CC)**	**VNM-JPN (CO)**	**VNM-EU**
16-Sep-2008	0.013$^{(*)}$	0.082	0.003$^{(*)}$	0.378
27-Apr-2010	0.511	0.548	0.118	0.518
12-Jun-2015	0.302	0.162	0.947	0.617
22-Mar-2018	0.130	0.319	0.341	0.940
24-Feb-2020	0.008$^{(*)}$	0.006$^{(*)}$	0.077	0.166
Unspecified date	0.077	0.182	0.017$^{(*)}$	0.689
AR(1)	0.679	0.028$^{(*)}$	0.069	0.223
AR(5)	0.557	0.067	0.035$^{(*)}$	0.255
AR(10)	0.171	0.005$^{(*)}$	0.628	0.026$^{(*)}$

Table A.11: Estimation results for Constant copula models

Here I report the multi-stage ML estimates, with asymptotic multi-stage ML standard errors in parentheses, of the parameters of the constant copula models. The log-likelihood at the estimated parameters is also presented. (*) indicates a rejection of the null hypothesis of insignificance at the 5% level. I reports the results for two copulas: the Gaussian and the Student's t. The coefficient $\bar{\rho}$ represents the overall strength of the dependence. ν^{-1} denotes the inverse of the degrees of freedom. τ^u and τ^l represent the tail dependence coefficients.

VNM-US Pair					
Copula model	$\boldsymbol{\bar{\rho}}$	$\boldsymbol{\nu^{-1}}$	**Log-likelihood**	$\boldsymbol{\tau^u}$	$\boldsymbol{\tau^l}$
Normal	0.208$^{(*)}$ (0.017)		92.339	0.00000	0.00000
Student t	0.208$^{(*)}$ (0.017)	0.037$^{(*)}$ (0.013)	94.864	0.00020	0.00020
VNM-JPN Pair (CC returns)					
Copula model	$\boldsymbol{\bar{\rho}}$	$\boldsymbol{\nu^{-1}}$	**Log-likelihood**	$\boldsymbol{\tau^u}$	$\boldsymbol{\tau^l}$
Normal	0.177$^{(*)}$ (0.018)		66.059	0.00000	0.00000
Student t	0.179$^{(*)}$ (0.018)	0.061$^{(*)}$ (0.018)	72.960	0.00283	0.00283
VNM-JPN Pair (CO returns)					
Copula model	$\boldsymbol{\bar{\rho}}$	$\boldsymbol{\nu^{-1}}$	**Log-likelihood**	$\boldsymbol{\tau^u}$	$\boldsymbol{\tau^l}$
Normal	0.237$^{(*)}$ (0.019)		120.983	0.00000	0.00000
Student t	0.237$^{(*)}$ (0.019)	0.109$^{(*)}$ (0.019)	142.359	0.03097	0.03097
VNM-EU Pair					
Copula model	$\boldsymbol{\bar{\rho}}$	$\boldsymbol{\nu^{-1}}$	**Log-likelihood**	$\boldsymbol{\tau^u}$	$\boldsymbol{\tau^l}$
Normal	0.162$^{(*)}$ (0.017)		55.708	0.00000	0.00000
Student t	0.163$^{(*)}$ (0.017)	0.035$^{(*)}$ (0.017)	57.770	0.00007	0.00007

Table A.12: Estimation results for time-varying copula models (Student's t GAS copula)

The table reports the multi-stage ML estimates, with asymptotic multi-stage ML standard errors in parentheses, of the parameters of the dynamic copula models. The log-likelihood at the estimated parameters is also presented. (*) indicates a rejection of the null hypothesis of insignificance at the 5% level. The coefficient w represents the constant term in the GAS framework. a denotes the coefficient on the scaled score of the copula-likelihood. b represents the persistence in the GAS framework. ν^{-1} denotes the inverse of the degrees of freedom.

Coefficient	VNM-US Pair	VNM-JPN Pair (CC)	VNM-JPN Pair (CO)	VNM-EU Pair
$\boldsymbol{w}$	$0.016^{(*)}$ (0.003)	0.015 (0.023)	0.002 (0.003)	$0.009^{(*)}$ (0.004)
$\boldsymbol{a}$	$0.032^{(*)}$ (0.014)	$0.050^{(*)}$ (0.011)	$0.035^{(*)}$ (0.011)	$0.031^{(*)}$ (0.007)
$\boldsymbol{b}$	$0.963^{(*)}$ (0.009)	$0.958^{(*)}$ (0.026)	$0.996^{(*)}$ (0.006)	$0.970^{(*)}$ (0.006)
$\boldsymbol{\nu^{-1}}$	$0.036^{(*)}$ (0.011)	$0.046^{(*)}$ (0.014)	$0.091^{(*)}$ (0.025)	$0.036^{(*)}$ (0.008)
Log-likelihood	101.837	86.942	202.892	64.773

Table A.13: Chosen VAR-BEKK-GARCH models for each pair of markets

The table reports the optimal VAR-BEKK-GARCH models for each pair of markets. The models are selected based on the information criteria (i.e., BIC and AIC) and the likelihood ratio test. Due to difficulties in estimating the complex VAR-BEKK-GARCH model as well as concerns about "overfitting" issue, I narrow the order-selection process: I consider the VAR model up to order four in conjunction with the BEKK-GARCH specification of order one.

Pair	Chosen model
VNM - US	Bivariate VAR(1) -BEKK-GARCH(1,1,1)
VNM – JPN (CC)	Bivariate VAR(1) -BEKK-GARCH(1,1,1)
VNM – JPN (CO)	Bivariate VAR(4) -BEKK-GARCH(1,1,1)
VNM – EU	Bivariate VAR(1) -BEKK-GARCH(1,1,1)

Table A.14: Estimation results of Gaussian VAR-BEKK-GARCH model for each pair of markets

Here I report the ML estimates, with HAC standard errors, of the parameters of Gaussian VAR-BEKK-GARCH model. The log-likelihood at the estimated parameters is also presented. (*) indicates a rejection of the null hypothesis of insignificance at the 5% level.

Pair	VNM-US		VNM-JPN (CC returns)		VNM-JPN (CO returns)		VNM-EU	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
μ_1	0.014	0.012	0.027	0.025	0.049(*)	0.014	0.019	0.023
φ_{11}^1	0.159(*)	0.019	0.152(*)	0.020	0.198(*)	0.022	0.147(*)	0.028
φ_{12}^1	0.227(*)	0.030	0.027	0.019	-0.002	0.026	0.158(*)	0.021
φ_{11}^2					0.048(*)	0.021		
φ_{12}^2					0.004	0.041		
φ_{11}^3					0.070	0.103		
φ_{12}^3					-0.008	0.044		
φ_{11}^4					0.049	0.027		
φ_{12}^4					0.009	0.070		
μ_2	0.032(*)	0.013	0.025	0.029	0.051(*)	0.025	0.008	0.015
φ_{21}^1	0.011	0.059	0.026	0.019	-0.006	0.013	0.013	0.076
φ_{22}^1	-0.049	0.040	-0.154(*)	0.020	0.027	0.113	-0.001	0.003
φ_{21}^2					0.010	0.053		
φ_{22}^2					-0.009	0.059		
φ_{21}^3					-0.013	0.023		
φ_{22}^3					0.012	0.085		
φ_{21}^4					-0.011	0.040		
φ_{22}^4					-0.001	0.008		
o_{11}	0.168(*)	0.039	0.162(*)	0.031	0.058(*)	0.027	0.170(*)	0.055
o_{21}	0.021	0.029	-0.012	0.010	0.053	0.086	0.011	0.051
o_{22}	0.140(*)	0.052	0.240(*)	0.023	0.120(*)	0.034	0.144(*)	0.023
a_{11}	0.377(*)	0.073	0.354(*)	0.030	0.320(*)	0.080	0.366(*)	0.037
a_{21}	-0.079	0.146	0.012	0.016	0.001	0.008	-0.029	0.038
a_{12}	0.026	0.049	-0.032	0.032	0.002	0.020	0.014	0.014
a_{22}	0.078	0.433	0.126(*)	0.031	0.154(*)	0.050	-0.005	0.016
g_{11}	-0.066	0.598	0.100	0.052	0.089	0.110	0.104	0.254
g_{21}	0.077	0.202	0.036	0.028	0.101	0.073	0.018	0.101
g_{12}	0.021	0.069	0.093(*)	0.022	0.032	0.022	0.015	0.075
g_{22}	0.416(*)	0.071	0.348(*)	0.032	0.303(*)	0.065	0.387(*)	0.036
b_{11}	0.920(*)	0.021	0.928(*)	0.012	0.945(*)	0.028	0.923(*)	0.018
b_{21}	0.002	0.006	-0.004	0.005	-0.015	0.019	0.004	0.004
b_{12}	-0.010	0.013	0.015	0.011	-0.002	0.004	-0.008	0.005
b_{22}	0.938(*)	0.047	0.929(*)	0.009	0.945(*)	0.010	0.954(*)	0.010
Log-likelihood	**-11681.850**		**-13003.370**		**-8472.463**		**-12566.012**	

Table A.15: Estimation results of VAR-BEKK-t-GARCH model for each pair of markets

Here I report the ML estimates, with HAC standard errors, of the parameters of VAR-BEKK-t-GARCH model. The log-likelihood at the estimated parameters is also presented. (*) indicates a rejection of the null hypothesis of insignificance at the 5% level.

Pair	VNM-US		VNM-JPN (CC returns)		VNM-JPN (CO returns)		VNM-EU	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
$\boldsymbol{\mu_1}$	0.044$^{(*)}$	0.015	0.055$^{(*)}$	0.015	0.059$^{(*)}$	0.008	0.043	0.029
$\boldsymbol{\varphi_{11}^{1}}$	0.150$^{(*)}$	0.019	0.147$^{(*)}$	0.018	0.176$^{(*)}$	0.019	0.138$^{(*)}$	0.019
$\boldsymbol{\varphi_{12}^{1}}$	0.219$^{(*)}$	0.019	0.023	0.015	-0.007	0.006	0.141$^{(*)}$	0.017
$\boldsymbol{\varphi_{11}^{2}}$					0.047$^{(*)}$	0.018		
$\boldsymbol{\varphi_{12}^{2}}$					-0.004	0.009		
$\boldsymbol{\varphi_{11}^{3}}$					0.061$^{(*)}$	0.017		
$\boldsymbol{\varphi_{12}^{3}}$					-0.003	0.005		
$\boldsymbol{\varphi_{11}^{4}}$					0.050$^{(*)}$	0.016		
$\boldsymbol{\varphi_{12}^{4}}$					0.003	0.005		
$\boldsymbol{\mu_2}$	0.059$^{(*)}$	0.009	0.052$^{(*)}$	0.017	0.059$^{(*)}$	0.011	0.031	0.026
$\boldsymbol{\varphi_{21}^{1}}$	0.005	0.006	0.026	0.027	0.000	0.001	0.017	0.018
$\boldsymbol{\varphi_{22}^{1}}$	-0.047$^{(*)}$	0.015	-0.150$^{(*)}$	0.016	0.024	0.017	-0.006	0.013
$\boldsymbol{\varphi_{21}^{2}}$					0.008	0.009		
$\boldsymbol{\varphi_{22}^{2}}$					-0.015	0.012		
$\boldsymbol{\varphi_{21}^{3}}$					-0.012	0.017		
$\boldsymbol{\varphi_{22}^{3}}$					0.012	0.034		
$\boldsymbol{\varphi_{21}^{4}}$					-0.011	0.016		
$\boldsymbol{\varphi_{22}^{4}}$					-0.009	0.022		
$\boldsymbol{o_{11}}$	0.190$^{(*)}$	0.045	0.156$^{(*)}$	0.032	0.062$^{(*)}$	0.012	0.166$^{(*)}$	0.037
$\boldsymbol{o_{21}}$	-0.008	0.007	-0.034	0.040	0.041	0.032	0.000	0.000
$\boldsymbol{o_{22}}$	0.130$^{(*)}$	0.013	0.221$^{(*)}$	0.021	0.105$^{(*)}$	0.021	0.147$^{(*)}$	0.020
$\boldsymbol{a_{11}}$	0.463$^{(*)}$	0.036	0.411$^{(*)}$	0.031	0.382$^{(*)}$	0.035	0.412$^{(*)}$	0.029
$\boldsymbol{a_{21}}$	-0.084$^{(*)}$	0.034	0.010	0.018	-0.034	0.018	-0.032	0.021
$\boldsymbol{a_{12}}$	0.009	0.006	-0.033$^{(*)}$	0.012	0.002	0.004	0.001	0.001
$\boldsymbol{a_{22}}$	0.029	0.019	0.094$^{(*)}$	0.027	0.152$^{(*)}$	0.024	-0.030	0.031
$\boldsymbol{g_{11}}$	-0.054	0.063	0.129	0.070	0.115$^{(*)}$	0.051	0.148$^{(*)}$	0.059
$\boldsymbol{g_{21}}$	0.064$^{(*)}$	0.028	0.019	0.023	0.092$^{(*)}$	0.024	-0.006	0.008
$\boldsymbol{g_{12}}$	0.033$^{(*)}$	0.011	0.095$^{(*)}$	0.021	0.020	0.028	0.037	0.055
$\boldsymbol{g_{22}}$	0.447$^{(*)}$	0.030	0.335$^{(*)}$	0.026	0.309$^{(*)}$	0.039	0.389$^{(*)}$	0.032
$\boldsymbol{b_{11}}$	0.886$^{(*)}$	0.022	0.906$^{(*)}$	0.013	0.920$^{(*)}$	0.014	0.905$^{(*)}$	0.016
$\boldsymbol{b_{21}}$	-0.003	0.003	0.006	0.009	-0.007	0.007	0.006$^{(*)}$	0.003
$\boldsymbol{b_{12}}$	0.001	0.002	0.013	0.007	-0.001	0.003	-0.003	0.005
$\boldsymbol{b_{22}}$	0.932$^{(*)}$	0.008	0.937$^{(*)}$	0.007	0.955$^{(*)}$	0.009	0.949$^{(*)}$	0.009
$\boldsymbol{\nu^{-1}}$	0.153$^{(*)}$	0.012	0.128$^{(*)}$	0.012	0.133$^{(*)}$	0.012	0.131$^{(*)}$	0.012
Log-likelihood	**-11405.428**		**-12818.899**		**-8232.664**		**-12355.660**	

Table A.16: p-values of the Granger-causality test in the mean equations

Here I report the p-values of the Granger-causality test on return linkages for each pair of markets. Market 1 is the Vietnamese stock market, whereas market 2 is one of the other considered markets (i.e., US, Japanese, or European markets). The symbol (*) indicates a rejection of the null hypothesis at the 5% level. Taking the multiple hypothesis problem into account, the decisions are made in comparison with the ratio of 0.05/k (where k is the number of simultaneous tests) (Bonferroni correction).

Null Hypothesis	VNM-US	VNM-JPN	VNM-EU
No Granger causality between market 1 and market 2	0.0000$^{(*)}$	0.4897	0.0000$^{(*)}$
Market 2 does not Granger-cause market 1	0.0000$^{(*)}$	0.4878	0.0000$^{(*)}$
Market 1 does not Granger-cause market 2	0.3958	0.8795	0.3502

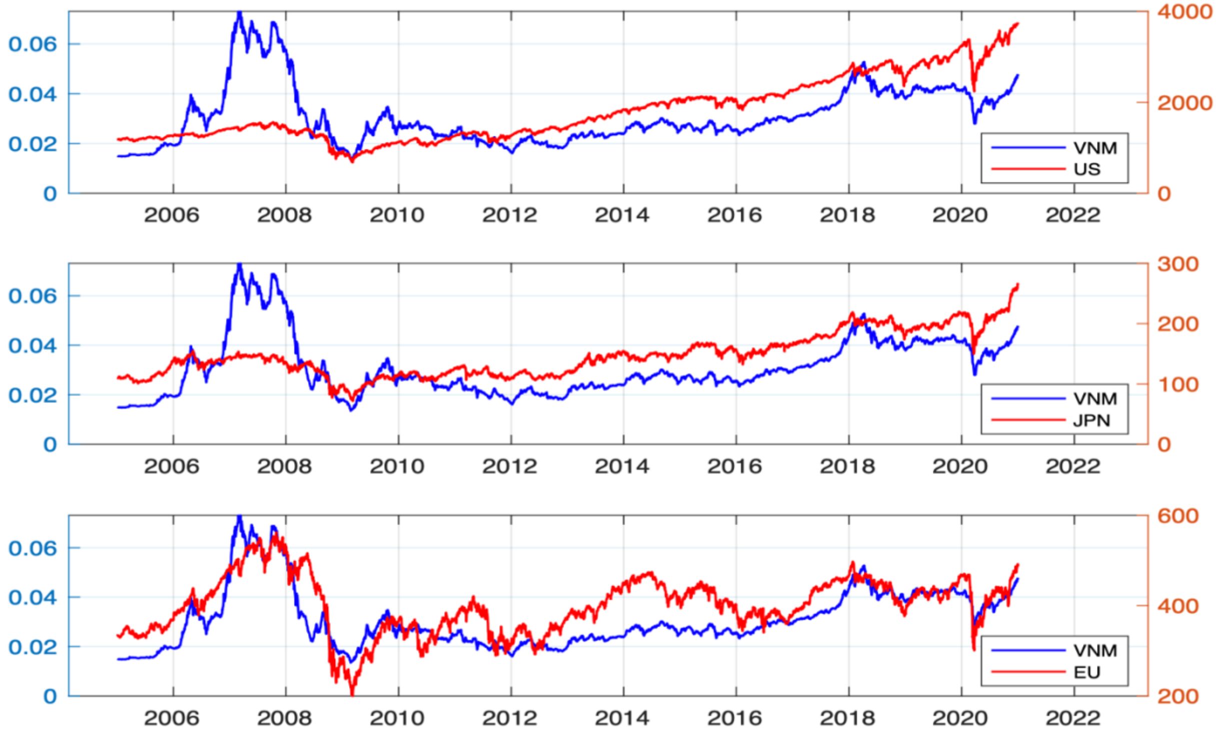
Table A.17: p-values of the second-order Granger-type causality test in the variance equations

Here I report the p-values of the second-order Granger-type causality test on volatility transmissions for each pair of markets. Market 1 is the Vietnamese stock market, whereas market 2 is either the US, or Japanese, or European market. The symbol (*) indicates a rejection of the null hypothesis at the 5% level. Taking the multiple hypothesis problem into account, the decisions are made in comparison with the ratio of 0.05/k (where k is the number of simultaneous tests) (Bonferroni correction).

Null Hypothesis	VNM-US	VNM-JPN	VNM-EU
No second-order causality between market 1 and market 2	0.0000$^{(*)}$	0.0000$^{(*)}$	0.0000$^{(*)}$
No second-order causality from market 2 to market 1	0.0078$^{(*)}$	0.0001$^{(*)}$	0.0145$^{(*)}$
No second-order causality from Market 1 to Market 2	0.0000$^{(*)}$	0.7010	0.3596

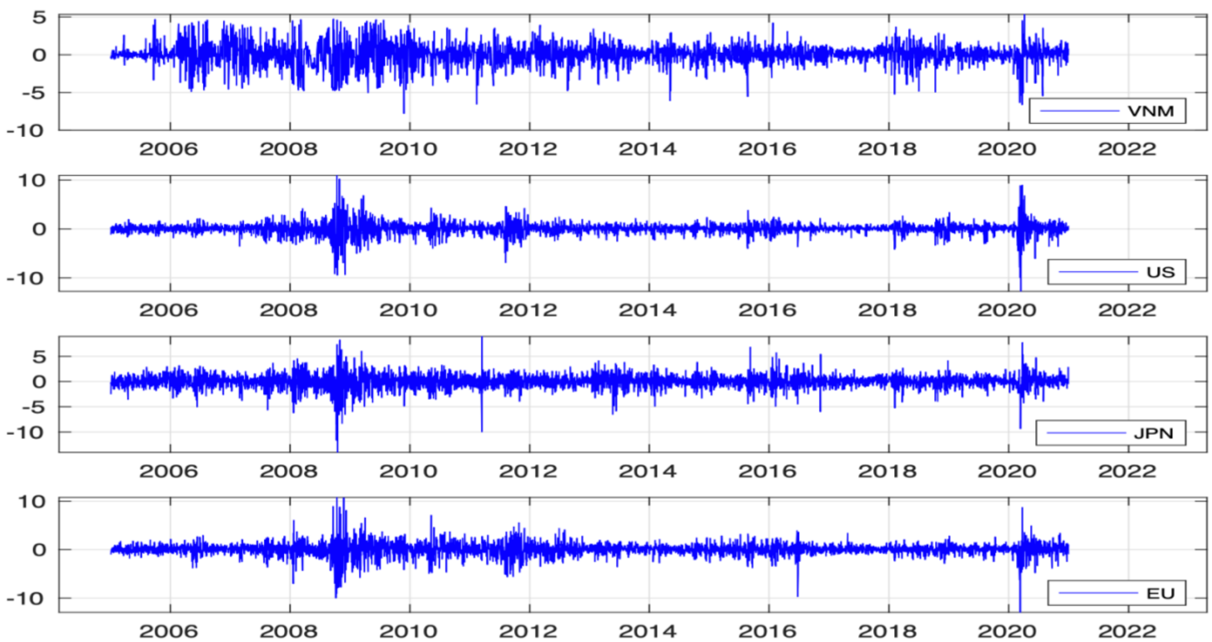
APPENDIX B

Figure B.1 - Pairwise daily closing prices



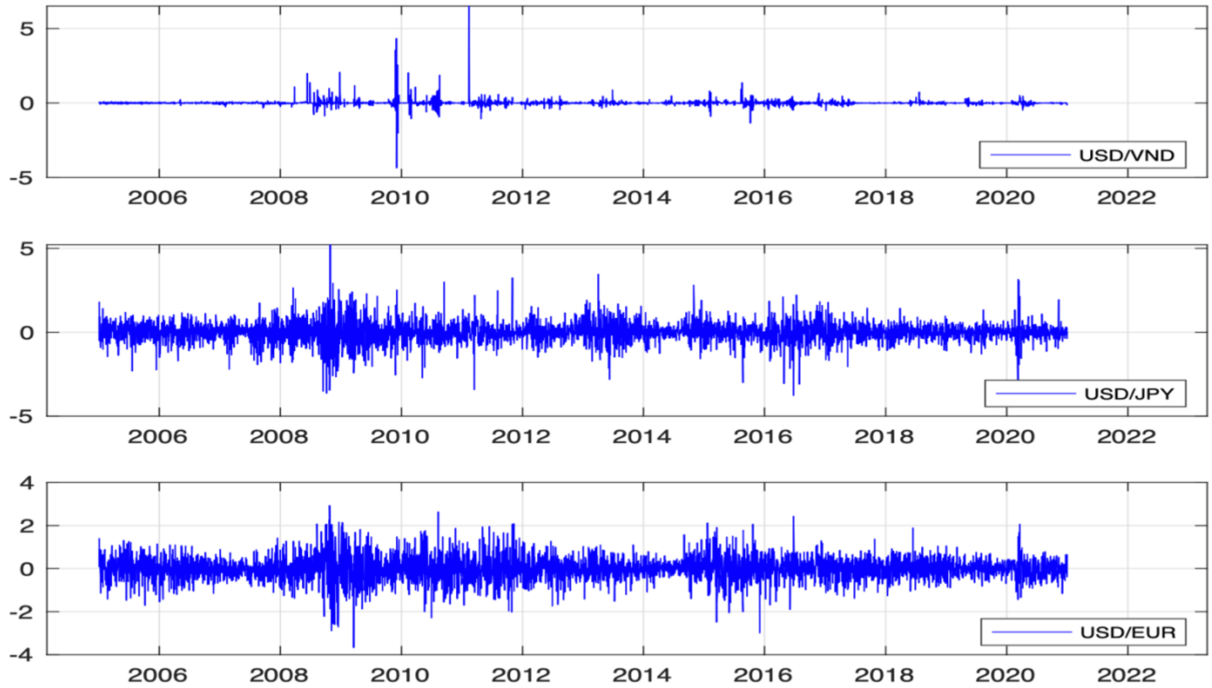
This figure illustrates the time path of daily closing prices in the Vietnamese stock market in comparison with those in the other considered markets.

Figure B.2 - Daily close-to-close log-returns



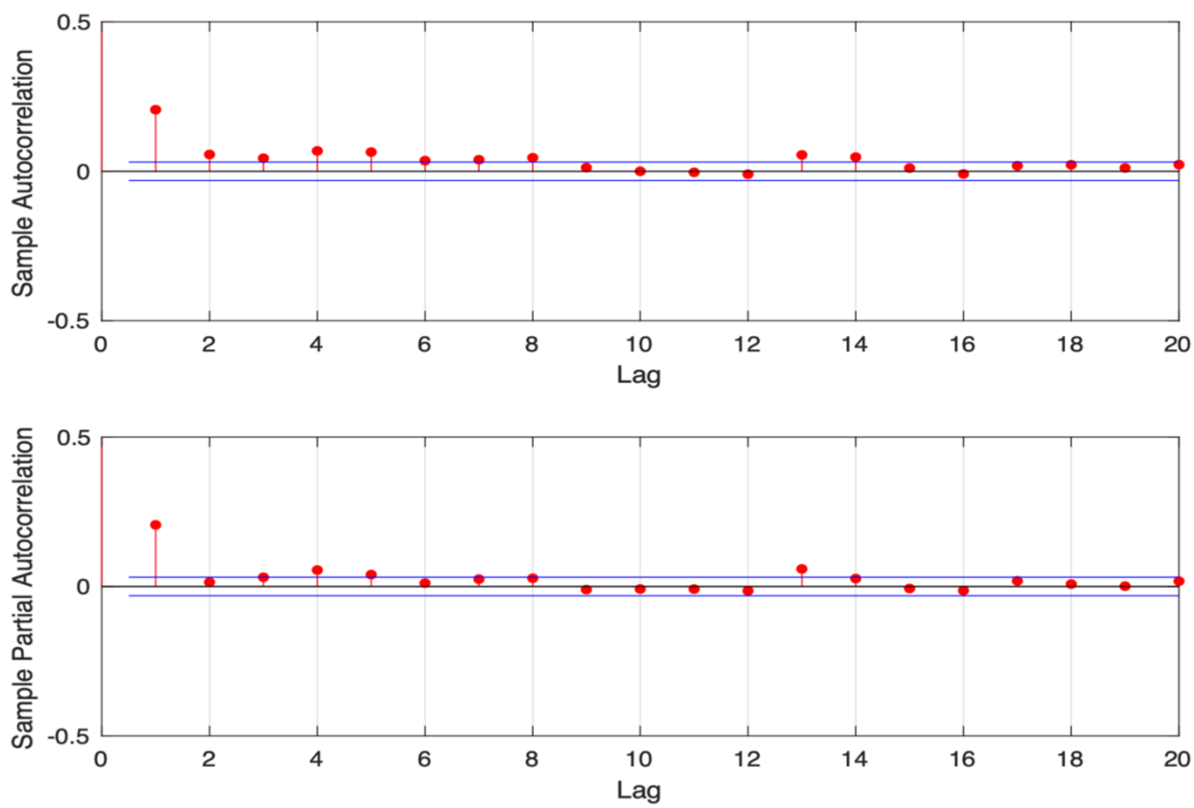
This figure illustrates the time path of daily close-to-close returns in the considered markets.

Figure B.3 - Daily Exchange-Rate log-returns



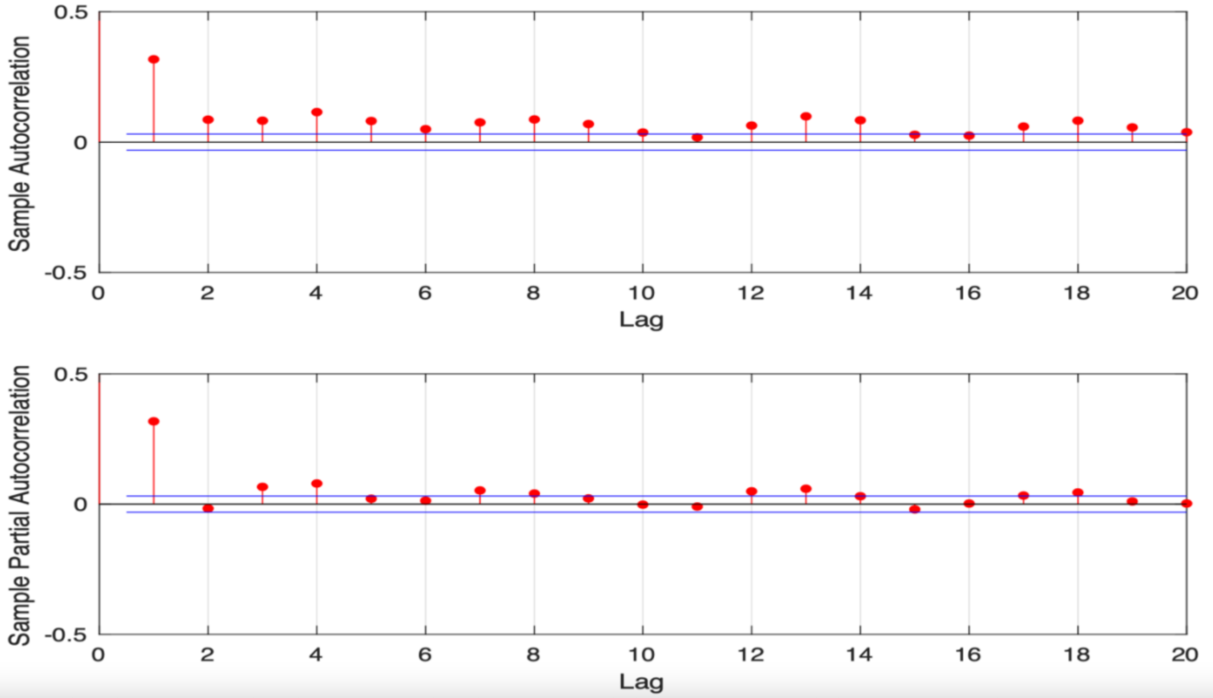
This figure describes the time path of daily close-to-close returns of cross-currency rates of USD/VND, USD/JPY, and USD/EUR.

Figure B. 4 : ACF and PACF for log-returns of VNM(CC)



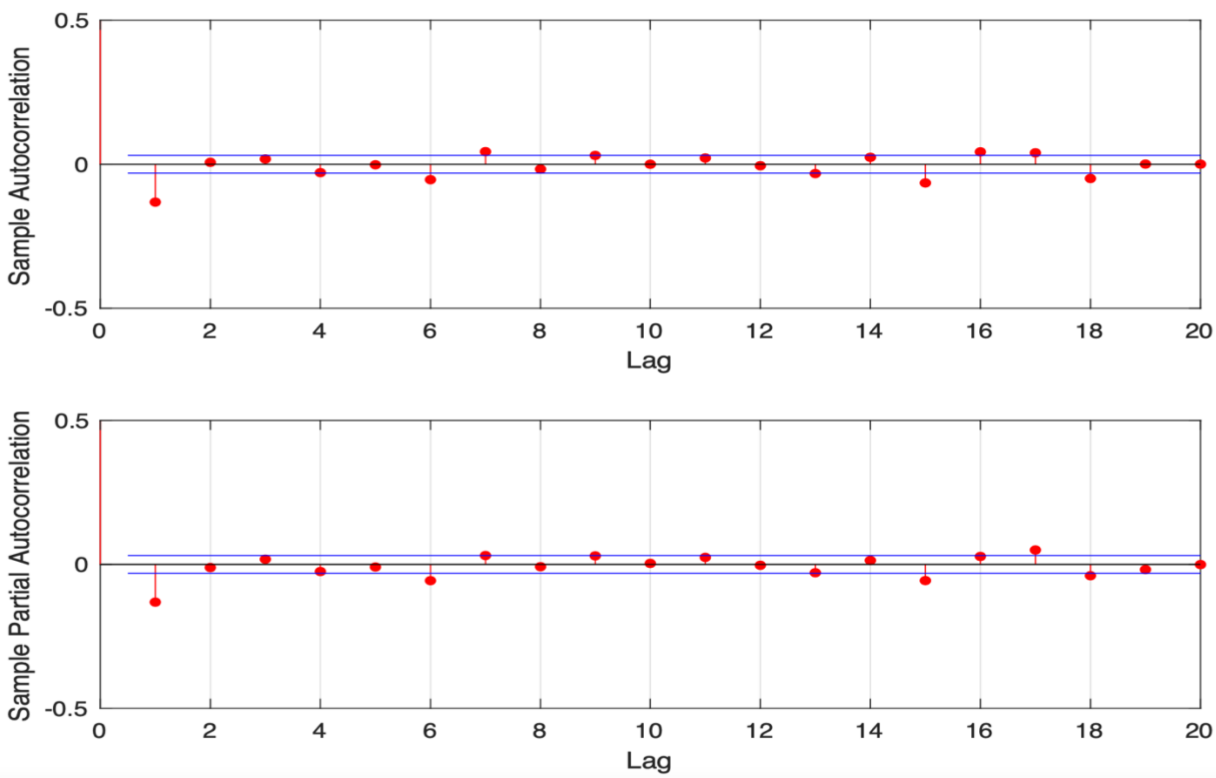
This figure plots the ACF and PACF within 20 lags for close-to-close returns in the Vietnamese market.

Figure B. 5 : ACF and PACF for log-returns of VNM(CO)



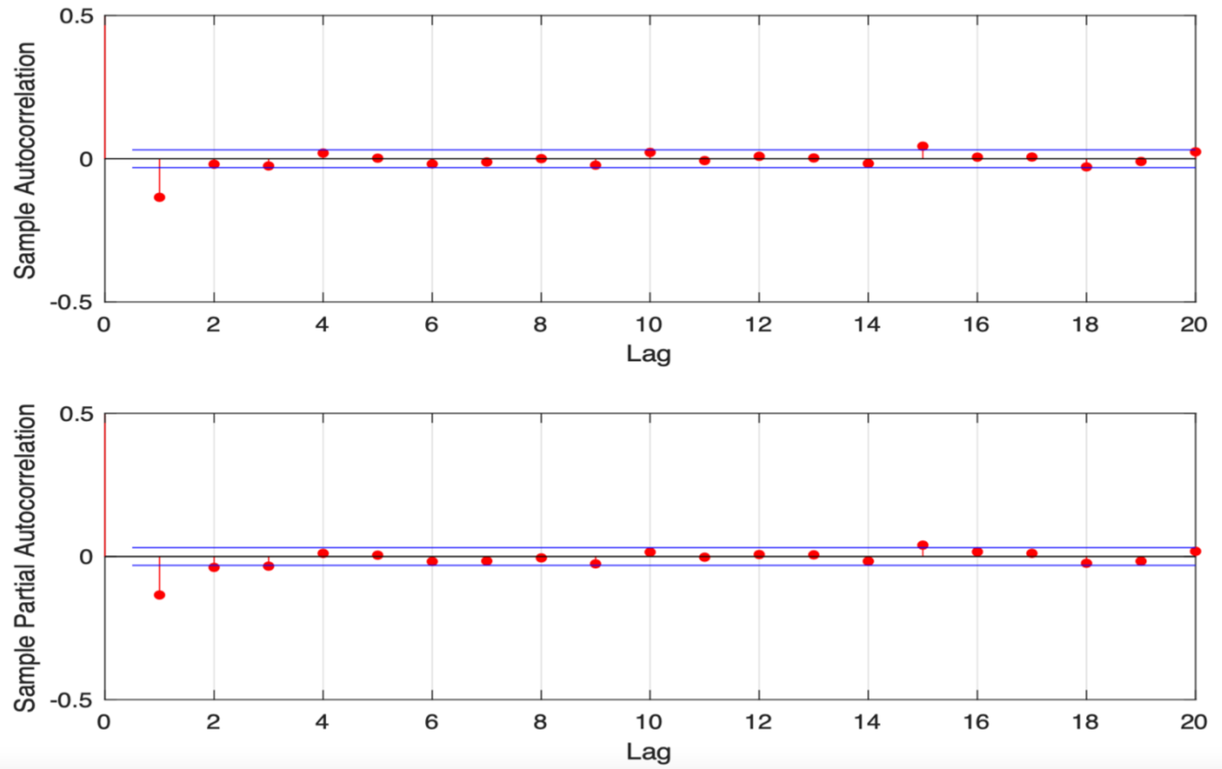
This figure plots the ACF and PACF within 20 lags for close-to-open returns in the Vietnamese market.

Figure B. 6 : ACF and PACF for log-returns of US



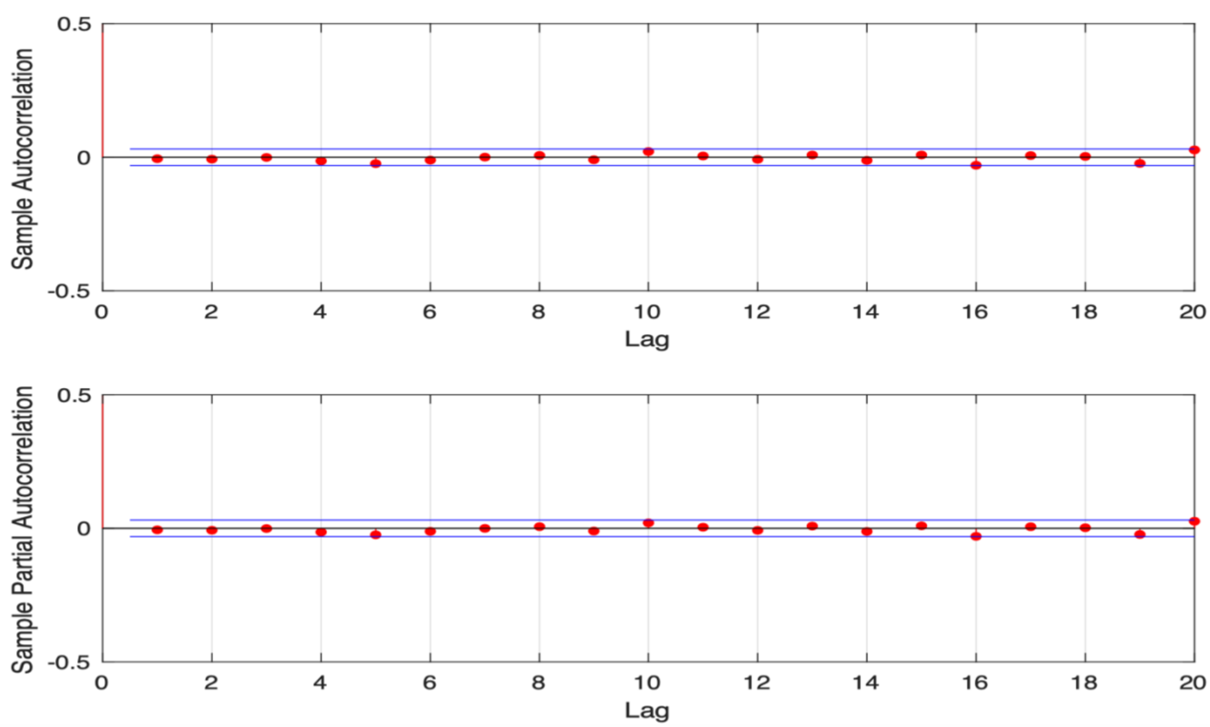
This figure plots the ACF and PACF within 20 lags for close-to-close returns in the American market.

Figure B. 7 : ACF and PACF for log-returns of JPN(CC)



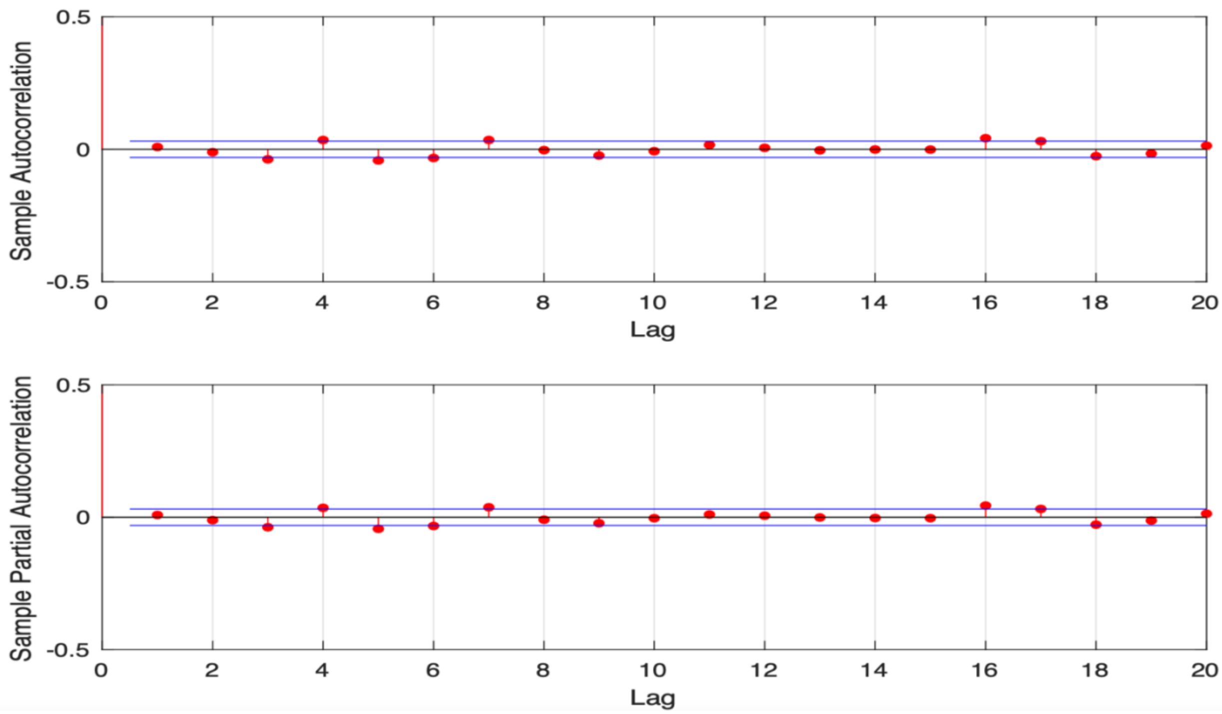
This figure plots the ACF and PACF within 20 lags for close-to-close returns in the Japanese market.

Figure B. 8 : ACF and PACF for log-returns of JPN(CO)



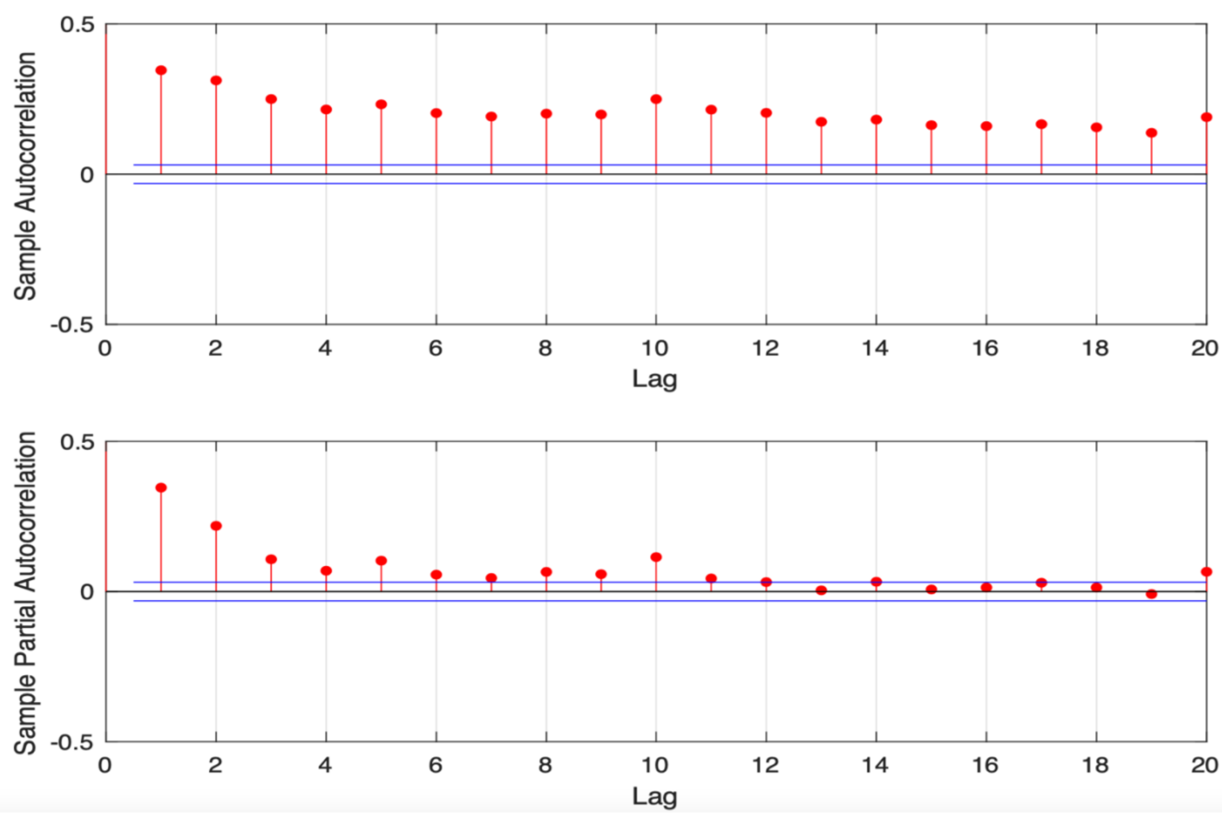
This figure plots the ACF and PACF within 20 lags for close-to-open returns in the Japanese market.

Figure B. 9 : ACF and PACF for log-returns of EU



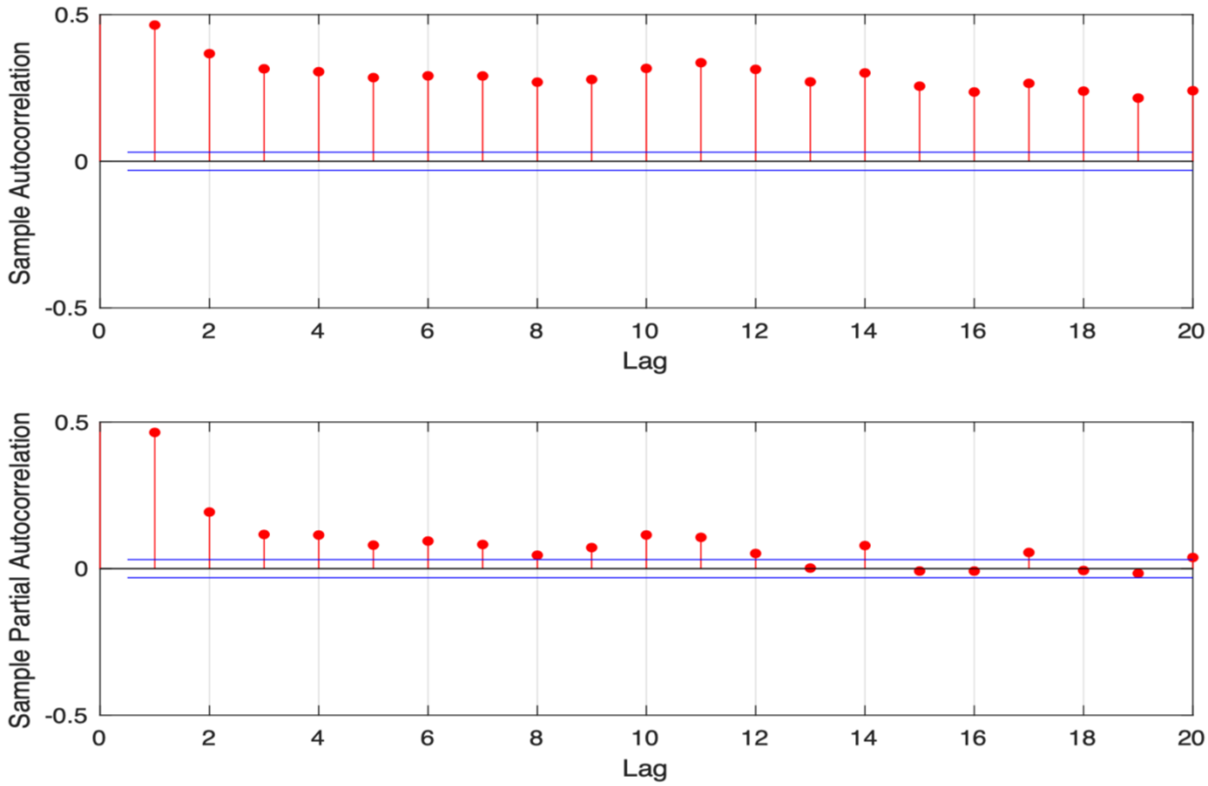
This figure plots the ACF and PACF within 20 lags for close-to-close returns in the European market.

Figure B. 10 : ACF and PACF for squared log-returns of VNM(CC)



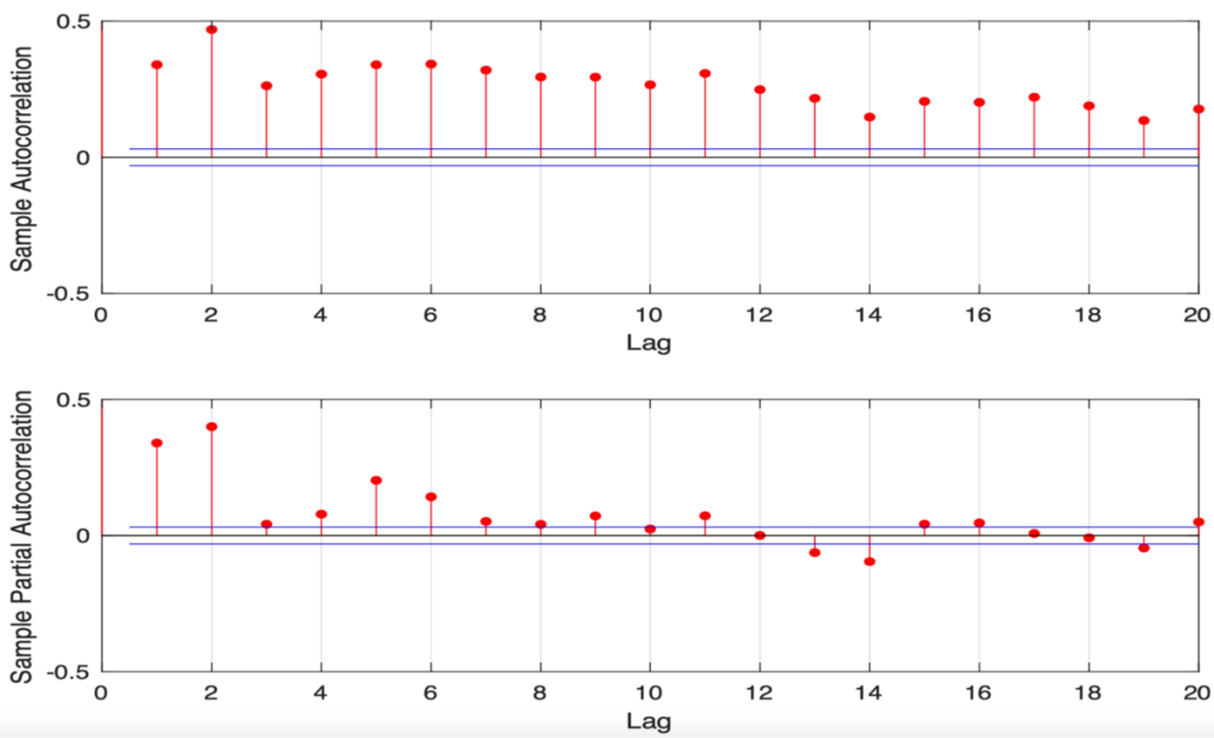
This figure plots the ACF and PACF within 20 lags for squared close-to-close returns in the Vietnamese market.

Figure B. 11 : ACF and PACF for squared log-returns of VNM(CO)



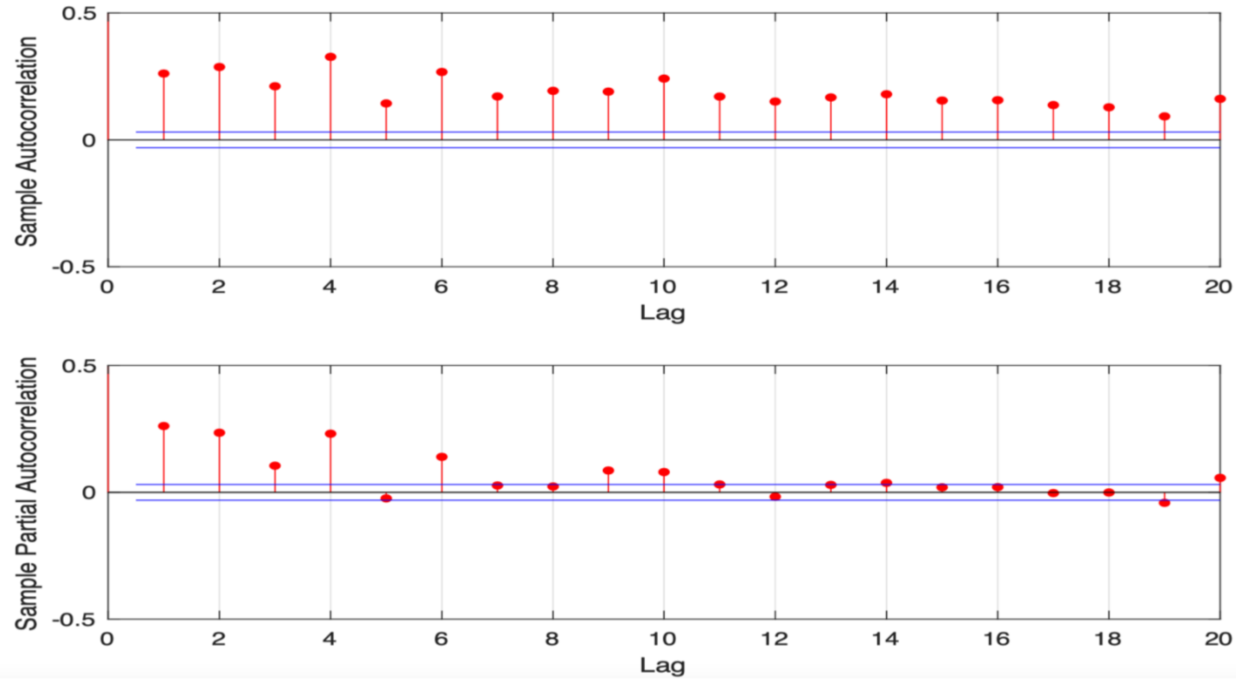
This figure plots the ACF and PACF within 20 lags for squared close-to-open returns in the Vietnamese market.

Figure B. 12 : ACF and PACF for squared log-returns of US



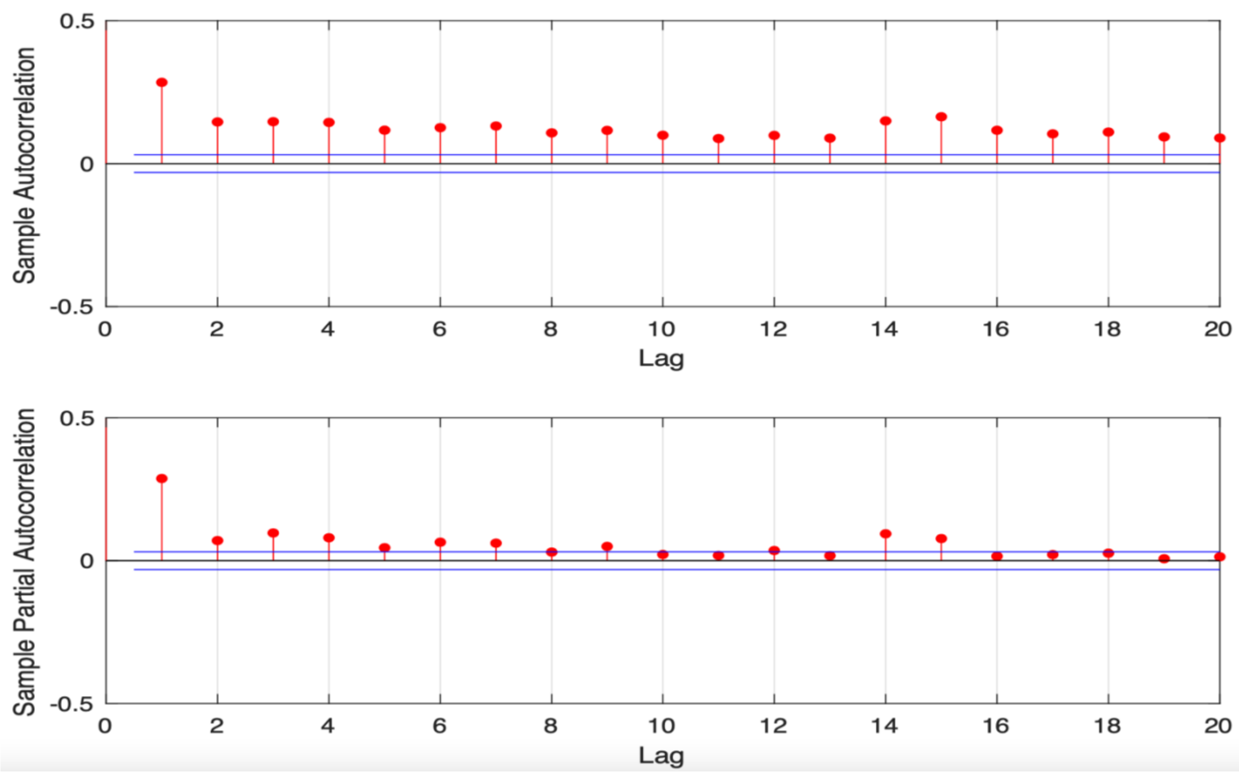
This figure plots the ACF and PACF within 20 lags for squared close-to-close returns in the American market.

Figure B. 13 : ACF and PACF for squared log-returns of JPN(CC)



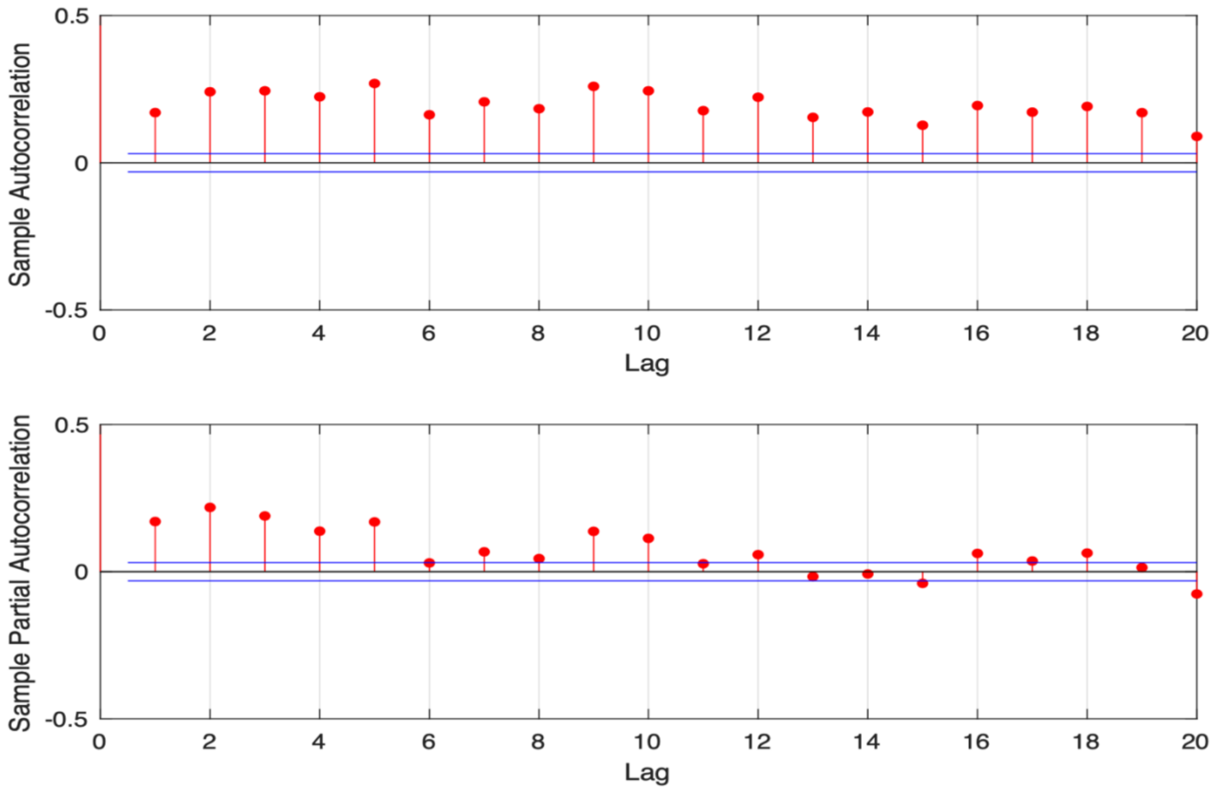
This figure plots the ACF and PACF within 20 lags for squared close-to-close returns in the Japanese market.

Figure B. 14 : ACF and PACF for squared log-returns of JPN(CO)



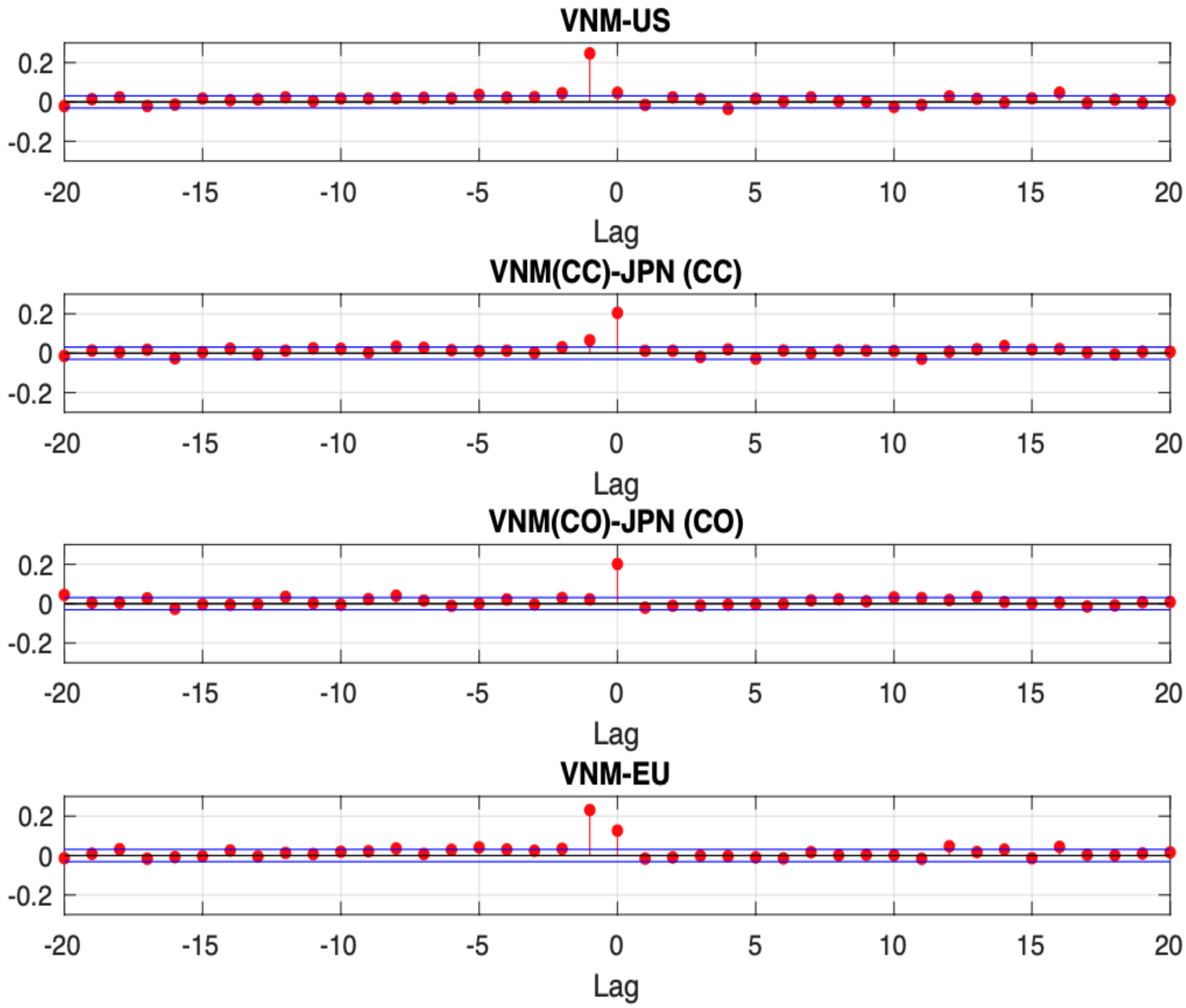
This figure plots the ACF and PACF within 20 lags for squared close-to-open returns in the Japanese market.

Figure B. 15 : ACF and PACF for squared log-returns of EU

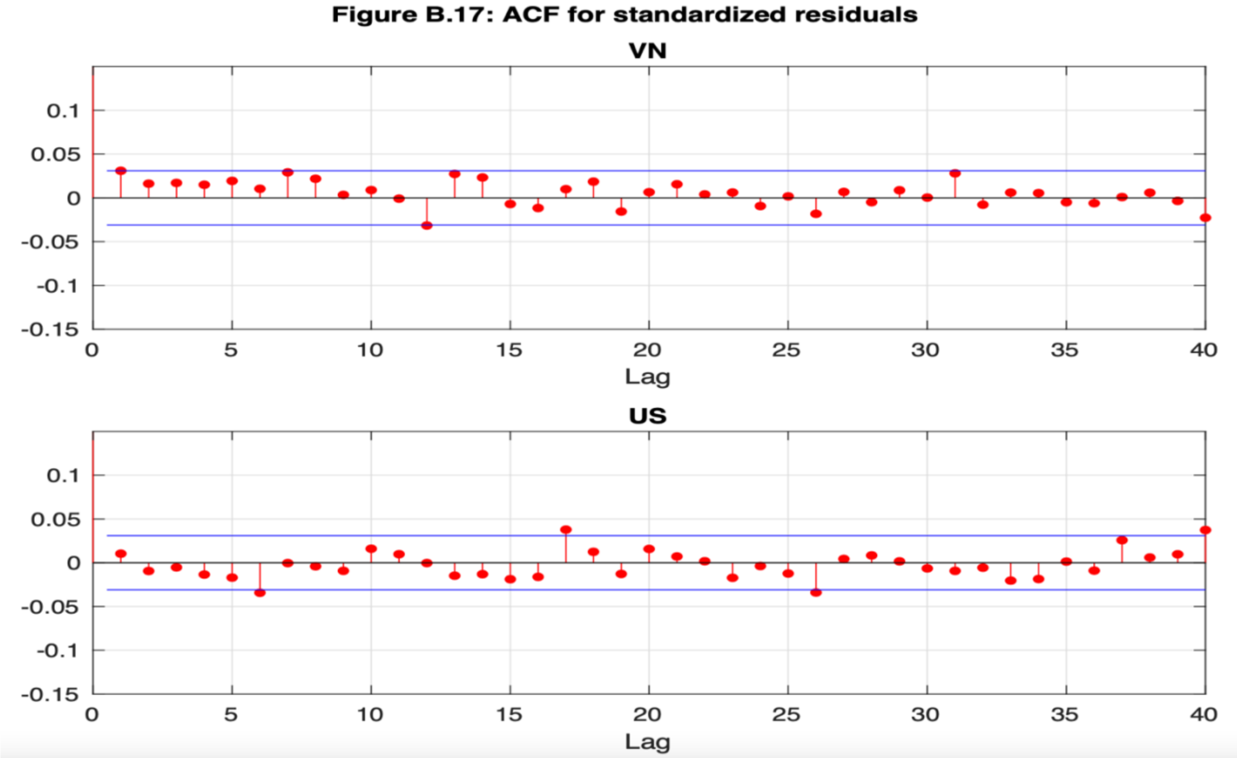


This figure plots the ACF and PACF within 20 lags for squared close-to-close returns in the European market.

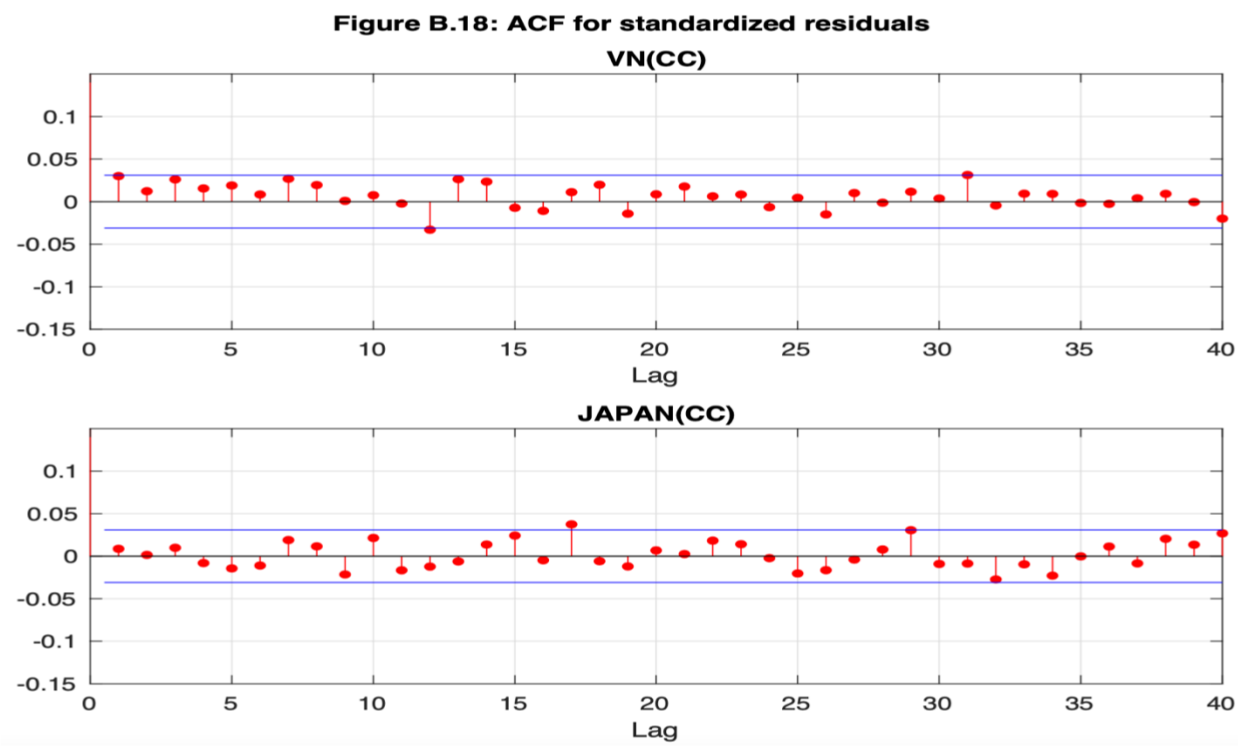
Figure B.16: Cross-correlation function



This figure plots the cross-correlation function (CCF) between each pair of return series within +/-20 lags. CC denotes the close-to-close return series. CO represents the close-to-open return series.

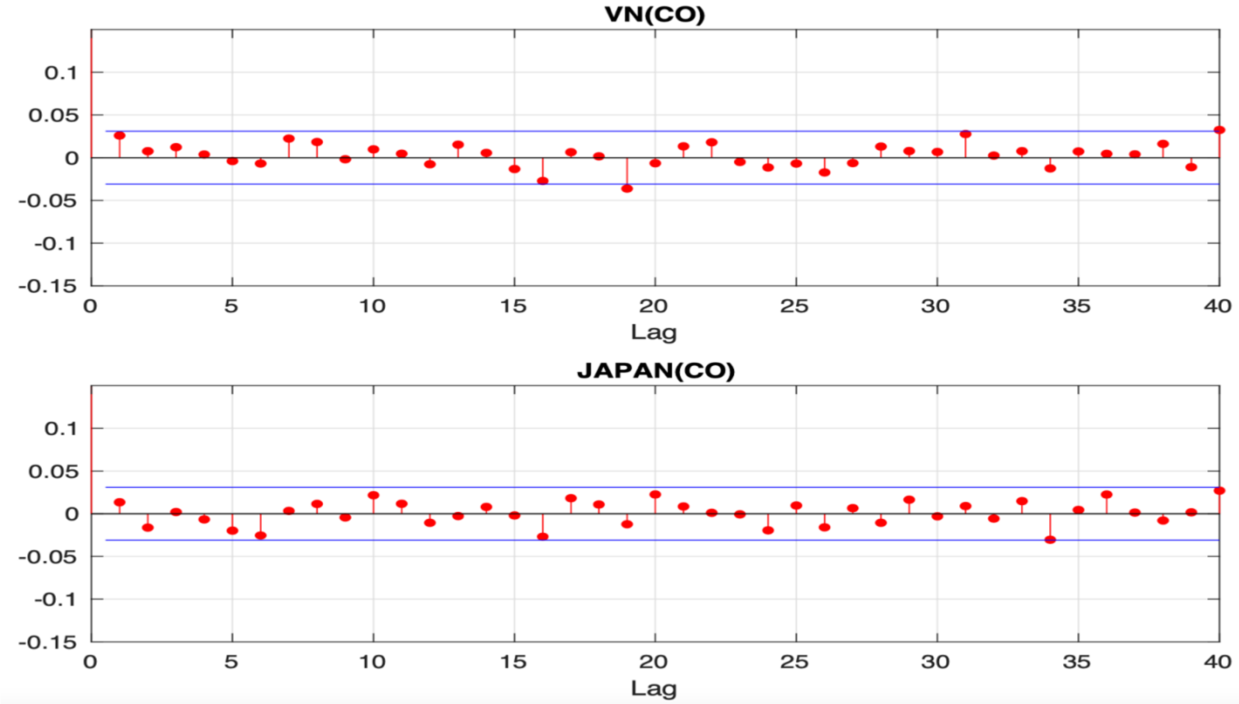


This figure plots the ACF within 40 lags for fitted standardized residuals estimated with ARMA-GARCH models for Vietnamese and American markets.



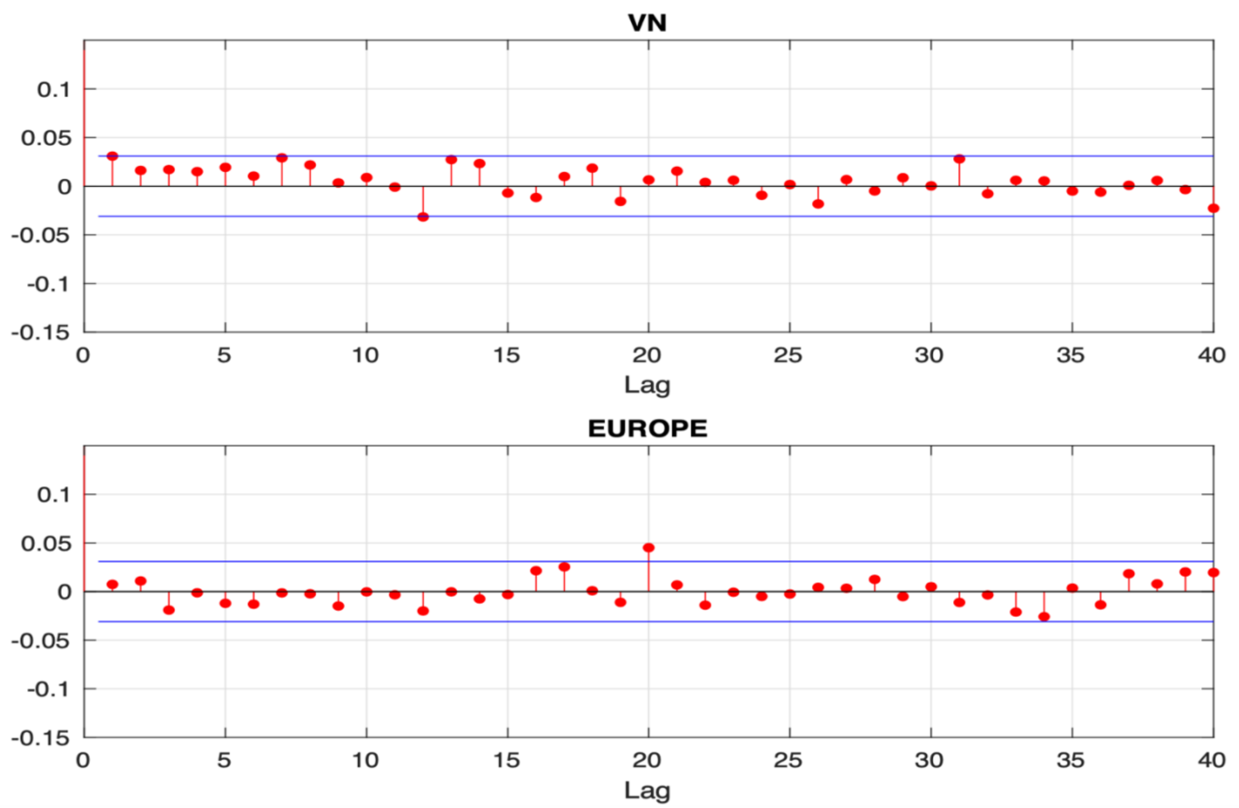
This figure plots the ACF within 40 lags for fitted standardized residuals estimated with ARMA-GARCH models for Vietnamese and Japanese markets (using CC returns).

Figure B.19: ACF for standardized residuals



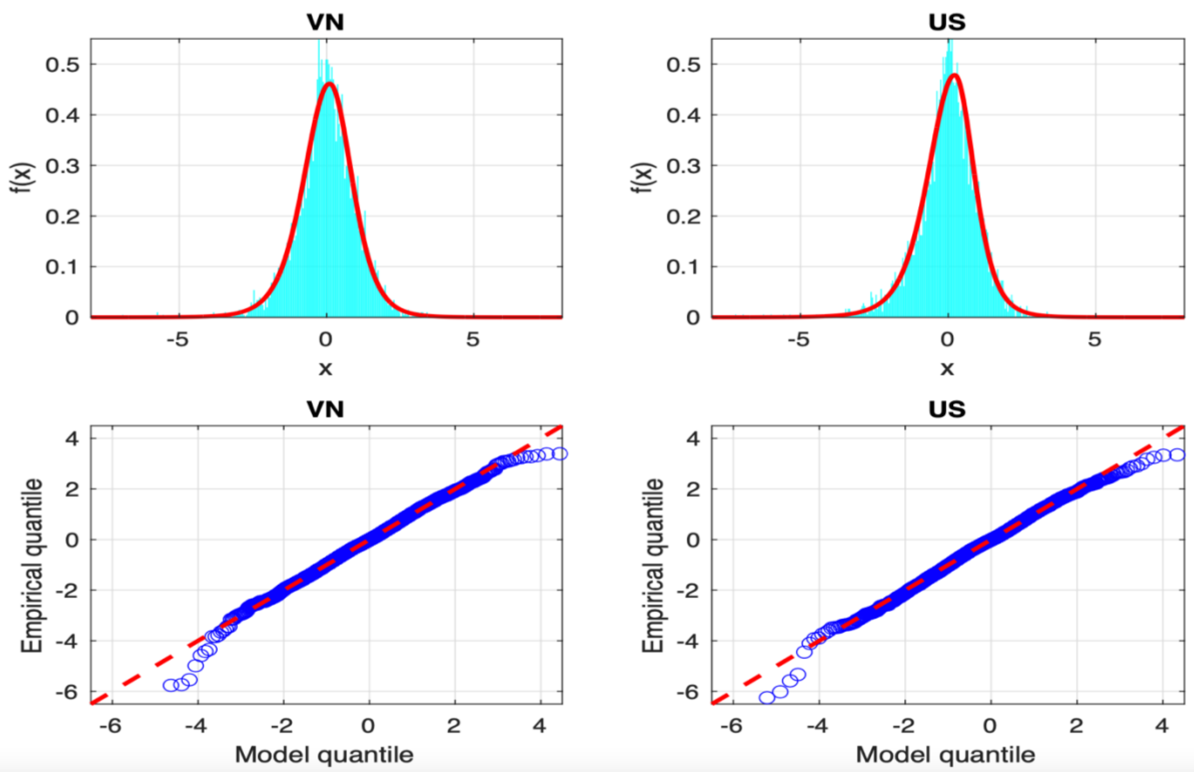
This figure plots the ACF within 40 lags for fitted standardized residuals estimated with ARMA-GARCH models for Vietnamese and Japanese markets (using CO returns).

Figure B.20: ACF for standardized residuals



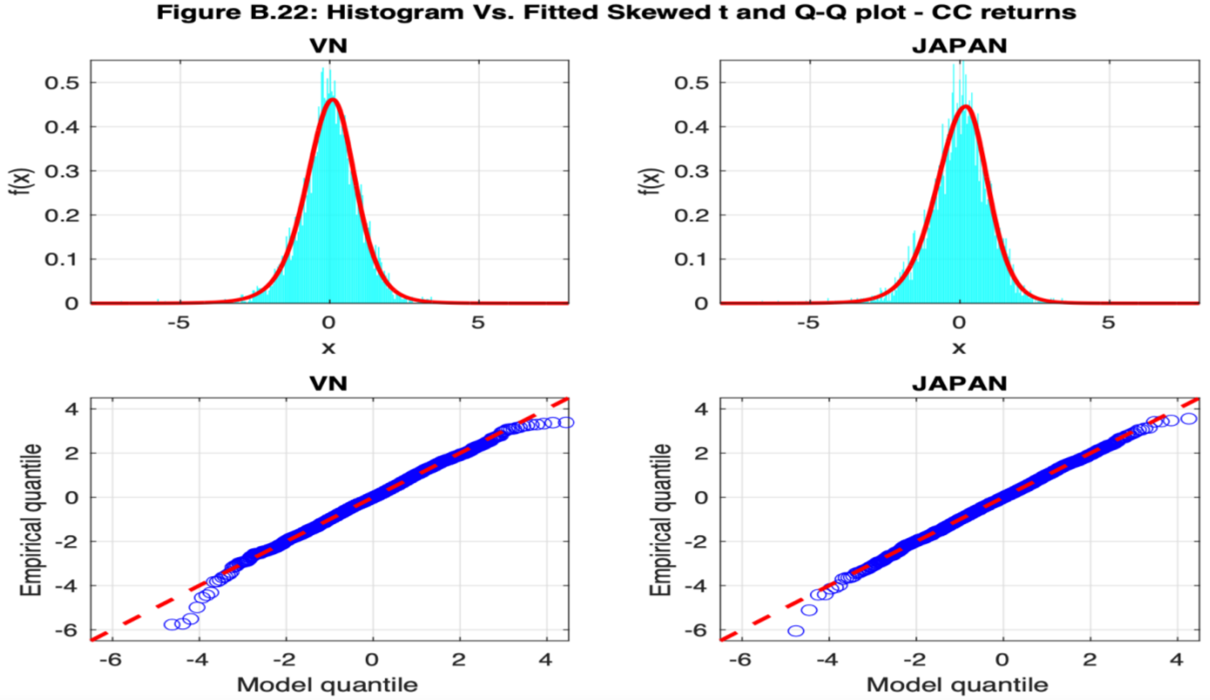
This figure plots the ACF within 40 lags for fitted standardized residuals estimated with ARMA-GARCH models for Vietnamese and European markets.

Figure B.21: Histogram Vs. Fitted Skewed t and Q-Q plot



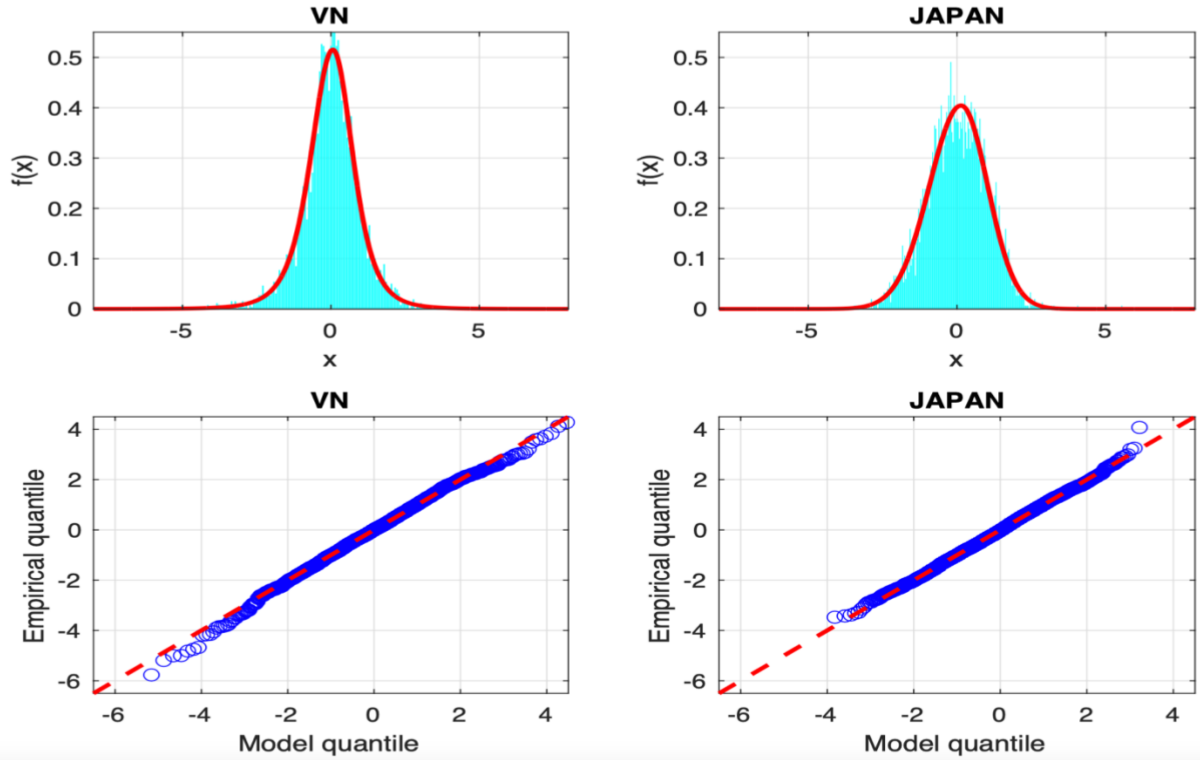
This figure describes on the top the histogram and fitted skewed Student's t distribution. At the bottom are the Q-Q plots. The plots for the Vietnamese market are displayed on the left-hand side, while those for the American market are on the right-hand side.

Figure B.22: Histogram Vs. Fitted Skewed t and Q-Q plot - CC returns



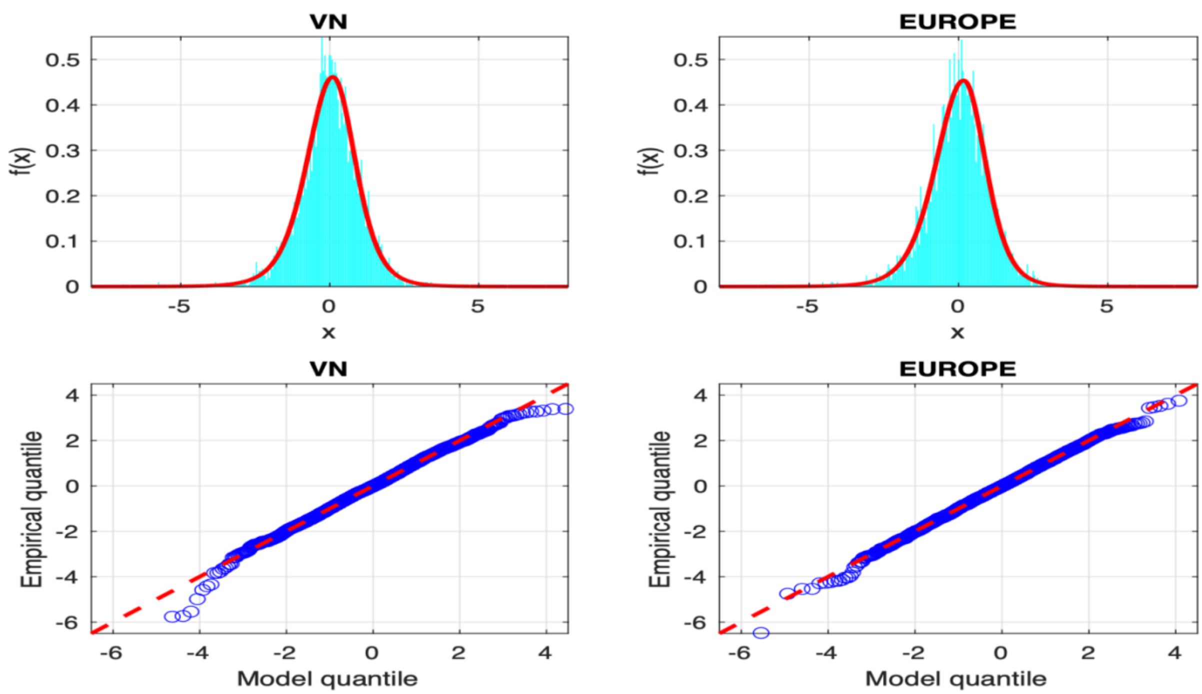
This figure describes on the top the histogram and fitted skewed Student's t distribution. At the bottom are the Q-Q plots. The plots for the Vietnamese market are displayed on the left-hand side, while those for the Japanese market are on the right-hand side.

Figure B.23: Histogram Vs. Fitted Skewed t and Q-Q plot - CO returns



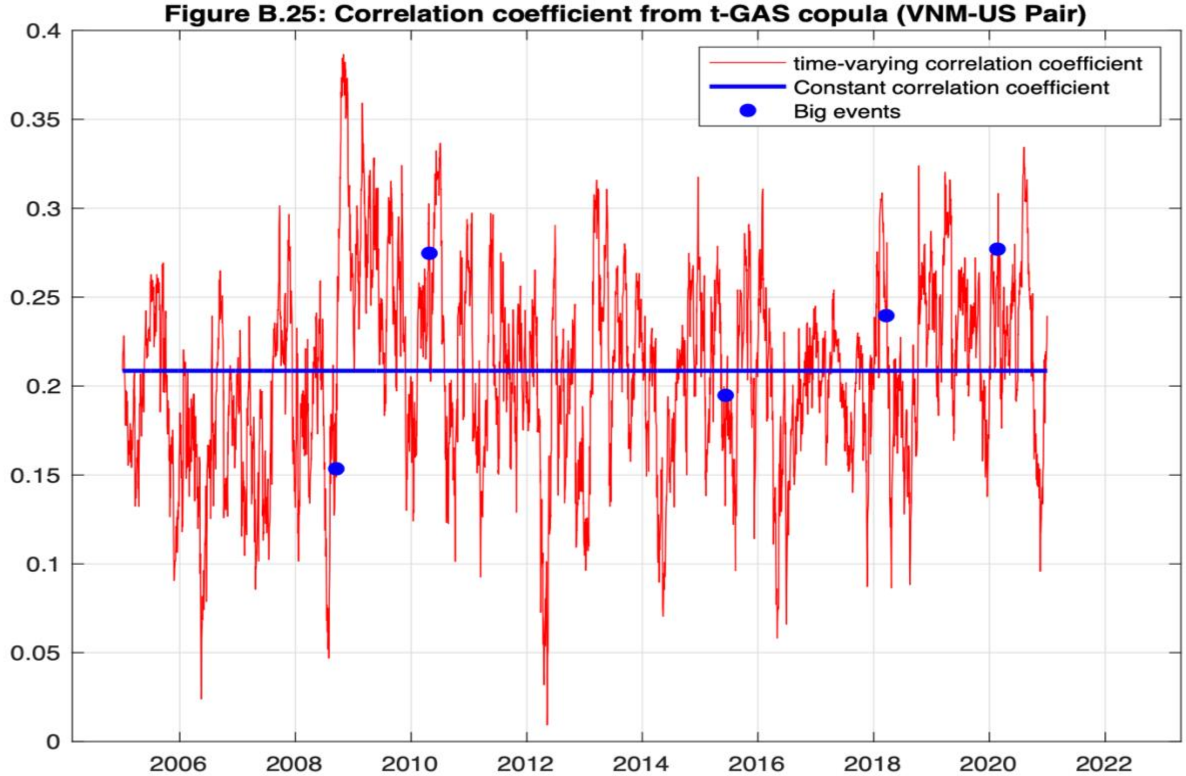
This figure describes on the top the histogram and fitted skewed Student's t distribution. At the bottom are the Q-Q plots. The plots for the Vietnamese market are displayed on the left-hand side, while those for the Japanese market are on the right-hand side.

Figure B.24: Histogram Vs. Fitted Skewed t and Q-Q plot



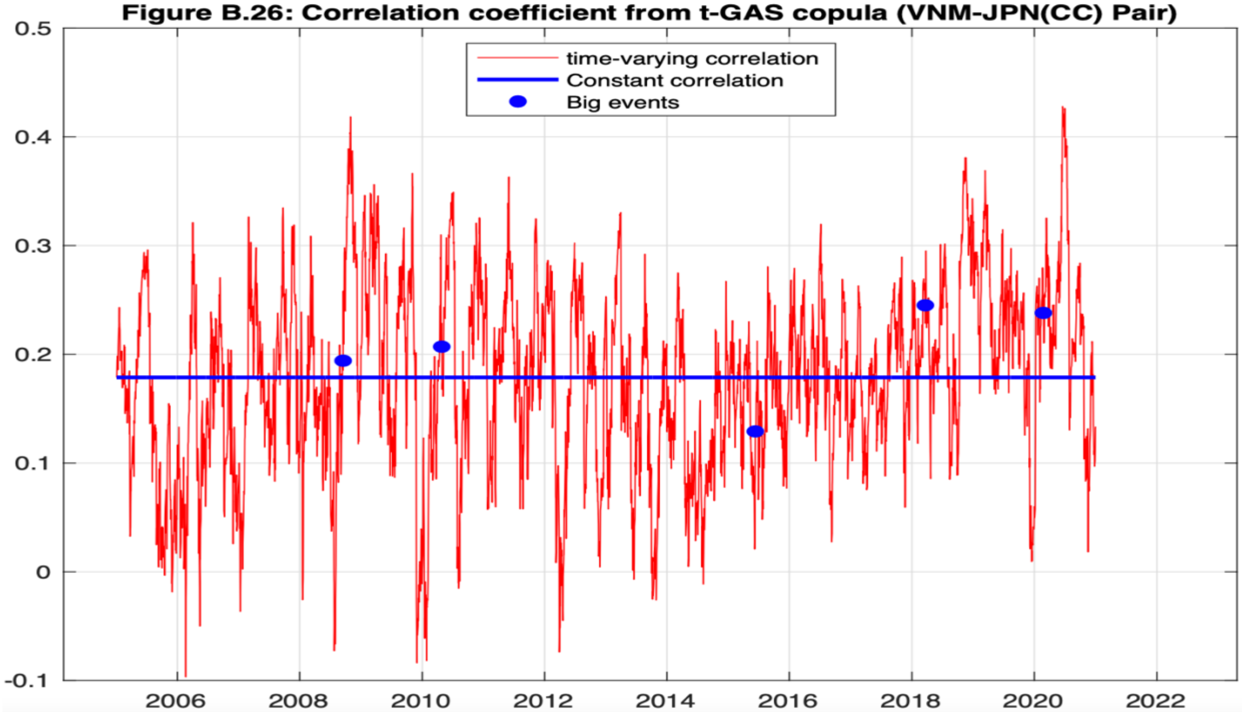
This figure describes on the top the histogram and fitted skewed Student's t distribution. At the bottom are the Q-Q plots. The plots for the Vietnamese market are displayed on the left-hand side, while those for the European market are on the right-hand side.

Figure B.25: Correlation coefficient from t-GAS copula (VNM-US Pair)

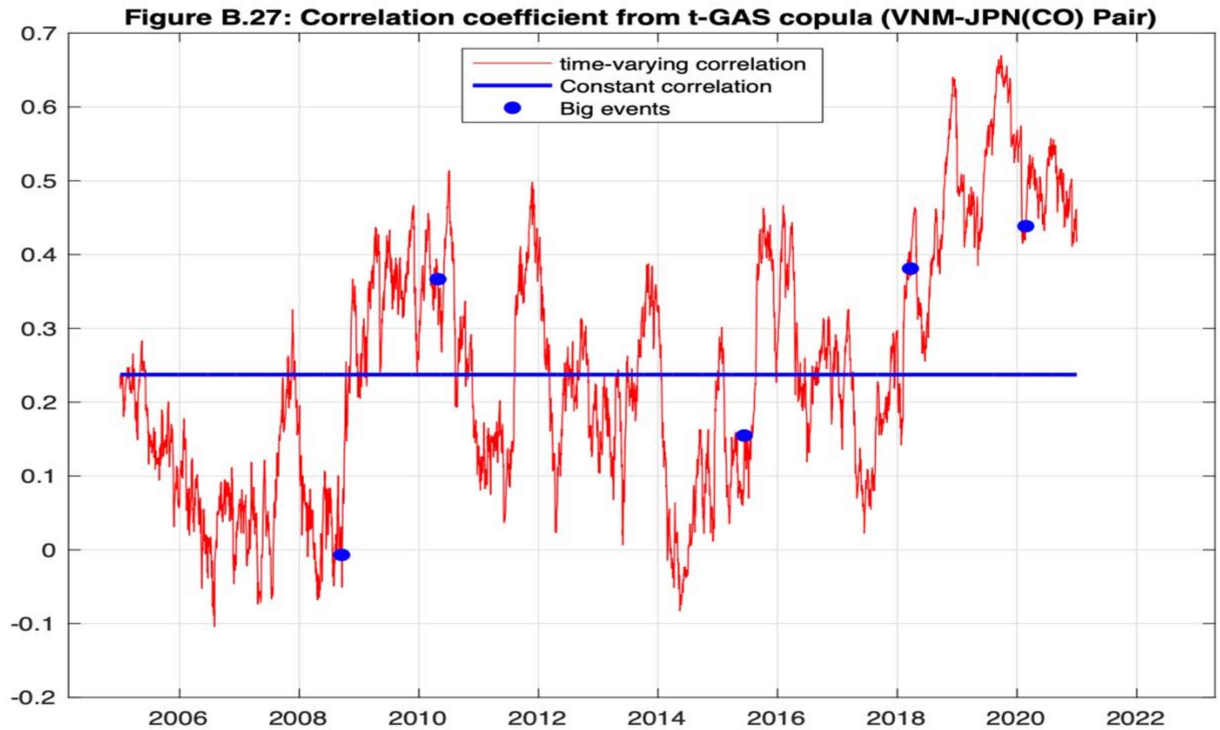


The figure illustrates the time-varying evolution of the correlation coefficient estimated from the Student's t-GAS copula. The blue dots represent the "big" events listed in Table A.9.

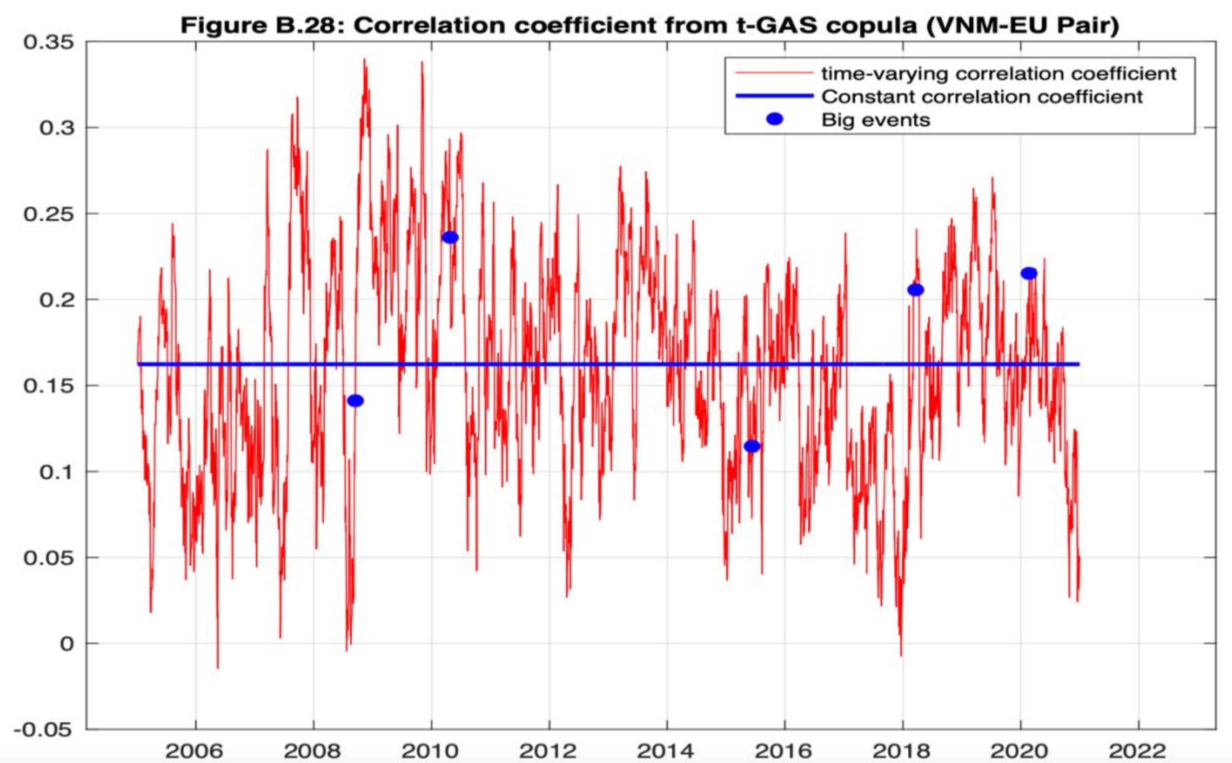
Figure B.26: Correlation coefficient from t-GAS copula (VNM-JPN(CC) Pair)



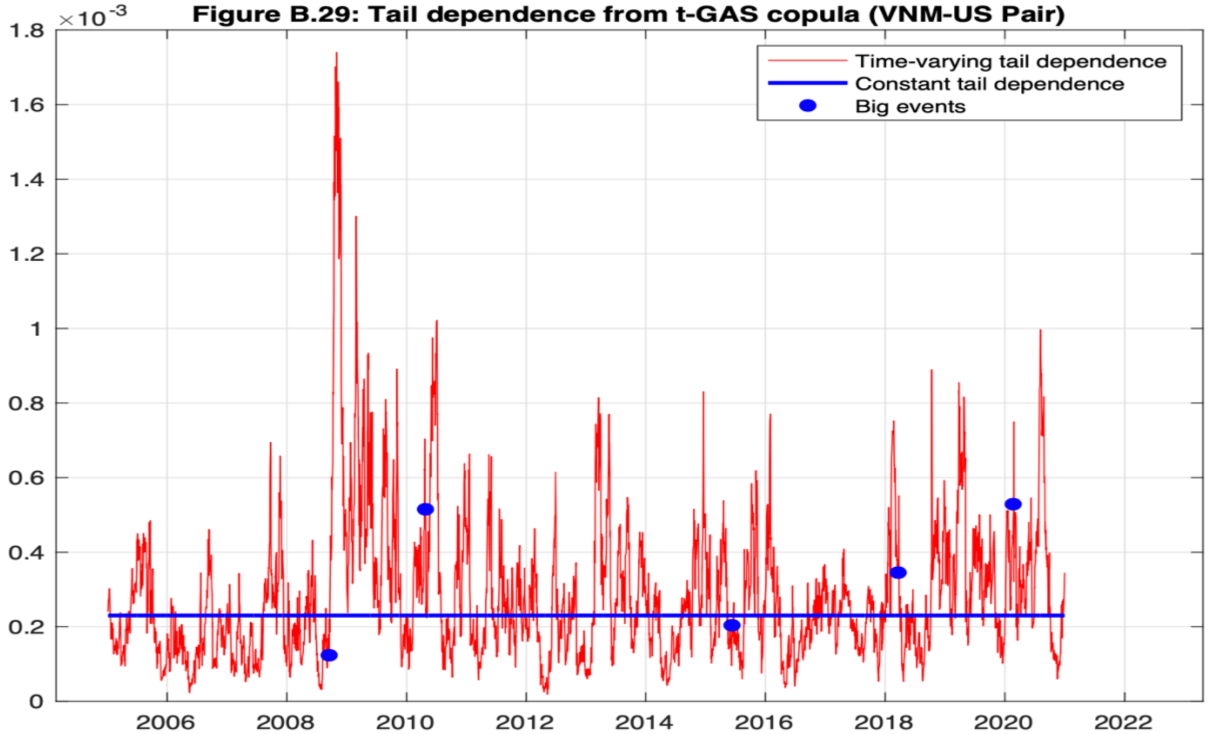
The figure illustrates the time-varying evolution of the correlation coefficient estimated from the Student's t-GAS copula. The blue dots represent the "big" events listed in Table A.9.



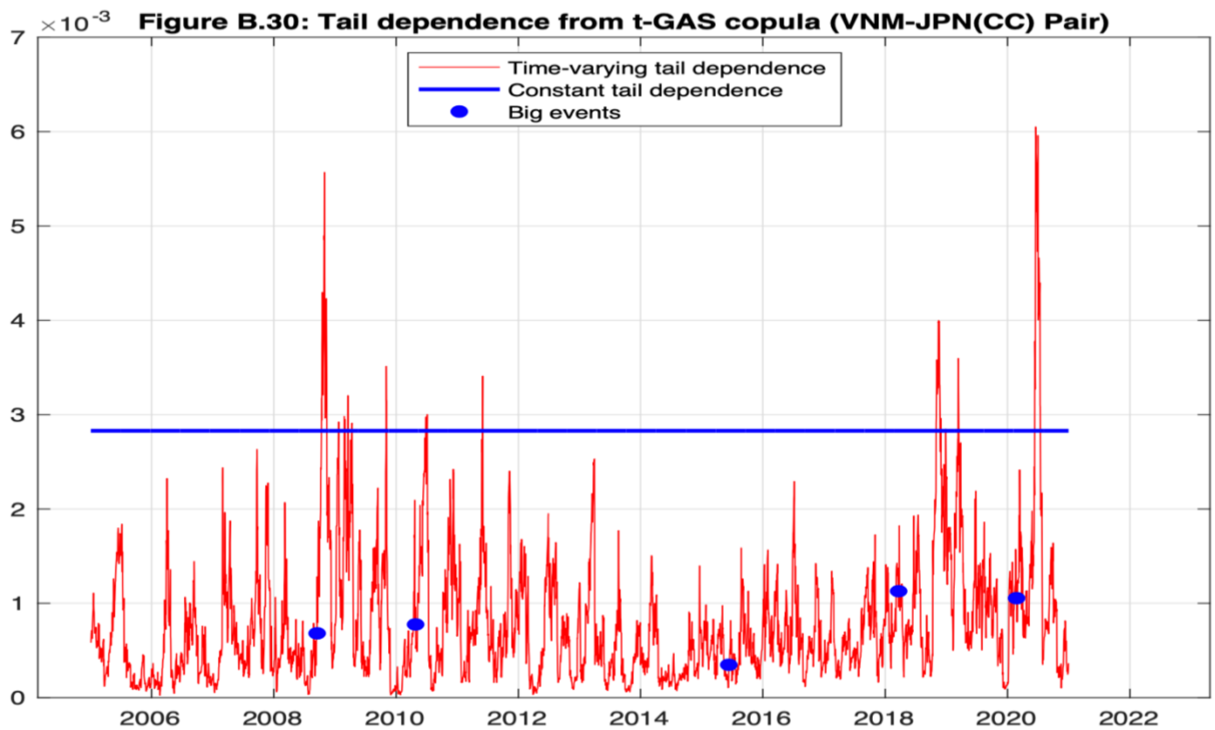
The figure illustrates the time-varying evolution of the correlation coefficient estimated from the Student's t-GAS copula. The blue dots represent the "big" events listed in Table A.9.



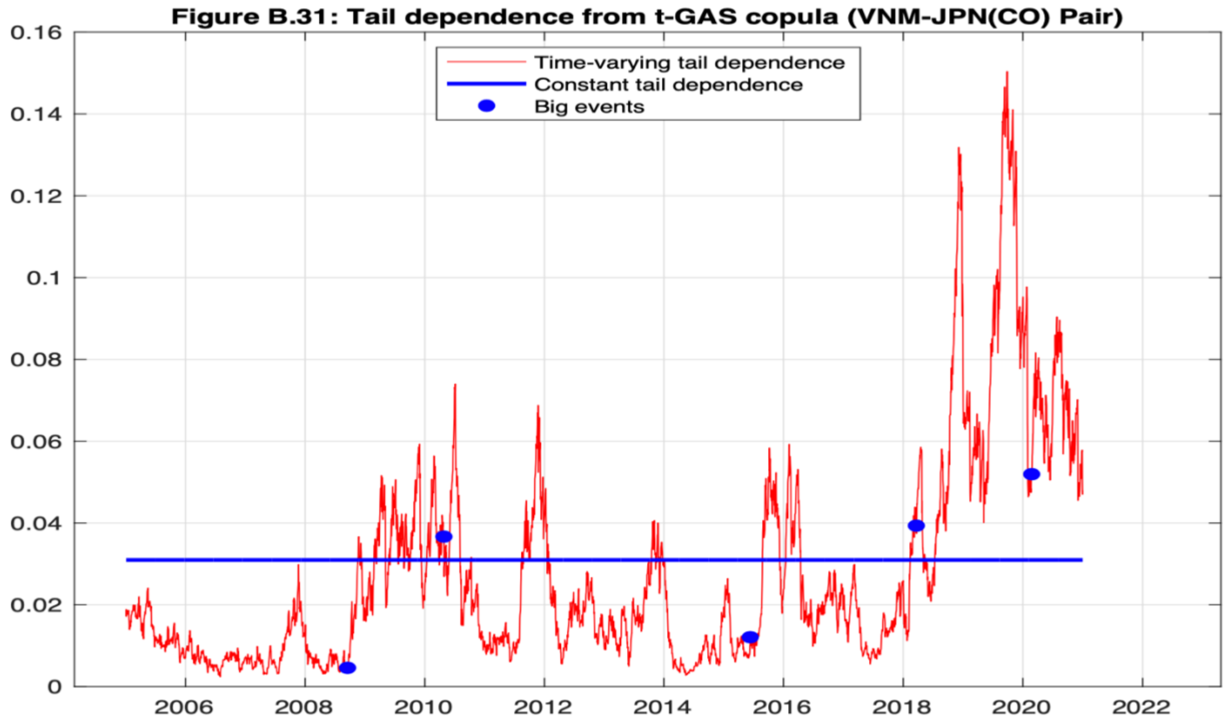
The figure illustrates the time-varying evolution of the correlation coefficient estimated from the Student's t-GAS copula. The blue dots represent the "big" events listed in Table A.9.



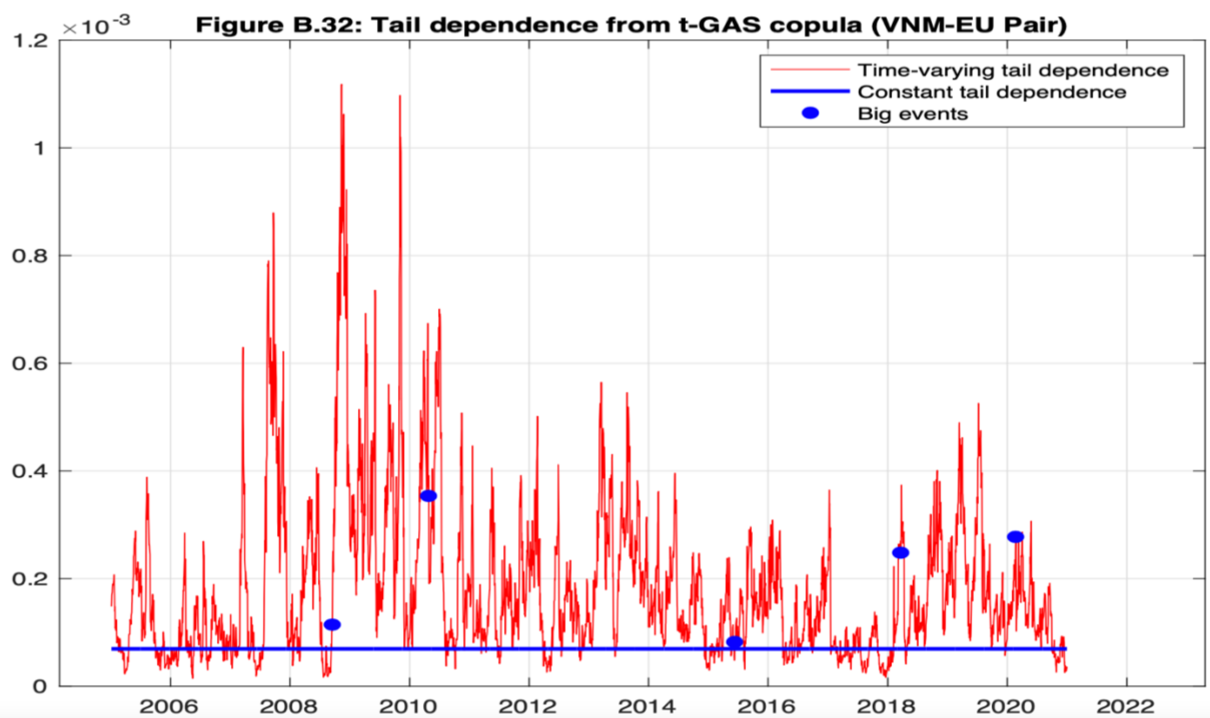
The figure illustrates the time-varying evolution of the tail dependence coefficient estimated from the Student's t-GAS copula. The blue dots represent the "big" events listed in Table A.9.



The figure illustrates the time-varying evolution of the tail dependence coefficient estimated from the Student's t-GAS copula. The blue dots represent the "big" events listed in Table A.9.

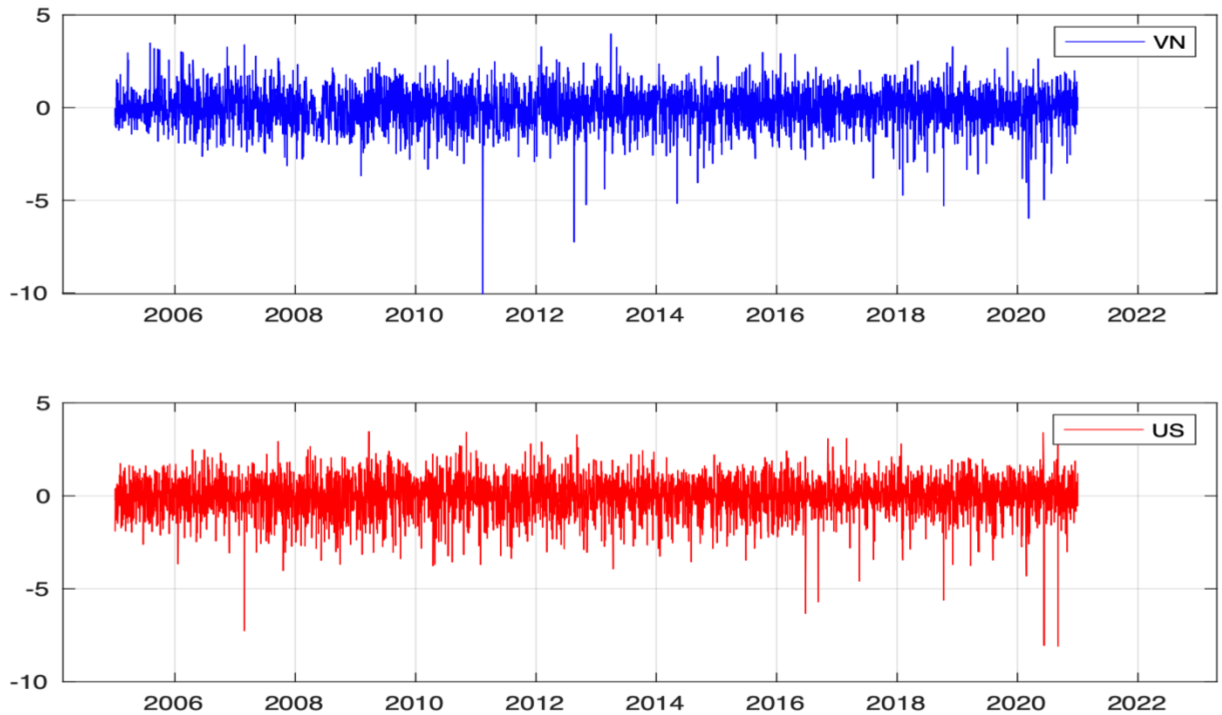


The figure illustrates the time-varying evolution of the tail dependence coefficient estimated from the Student's t-GAS copula. The blue dots represent the "big" events listed in Table A.9.



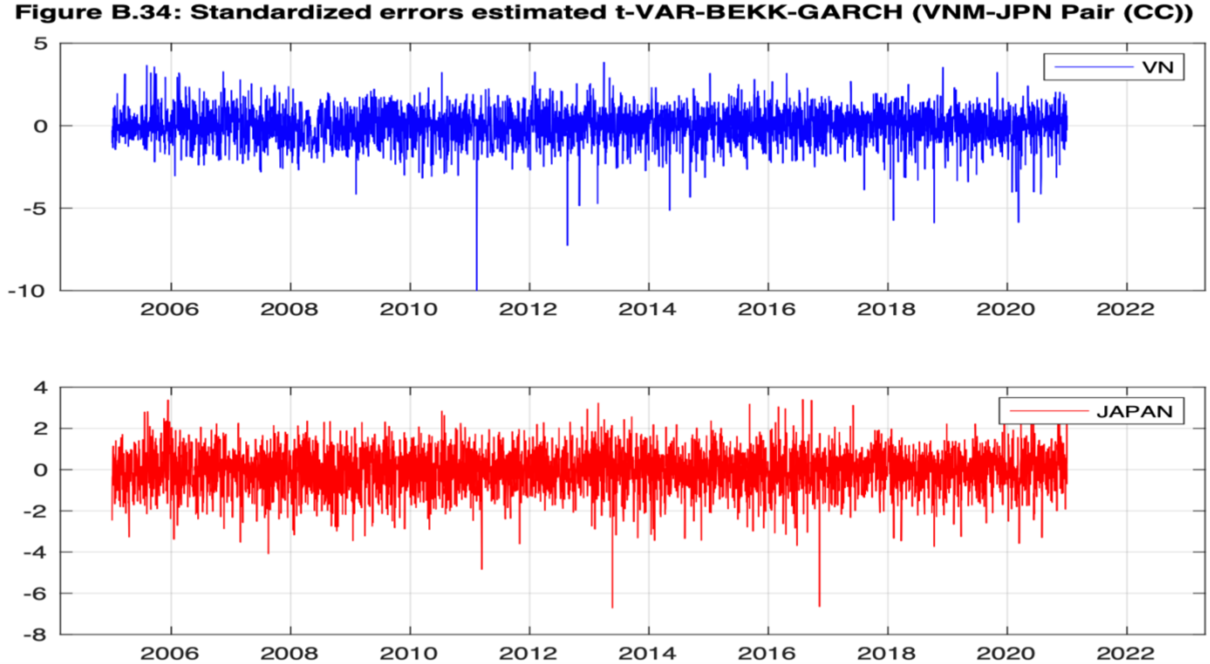
The figure illustrates the time-varying evolution of the tail dependence coefficient estimated from the Student's t-GAS copula. The blue dots represent the "big" events listed in Table A.9.

Figure B.33: Standardized errors estimated from t-VAR-BEKK-GARCH (VNM-US Pair)



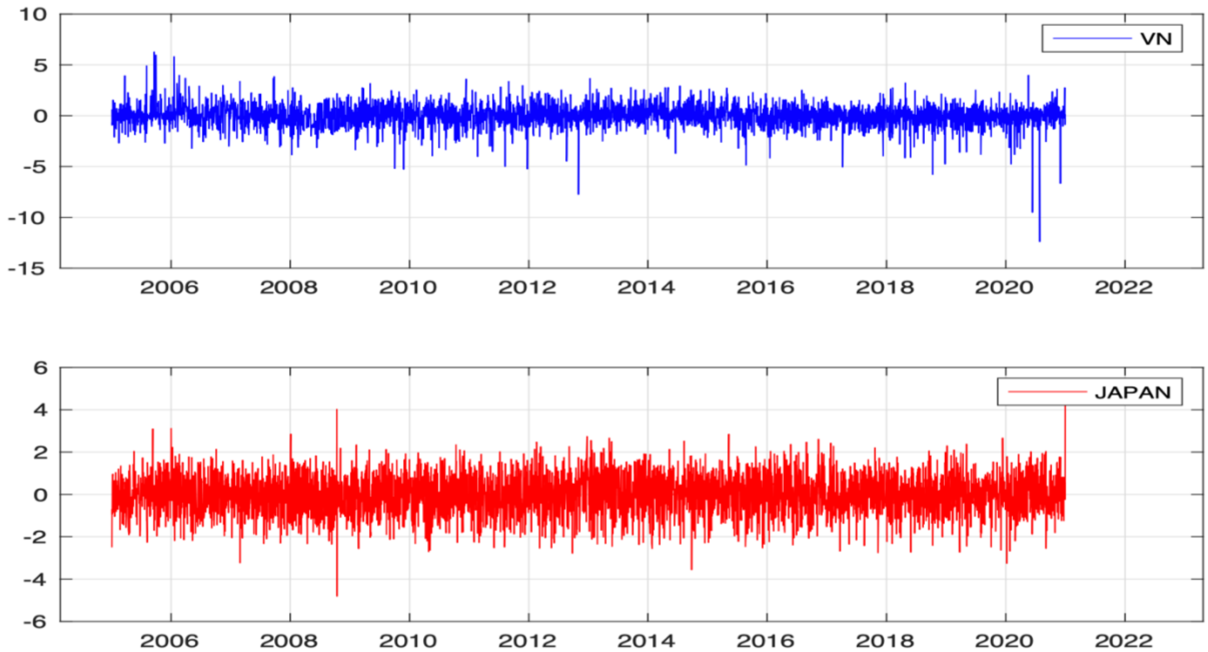
The figure illustrates the time path of fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and American markets.

Figure B.34: Standardized errors estimated t-VAR-BEKK-GARCH (VNM-JPN Pair (CC))



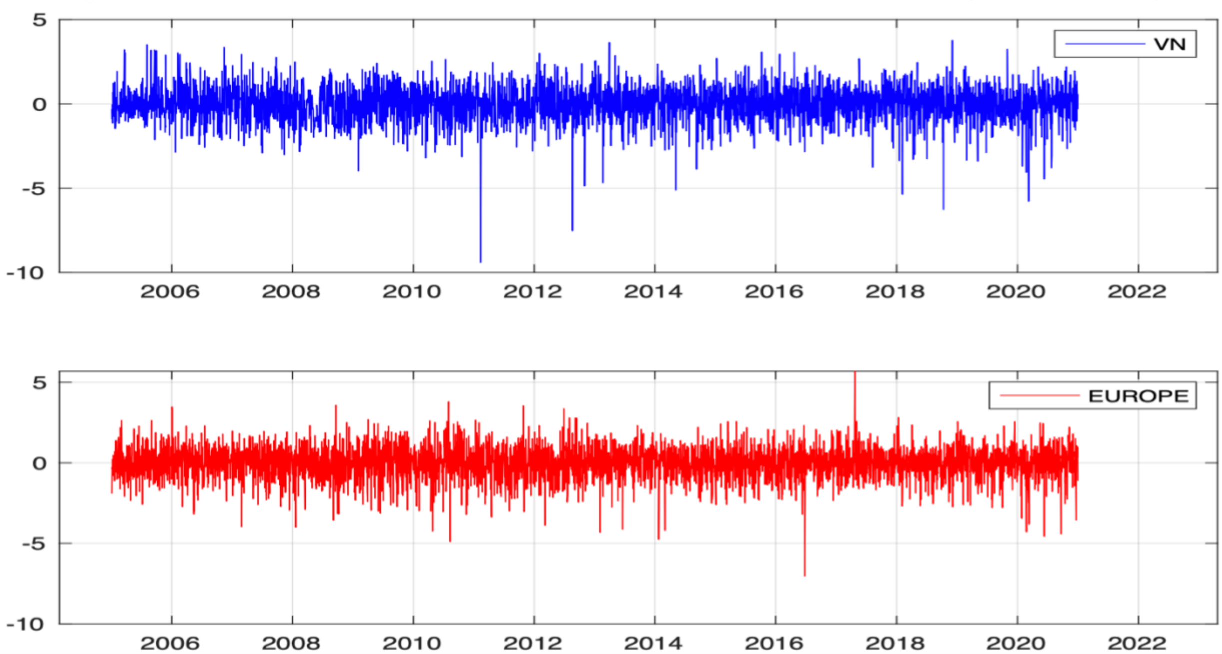
The figure illustrates the time path of fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and Japanese markets (using CC returns).

Figure B.35: Standardized errors estimated t-VAR-BEKK-GARCH (VNM-JPN Pair (CO))



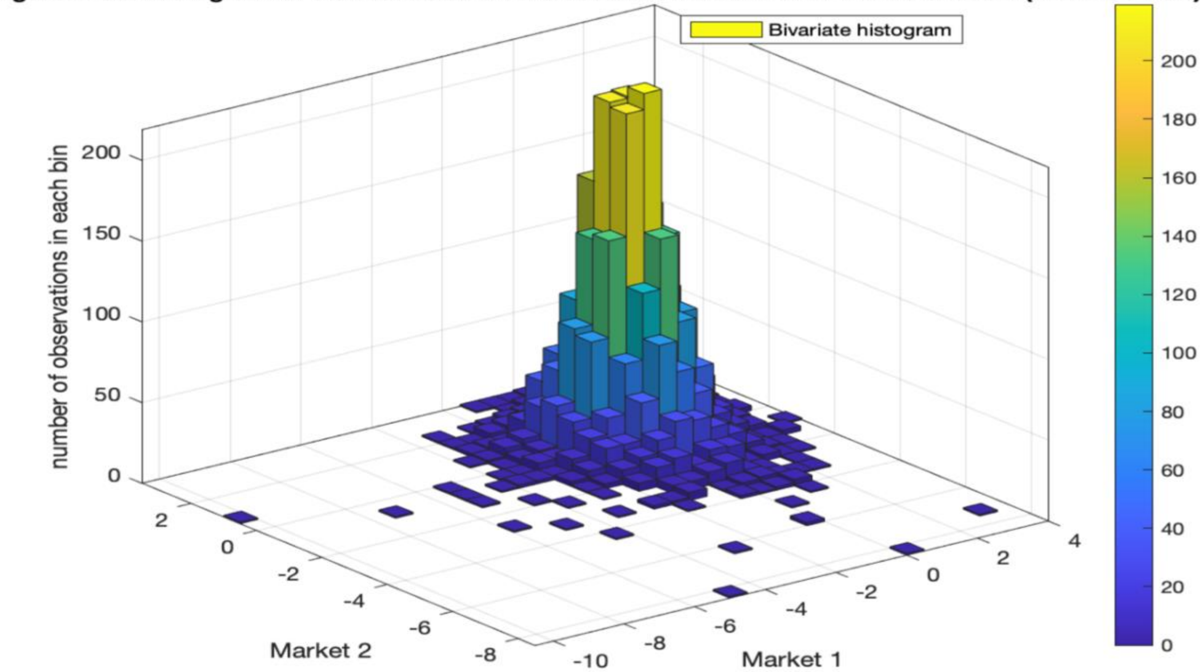
The figure illustrates the time path of fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and Japanese markets (using CO returns).

Figure B.36: Standardized errors estimated t-VAR-BEKK-GARCH (VNM-EU Pair)



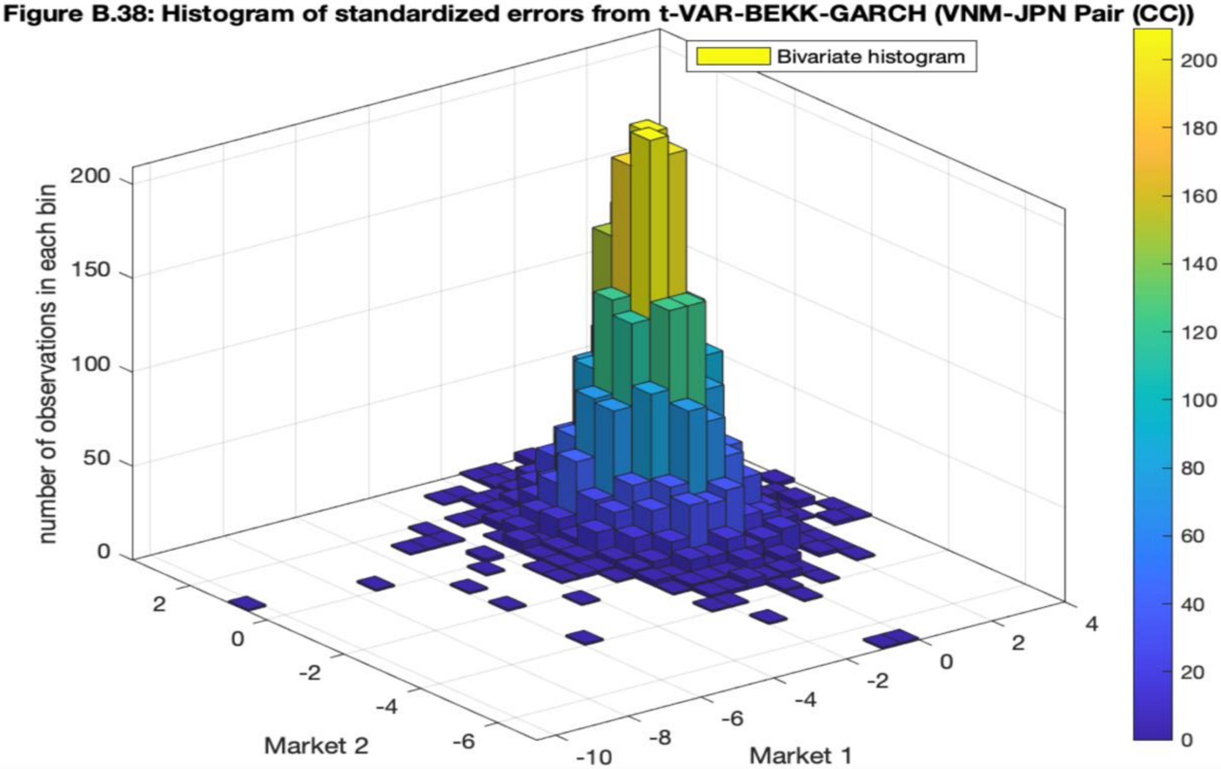
The figure illustrates the time path of fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and European markets.

Figure B.37: Histogram of standardized errors estimated from t-VAR-BEKK-GARCH (VNM-US Pair)



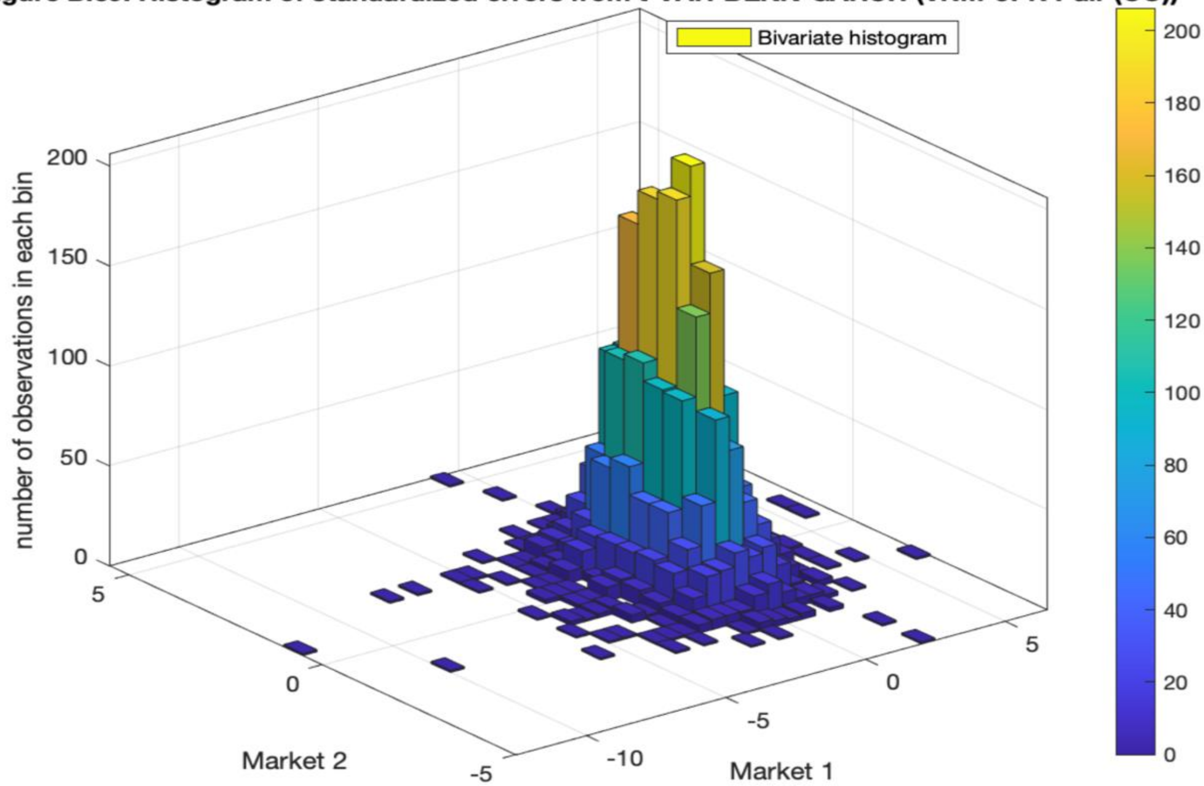
The figure illustrates the multivariate histogram of fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and American markets.

Figure B.38: Histogram of standardized errors from t-VAR-BEKK-GARCH (VNM-JPN Pair (CC))



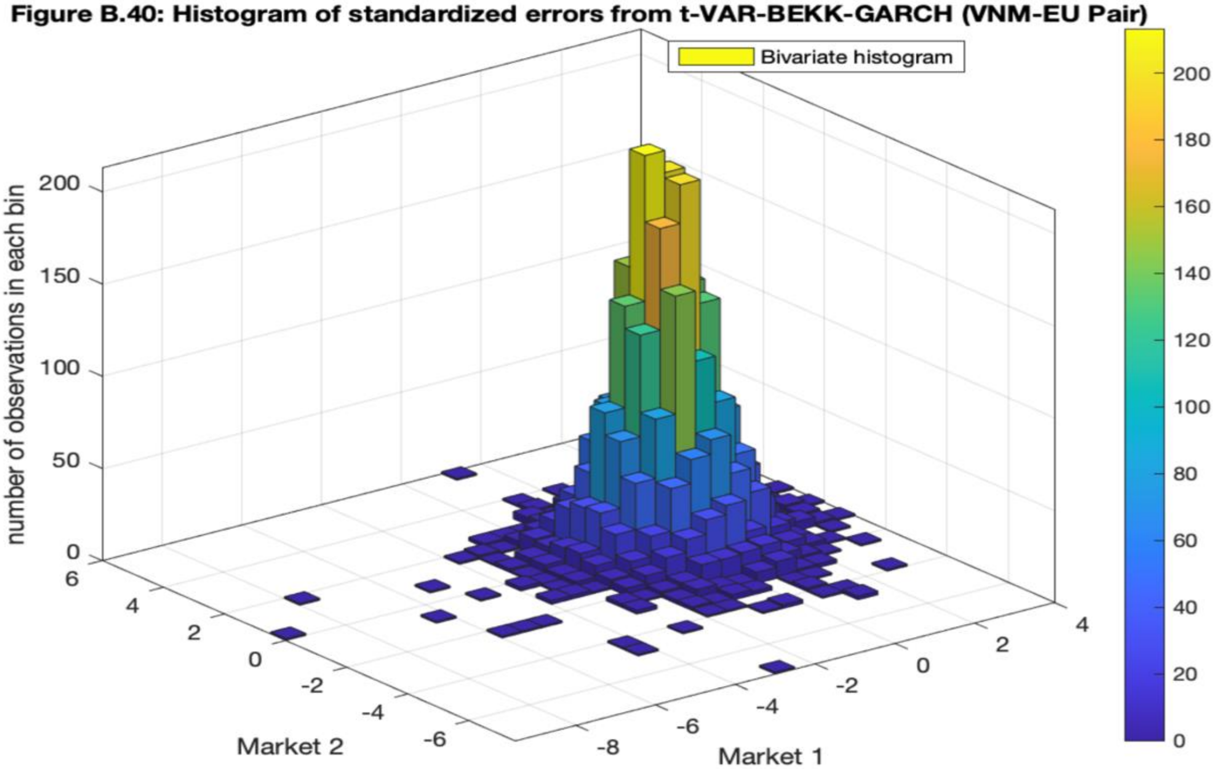
The figure illustrates the multivariate histogram of fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and Japanese markets (using CC returns).

Figure B.39: Histogram of standardized errors from t-VAR-BEKK-GARCH (VNM-JPN Pair (CO))



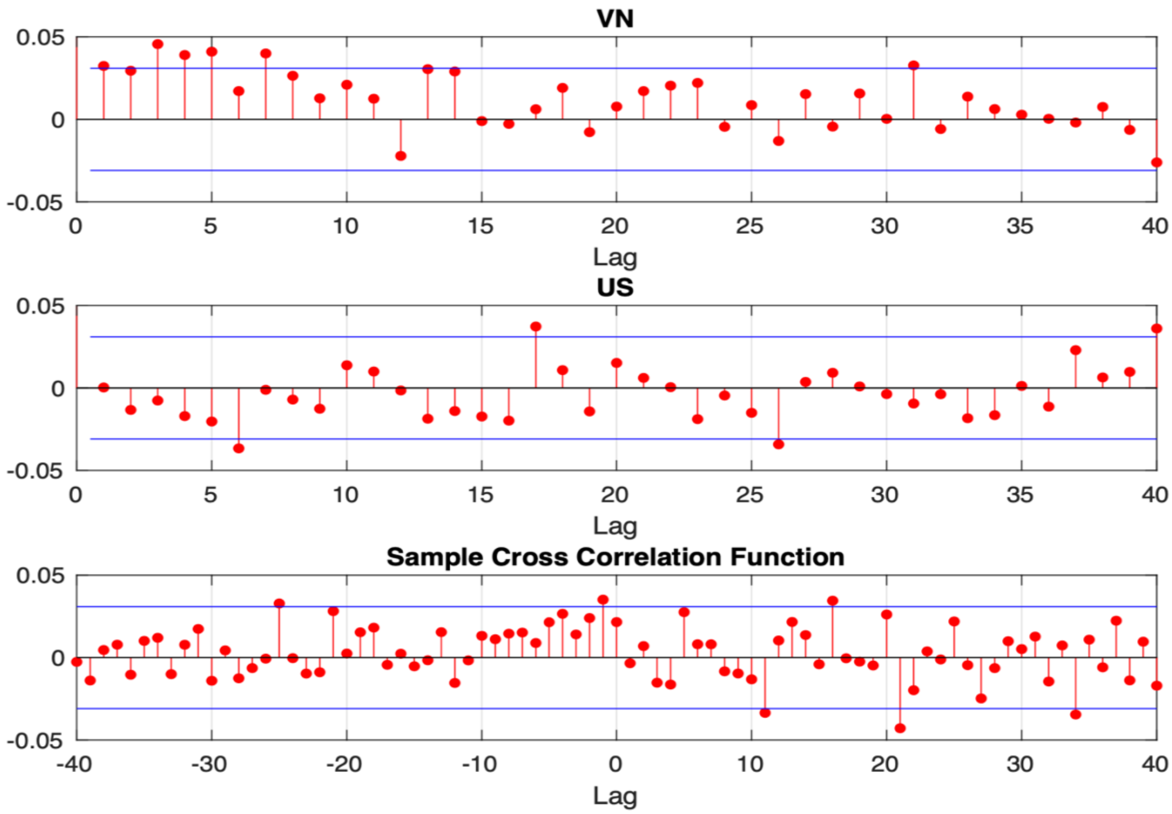
The figure illustrates the multivariate histogram of fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and Japanese markets (using CO returns).

Figure B.40: Histogram of standardized errors from t-VAR-BEKK-GARCH (VNM-EU Pair)



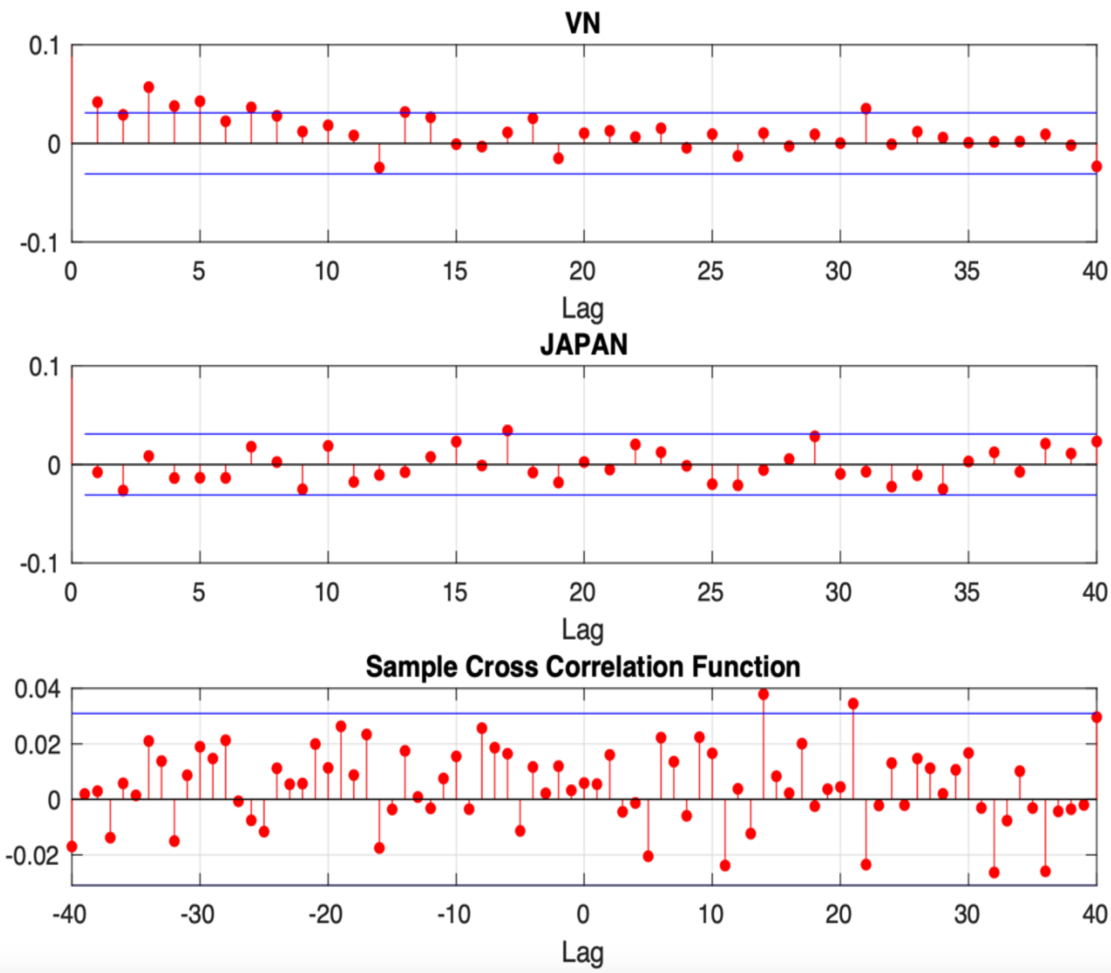
The figure illustrates the multivariate histogram of fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and European markets.

Figure B.41: ACF & XCF for Standardized residuals from t-VAR-BEKK-GARCH (VNM-US Pair)



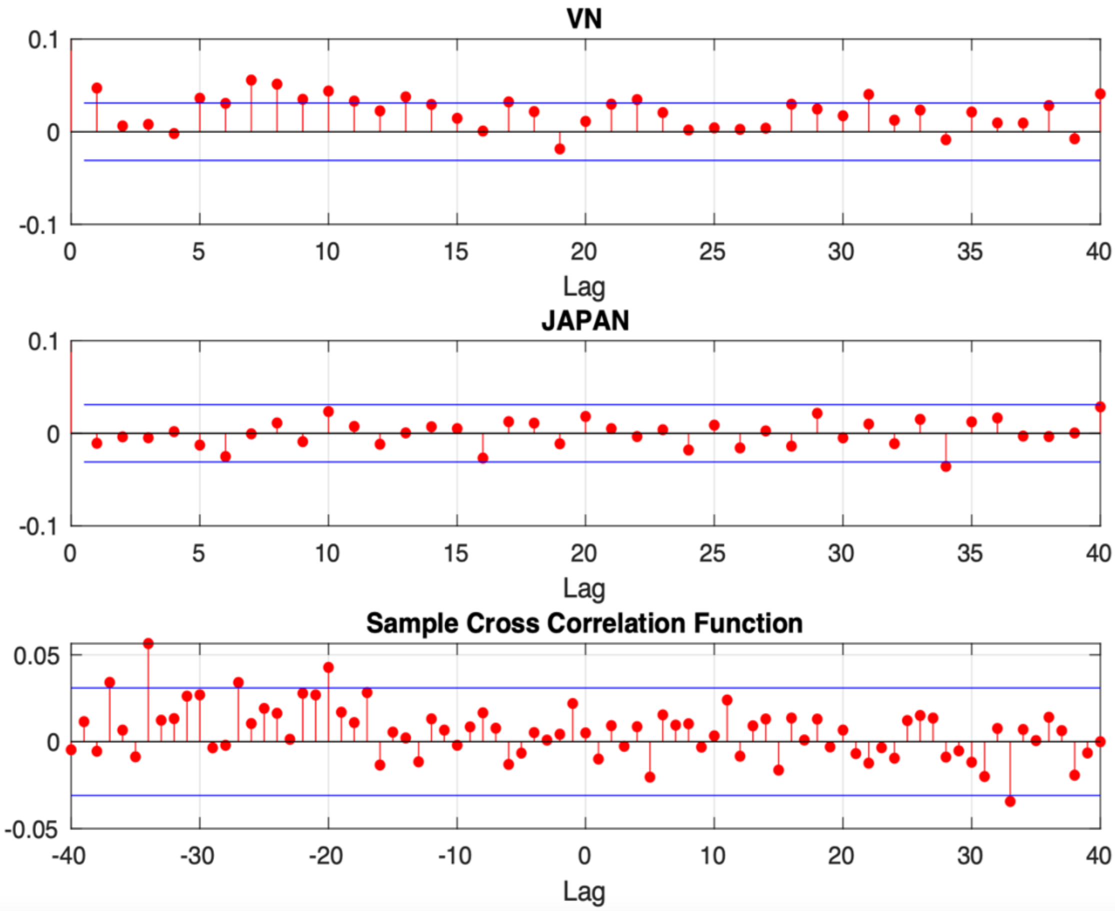
The figure plots the ACF and cross-correlation function (XCF) for fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and American markets. On the top are the ACF for Vietnamese and American markets respectively. At the bottom is the XCF between the two series.

Figure B.42: ACF & XCF for Standardized residuals from t-VAR-BEKK-GARCH (VNM-JPN Pair (CC))



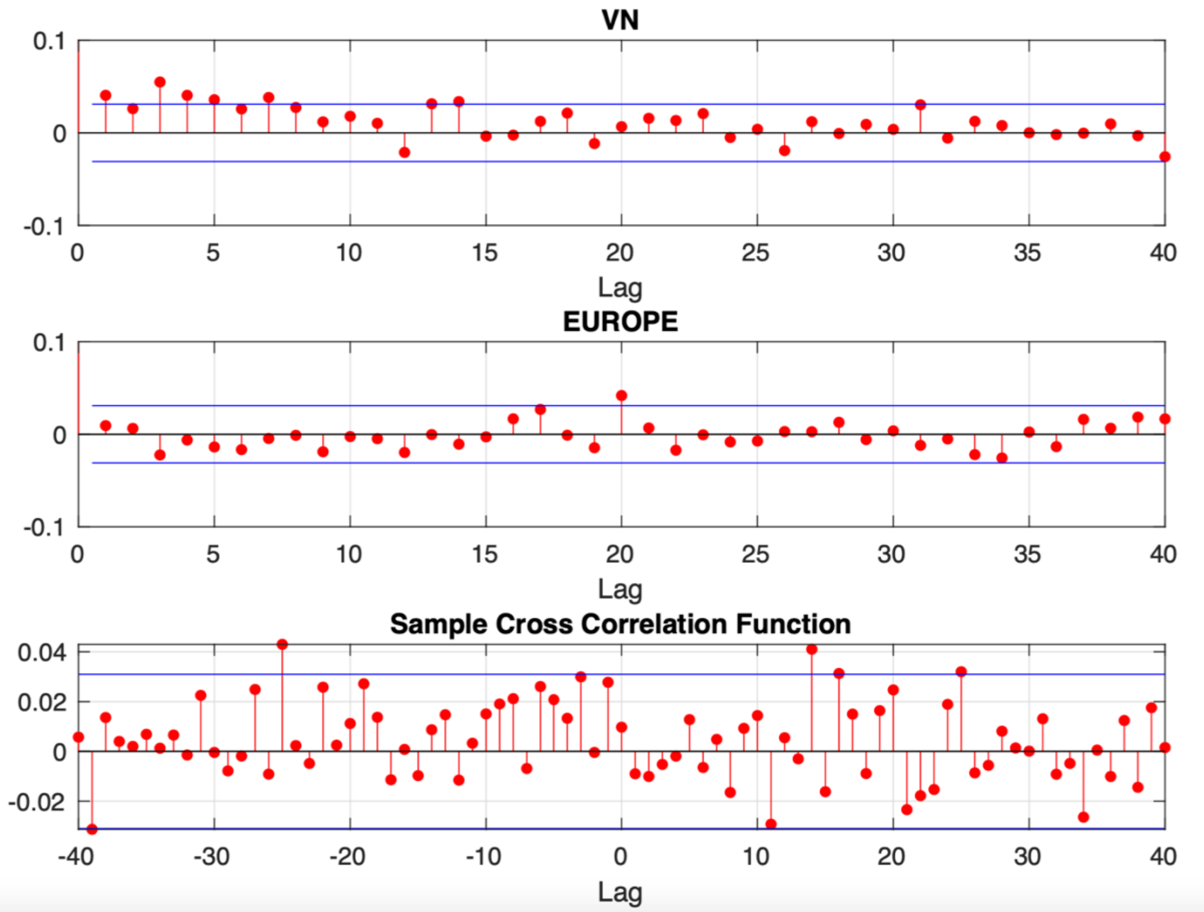
The figure plots the ACF and cross-correlation function (XCF) for fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and Japanese markets (using CC returns). On the top are the ACF for Vietnamese and Japanese markets respectively. At the bottom is the XCF between the two series.

Figure B.43: ACF & XCF for Standardized residuals from t-VAR-BEKK-GARCH (VNM-JPN Pair (CO))

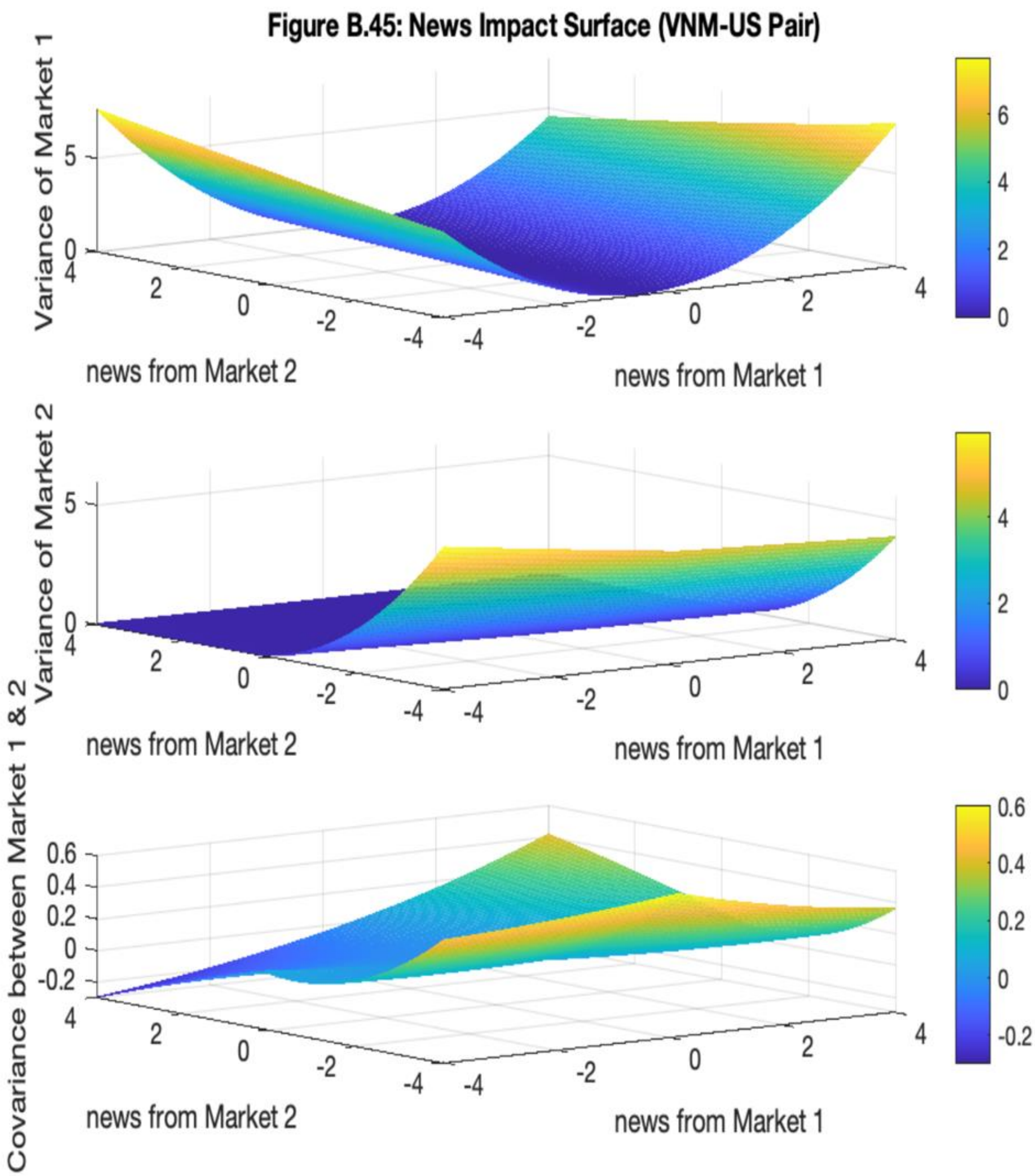


The figure plots the ACF and cross-correlation function (XCF) for fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and Japanese markets (using CO returns). On the top are the ACF for Vietnamese and Japanese markets respectively. At the bottom is the XCF between the two series.

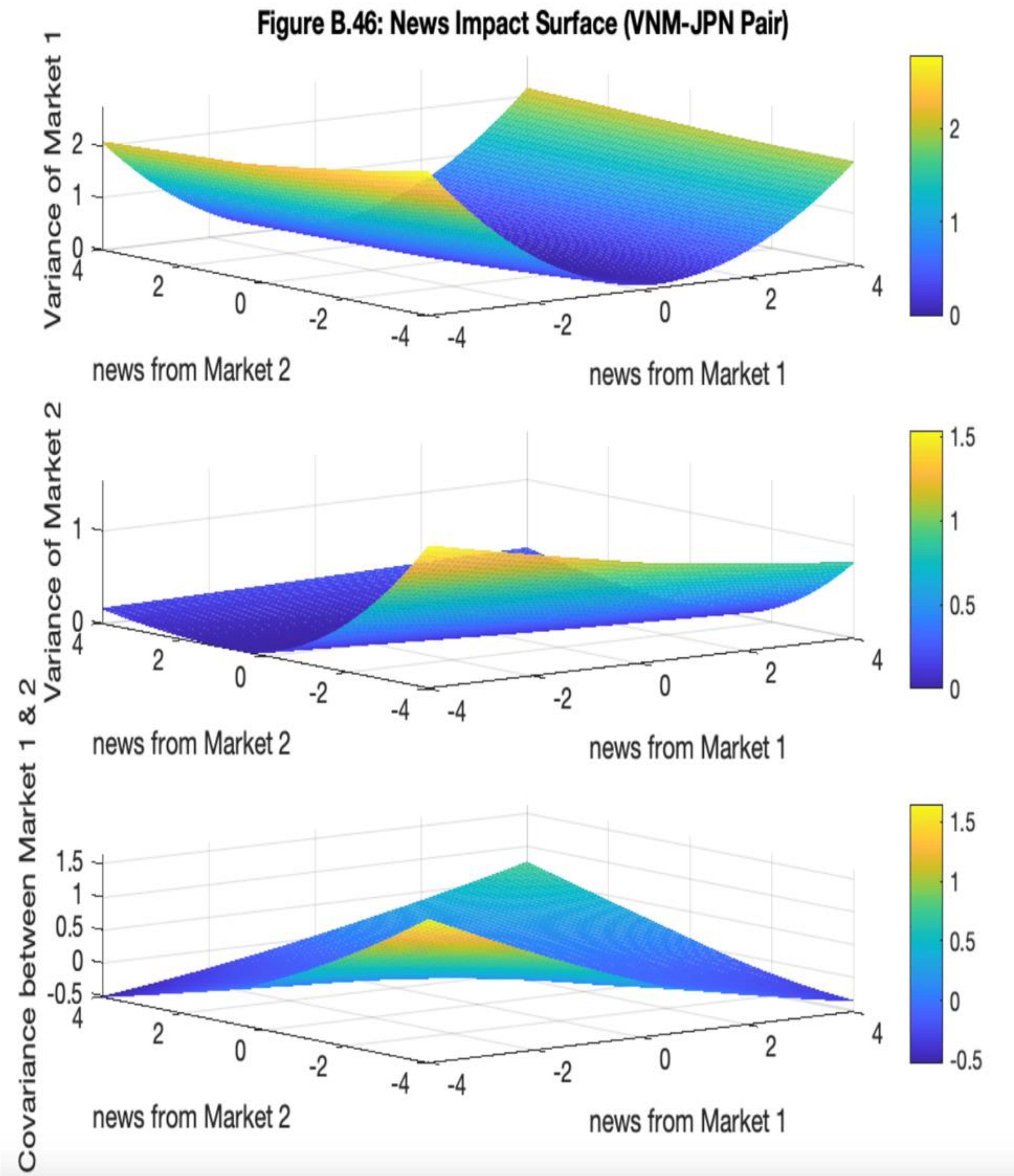
Figure B.44: ACF & XCF for Standardized residuals from t-VAR-BEKK-GARCH (VNM-EU Pair)



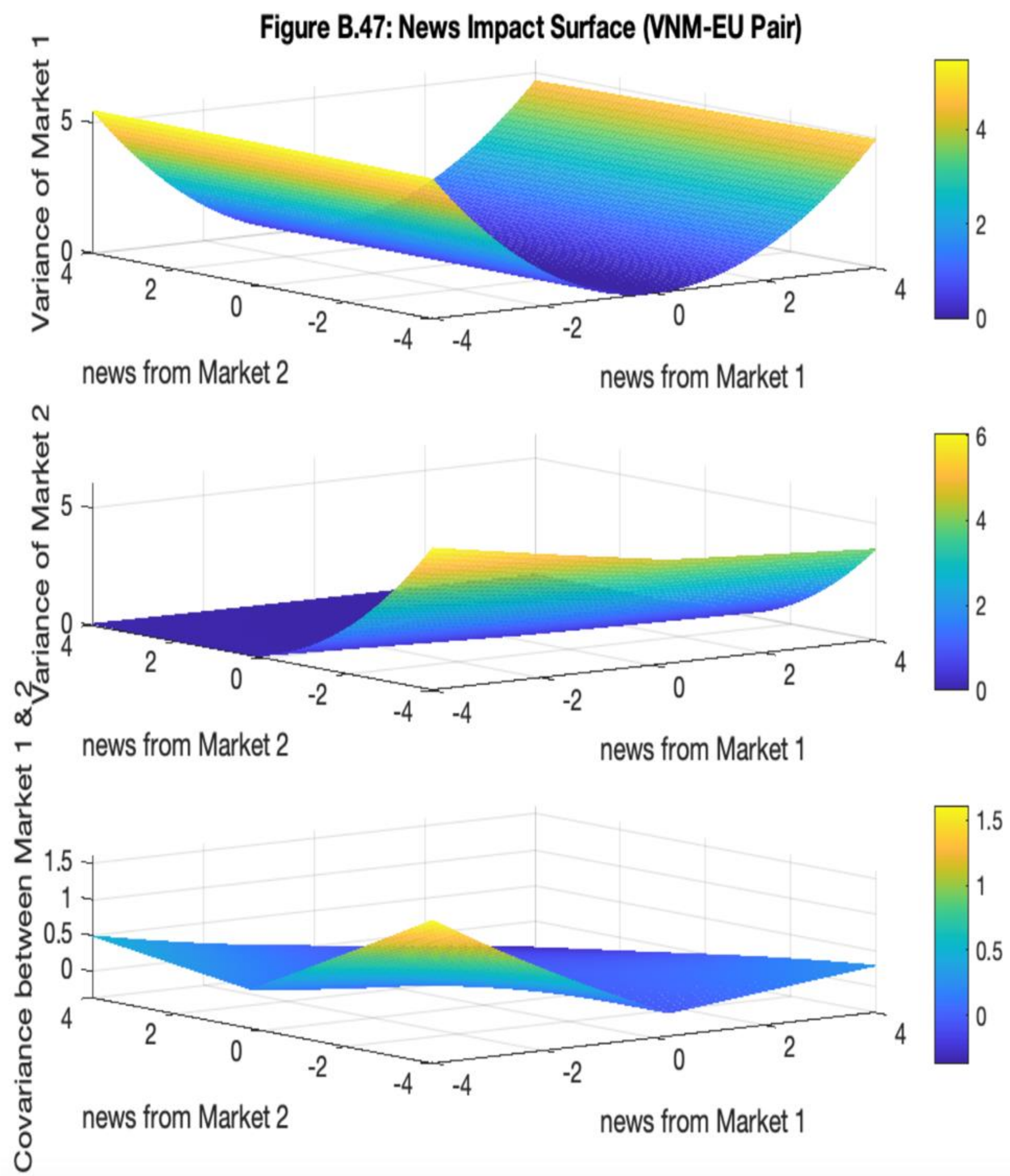
The figure plots the ACF and cross-correlation function (XCF) for fitted standardized residuals obtained from VAR-BEKK-t-GARCH models. This plot is for the pair of Vietnamese and European markets. On the top are the ACF for Vietnamese and European markets respectively. At the bottom is the XCF between the two series.



The graph illustrates the NIS for the pair of VNM-US. On the top are the variance NIS for Market 1 (VNM) and Market 2 (US) in order. At the bottom is the covariance NIS.



The graph illustrates the NIS for the pair of VNM-JPN. On the top are the variance NIS for Market 1 (VNM) and Market 2 (JPN) in order. At the bottom is the covariance NIS.



The graph illustrates the NIS for the pair of VNM-EU. On the top are the variance NIS for Market 1 (VNM) and Market 2 (EU) in order. At the bottom is the covariance NIS.