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TIME-VARYING CORRELATION BETWEEN SEAFOOD AND MEAT INDEX IN THE PRESENCE OF OCEAN POLLUTION SHOCK

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ABSTRACT

This study examines the complex relationships between global meat and seafood markets, focusing on the time-varying correlation between the Meat Index Market and the Seafood Index after Japan's nuclear wastewater release. Employing a Bayesian technique combined with the Skewed Multivariate Generalized Error Distribution, the study efficiently captures the time-varying correlations, with causality tests determining directional influences between the indices. The results reveal significant disruptions in seafood markets, highlighting the geopolitical impact on market dynamics. By offering a fresh perspective on market interdependencies during environmental crises, the study aids in risk assessments and effective risk mitigation strategies, introducing a Bayesian perspective into traditional financial econometrics and signifying a methodological shift in advanced model selection. Ultimately, understanding the dynamic relationships between meat and seafood markets can help traders, decision-makers, and market players navigate the financial effects of external shocks on global seafood market dynamics.

Keywords: Seafood index price, Meat-related index price, Bayesian M-Garch Model, Dynamic conditional correlation, Ocean pollution shock

INTRODUCTION

In the past decade, global financial markets have experienced significant disruptions, prompting extensive research into understanding co-movements, integration, and interconnectedness. Scholars have focused on unravelling the complexities of financial volatility, essential for portfolio diversification and policy formulation. Market instability poses challenges for investors and decision-makers, necessitating adept investment management and the creation of policies fostering financial and economic stability (BenSaïda, 2019). Financial shocks and transmissions, defined by (Engle et al., 1990), encompass causality in market variance and volatility spillovers, with (Forbes & Rigobon, 2002) introducing the concept of "variance contagion." While prior studies have explored market integration and linkages, this research addresses the novel dynamic cross-market connectivity, specifically examining the time-varying correlation between the Seafood Index and Meat Index Market in the context of an ocean pollution shock. Researchers who have studied the difficulties of information transmission and asymmetries in market connections and spillovers include (Baruník et al., 2016) and Baruník & Křehlík, 2018). The challenge that follows is the lack of comprehensive knowledge regarding how the market responds to these inequalities (Brown, G. 2012). Increased volatility is mostly caused by factors including a nation's risk profile, financial openness, investor protection, creative thinking, and progress (Liu, 2013). Volatility transmissions have been recognized by the research community as a critical issue, mostly caused by macro- and economic-policy initiators. Factors associated with a company's or nation's origin also contribute to the complexity of interpreting market reactions (Brown, G. 2012). Although a great deal of research has been done on market integration and correlation, dynamic cross-market connectivity, the main subject of this study still requires special attention.

The significant shift in seafood consumption from domestic to international markets has transformed seafood into a major component of international trade. Trade liberalization, globalization, increased demand, and advancements in production and logistics have driven the growth of the seafood industry (Asche, 2008; Tveterås et al., 2012; Asche et al., 2015). Global trade has more than doubled between 72 billion USD in 2004 and 148 billion USD in 2014, according to the Food and Agriculture Organization (FAO, 2016). Seafood exports account for 9% of global agricultural exports, with a value greater than that of the combined trade in sugar, maize, coffee, rice, cocoa, chicken, and pigs (*Asche, F., et al, 2015*) (Zhang et al., 2021). The recent decision by the Japanese government to release nuclear wastewater into the ocean has raised concerns globally, impacting the seafood market and leading to geopolitical repercussions, such as China's prohibition of seafood imports from Japan (Holland, J. 2023). These geopolitical events underscore the importance of in-depth analyses, emphasizing the role of government policies in influencing sectors' resilience to unforeseen environmental and socio-political shocks (Guo et al., 2022).

At the same time, a kind of challenges, such as divergent consumer preferences, hinder the global fish trade, of which Japan is a prominent part. Despite these obstacles, the government continues to view this issue as a top priority. For this reason, thorough analyses must be carried out (Guo et al., 2022). The way government policies become linchpins, impacting the sector's capacity to adapt to unanticipated environmental and socio-political shocks, emphasizes the need for cogent and informed planning (Love et al., 2021); (Pelletier et al., 2014) and (Graziano et al., 2018). Such geopolitical events have historically shown to have a considerable impact on financial markets, presenting important obstacles for investors and decision-makers. (Wu et al., 2023) highlighted the decline in the market for Japanese fishery products due to pollution. Their investigation was able to provide significant insights into the short-term drop in the final demand for Japanese fishing items through the application of models such as the Multi-Region Input-Output Model (MRIO) and the Inoperability Input-Output Model

(IIM). Their analysis of market integration in the seafood industry from 1990 to 2015, (Dahl & Jonsson, 2018) found that there were notable and time-varying volatility spillover effects among the major seafood markets, underscoring the intricate relationships that exist between market dynamics, environmental factors, and economic events.

The Meat Index, performing as a comprehensive indicator for meat-related markets comprising beef, pig, and poultry, plays a significant role in analysing consumer preferences, economic conditions, and global trade. While existing literature has extensively explored market dynamics, environmental factors, and economic events, the present study narrows its focus to the time-varying correlation between the Meat Index and the Seafood Index following the Fukushima incident (Buesseler et al., 2012). The unprecedented release of nuclear wastewater into the ocean has led to heightened concerns about the safety and sustainability of seafood from affected areas. This study aims to contribute a fresh perspective on market interdependencies amid global environmental crises, guiding risk assessments and adaptation strategies (Hirabayashi et al., 2019; Smith et al., 2017; Johnson, 2018).

In financial econometrics, the Maximum Likelihood method has been the primary tool for estimating the univariate GARCH model (Bollerslev, 1990). However, when examining the link between volatilities and co-volatilities of multiple markets, this approach has limitations (Bollerslev, 1986; Tse & Tsui, 2000). The flexibility of the model proposed by (Engle, 2002) in capturing dynamic correlations over time makes it suitable for investigating the evolving relationship between the Meat Index and the Blue Finance Index in response to environmental shocks. The inclusion of the M-GARCH component, as described by (Engle, 2001), allows for efficient modelling of volatility dynamics, crucial for comprehending the impact of ocean pollution on market volatility. The chosen DCC M-GARCH model (Cappuccio, 2019) is well-suited for a comprehensive investigation of the combined performance of the Meat Index and the Blue Finance Index, given its design for multivariate time series analysis. Leveraging the Bayesian framework (Lopes & Tsay, 2011), the model can effectively address uncertainty in the context of environmental shocks. Additionally, its ability to handle asymmetry (Asai et al., 2017) and incorporate regime-switching features (Bauwens et al., 2006) enhances its suitability for examining the intricate relationship between these financial indices amid ocean pollution shocks.

The research aims to employ the Bayesian DCC-Multivariate GARCH approach to investigate potential correlations between seafood index prices in Japan, the US, Norway, and Australia (Maruha Nichiro Corporation (MNC), Marine Harvest ASA (MNHVF), Austevoll Seafood ASA (AUSS)) and stock related to the Meat Index (BRF S.A (BRFS) of Brazil, Prima Meat Packers Ltd. (ABC) of Japan, and Beyond Meat (BYN) of the US). This research builds upon previous studies and methodologies, such as the Multi-Region Input-Output Model (MRIO), the Inoperability Input-Output Model (IIM) (Wu et al., 2023), and copula-ADCC-EGARCH models (Tiwari et al., 2019).

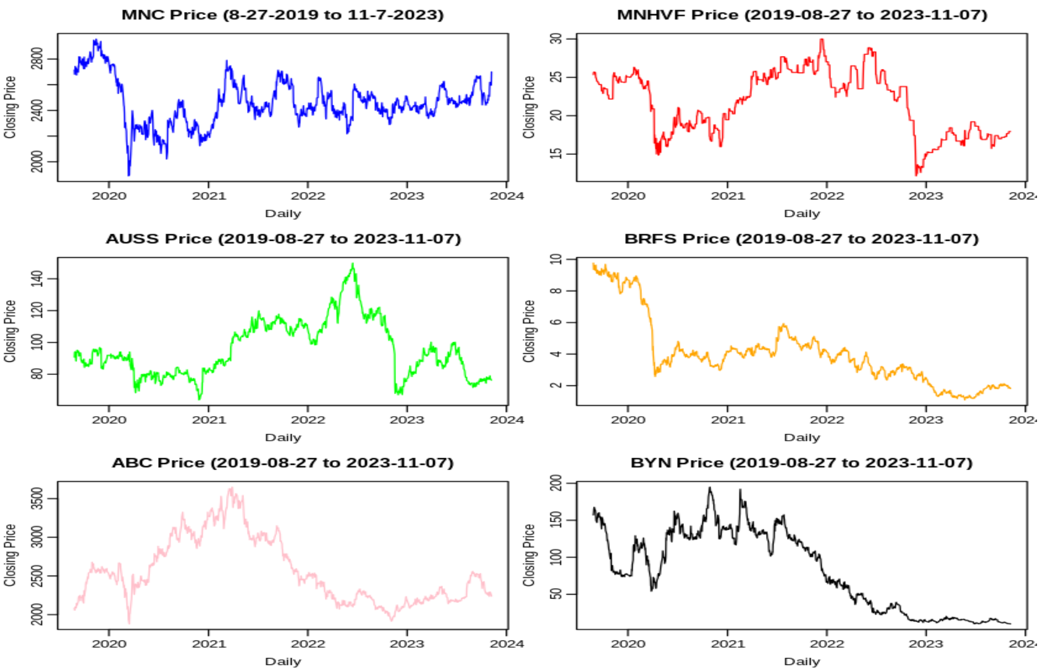


Figure 1: The seafood and Meat Index prices

By applying Bayesian techniques with the Markov Chain Monte Carlo (MCMC) method under various error distributional assumptions (Ardia, D., 2006; Fioruci et al., 2014), this research aims to provide insights into the time-varying correlation dynamics between these financial indices, offering valuable contributions to both financial econometrics and the understanding of market interdependencies amid environmental shocks. Leveraging insights from the Fukushima incident's impact on seafood markets (Buesseler et al., 2012), the research seeks to contribute a fresh perspective to understanding market interdependencies amidst global environmental crises.

Financial and Economic Theories

Various financial and economic theories are related to the research problem and provide insight into different aspects. The Portfolio Theory, introduced by (Markowitz, 1952), emphasizes the significance of investment diversification to maximize returns on risk. This idea is relevant to our research since it supports the diversification approach that investors may use as we analyses the time-varying correlation between the Blue Finance Index (Seafood Index) and the Meat Index. According to (Baumol & Oates, 1988), environmental economics looks at how environmental problems affect the economy. This idea adds to our understanding of the wider economic effects of environmental disturbances, given the potential impact of an ocean pollution shock on the seafood markets. The Efficient Market Hypothesis (Fama, 1970) emphasizes that asset prices represent all available information, which serves as a framework for our study of how well markets incorporate knowledge regarding the effects of ocean pollution shocks on the Meat Index and the Blue Finance Index. Last but not least, (Pfeffer & Salancik, 1978)'s theory "Resource Dependency Theory" emphasizes how organizations, in this example, the meat and seafood markets, adapt to external shocks. Understanding the time-varying correlation can help you better understand how markets adjust to changing environmental conditions.

Hypotheses

Hypothesis 1 (H1): There is a time-varying correlation between the Blue Finance Index (Seafood Index) and the Meat Index market. This hypothesis builds on the expectation that these markets, influenced by common environmental factors, may exhibit dynamic correlations over time.

Hypothesis 2 (H2): The impact of ocean pollution shocks on the correlation is asymmetric, with a stronger effect during periods of environmental distress compared to periods of normal environmental conditions. This hypothesis implies that the correlation dynamics may vary asymmetrically based on the severity of environmental conditions.

Hypothesis 3 (H3): The time-varying correlation between the Blue Finance Index and the Meat Index market is influenced by regulatory and policy responses to mitigate the effects of ocean pollution. This hypothesis acknowledges the role of regulatory frameworks in shaping the correlation dynamics, aligning with broader discussions on the impact of policies on financial markets.

The paper is organized as follows: Section 2 discusses the data and method; Sections 3 and 4 offer Analysis and Interpretation of results while Section 4 finalises with a discussion and conclusion.

MATERIALS AND METHODS

Data

The daily returns of the seafood stock index for Japan, the US, Norway, and Australia (Maruha Nichiro Corporation (MNC), Marine Harvest ASA (MNHVF), and Austevoll Seafood ASA (AUSS), respectively. Also, the stocks related to the Meat index considered in the research are BRF S.A (BRFS) of Brazil, Prima Meat Packers Ltd. (ABC) of Japan, and Beyond Meat (BYN) of the US. The data were sourced from Yahoo Finance from January 5, 2015, to November 7, 2023, and Figure 1 represents the daily closing price. The return is computed as:

$$y_t = 100 \times [ln(p_t) - ln(p_{t-1})] \qquad (1)$$

Where p_t is the index closing price at time t, the percent constantly compounded yields y_t. The plot of seafood stock indices market returns against time is presented in Figure 2.

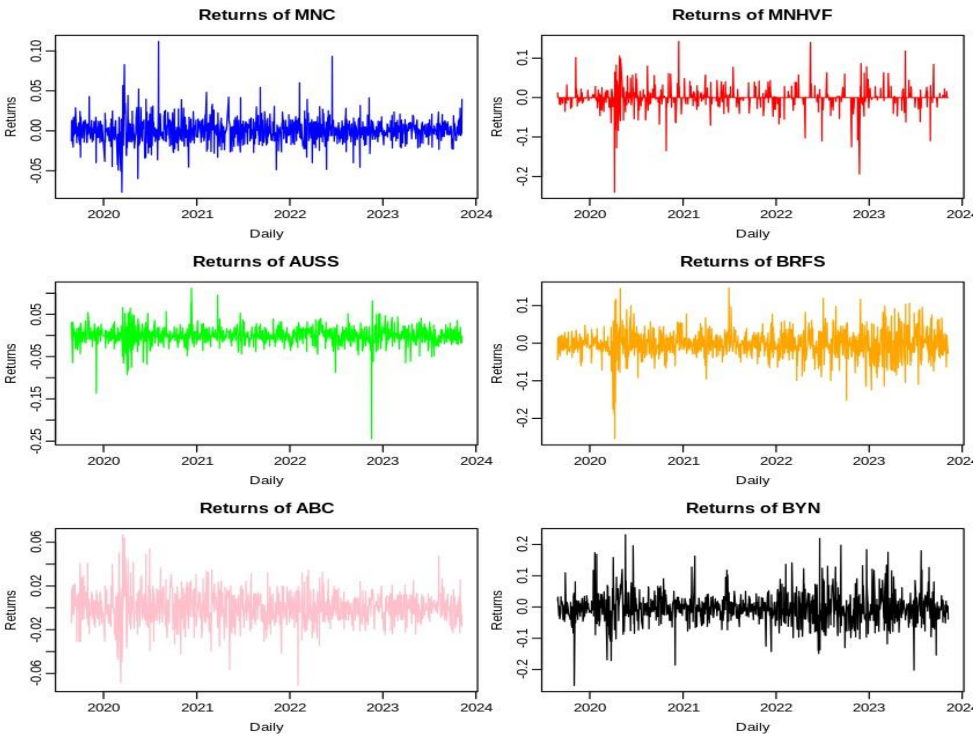


Figure 2: The Seafood and Meat Index return prices

Multivariate GARCH models

Several MGARCH models were put up to investigate the correlations between various financial market uncertainties. To represent the time-invariant conditional correlation matrix, for example, (Bollerslev, 1990) suggested the constant conditional correlation (CCC) technique. However, in the majority of empirical applications, the assumption of constant conditional correlation over time is impractical. In light of this, (Engle, 2002) and (Tse & Tsui, 2000) separately suggested expanding upon the CCC model of (Bollerslev, 1990) by permitting the conditional correlation matrix to fluctuate over time. A DCC GARCH model is the name given to the generated model. Assume that we have the covariance matrix $\boldsymbol{H}_t$ and the returns, $\boldsymbol{y}_t$, of index price, with an expected value of $\mathbf{0}$. The DCC model proposed by (Engle, 2002) is defined as follows:

Let $\boldsymbol{y}_t$ be a multivariate time series of returns with $\boldsymbol{y}_t = (y_{1t}, \ldots, y_{nt})'$ and $E(\boldsymbol{y}_t) = \boldsymbol{0}$. According to the model,

$$\boldsymbol{y}_t = \boldsymbol{H}_t^{1/2}\boldsymbol{\epsilon}_t \quad (2)$$

is conditionally heteroskedastic. Where $\boldsymbol{H}_t^{1/2}$ is any $n \times n$ positive definite matrix at time t that depends on a finite vector of parameters $\boldsymbol{\theta}$, such that the conditional variance of $\boldsymbol{y}_t$ is $\boldsymbol{H}_t$. The $n \times 1$ error vectors are assumed to be independently and identically distributed with $E(\epsilon_t) = 0$ and $E(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t') = \boldsymbol{I}_n$, where $\boldsymbol{I}_n$ is the identity matrix of order n. There are different possible specifications for $\boldsymbol{H}_t$. In this paper, we focus on the so-called conditional correlation models which allow specifying separately the individual conditional variances and the conditional correlation matrix. (Bollerslev, 1990) proposed a parsimonious approach in which the conditional covariance is proportional to the product of the corresponding conditional standard deviations. The constant conditional correlation model is defined as, $\boldsymbol{H}_t = \boldsymbol{D}_t\boldsymbol{R}\boldsymbol{D}_t$, where $\boldsymbol{D}_t = diag\left(h_{11,t}^{1/2}, \ \ldots \ , h_{nn,t}^{1/2}\right)$, $\boldsymbol{R}$ is asymmetric positive definite matrix which elements are the conditional correlations ρ_{ij} , $i, j = 1, \ldots, n$. Each conditional covariance is then given by: $h_{ij,t} = \rho_{ij}\sqrt{\rho_{ii,t}\rho_{jj,t}}$. Besides, each conditional variance in $\boldsymbol{D}_t$ is specified as a univariate GARCH model. Here a GARCH (p, q) model for each conditional variance is given by:

$$h_{ii,t} = \omega_i + \sum_{p=1}^{P_i}\alpha_{ip}y_{ii,t-p}^2 + \sum_{q=1}^{Q_i}\beta_{iq}h_{ii,t-q}, \quad i = 1, \ \ldots \ , n \quad (3)$$

With $\omega_i > 0, \ \alpha_i \geq 0, \ \beta_i \geq 0, \ and \ \sum_{p=1}^{P_i}\alpha_{ip} + \sum_{q=1}^{Q_i}\beta_{iq} < 1, i = 1, \ \ldots \ , n$. Note that the subscripts p and q are the lag lengths. The GARCH model is not limited to the standard GARCH (p, q), and the optimal lag order is chosen by the Bayesian calculation process. We used the simplest GARCH(1,1) following (Fioruci et al., 2014).

$$h_{ii,t} = \omega_i + \alpha_i y_{i,t-1}^2 + \beta_i h_{ii,t-1}, \qquad i = 1, \ \ldots \ , n \quad (4)$$

$\boldsymbol{H}_t$ is positive definite if and only if $h_{ii,t} > 0$, $i = 1, \ldots, n$ and $\boldsymbol{R}$ is positive definite.

(Christodoulakis & Satchell, 2002); (Engle, 2002) and (Tse & Tsui, 2000) independently proposed generalizations by allowing the conditional correlation matrix to be time-dependent. The resulting model is then called a Dynamic conditional correlation (DCC) MGARCH model. We adopted the same approach (Engle, 2002) by setting the following parsimonious formulation for the correlation matrix,

$$\boldsymbol{R}_t = diag(\boldsymbol{Q}_t)^{-1/2}\boldsymbol{Q}_t diag(\boldsymbol{Q}_t)^{-1/2}$$

Where $\boldsymbol{Q}_t$ are $n \times n$ symmetric positive-definite matrices given by,

$$\boldsymbol{Q}_t = (1 - a - b)\bar{\boldsymbol{Q}} + a\boldsymbol{u}_{t-1}\boldsymbol{u}_{t-1}' + bQ_{t-1} \quad (5)$$

Where $\boldsymbol{u}_{t-1}\boldsymbol{u}_{t-1}'$ is the lagged function of the standardized residuals $\boldsymbol{u}_t = \boldsymbol{D}_t^{-1}\boldsymbol{y}_t$. $\bar{\boldsymbol{Q}}$ is the $n \times n$ unconditional covariance matrix of $\boldsymbol{u}_t$, and Q_t is the unconditional variance between series $i, and \ j$. The conditional covariances are given by $h_{ij,t} = q_{ij,t}\sqrt{h_{ii,t}h_{jj,t}}/\sqrt{q_{ii,t}q_{jj,t}}$.

Estimation

The conditional likelihood function of the model (2), for a return, $\boldsymbol{y} = (y_1, \ldots, y_n)$ can be written as

$$l(\theta) = \prod_{t=1}^{k}|\boldsymbol{H_t}|^{-1/2} p_\epsilon\left(\boldsymbol{H}_t^{-1/2}\boldsymbol{y}_t\right) = \prod_{t=1}^{k}\left[\prod_{i=1}^{n}h_{ii,t}^{-1/2}\right]|\boldsymbol{R}_t|^{-1/2}p_\epsilon\left((\boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t)^{-1/2}\boldsymbol{y}_t\right) \quad (6)$$

where p_ϵ is the joint density function for $\boldsymbol{\epsilon}_t$.

The set of all model parameters is represented by: $\boldsymbol{\theta} = (\omega_1, \alpha_1, \beta_1, \ \ldots \ , \omega_n, \alpha_n, \beta_n, \rho_{12}, \ \ldots \ , \rho_{n-1,n})$.

Bayesian DCC-MGARCH models

Skewed Distributions

(Bauwens & Laurent, 2005) proposed to construct a multivariate skew distribution from a symmetric one by changing the scale on each side of the mode for each coordinate of the multivariate density such as Multivariate Normal Distribution (MVND), Multivariate Student t Distribution (MVTD), Multivariate Generalized Error Distribution (MVGED). This is a multivariate extension of what (Fernandez & Steel, 1998) has proposed. The error term is also assumed to follow an SMVTD or a skew-MVGED. The SMVGED was considered to capture the excess kurtosis and skewness, which is observed in our study of seafood and Meat index market returns. Therefore, for the distributions of the errors, the $\boldsymbol{\epsilon}_t$ in Equation (2), we consider the above-mentioned three skewed multivariate distributions to fit the Bayesian DCC-MGARCH.

The multivariate skew distributions proposed density functions are given as follows:

$$s(\boldsymbol{y}|\gamma) = 2^n\left(\prod_{i=1}^{n}\frac{\gamma_i}{1+\gamma_i^2}\right)f(\boldsymbol{y}^*) \quad (7)$$

where $f(\cdot)$ is a symmetric multivariate density, $y^* = (y_1^*, \ \ldots \ , y_n^*)$ such that $y_i^* = {y_i}/{\gamma_i}$ and $y_i^* = y_i\gamma_i$ if $y_i < 0$, $i = 1, \ldots, n$. The parameters γ_i control the degree of skewness on each margin, right (left) marginal skewness corresponding to $\gamma_i > 1$ $(\gamma_i < 1)$. Also, the existence of the moments of Equation (5) depends only on the existence of the marginal moments $E(X_i^r)$ in the original symmetric distribution. The interpretation of each i is the same as in (Fernandez & Steel, 1998), i.e. $\gamma_i^2 = P(X_i \geq 0)/P(X_i < 0)$ which helps with the specification of a prior distribution. Besides the multivariate skew normal distribution, we allow the error term to follow a multivariate skewed t or a multivariate skew GED as well. In all cases, setting $\gamma_i = 1$, $i = 1, \ldots, n$ recovers the original symmetric density.

A normalized multivariate normal distribution would be a logical first choice for the error distribution in (2). Since most financial asset returns have broader tails in their unconditional distribution than this model with normal errors suggests, the normality assumption is rejected in the majority of applications. Student t-distributed errors have been most frequently used to account for the excess of (unconditional) kurtosis in the univariate case (Baillie & Bollerslev, 1989)). The multivariate Student t distribution (Fiorentini et al., 2003), which has the additional degrees of freedom parameter v to be estimated, is therefore a logical option in the multivariate scenario. For $\boldsymbol{H}_t$ to always be understood as a conditional covariance matrix, we assume that $v > 2$. This multivariate t distribution's density function is given by.

$$p(\epsilon_t) = \frac{\Gamma\left(\frac{v+n}{2}\right)}{\Gamma\left(\frac{v}{2}\right)[\pi(v-2)]^{n/2}}\left[1 + \frac{\epsilon_t'\epsilon_t}{v-2}\right]^{-\frac{v+n}{2}} \quad (8)$$

where $\Gamma(\cdot)$ is the Gamma function, and (6) can be used to obtain the probability function. It should be noted that $Var(\epsilon_t) = \boldsymbol{I}_n$ and $E(\epsilon_t) = 0$ represent the standardized form of the multivariate Student t distribution. This distribution is spherically symmetric about the origin, as are the conventional multivariate normal distributions. In this case, y_t has an elliptically symmetric distribution, and $p(y_t) \propto |\boldsymbol{H}_t|^{-1/2}g(\boldsymbol{y}_t'\boldsymbol{H}_t^{-1}\boldsymbol{y}_t)$ for a nonnegative scalar function $g(\cdot)$. While elliptical distributions can represent heavy tails, they are unable to represent asymmetric dependence structures. Lastly, it is important to note that there are a lot of possibilities for the multivariate generalization of the Student t distribution (Kotz & Nadarajah, 2004).

Lastly, (Fioruci et al., 2014) state that another name for the SMGED is the multivariate exponential power distribution. Its density function is thus expressed as follows:

$$s(\boldsymbol{y}|\boldsymbol{\delta}) = 2^n \left(\prod_{i=1}^{n} \frac{\gamma_i \delta_{\gamma_i}}{1+\gamma_i^2}\right) \left[\frac{\Gamma\left(\frac{3}{\delta}\right)}{\Gamma\left(\frac{1}{\delta}\right)}\right]^{\frac{n}{2}} \frac{1}{\left[2\Gamma\left(\frac{\delta+1}{\delta}\right)\right]^n} \exp\left\{-\left[\frac{\Gamma\left(\frac{3}{\delta}\right)}{\Gamma\left(\frac{1}{\delta}\right)}\right]^{\frac{\delta}{2}} \sum_{i=1}^{n} |y_i|^{\delta}\right\} \tag{9}$$

where δ is a common tail parameter, $y_i^* = {(y_i\delta_i + \mu_{\gamma_i})}/{\gamma_i} \ if \ \gamma_i \geq -{\mu_{\gamma_i}}/{\delta_{\gamma_i}}$ and $y_i^* = (y_i\delta_i + \mu_{\gamma_i})\gamma_i - {\mu_{\gamma_i}}/{\delta_{\gamma_i}}$

Consequently, there wouldn't need to be an additional parameter determined if the errors ϵ_t in Equation (1) were assumed to follow SMN. However, when the errors $\boldsymbol{\epsilon_t}$ are SMST, the extra degrees of freedom parameter v will be estimated (Fiorentini et al., 2003) and when the errors $\boldsymbol{\epsilon_t}$ are SMGED, the extra parameter δ will be determined.

Prior Distribution

With the completion of the model specification, all relevant parameters' previous distributions are specified. According to (Fiorentini et al., 2003), these are assumed to be normally distributed, truncated to the intervals that define each one, and a priori independent. These previous distributions for the GARCH(1,1) coefficients in (2) are the same as those suggested by (Ardia, D., 2006), $\omega_i \sim N\left(\mu_{\omega_i}, \sigma_{\omega_i}^2\right) I_{(\omega_i>0)}$, $\alpha_i \sim N\left(\mu_{\alpha_i}, \sigma_{\alpha_i}^2\right) I_{(0<\alpha_i<1)}$ and $\beta_i \sim N\left(\mu_{\beta_i}, \sigma_{\beta_i}^2\right) I_{(0<\beta_i<1)}$, $i = 1, \ . \ . \ . \ , n$. The multivariate Student t or GED, respectively, assigns a truncated normal distribution to the tail parameter, denoted as $v \sim N(\mu_v, \sigma_v^2) I_{(v>0)}$ or $\delta \sim N\left(\mu_\delta, \sigma_\delta^2\right) I_{(\delta>0)}$. subsequently, a similar strategy is used for the parameters α and β in equation (3) i.e. $\alpha \sim N(\mu_\alpha, \sigma_\alpha^2) I_{(<0\alpha<1)}$ and $\beta \sim N(\mu_\beta, \sigma_\beta^2) I_{(<0\beta<1)}$. As for skewness parameters, we use truncated normal distributions on positive values, i.e. $\gamma_i \sim N\left(\mu_{\gamma_i}, \sigma_{\gamma_i}^2\right) I_{(\gamma_i>0)}, i = 1, \ . \ . \ . \ , n.$ Using the joint posterior distributions as a framework, the Markov chain Monte Carlo (MCMC) approach was utilized to extract samples. The simplest sampling is produced by applying the Metropolis-Hastings algorithm.

The Performance of the Fitted Bayesian DCC-MGARCH

We used the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Deviance Information Criterion (DIC) to determine which of the three innovation distributions best fits the Bayesian DCCMGARCH. The best-fitting DCC-MGARCH models are identified using the AIC, BIC, and DIC. Before determining the fitted DCCMGARCH model, it is important to comprehend the statistical characterization for the price returns series for Seafood and food indexes. To prevent pseudo-regression issues, we used the Augmented Dickey-Fuller (ADF) tests to determine the stationarity of our test variables. On the other hand, we used the Shapiro–Wilk (SW) and Jarque–Bera (JB) tests to determine the normality, skewness, and kurtosis of the sample distribution. Lastly, Engle's Lagrange multiplier (LM) test is utilized to determine the effects of autoregressive conditional heteroscedastic (ARCH) for each of the returns.

RESULTS AND DISCUSSION

Descriptive summary

The unit root test for each price return series is shown in Table 1. The results of the ADF tests demonstrate that each price series becomes stationary from the first difference and the null hypothesis of non-stationarity is rejected in each of the returns series at a 5% level of significance. The summary statistics results show JB statistic is statistically significant at the 5% level, indicating that all of the return series have excess kurtosis and skewness. Additionally, the SW statistic is also statistically significant at the 5% level, indicating that the return series does not originate from a normally distributed population. Therefore, all of the return series violate the assumptions of normality, and their asymmetric distributions must be taken into consideration. Additionally, the results of Engle's LM test are statistically significant at the 5% level, indicating that ARCH effects exist for all of the return series; the stationarity test was considered to be an essential precondition for avoiding problems associated with false regression, by applying ADF, the test suggested by (Zivot, E., et al. 1992), stationarity was found in the price returns of Seafood and Meat Index. As a result, three possible Bayesian DCC-MGARCH (1,1) models can be fitted using the Skewed Multivariate Normal Distribution (SMVND), Skewed Multivariate t Distribution (SMVTD), and Skewed Multivariate Generalised Error Distribution (SMVGED).

Table 1: Statistical properties of seafood and Meat Index returns

	$\boldsymbol{Min.}$	$\boldsymbol{Max.}$	$\boldsymbol{Mean}$	$\boldsymbol{SD}$	$\boldsymbol{kurtosis}$	$\boldsymbol{JB}$	$\boldsymbol{LM}$	$\boldsymbol{SW}$	$\boldsymbol{ADF}$
$\boldsymbol{MNC}$	-7.69	11.19	$2.36E-17$	1.53	0.66	1772.37	0.063593	0.93767	-24.097
$\boldsymbol{MNHVF}$	-23.97	14.27	$-1.95E-17$	2.44	-1.40	18148.52	0.32388	0.630858	-22.155
$\boldsymbol{AUSS}$	-24.45	11.24	$5.03E-17$	2.19	-1.58	14743.53	0.083798	0.88733	-23.098
$\boldsymbol{BRFS}$	-25.30	14.86	$3.41E-17$	3.77	-0.49	719.40	0.064055	0.958715	-21.325
$\boldsymbol{ABC}$	-7.12	6.68	$-1.78E-17$	1.45	0.04	261.27	0.041323	0.97438	-22.149
$\boldsymbol{BYN}$	-24.86	23.39	$-3.71E-17$	4.89	0.41	529.77	0.081553	0.948749	-22.148

Analysis of the causality test performed; the results, in Table 2 below, show that variations in the prices of BYN are caused by changes in MNC, but not the other way around. In a similar vein, changes in BRFS and AUSS prices are Granger-caused by MNHVF without the reverse causal relationship. It has been noted that changes in MNHVF and BRFS prices are Granger-caused by AUSS, but not the other way around. The prices of the remaining Seafood and Meat Indexes can be interpreted similarly.

Table 2: The Granger causality test results of price returns; the p-values within the parenthesis.

	MNC	$MNHVF$	$AUSS$	$BRFS$	ABC	BYN
MNC		0.69 (0.503)	0.59 (0.556)	1.57(0.209)	0.20 (0.816)	2.54 (0.079)
$MNHVF$	1.32 (0.267)		7.45(0.000) **	13.54 (0.000) **	2.47 (0.085)	0.259 (0.772)
$AUSS$	0.941 (0.391)	3.09 (0.046) *		1.99 (0.137)	0.59 (0.552)	0.87 (0.419)
$BRFS$	1.11 (0.330)	7.21 (0.000) **	4.72 (0.009) **		1.65 (0.192)	1.14 (0.321)
ABC	0.31 (0.732)	0.55 (0.575)	1.47 (0.229)	1.20 (0.301)		0.16 (0.852)
BYN	3.19 (0.042)	0.38 (0.687)	1.58 (0.206)	1.56 (0.211)	1.47 (0.230)	

* Denotes statistical significance at the 5% level of significance.
**Denotes statistical significance at the 1% level of significance.

Table 3 shows the goodness of fit statistics, such as AIC, BIC, and DIC values, for the various Bayesian DCC-MGARCH models. Based on the AIC, BIC, and DIC values, the Bayesian DCC-MGARCH with MVSGED model provided a better fit compared to other models because it has the lowest information criteria (IC) Value and was able to capture the fat tails and skewed features present in the Seafood and Meat Index prices. Exactly 20,000 samples were drawn from the posterior distribution using the Metropolis-Hasting Algorithm MCMC sampling algorithm. The first 5000 samples were discarded as part of the burn-in phase, leaving 15,000 subsequent samples for the estimation.

Table 3: Information criteria for DCC-MGARCH models

$Critatia$	$SMVTD$	$SMVGED$	$SMVND$
$EAIC$	26646.24	25521.66	27601.77
$EBIC$	26779.39	25654.81	27729.99
DIC	26610.57	25483.64	27569.77

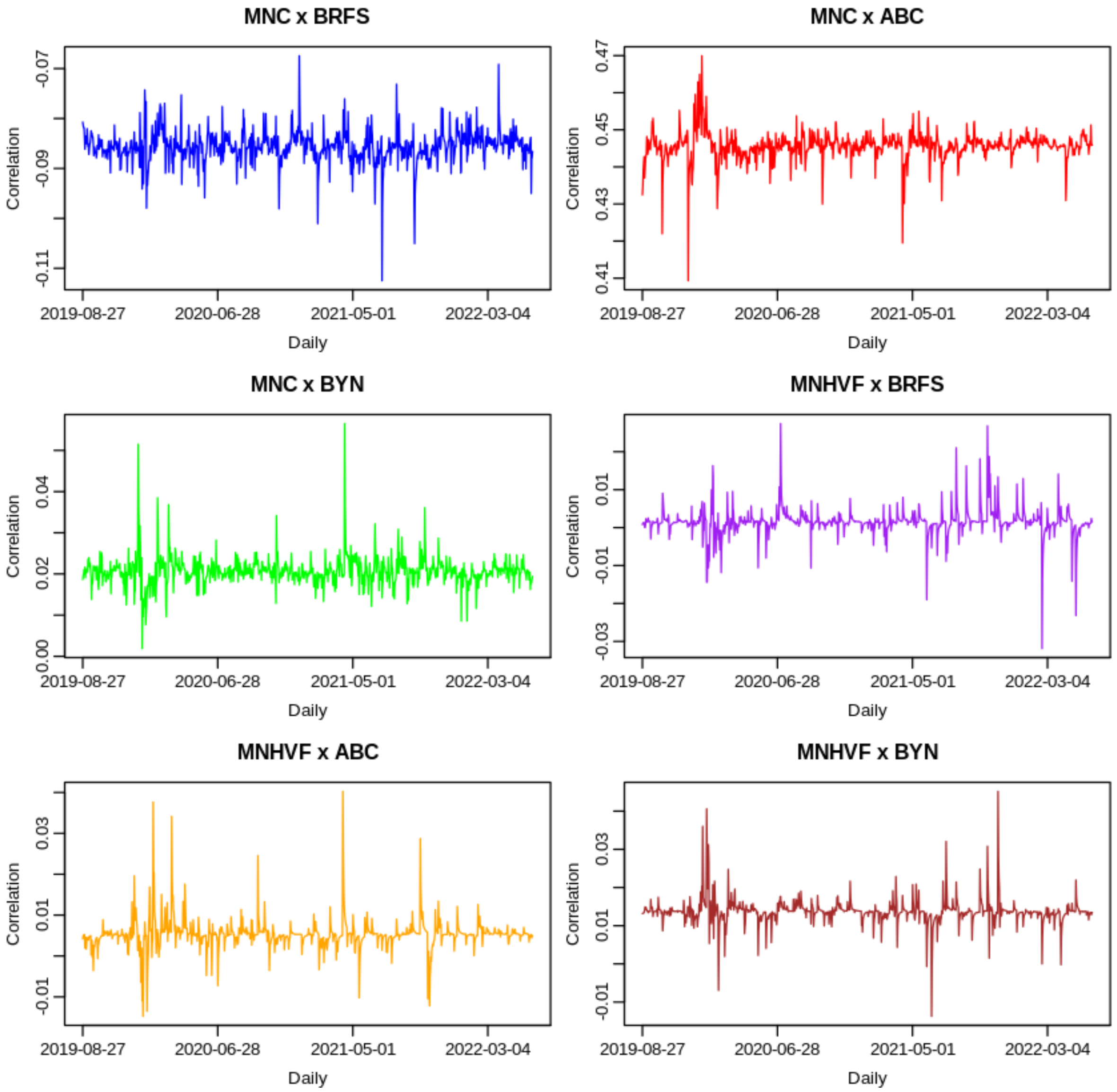
In Table 4, the Bayesian estimates using the MCMC technique for the DCC-MGARCH (1,1) model with SMVGED are presented. This table encompasses the posterior means, medians, and standard deviation with 2.5% to 97.5% credible intervals, the skewness parameters γ_i in Equation (7) exhibit statistically significant posterior densities, implying asymmetry in all returns; (Fioruci et al., 2014). Furthermore, the conditional variance results show high significance across all indices, affirming the presence of GARCH effects in the return series.

Table 4: Summary of the MCMC simulations for the model with skewed MVGED.

		$Mean$	SD	2.5%	25%	50%	75%	97.5%
	δ	0.518666	0.017552	0.485858	0.505602	0.518724	0.530248	0.553969
MNC	γ	1.005012	0.017874	0.977766	0.996218	0.999912	1.016911	1.044307
	ω	1.28485	0.383475	0.652473	0.988803	1.278508	1.544248	2.100214
	α	0.249126	0.086881	0.134661	0.169132	0.242398	0.320128	0.409509
	β	0.694949	0.084831	0.551004	0.622529	0.697168	0.765568	0.834356
$MNHVF$	γ	0.966041	0.002664	0.959106	0.964684	0.966423	0.967782	0.970546
	ω	0.32025	0.060133	0.197535	0.279277	0.320782	0.364064	0.434171
	α	0.019595	0.006501	0.009929	0.014357	0.018578	0.024071	0.032653
	β	0.539409	0.070871	0.408734	0.489411	0.536589	0.586296	0.684896
$AUSS$	γ	1.001002	0.013192	0.976494	0.995035	0.997504	1.003837	1.039281
	ω	2.748827	0.719875	1.502256	2.19799	2.718225	3.21608	4.217363
	α	0.427235	0.083504	0.256979	0.369592	0.432681	0.486194	0.58594
	β	0.49418	0.09201	0.308416	0.435409	0.495966	0.556251	0.669695
$BRFS$	γ	1.008711	0.010343	0.98818	1.00234	1.008612	1.014209	1.030855
	ω	10.26617	3.2337	4.669905	7.856199	10.15323	12.39062	17.38735
	α	0.382847	0.099958	0.211659	0.304731	0.382117	0.456359	0.577016
	β	0.538087	0.110805	0.328564	0.460237	0.532634	0.619422	0.738853
ABC	γ	1.022563	0.022021	0.981235	1.005937	1.024116	1.039678	1.061058
	ω	2.124207	0.830382	0.534446	1.573473	2.208756	2.71183	3.629322
	α	0.235861	0.080263	0.074058	0.179221	0.236067	0.29626	0.382294
	β	0.537435	0.14991	0.307615	0.431212	0.515622	0.611901	0.858884
BYN	γ	1.028623	0.028159	0.96922	1.006667	1.030595	1.051955	1.072231
	ω	9.945769	3.369216	4.952078	7.438891	9.593609	11.84671	17.74216
	α	0.271935	0.061387	0.168018	0.228198	0.26709	0.314033	0.406375
	β	0.684818	0.070701	0.533215	0.639043	0.696426	0.736398	0.801073
	a	0.003292	0.001945	0.00061	0.001827	0.002932	0.004341	0.008015
	b	0.425829	0.256819	0.025668	0.223393	0.421223	0.598329	0.932121

Observing the summary, something interesting is evident that, the marginal posterior distributions of the DCC conditional correlation parameters a and b show that their coefficients are highly significant, firmly rejecting the CCC model hypothesis (a = b = 0). As a result, it may be incorrect or misleading to assume that returns of Seafood and Meat index return price pairs always correlations are constant. Moreover, the correlation parameter estimates satisfy the required requirement $a + b = 0.4297 < 1$, confirming that the Bayesian DCC-MGARCH model is appropriate for capturing time-varying conditional correlations.

The relationships between the prices of seafood and Meat markets, as represented by the Bayes DCC-MGARCH model with a skewed multivariate generalized error distribution, are shown in Figure 3. These conditional correlations show volatility, with sharp fluctuations at different times, rather than being static. This means that these markets were simultaneously recording significant volatilities.



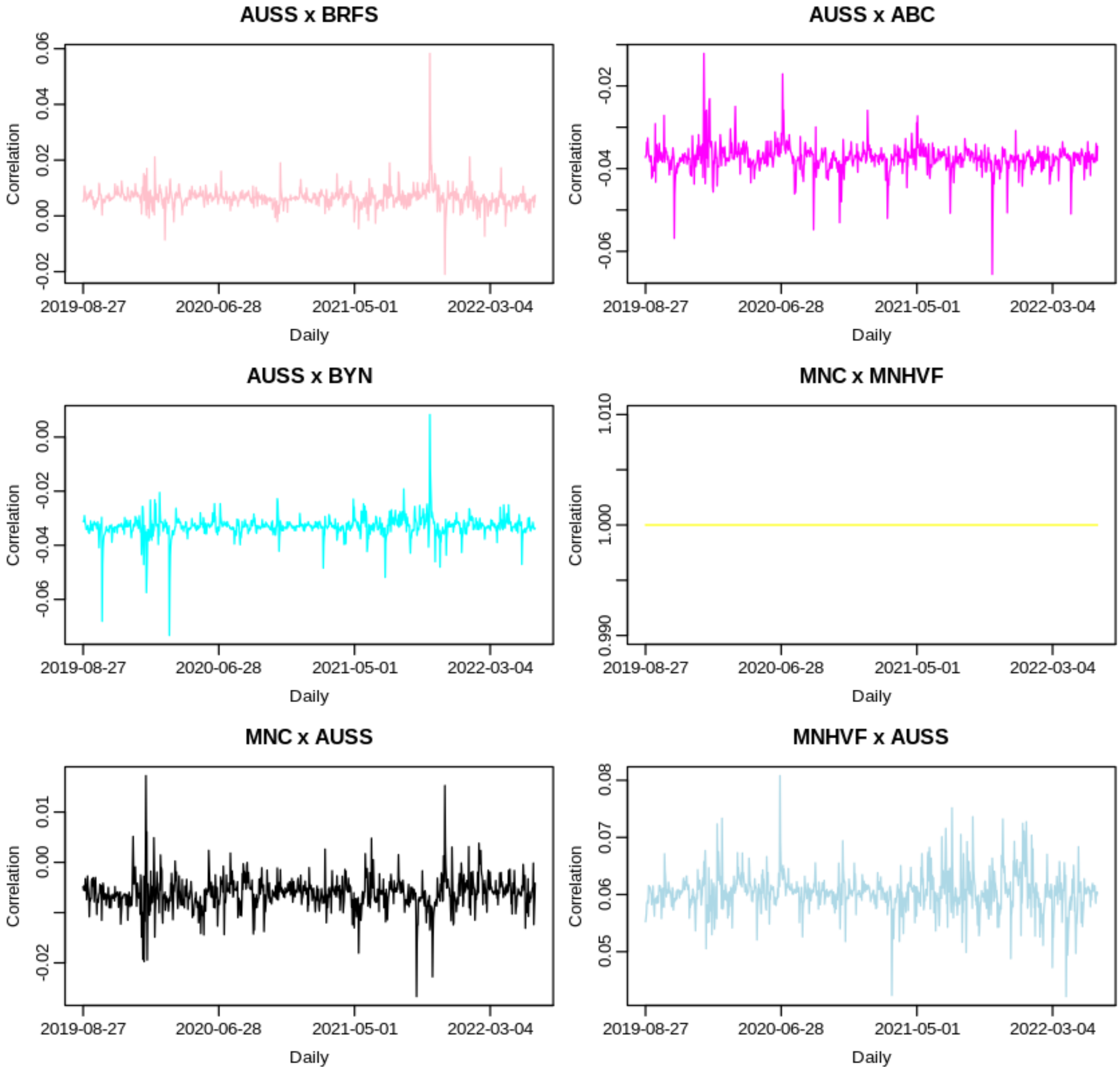


Figure 3: The dynamic correlation between Seafood and Meat Index price returns from Bayesian DCC-MGARCH models under the SMVGED

The results of the Dynamic Conditional Correlation (DCC) analysis for the return indices of BRF S.A. (BRFS) and Maruha Nichiro Corporation (MNC) are shown in Figure 3. Interestingly, there is a negative range of -0.01 to -0.08 for the correlation between these entities. This range is especially significant in the times preceding the announcement by the Japanese government that they intended to release nuclear wastewater from Fukushima into the sea. It's interesting to note that this correlation exhibits a less volatile range than the DCC between Prima Meat Packers Ltd. (ABC) and Maruha Nichiro Corporation (MNC), represented as (MNC x ABC), which shows a stronger correlation range of 0.41 to 0.47. The latter correlation exhibits a slightly increased variation between December 2019 and January 2020. An analysis of the time-varying connection between different meat stock indices and Marine Harvest (MNHVF) indicates oscillations between positive and negative correlations. In particular, there are significant positive and negative peaks in the correlation between MNHVF and BRFS in June 2020 and March 2022. The correlation fluctuates between -0.031 and 0.02. Following the announcement, there is volatility in the correlation. Similar to (MNHVF x BYN), the correlation ranges between MNHVF and ABC is -0.018 to 0.04, with noticeable rotations in the correlation dynamics. After the announcement, there is an evident rise in both positive and negative correlation that spans from May to August 2021.

Looking into Austevoll Seafood ASA (AUSS), after the announcement, the DCC with BRFS fluctuates rapidly between positive and negative correlation, primarily moving around 0.01. The range of values is -0.02 to 0.06. There are multiple instances of increasing correlation in the negative correlation range of -0.01 to -0.03 observed in the DCC between AUSS and ABC. The correlation between BYN and AUSS, on the other hand, varies from -0.06 to 0.01; it was initially negative but changed to positive following the announcement. Finally, looking at DCC in the context of the seafood index shows how various seafood markets are connected. The strongest association between MNC and MNHVF was observed after the announcement, which may have something to do with MNC's operations in Japan. After the announcement in August 2021, the DCC between MNC and AUSS shows swings with peaks in both negative and positive correlation, ranging from -0.03 to 0.018. Last but not least, the DCC between AUSS and MNHVF mainly fluctuates about 0.06, with the lowest correlation found after the announcement.**Robustness**

Robustness to the number of Samples

It can be high and time costly to generate 20,000 samples from the posterior distribution in the MCMC sampling, particularly when considering the amount of time needed to finish the process. Therefore, it might be better to produce fewer samples for concluding the Bayesian DCC MGARCH model. To verify this, 20,000 samples (5000 burn-in and 15,000 for estimation) and 10,000 samples (2000 burn-in and 8000 for estimation) were generated to re-estimate the model. Table 5 presents the findings of how the model is robust to the number of samples. The posterior means and standard deviations show relatively little variation

Table 5: Sensitivity analysis of the Bayes DCC-MGARCH model to the number of the MCMC sampling for the bivariate combination of MNHVF and BRFS price returns

$Sample$		δ	$MNHVF$				$BRFS$				a	b
			γ	ω	α	β	γ	ω	α	β		
20,000	$Mean$	$2.939e-01$	$9.660e-01$	$1.782e-01$	$6.512e-06$	$8.915e-01$	$9.300e-01$	$2.509e+01$	$1.415e-01$	$8.184e-01$	$2.250e-04$	$6.583e-01$
	$Std.$	$1.340e-04$	$2.212e-05$	$1.876e-04$	$1.851e-06$	$1.663e-04$	$2.590e-03$	$2.485e+00$	$2.522e-02$	$2.628e-02$	$1.440e-04$	$8.076e-02$
10,000	$Mean$	$2.972e-01$	$9.619e-01$	$1.486e-01$	$7.210e-06$	$8.842e-01$	$9.786e-01$	$2.153e+01$	$1.796e-01$	$7.861e-01$	$5.001e-04$	$3.918e-02$
	$Std.$	$2.598e-05$	$2.717e-05$	$1.370e-04$	$2.554e-06$	$6.175e-05$	$2.756e-03$	$3.321e+00$	$2.044e-02$	$2.353e-02$	$9.488e-05$	$2.102e-02$

Robustness to prior specification

Assessing the sensitivity of the posterior estimates to the prior specification and initial values for the DCC MGARCH model parameters is crucial (the three informative priors for alpha and beta parameters are as follows).

$Prior$ 1: $\alpha \sim N(0.02, \quad 0.002), \quad \beta \sim N(0.5, \quad 0.002)$

$Prior$ 2: $\alpha \sim N(0.04, \quad 0.010), \quad \beta \sim N(0.8, \quad 0.008)$

$Prior$ 3: $\alpha \sim N(0.06, \quad 0.020), \quad \beta \sim N(0.9, \quad 0.010)$

Table 6: Robustness to prior specification for the price returns

		$Prior$ 1		$Prior$ 2		$Prior$ 3	
		$Mean$	SD	$Mean$	SD	$Mean$	SD
	δ	0.507202	0.013584	0.515978	0.015824	0.520171	0.028538
MNC	γ	0.999766	0.012945	0.994723	0.014205	0.992534	0.008687
	ω	1.712904	0.652144	1.252284	0.419577	1.186445	0.414735
	α	0.284833	0.058399	0.27503	0.071014	0.227653	0.050851
	β	0.632951	0.081311	0.690218	0.077849	0.719069	0.068113
$MNHVF$	γ	0.965697	0.00257	0.967014	0.001816	0.966122	0.002004
	ω	0.328887	0.050946	0.307956	0.06359	0.321801	0.077804
	α	0.017491	0.006681	0.017828	0.005612	0.01537	0.005864
	β	0.525504	0.057969	0.576406	0.075059	0.547258	0.102665
$AUSS$	γ	0.990546	0.025634	0.980377	0.030059	0.989664	0.02391
	ω	2.861549	0.695365	2.817872	0.66423	2.646624	1.040133
	α	0.410414	0.114809	0.43535	0.090695	0.395521	0.122519
	β	0.510721	0.102418	0.496791	0.082643	0.534262	0.125321
$BRFS$	γ	1.012419	0.012067	1.005925	0.009921	1.004826	0.010699
	ω	14.1368	3.854958	10.39616	3.763352	9.96787	3.653897
	α	0.435384	0.14248	0.350895	0.098073	0.372635	0.11987
	β	0.423576	0.13087	0.549953	0.123959	0.547825	0.131215
ABC	γ	1.025684	0.01839	1.026331	0.01944	1.0128	0.034484
	ω	3.307085	0.818285	1.996729	0.815058	2.684762	1.380699
	α	0.303147	0.076782	0.247818	0.084009	0.262142	0.09853
	β	0.329917	0.124872	0.553967	0.149218	0.438564	0.227805
BYN	γ	1.045089	0.025235	1.018114	0.034086	1.023021	0.036524
	ω	10.62482	3.982272	11.62231	3.251449	10.27277	5.921141
	α	0.268728	0.087802	0.317466	0.087315	0.261724	0.123711
	β	0.682563	0.095751	0.631969	0.086958	0.685093	0.132678
	a	0.002428	0.001703	0.002789	0.002159	0.002679	0.002532
	b	0.5503	0.252158	0.578129	0.217831	0.547939	0.27143

These priors are derived by making minor adjustments to the informative priors provided by (Fioruci et al., 2014). Table 6 reports the posterior outcomes for the aforementioned priors. Nearly all metrics showed sensitivity to changes in the prior under any of the three priors.

Discussion

This paper examines the complex dynamics that affect the seafood market, which are further complicated by the subtle difficulties that resulted from the Japanese government's announcement that it planned to dump nuclear waste. Seafood is becoming more and more of a commodity in the global economy due to factors like trade liberalization, technological improvements, and rising demand (Asche, 2008); (Tveterås et al., 2012); and (*Asche, F., et al, 2015*). But the announcement from Japan has sent major shockwaves across the world seafood market, raising serious questions about the sustainability and safety of seafood coming from areas hit by this natural disaster. The study breaks from the traditional Maximum Likelihood approach in financial econometrics by introducing the use of a Bayesian Dynamic Conditional Correlation-Multivariate Generalized Autoregressive Conditional Heteroskedasticity (DCC-MGARCH) framework. The Bayesian approach, based on the Markov Chain Monte Carlo (MCMC) method and inspired by earlier works (Ardia, D., 2006); (Fioruci et al., 2014), provides an advanced perspective through which to examine the complex correlation dynamics between seafood (MNC, MNHVF, AUSS) and meat (BRFS, ABC, BYN) market index prices.

Asymmetric features found in the observed fat tails of seafood and meat index prices are one way that the model's suitability for representing the complexities of time-varying conditional correlations is demonstrated by the application of the Skewed Multivariate Generalized Error Distribution (SMVGED) within the Bayesian approach. This adds to the set of financial econometrics methods by demonstrating the effectiveness of Bayesian frameworks in managing difficult and sensitive financial time series data. The causality test reveals directional influences between the prices of the meat and seafood indices by utilizing knowledge from Granger causality and Engle's LM test. This causality assessment provides us with information about influences and precedence, which is important when developing complex risk mitigation techniques in unstable market settings, as demonstrated by earlier research (Zivot, E., et al., 1992).

CONCLUSION

Given the environmental instability caused by the Fukushima nuclear wastewater release, this research is essential for understanding the complex relationships within the global meat and seafood markets. Demonstrating the evolving field of financial econometrics, the Bayesian DCC-MGARCH framework, enhanced by the SMVGED, serves as an advanced tool for capturing time-varying correlations. Integrating various findings clarifies the critical role seafood plays in international trade and highlights the significant effects that the Fukushima incident may have had on global seafood markets. The dynamic correlations identified through the Bayesian approach provide a comprehensive overview of the intricate relationships governing seafood and meat indices. The study shifts from the conventional Maximum Likelihood technique in financial econometrics by introducing a Bayesian perspective, aligning with contemporary advancements in the field. Sensitivity evaluations confirm the robustness of the Bayesian framework and emphasize its effectiveness in addressing the inherent complexity of financial time series data. This underscores the paradigm shifts necessary for advanced model selection and parameterization. The insights gained offer significant implications for traders, legislators, and market participants, aiding in the management of market volatility and contributing to broader discussions on the financial impacts of external shocks on global market dynamics.

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