COVID-19 impact on the agro-food and marine industries through a Bayesian stochastic volatility Fourier Series Model

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Abstract

In this paper, we construct a hybrid model, consisted of a Bayesian Vector Autoregressive structure with Bayesian stochastic volatility (SVAR-SV), as well as, Fourier Series (FS). We test the model's performance in terms of forecasting ability, comparing it with simple Bayesian stochastic volatility (SV), and also with a classical econometric autoregressive model. By estimating the average prices of the major Food futures in the stock market, and the average prices of the biggest Marine companies' stocks, we test the effect of Covid-19 on these stocks, through the proposed hybrid model, and the impulse-response functions between the aforementioned. Through this approach, we test whether the Covid-19 pandemic hindered the performance of marine companies and affected the food prices, with those two affecting one another. Based on the findings, a shock is apparent from the Food futures to the Marine companies' stocks, and the hybrid model proposed is the best, in terms of forecasting ability.

Keywords: COVID-19; Bayesian stochastic; Fourier; marine stocks; food prices; futures.

JEL codes: C58, C50, C51, C11

1.Introduction

COVID-19 had an important impact on agriculture in many ways. To begin with, this pandemic affected the global food supply chains (Siche, 2020), the food demand and the food security (Torero, 2020), especially for the most vulnerable population. It also affected the global food systems through agricultural input and output markets, the food processing, and the employment along food chains (Huang, 2020).
Another important issue is labor availability in the agricultural sector. Lockdown measures and quarantine caused an important loss of workforce during the COVID-19 era. Substantial restrictions on international labor movements and worker programs caused bottlenecks in many global agriculture systems (Stephens et al., 2020). To make matters worse, the global decrease in the demand for tourism-related activities, such as hotels and restaurants, has also caused specific agricultural commodities' prices to drop significantly (Bhosale, 2020). On the other hand, other goods have been

the objects of panic-buying, with consumers stockpiling certain food supplies at home (The Guardian, 2020), an incident that could cause food shortages in specific products.

On the other hand, COVID-19 affected also the marine industry. More precisely, vessel activity, fishing activity, and passenger traffic, reduced by 69%, 84%, and 78%, respectively during the lockdown measures (Depellegrina et al., 2020). Furthermore, many ports reduced their activity or even shut down, causing disruption to the global supply chain system.

Since many agricultural products are transported by sea, agriculture and marine transportation are interconnected. Although the subject's importance, the literature has not sufficiently investigated the direction of this relationship. In other words, there are not empirical evidences whether during COVID-19 a shock is transmitted from the marine transportation to the food industry, or the opposite. In the present paper, we investigate this hypothesis, by testing the direction and the statistical significance of this relationship, contributing in this way to the economic literature. Finally, we construct a novel hybrid forecasting model, based on Fourier and Bayesian stochastic volatility methods, to forecast the values of the marine transportation and food futures, contributing also to the forecasting literature.

The paper is structured as follows: Section 2 presents the literature review, section 3 describes the methodology used, Section 4 presents the data and the results, and finally, Section 5 discusses and concludes the paper.

2.Literature Review

Although the current economic crisis due to COVID-19 is of great importance, there are not many studies empirically examining the repercussions of COVID-19 on the fields of marine and food industries, not to mention the lack of examination in the industries' connection.

To begin with, sectors that were associated with food services and those dependent on airfreight faced many disruptions (Greenville et al., 2020). Agricultural export relied on bulk shipping, was less disrupted than those that relied on other forms of transport such as air freight (ABARES, 2020). Restrictions imposed on international labor movements and worker programs caused many problems in global agriculture systems (Stephens et al., 2020). Barman et al. (2021) proposed that food supply chains should focus on facilities such as the maintenance of employees' safety and health, and the change of working conditions, avoiding also certain policies, such as the protectionist policy.

Furthermore, the lockdown measures forced the closure of many companies, affecting small and medium enterprises in the food industry. Although this phenomenon is global, not all regions in the world were affected in the same magnitude, since, for instance, in Australia, a decrease in the agricultural sector was present, but not as high as was expected and forecasted (Snow et al., 2021).

Additionally, the consumer behavior during COVID-19 also changed, as a phenomenon known as panic buying emerged (Addo et al., 2020; Nicola et al., 2020). This phenomenon led to an imbalance between supply and demand, rendering the food supply chain unable to face the problems that arose due to the COVID-19 pandemic (Ali et al., 2021). Consumption preferences have also changed, from eating out of the home, to meals prepared and consumed at home (Goddard, 2020; Nakat and Bou-Mitri, 2021).

The size and the type of production were two important factors that played a significant role for the companies' performance during COVID-19 (Hailu, 2020). In this context, the productions that were impacted include flour and cooking oil (Brewin, 2020), fruits and vegetables (Richards & Rickard, 2020), dairy, egg, poultry (Weersink, 2020), cocoa and fish (McEwan et al., 2020; Nakat and Bou-Mitri, 2021).
Moreover, Panzone et al. (2021) measured the impact of the COVID-19 shock on the sales of the UK food retailers and restaurants, with empirical methods, concluding that restrictions affected positively the food retailers, while negatively the non-food stores, and the food and beverage serving services.
Galanakis et al. (2021) examined Internet and Communication Technologies, blockchain in the food supply chain, and other Industry applications, regarding the COVID-19 era, arguing that there are approaches that redefine the way we consume food, for instance plant-based alternatives of meat, valorization of a vast range of bioresources, and lab-grown meat.
On the other hand, the marine industry was also affected by COVID-19. To begin with, Depellegrin et al. (2020) analyzed the impact of lockdown measures on marine activities, showing that the fishing vessels, cargo, tanker vessels reduced their activity. Zhou et al. (2020) propose that blockchain technology has the potential to improve the function of maritime businesses, especially during COVID-19, but, according to the authors, there are very few studies investigating this specific subject.
Moreover, since many goods are transported by sea (Gray, 2020), these two industries (food and marine) are interconnected. In cases of emergency, such as pandemics, dry bulk trade is affected, since international maritime transportation connections are hindered (Arifin, 2020).
Summing up, based on the literature, COVID-19 has affected the food and marine industries. Since these industries are interconnected, a shock from the one could affect the other. However, the mechanism and the direction of the shock transmission between these two industries is not clear, as not sufficient empirical evidence exists. The present paper fills this gap in the literature, shedding light on this relationship through empirical evidence, utilizing also a novel forecasting methodology.

3.Methodology

3.1.Econometric modeling

In this work, we perform a stationarity test, and more precisely, the KPSS test (Kwiatkowski et al., 1992). Its null hypothesis is that the timeseries is stationary. If variables are non-stationary, we then perform a co-integration test.

Co-integration test:

If variables are non-stationary, we implement a co-integration test to test the presence of co-integration among the variables, which, if exists, should be included in the econometric models. To do so, we chose to perform the Johansen co-integration test (Johansen, 1988).

Econometric model:

In this work, we implement a classical econometric model, to test the forecasting superiority of our proposed hybrid model. More precisely, we use a vector autoregressive model (VAR) as a baseline model, in case of the absence of co-integration relationships among the variables, or a vector error correction model (VECM) in case of co-integration.

We also derive the orthogonal impulse-response functions to test the statistical significance and the direction of a possible effect from each sector to the other.

3.2 Bayesian stochastic volatility modeling

To begin with, we base our stochastic approach on Kastner (2016) and Hosszejni and Kastner (2021) to find the posterior distribution of each of the parameters. This will be used as the baseline stochastic model (second baseline model of our analysis), that will be also compared with our proposed hybrid model.

Baseline stochastic volatility model:

Inspired by the model in Kastner (2016) and Hosszejni and Kastner (2021), we adjust the baseline stochastic volatility model:

$$\begin{cases} y_t = x_t\beta + \exp\left(\frac{h_t}{2}\right)\epsilon_t \\ h_{t+1} = \mu + \phi(h_t - \mu) + \sigma\eta_t \end{cases} \quad (2.1)$$

where $\begin{pmatrix}\epsilon_t \\ \eta_t\end{pmatrix} \sim N_2\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}1 & \rho \\ \rho & 1\end{pmatrix}\right)$

to the corresponding model:

$$\begin{cases} y_1(t+1) = ay_1(t) + by_2(t) + cx(t) + \exp\left(\frac{h_1(t)}{2}\right)Z_1(t) \\ h_1(t+1) = \mu_1 + \phi_1(h_1(t) - \mu_1) + \sigma_{\eta_1}M_1(t) \\ y_2(t+1) = \tilde{a}y_1(t) + \tilde{b}y_2(t) + \tilde{c}x(t) + \exp\left(\frac{h_2(t)}{2}\right)Z_2(t) \\ h_2(t+1) = \mu_2 + \phi_2(h_2(t) - \mu_2) + \sigma_{\eta_2}M_2(t) \end{cases} \quad (2.2)$$

where $\begin{pmatrix}Z_1(t) \\ M_1(t)\end{pmatrix} \sim N_2\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}1 & \rho_1 \\ \rho_1 & 1\end{pmatrix}\right)$ and $\begin{pmatrix}Z_2(t) \\ M_2(t)\end{pmatrix} \sim N_2\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}1 & \rho_2 \\ \rho_2 & 1\end{pmatrix}\right)$

We adopt a Bayesian approach to this model, hence we compute the posterior of the parameters $(a, b, c, \mu_1, \phi_1, \sigma_{\eta_1}, \tilde{a}, \tilde{b}, \tilde{c}, \mu_2, \phi_2, \sigma_{\eta_2}, \rho_1, \rho_2)$ setting in the first place their priors. Moreover, the exponential stochastic volatilities $\{h_1(t): t \in [0, T]\}, \{h_2(t): t \in [0, T]\}$ are not observable and therefore they are treated as latent variables which must be simulated within the algorithm.

Novel hybrid stochastic volatility model with Fourier series:

In this methodological approach, we develop the model assumptions of model (I) for a given horizon $T > 0$ which is actually the maximum time we would like to forecast our time series. We expand the idea of the model (I) based on the following:

(1) We model the dynamics of a time series $y(t)$ using two components. The first component is an AR (1) process along with some dependance on the other stochastic processes. The second component is the Fourier series for the unknown time series $y(t)$ at time t, with unknown constants. The reason to do so is that any time series y is a continuous function on a given interval $[0, T]$and therefore, the function $y(t)$ can be written as a convergent Fourier series of the form:

$$S_k[y](t) = u_0\sqrt{\frac{1}{T}} + \sqrt{\frac{2}{T}}\sum_{n=1}^{k} u_n \sin\left(\frac{2\pi nt}{T}\right) + \sqrt{\frac{2}{T}}\sum_{n=1}^{k} v_n \cos\left(\frac{2\pi nt}{T}\right) \quad (2.3)$$

such that:

$\mu\left(\left\{t \in [0,T]: \lim_{k\to+\infty} S_k[y](t) \neq y(t)\right\}\right) = 0$, where μ is the Lebesgue measure restricted on the interval $[0,T]$.

(2) In addition, we assume that the volatility of each process is also a stochastic process with leverage.

(3) We will treat this model in a Bayesian perspective, hence all the unknown parameters of the model will be treated as random variables. The motivation to do so is that the Fourier expansion can calibrate the model so that not only it fits better to the data but also it has better forecasting ability.

All the above information can be written in a compact form in the following system:

$$\begin{cases} y_1(t+1) = ay_1(t) + by_2(t) + cx(t) + u_0\sqrt{\frac{1}{T}} + \sqrt{\frac{2}{T}}\sum_{n=1}^{+\infty} u_n \sin\left(\frac{2\pi nt}{T}\right) + \sqrt{\frac{2}{T}}\sum_{n=1}^{+\infty} v_n \cos\left(\frac{2\pi nt}{T}\right) + \exp\left(\frac{h_1(t)}{2}\right. \\ h_1(t+1) = \mu_1 + \phi_1(h_1(t) - \mu_1) + \sigma_{\eta_1} M_1(t) \\ y_2(t+1) = \tilde{a}y_1(t) + \tilde{b}y_2(t) + \tilde{c}x(t) + \widetilde{u_0}\sqrt{\frac{1}{T}} + \sqrt{\frac{2}{T}}\sum_{n=1}^{+\infty} \widetilde{u_n} \sin\left(\frac{2\pi nt}{T}\right) + \sqrt{\frac{2}{T}}\sum_{n=1}^{+\infty} \widetilde{v_n} \cos\left(\frac{2\pi nt}{T}\right) + \exp\left(\frac{h_2(t)}{2}\right. \\ h_2(t+1) = \mu_2 + \phi_2(h_2(t) - \mu_2) + \sigma_{\eta_2} M_2(t) \end{cases}$$

where $\begin{pmatrix} Z_1(t) \\ M_1(t) \end{pmatrix} \sim N_2\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_1 \\ \rho_1 & 1 \end{pmatrix}\right)$, $\begin{pmatrix} Z_2(t) \\ M_2(t) \end{pmatrix} \sim N_2\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_2 \\ \rho_2 & 1 \end{pmatrix}\right)$

and:

$$u_0 = \int_0^T y_1(t)dt, \widetilde{u_0} = \int_0^T y_2(t)dt \quad (2.5)$$

$$u_n = \int_0^T y_1(t)\sin\left(\frac{2\pi nt}{T}\right)dt, v_n = \int_0^T y_1(t)\cos\left(\frac{2\pi nt}{T}\right)dt \quad (2.6)$$

$$\widetilde{u_n} = \int_0^T y_2(t)\sin\left(\frac{2\pi nt}{T}\right)dt, \widetilde{v_n} = \int_0^T y_2(t)\cos\left(\frac{2\pi nt}{T}\right)dt \quad (2.7)$$

The parameter space is:

$\theta =$
$\left(\alpha, b, c, u_0, (u_n)_n, (v_n)_n, \tilde{a}, \tilde{b}\ , \tilde{c}\ , \widetilde{u_0}, (\widetilde{u_n})_n, (\widetilde{v_n})_n, \mu_1, \varphi_1, \sigma_{\eta_1}, \rho_1, \mu_2, \varphi_2, \sigma_{\eta_2}, \rho_2\right)$
while the exponential stochastic volatilities $\{h_1(t): t \in [0, T]\}, \{h_2(t): t \in [0, T]\}$ are not observable and therefore they are treated as latent variables which must be simulated within the algorithm.
Prior selection for the models (I) and (II):
At this point, we specify the prior distribution we chose for each one of the parameters.

- φ_1, φ_2

We set $\frac{1+\varphi_1}{2}\ , \frac{1+\varphi_2}{2} \sim Beta(a_0, b_0)$ where $a_0 = 20, b_0 = 1.5$

- $\sigma_{\eta_1}, \sigma_{\eta_2}$

We set $\sigma_{\eta_1}^2, \sigma_{\eta_2}^2 \sim G\left(\frac{1}{2}, \frac{1}{2} B_\sigma\right)$ where B_σ is a hyperparameter. In our case we choose

$$B_\sigma = 0.1$$

- $\mu_1, \mu_2 \sim N(0,1)$

- ρ_1, ρ_2

We set $\frac{1+\rho_1}{2}\ , \frac{1+\rho_2}{2} \sim B(4,4)$ following Kastner (2016) and Hosszejni and Kastner (2021).

Regressors

For the regressors $\alpha, b, c, u_0, (u_n)_n, (v_n)_n, \tilde{a}, \tilde{b}\ , \tilde{c}\ , \widetilde{u_0}, (\widetilde{u_n})_n, (\widetilde{v_n})_n$ we set as prior the non-informative $N(0,1)$. Furthermore, it is obvious that we cannot have as many estimates on the Fourier coefficients $(u_n)_n, (v_n)_n, (\widetilde{u_n})_n, (\widetilde{v_n})_n$ as we want, since this would require infinitely amount of data. Therefore we choose by trial a specific $N \geq 1$which seems reasonable to fit the data and then find the posterior distribution of the Fourier coefficients, $(u_1, \cdots, u_N), (v_1, \cdots, v_N), (\widetilde{u_1}, \cdots, \widetilde{u_N}), (\widetilde{v_1}, \cdots, \widetilde{v_N})$. By testing several number of Fourier components, we concluded to 10 Fourier orders being optimal in this case study.
This novel hybrid model is our proposed model due to its forecasting superiority, and therefore, it is sated as the alternative model, throughout the remaining of the present paper, to differentiate from the other two baseline models that are employed to prove the proposed model's forecasting superiority.

4.Empirical Analysis

4.1 Data and variables

The data used in the present work are the global confirmed cases of the COVID-19 in daily cumulative summed cases downloaded by the John Hopkins University database. Moreover, we used financial stocks of some of the biggest marine companies. These are the Dynangas (DLNG), Euronav (EURN), Euroseas (ESEA), Frontline (FRO), Nordic American Tanker (NAT), Scorpio Bulkers (SALT), Sino-Global Shipping (SINO), Teekay Tankers (TNK), Tsakos Energy Navigation (TNP), Torm (TRMD) derived from Yahoo Finance in daily frequency. We also used future prices related to the agricultural sector of the economy, namely corn (ZC=F), oat (ZO=F), wheat (KE=F), rough (ZR=F), soybean meal (ZM=F), soybean oil (ZL=F), soybean (ZS=F), feeder cattle (GF=F), lean hogs (HE=F) and live cattle (LE=F), all derived from Yahoo Finance in daily frequency, as well. All data span the period 22 January until 22 February of the year 2021. To avoid extreme algorithmic complexity, we took the average of the marine industry and the respective average of the Food-related futures, to examine a possible relationship between these two sectors, using our novel forecasting technique. The time-series were transformed into a logarithmic scale. The descriptive statistics of the logarithmic time-series are depicted in Table 1.

Tab. 1: *Descriptive statistics of the logarithmic timeseries.*

Variable	Mean	Std	Min	Max
Food	2.622985	0.03705	2.559682	2.706639
Marine	0.888261	0.065737	0.755818	1.106049
Covid	6.876065	1.137804	2.745855	8.04434

4.2Results

We first test for a unit root, implementing the KPSS test (1988). The results in Table 2 show that Food and Marine time-series are non-stationary.

Tab. 2: *KPSS stationarity test results.*

Variable	Value Test	Stationarity
Critical Value	**0.347**	
Confirmed cases	4.074	NO
Maritime	2.170	NO
Food	2.436	NO

Since all variables are non stationary, we test for co-integration, using the Johansen co-integration test. The results in Table 3 show that there is co-integration relationship among the variables.

Tab. 3: *Johansen co-integration test results.*

Johansen test	10pct critical values
1.122	6.500
9.095	12.910
55.888	18.900

We now set the models, which consist of two endogenous variables, namely, the Food prices and Marine stocks' performance. Furthermore, we incorporate an exogenous variable in the aforementioned model, which is the COVID-19 confirmed cases.
In this context, we set three models. First, a baseline classical econometric model, a vector error correction model (VECM). Furthermore, we set another baseline model, the Bayesian stochastic volatility model (BSVM), and finally, we set the alternative model specification, our proposed novel hybrid model, the Bayesian stochastic volatility with Fourier orders model (BSVFM). To compare the models in terms of forecasting ability, we use the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the root mean square error (RMSE). The examined forecasting horizon is stable in 20 days (1 business month).
The results are presented in Table 4, based on which, the alternative proposed hybrid model is the best in terms of forecasting ability, from both baseline models, with the VECM model being the worst in forecasting ability. These results give credit to our proposed model's forecasting superiority.

Tab. 4: *Forecasting results for the two baseline and the alternative models.*

Variable	Criterion	VECM	BSVM	BSVFM
	MAE	0.0273	0.0167	0.0154
	MAPE	0.0044	0.0027	0.0025
Food Prices	RMSFE	0.0312	0.0205	0.0189
	MAE	0.1205	0.1121	0.0853
	MAPE	0.0546	0.0512	0.0388
Marine Activity Prices	RMSFE	0.1558	0.1392	0.1122

Finally, we test the direction of a possible shock transmission, by deriving the orthogonal impulse-response functions from the Marine industry to the Food prices and also vice versa. These results are depicted in Figure 1 and Figure 2.

Fig. 1: *Impulse-response function from the Marine industry to the Food prices.*

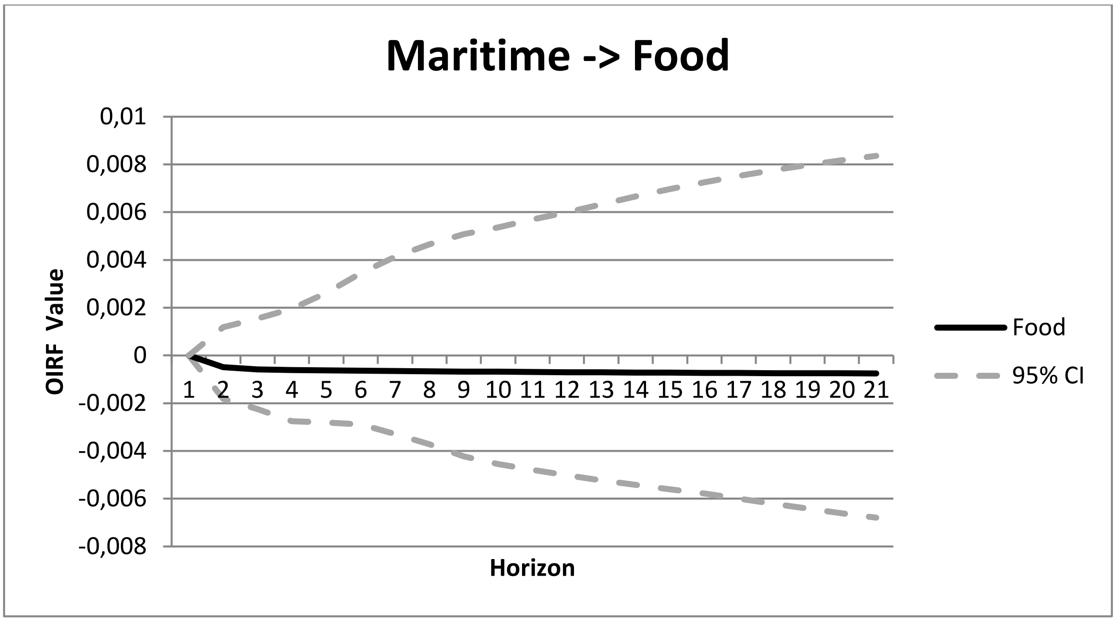
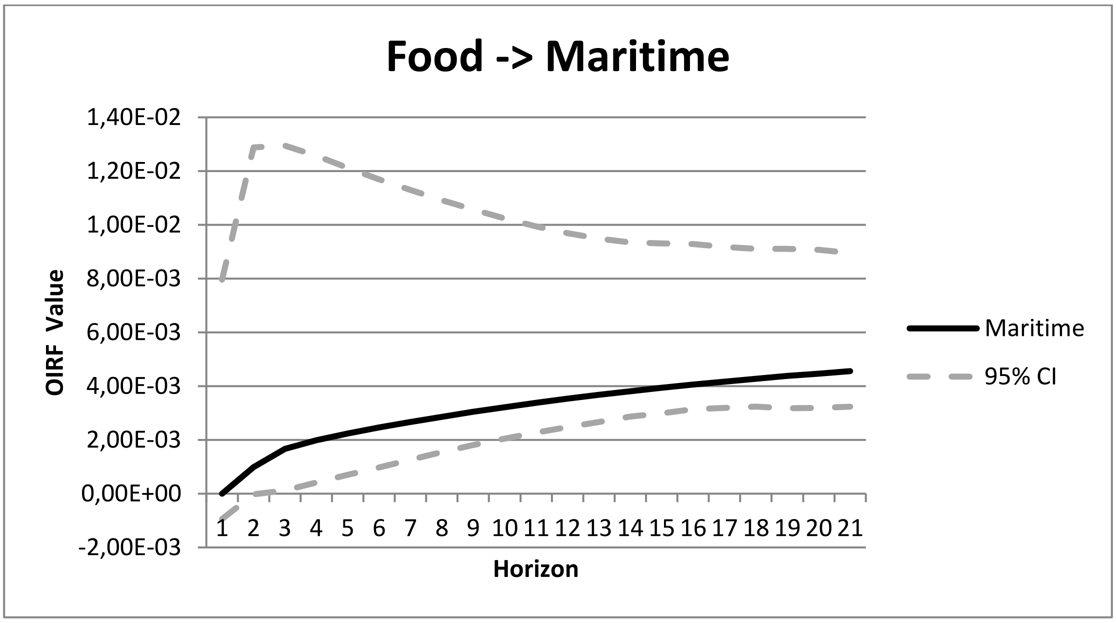


Fig. 2: *Impulse-response function from the Food prices to the Marine industry.*



The results in Figure 1 and Figure 2 show that a shock transmitted from the Marine industry to the Food prices is not statistically significant, while, on the other hand, a shock transmitted from the Food prices to the Marine industry is statistically significant.

5.Conclusion

In this study, we examine the effect of COVID-19 on the food futures and the marine companies' stock prices. More precisely, we set a novel forecasting hybrid model, integrating Bayesian stochastic volatility modeling with Fourier orders. To test the model's forecasting superiority, we compare it with two other models, a classical econometrical VEC model and a Bayesian stochastic volatility model. We also derive the impulse-response functions to investigate whether a shock in the marine industry affects the food sector, due to transport inability, or a shock in the food sector affects the marine industry since commodity demand affects the marine activity.

Based on the results, our novel hybrid model is superior in terms of forecasting ability, than both other two models employed. Furthermore, according to the findings, the shock is not transmitted from the Marine industry to the Food prices, since there is no statistical significance to provide such evidence. On the other hand, a shock is transmitted from the Food prices to the Marine industry since the results are statistically significant.

Based on the literature, Marine shipping comprises most of the global trade, so, food import and export is closely related to shipping activity (Yazır et al., 2020). This can be seen also by the present paper since the results imply a relationship between these two sectors. The suspension of cargo ships during the quarantine period impacted the global maritime trade, causing serious economic problems (Yazır et al., 2020), but in our case-study, the food futures are those that transmit a shock to the marine industry, and not the opposite.

This can be explained by the fact that the marine industry was already bottlenecked due to lockdown measures, and was further affected by excessive demand from the food sector, which could not provide (as a supplier). On the other hand, since the marine industry's activity was stopped, it could not affect even more the food industry which was already impacted by other factors some of them related to COVID-19. Such factors are the restrictions imposed on international labor movements and worker programs (Stephens et al., 2020), the global decrease in the demand for tourism-related activities for instance, hotels and restaurants (Bhosale, 2020), the changes in food processing, and in the employment along food chains (Huang, 2020). There are also other more general factors that are known to affect food commodity prices, for instance the consumer behavior (Addo et al., 2020; Nicola et al., 2020), the imbalance between supply and demand (Ali et al., 2021), and also other factors such as weather, employment, technological advancements, and of course, oil prices. Those factors are known to impact significantly the Food prices, which in turn affect the Marine industry (through supply and demand), since it is the main distributer of those commodities to the global market.

The present paper not only amplifies the evidence of an existing relationship between the marine and the food sectors, already stated by the literature, but also provides evidence about the direction of the shock transmission during COVID-19 pandemic, with data span from 22 January of the year 2020 till 22 February of the year 2021. Finally, the paper's contribution to the forecasting literature is the proposed novel hybrid forecasting structure, utilizing Bayesian stochastic volatility with Fourier analysis, which we proved that is superior in forecasting, compared to the existing similar models.

These results could be expanded and further analyzed in probable future work, implementing panel data analysis, or other models, including many countries in the analysis, to investigate the impact of COVID-19 on the agro-food sector, and also on other sectors of the economy.

References:

ABARES (2020) Agricultural Overview, *Agricultural Commodities: September Quarter 2020*, Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra, CC BY 4.0.

Ali Mohd Helmi, Suleiman Norhidayah, Khalid Norlin, Tan Kim Hua, Tseng Ming-Lang, Kumar Mukesh (2021) Supply chain resilience reactive strategies for food SMEs in coping to COVID-19 crisis, *Trends in Food Science & Technology*, 109, 94–102.

Arifin MD. (2020) *Impacts of Coronavirus COVID-19 on the Global Shipping and Maritime Industry in Indonesia and How to Overcome the Coronavirus Outbreak Based on WHO and IMO recommendations*, Project: Coronavirus COVID-19, https://doi.org/10.31224/osf.io/6wy5c

Barman Abhijit, Das Rubi, De PijusKanti (2021), Impact of COVID-19 in food supply chain: Disruptions and recovery strategy, *Current Research in Behavioral Sciences*, 2, 100017.

Bhosale J. (2020) Prices of agricultural commodities drop 20% post COVID-19 outbreak. https://economictimes, Indiatimes, com/news/economy/agriculture/prices-of-agricultural-commodi-ties-drop-20-post-covid-19outbreak/articleshow/74705537.cms

Brewin D. (2020) The impact of COVID-19 on the grains and oilseeds sector, *Canadian Journal of Agricultural Economics*, https://doi.org/10.1111/cjag.12239.

Depellegrin Daniel, Bastianini Mauro, Fadini Amedeo, Menegon Stefano (2020) The effects of COVID-19 induced lockdown measures on maritime settings of a coastal region, *Science of the Total Environment*, 740, 140123.

Depellegrina Daniel, Bastianini Mauro, Fadini Amedeo, Menegon Stefano (2020), The effects of COVID-19 induced lockdown measures on maritime settings of a coastal region, Science of The Total Environment, Volume 740, 140123.

Galanakis Charis M., RizouMyrto, Aldawoud Turki M.S., UcakIlknur, Rowan Neil J. (2021) Innovations and technology disruptions in the food sector within the COVID-19 pandemic and post-lockdown era, *Trends in Food Science & Technology*, 110, 193–200.

Goddard E. (2020) The impact of COVID-19 on food retail and food service in Canada: A preliminary analysis, *Canadian Journal of Agricultural Economics*, 68.

Gray R. (2020) Agriculture, transportation, and the COVID-19 crisis, *Canadian Journal of Agricultural Economics*, 68(2): 239–243, doi: 10.1111/cjag.12235.

Greenville J., McGilvray H., Black S. (2020) Analysis of Australian agricultural trade and the COVID-19 pandemic, *ABARES Insights*, 1–10, Issue 5.

Hailu G. (2020) Economic thoughts on COVID-19 for Canadian food processors, *Canadian Journal of Agricultural Economics*, 68.

HosszejniDarjus and Kastner Gregor (2021) Modeling Univariate and Multivariate Stochastic Volatility in R with stochvol and factorstochvol, *arXiv*, arXiv:1906.12123.

Huang Ji-kun - Editorial board (2020) Impacts of COVID-19 on agriculture and rural poverty in China, *Journal of Integrative Agriculture*, 19(12): 2849–2853.

Johansen Søren (1988), Statistical analysis of cointegration vectors, *Journal of Economic Dynamics and Control*, Volume 12, Issues 2–3, Pages 231-254.

Journal of Agricultural Economics, 68.

Kastner Gregor (2016) Dealing with Stochastic Volatility in Time Series Using the R Package stochvol, *Journal of Statistical Software*, Vol 69, Issue 5, 10.18637/jss.v069.i05.

Kwiatkowski, D.; Phillips, P. C. B.; Schmidt, P.; Shin, Y. (1992), Testing the null hypothesis of stationarity against the alternative of a unit root, *Journal of Econometrics*, 54 (1–3): 159–178.

McEwan K., Marchand L., Shang M., and Bucknell D. (2020), Potential implications of COVID-19 on the Canadian pork industry, *Canadian Journal of Agricultural Economics*, 68.

Nakat Zeina and Bou-Mitri Christelle (2021) COVID-19 and the food industry: Readiness assessment, *Food Control*, 121, 107661.

Nicola M, Alsafi Z, Sohrabi C, et al.(2020) The socio-economic implications of the coronavirus pandemic (COVID-19): A review, International Joournal of Surgery, 78: 185–193, doi:10.1016/j.ijsu.2020.04.018, indexed in Pubmed: 32305533.

Panzone Luca A., Larcom Shaun, She Po-Wen (2021) Estimating the impact of the first COVID-19 lockdown on UK food retailers and the restaurant sector, *Global Food Security*, 28 100495.

Siche Raul (2020) What is the impact of COVID-19 disease on agriculture?,*Scientia Agropecuaria*, 11(1):3, 3-6.

Snow Val, Rodriguez Daniel, Dynes Robyn, Kaye-Blake William, Mallawaarachchi Thilak, Zydenbos Sue, Cong Lei, Obadovic Irena, Agnew Rob, Amery Nicole, Bell Lindsay, Benson Cristy, Clinton Peter, Dreccer M. Fernanda, Dunningham Andrew, Gleeson Madeleine, Harrison Matthew, Hayward Alice, Holzworth Dean, Johnstone Paul, Meinke Holger, MitterNeena, Mugera Amin, Pannell David, Silva Luis F.P., RouraEugeni, Siddharth Prince, Siddique Kadambot H.M., Stevens David (2021) Resilience achieved via multiple compensating subsystems: The immediate impacts of COVID-19 control measures on the agri-food systems of Australia and New Zealand, *Agricultural Systems*, 187, 103025.

Stephens Emma C., Martin Guillaume, WijkMarkvan, Timsina Jagadish and Snow Val - Editorial board (2020), Impacts of COVID-19 on agricultural and food systems worldwide and on progress to the sustainable development goals, *Agricultural Systems*, Volume 183, 102873.

The Guardian (2020) MPs in plea to government over UK's COVID-19 stockpiling, World news, *The Guardian*, https://www.theguardian.com/world/2020/mar/21/mps-plea-government-uk-covid-19-stock-piling-coronavirus/

Torero M. (2020) Without food, there can be no exit from the pandemic. Countries must join forces to avert a global food crisis from COVID-19, *Nature*, 580, 588- 589, https://doi.org/10.1038/d41586-020-01181-3

Weersink A., von Massow M., and McDougall B. (2020) Economic thoughts of the potential implications of COVID-19 on the Canadian dairy and poultry sectors, *Canadian Journal of Agricultural Economics*, 68.

Yazır Devran, Şahin Bekir, Leung Yip Tsz , and Tseng Po-Hsing (2020) Effects of COVID-19 on maritime industry: a review, *International Maritime Health*, 71, 4: 253–264, 10.5603/IMH.2020.0044

Zhou Yusheng, Ying Soh Shan, Loh Hui Shan, Yuen Kum Fai (2020) The key challenges and critical success factors of blockchain implementation: Policy implications for Singapore's maritime industry, *Marine Policy*, 122, 104265.