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Impacts of the COVID-19 epidemic on carbon emissions from international shipping

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ABSTRACT

The COVID-19 epidemic made the most countries to take strict lockdown measures, what has seriously caused an unprecedented impact in the shipping industries, whereas these measures have also played a significant impact to control carbon emissions from international shipping. Here, we try to use the threshold generalized autoregressive conditional heteroscedasticity and the exponential generalized autoregressive heteroscedasticity to investigate whether the fluctuations of the control variable on carbon emissions from international shipping are asymmetric or not. On this basis, the GARCH-MIDAS model is introduced to discuss whether the newly confirmed cases are independent of control variables and have an impact on the fluctuation of carbon emissions. From the results, we find that the information contained in the newly confirmed cases cannot be covered when adding the other control variables. In addition, the newly confirmed cases have a negative impact on the volatility of carbon emissions, while the other control variables significantly increase carbon emissions. This study provides a quantitative research method for the analysis of the volatility and impact factors on international shipping carbon emissions, which helps to formulate more reasonable emission reduction measures and promote the low-carbon transformations of the global shipping industry.

1. Introduction

In recent year, the COVID-19 epidemic and the corresponding economic crisis have almost affected all aspect of global production, supply and consumption (Ha, 2022; Khan et al., 2022; Xu et al., 2022a). For this reason, the shipping activity decreased, and carbon emissions from the vessel-source pollution also declined 1 % (Meng et al., 2022; Xu et al., 2021a; Xu et al., 2022b). Compared with the information in 2019, total carbon emissions in 2020 from oil tanker and bulk carrier increased by 3.6 %, whereas the container was down by 2.4 %. However, cruise ship and vehicle carriers have turned overall situation of carbon emissions from growth to the reduction (Xu et al., 2021b; Zhou et al., 2022a, 2022b, 2022c; Yi et al., 2022; Chen et al., 2021). In summary, the COVID-19 epidemic effectively promotes the marine environmental improvement by destroying port production or interrupting shipping lines (Chen et al., 2022a; Chen et al., 2022b; Chen et al., 2022d).

Indeed, many scholars have discussed the impacts of the COVID-19 epidemic on the shipping industry (Pan et al., 2022; Xu et al., 2022c; Zhou et al., 2022a, 2022b, 2022c). However, the previous researchers focused on the shock of the COVID-19 epidemic on the port performance and shipping network, which can be thought to be the important factors of long-term trend in carbon emission from vessel-source pollution (Xu et al., 2021c; Bandyopadhyay and Bhatnagar, 2023; Wang et al., 2022a, 2022b, 2022c; Zhou et al., 2022a, 2022b, 2022c; Chen et al., 2022c). On this basis, there existed a discussion on carbon emissions in Western Singapore caused by marine traffic during the COVID-19 epidemic (Ju and Hargreaves, 2021). Here, they found that a significant decrease in carbon emission from June to August 2020, which has remained at a relatively lower level. Beyond that, Mujal-Colilles et al. (2022) observed that the decline in marine traffic was not correlated with a decrease in carbon emissions since the situation of vessels was switched from berthing to at anchor. Although the effect of post-epidemic period on carbon emission from international shipping has been significantly less obvious that of the early period, yet few literature explored the changes of carbon emission at the different stages. Specially, many scholars have used panel data to study and analyze the influencing factors of carbon emissions (Wang et al., 2022a; Wang et al., 2022b; Wang et al., 2023; Li et al., 2021; Li et al., 2022).

Meanwhile, the COVID-19 epidemic also contributes to carbon emissions through the macroeconomic fluctuations (Dirzka and Acciaro,

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2022; Gavalas et al., 2022; Zhou et al., 2022a, 2022b, 2022c). Different from the previous studies, we conducted a combined investigate on the COVID-19 epidemic and carbon emissions from the international shipping in this study. Here, we mainly discuss how the short-term component and long-term trend of COVID-19 epidemic can be reflected in various factors impacting carbon emission, further answer whether the factors have changed structurally in the different periods. Hence, we use the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model and threshold generalized autoregressive conditional heteroscedasticity (TGARCH) model to evaluate the short-term component and long-term trend of carbon emissions from the international shipping. Meanwhile, the GARCH-MIDAS model can be introduced to conduct a volatility decomposition to discuss whether control variable contains the information in the newly confirmed cases, further explore the main reasons on the volatility of carbon emissions from the long- and short-term component.

From the results, we obtain some interesting observations and managerial insights by the following points: firstly, the short-term volatility of carbon emissions is relatively large with many peaks and valleys, whereas the long-term volatility is more stable, which is with the general trend of COVID-19 epidemic. In addition, we observe that the newly confirmed cases reduce the volatility of carbon emissions, while the impact of other control variables is positive and not obvious. Finally, in order to decrease carbon emission, the ports should optimize the operation process and strength the regional cooperation, further the shipping line should adjust the shipping route and improve the multi-modal transport.

The remainder of this study is organized as follows. Section 2 gives the methodology considered and introduces the basic principle of GARCH model. Next, we explain the data source in Section 3. Further, Section 4 gives the empirical discussion. Section 5 concludes the contributions and gives a future direction.

2. Methodology

2.1. TGARCH and EGARCH models

In this research, Z_t and X_t are paired carbon emissions from international shipping. Further, if γ_t conforms to the first-order Markov process and is only related to the value of the previous period, we use the state space model to establish a cointegration strategy with the time-varying coefficients (Bollerslev, 1986), where the structure of GARCH (p, q) model can be summarized as follows

$$Z_t = d + \gamma_t X_t + \mu_t, where\ \mu_t|\Omega_t \sim iidN\left(0, \sigma_t^2\right) \tag{1}$$

where μ_t is the series of carbon emissions, here $\mathrm{E}[\mu_t] = 0$ and $\mathrm{Var}[\mu_t]=\sigma_t^2$. Meanwhile, the state variable $\gamma_t = \varphi_t\gamma_{t-1} + \varepsilon_t$, where ε_t is the autoregression coefficient of state variable. Note that the state space model is based on the Kalman filtering algorithm to realize real-time prediction and the update of carbon emission (Hoffman, 2021), where the information obtains the observed value of the current coefficient of carbon emission via the observation equation regression. Combined with the predicted value of the coefficient in state equation, the optimal value of the coefficient is obtained through the iterative update of the Kalman gain.

As an extension of ARCH model, the GARCH model is used to predict time series and describe volatility. Hence, the GARCH model is used to extract the volatility aggregation information of carbon emission series, and it is introduced into trading signal indicators after wavelet noise reduction processing to build a time-varying trading signal indicator system. Based on the generalized autoregressive conditional heteroscedasticity model, the fluctuation aggregation information of carbon emissions is expressed by GARCH (1,1) as

$$\sigma_t^2 = p_0 + \sum_{i=1}^{p}\phi_i\mu_{t-i}^2 + \sum_{j=1}^{q}\xi_j\sigma_{t-j}^2 \tag{2}$$

In the research of time series, GARCH model is one of the traditional and widely used method to consider the volatility. However, the determination of variance only takes into account the size, while not includes the sign. Hence, the positive and negative fluctuations are not distinguished; thus, it exists the extended models. In order to explore whether there is an asymmetric effect of control variable on carbon emissions from international shipping, we consider TGARCH and EGARCH model to balance the volatility. However, when the time series is also affected by other exogenous variables, simply considering the time series for modeling is often not very effective. Here, we can use the TGARCH model to improve the original model, where the expression is as follows

$$Z_t = d + \gamma_t X_t + \mu_t + \psi Y \tag{3}$$

$$\sigma_t^2 = p_0 + \sum_{i=1}^{p}\phi_i\mu_{t-i}^2 + \sum_{k=1}^{r}\varpi_k I_{t-k}\mu_{t-k}^2 + \sum_{j=1}^{q}\xi_j\sigma_{t-j}^2 + \upsilon Y \tag{4}$$

where Z_t and σ_t^2 represent the mean and variance of carbon emission from international shipping, respectively. Further, Y is the set of control variables, where mainly includes the confirmed case, Brent oil price, port congestion level, port waiting time, containership idle rate and port calls level. Notice that I_{t-k} is a binary variable to distinguish the effects of time series. Here, if I_{t-k}=1, it results in the negative effect $\phi + \varpi$; otherwise, the positive effect is ϕ. However, the TGARCH model is still some limitations that cannot guarantee that the variance cannot be negative. On this basis, Nelson (1991) proposed the EGARCH model that changed the form of variance from σ_t^2 to $\log(\sigma_t^2)$ to ensure the non-negative condition of variance, where we can describe as follows

$$Z_t = e + \gamma_t X_t + \mu_t + \vartheta Y \tag{5}$$

$$log\left(\sigma_t^2\right) = f + \sum_{i=1}^{p} h_i\left|\frac{\mu_{t-i}}{\sqrt{\sigma_{t-i}}}\right| + \sum_{i=1}^{p} u_i\frac{\mu_{t-i}}{\sqrt{\sigma_{t-i}}} + \sum_{j=1}^{q} s_j log\left(\sigma_{t-j}^2\right) + lY \tag{6}$$

where f, h, m, u and l are the estimating parameters. Further, when $u_1 = u_2 = \cdots = 0$, this situation can be understood as a symmetric model; otherwise, here it results in the observation that the volatility of carbon emissions from international shipping; otherwise, the positive and negative shock are asymmetric. Notice that the positive value of h_i indicates the current variance is positively correlated with the previous variance.

2.2. GARCH-MIDAS model

In order to avoid information omission caused by the impacting factors, and to more accurately study the influences of newly confirmed cases from the COVID-19 epidemic on the fluctuation in carbon emissions, we employ the GARCH-MIDAS model to decompose the long- and short-term component of carbon emission fluctuations, and then use OLS for regression. Under the structure, the GARCH-MIDAS model makes the data in the high frequency via transferring the low-frequency variable to become directly the form of long-term component (Yaya et al., 2022). Thus, we introduce $r_{i,t}$ as the carbon emissions from international shipping on day i of month t, where t=1, 2, ⋯, T says the frequency in months and i=1, 2, ⋯, N_t denotes the frequency in days, with N_t indicates the number of days in month t. Hence, the GARCH-MIDAS model is constructed by two parts (mean and conditional variance) as follows

$$r_{i,t} = \mu + \sqrt{\tau_t \times g_{i,t}} \times \varepsilon_{i,t}, \text{where } \varepsilon_{i,t}|\psi_{i-1,t} \sim N(0,1) \tag{7}$$

where μ and $\psi_{i-1,\ t}$ mean the unconditional mean and available historical data of carbon emissions at day $i-1$ in month t, respectively.

Table 1
Descriptive statistics.

Variable	Emission	Covid	Price	Congestion	Waiting	Idle	Calls
Unit	Ton	Case	Dollar	million DWT	hour	%	time
Mean	1891.79	448,181.5	67.5	124.82	33.38	4.43	10,087.52
Median	1889.19	344,731	65.18	123.65	33.8	4.1	9972
Maximum	2567.02	4,042,767	127.98	142.89	47.2	9.4	12,315
Minimum	1391.68	0	19.33	104.43	23.7	3.2	8029
Std. Dev.	137.04	599,337.8	21.95	9.22	4.64	1.06	892.42
Skewness	0.002	2.87	0.52	0.18	−0.024	2.29	−0.3
Kurtosis	3.29	13.09	3.62	2.42	1.95	8.4	2.64
J-B	4.23	7002.77***	76.03***	23.73***	57.06***	2605.86***	25.02***

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

Table 2
Results of AR(1) model for carbon emissions from international shipping.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.55***	0.0045	1679.47	0.00
Emission(−1)	0.64***	0.021	30.62	0.00
R-squared	0.41	F-statistic	424.43	
Adjusted R-squared	0.40	Prob(F-statistic)	0.00	

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

Table 3
Estimation for ARCH(1) effects in Carbon Emissions from international shipping.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.0029***	0.00018	15.79	0.00
Emission^2(−1)	0.099***	0.028	3.52	0.00050
R-squared	0.0098	F-statistic	12.37	
Adjusted R-squared	0.014	Prob(F-statistic)	0.000017	
Prob. F(1,1244)	0.00050	Obs*R-squared	12.26	
Prob. Chi-Square(1)	0.00050			

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

Table 4
Estimation for ARCH(7) effects in carbon emissions from international shipping.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.0024***	0.00027	8.95	0.00
Emission^2(−1)	0.097***	0.028	3.44	0.00060
Emission^2(−2)	0.0024	0.028	0.085	0.93
Emission^2(−3)	−0.026	0.028	−0.90	0.37
Emission^2(−4)	0.021	0.028	0.73	0.46
Emission^2(−5)	0.016	0.028	0.58	0.57
Emission^2(−6)	−0.035	0.028	−1.25	0.21
Emission^2(−7)	0.17***	0.028	6.17	0.00
R-squared	0.040	F-statistic	7.26	
Adjusted R-squared	0.034	Prob(F-statistic)	0.00	
Prob. F(7,1232)	0.00	Obs*R-squared	49.10	
Prob. Chi-Square(7)	0.00			

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

Further, τ_t is the long-term component that can be understood as a fixed value in month t. On the other hand, $g_{i,\ t}$ is considered as the short-term component to illustrates the daily information. Here, we employ the stationary GJR-GARCH (1, 1) process to react the high frequency as follows

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t}, \tag{8}$$

where α and β are the constant of GARCH parameters, which are subject to $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$ for the stationary covariance process. According to the MIDAS regression method from the relative research (Ghysels et al., 2007; Zhao, 2022), we obtain the realized volatility in month t as

Table 5
ARCH(1) model for carbon emissions.

Mean equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.33***	0.17	13.38	0.00
Emission(−1)	0.69***	0.023	30.00	0.00

Variance equation	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0025	0.00011	21.84	0.00
Emission^2(−1)	0.17	0.031	5.59	0.00
R-squared	0.40			
Adjusted R-squared	0.40			

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{9}$$

Meanwhile, the long-term monthly frequency-varying component can be denoted by a short-term daily frequency via the days across months t are repeated without following the tracts of it; thus, it is defined in the relationship as

$$\tau_t = m_t + \theta_t \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) RV_{t-k} \tag{10}$$

where m_t says the constant of long-term component. Further, θ_t is the slope parameter to be the total weighted realized volatilities if the explanatory variables are not considered; otherwise, is the predictable measure for the daily carbon emissions from the international shipping. Here, we set the lag period to 15 for the calculation, which is mainly because the slope parameter becomes negative and is consistent with the results of OLS regression. In addition, we consider the logarithm of long-term volatility to avoid the uncertainty of low-frequency exogenous variables. Meanwhile, φ_k is the two-parameter positive polynomial function of lagged variables, which is described as follows

$$\varphi_k(\omega_1, \omega_2) = k^{\omega_1-1}(K-k)^{\omega_2-1} \Big/ \sum_{k=1}^{K} k^{\omega_1-1}(K-k)^{\omega_2-1} \tag{11}$$

where ω_1 and ω_2 are the weight to be estimated. Here, in order to ensure that the weight of the lagged term is in a declining trend, that is, the smaller the lagged period, the greater the effect on the current period,

Table 6
Estimation for newly confirmed case.

Mean equation	TGARCH				EGARCH			
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	3.87***	0.20	18.96	0.00	4.22***	0.18	22.95	0.00
Emission(−1)	0.49***	0.027	18.23	0.00	0.45***	0.024	18.40	0.00
Covid	−0.0034***	0.00030	−11.31	0.00	−0.0036***	0.00028	−12.85	0.00

Variance equation	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0019*	0.0011	1.75	0.080	−6.60	4.42	−1.49	0.14
RSD(−1)^2	0.037	0.032	1.18	0.24				
RSD(−1)^2*(RESID(−1) < 0)	−0.0062	0.044	−0.14	0.89				
RSD(−2)^2	0.018	0.028	0.64	0.52				
RSD(−3)^2	−0.040***	0.012	−3.29	0.0010				
RSD(−4)^2	0.030	0.036	0.84	0.40				
RSD(−5)^2	0.0042	0.032	0.13	0.90				
RSD(−6)^2	0.0061	0.031	0.20	0.84				
RSD(−7)^2	0.084***	0.029	2.86	0.0042				
GARCH(−1)	0.21	0.45	0.47	0.64				
GARCH(−2)	−0.0030	0.42	−0.0070	0.99				
GARCH(−3)	−0.0074	0.39	−0.019	0.98				
GARCH(−4)	−0.0088	0.34	−0.026	0.98				
GARCH(−5)	−0.0089	0.39	−0.023	0.98				
GARCH(−6)	−0.0074	0.35	−0.021	0.98				
GARCH(−7)	−0.0065	0.29	−0.023	0.98				
ABS(RSD(−1)/SQRT(GARCH(−1)))					0.087*	0.047	1.83	0.067
ABS(RSD(−2)/SQRT(GARCH(−2)))					0.12*	0.068	1.74	0.082
ABS(RSD(−3)/SQRT(GARCH(−3)))					0.0080	0.055	0.15	0.88
ABS(RSD(−4)/SQRT(GARCH(−4)))					0.079**	0.039	2.03	0.043
ABS(RSD(−5)/SQRT(GARCH(−5)))					0.16***	0.052	3.10	0.0019
ABS(RSD(−6)/SQRT(GARCH(−6)))					0.042	0.074	0.57	0.57
ABS(RSD(−7)/SQRT(GARCH(−7)))					0.15***	0.056	2.71	0.0067
LOG(GARCH(−1))					−0.42***	0.11	−3.93	0.00010
LOG(GARCH(−2))					0.23	0.14	1.62	0.11
LOG(GARCH(−3))					0.15*	0.090	1.65	0.099
LOG(GARCH(−4))					−0.42***	0.064	−6.63	0.00
LOG(GARCH(−5))					−0.49***	0.10	−4.67	0.00
LOG(GARCH(−6))					0.18	0.14	1.30	0.19
LOG(GARCH(−7))					0.77***	0.099	7.81	0.00
Covid	9.81E-06	1.63E-05	0.60	0.55	0.021	0.017	1.23	0.22
R-squared	0.46				0.46			
Adjusted R-squared	0.46				0.46			

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

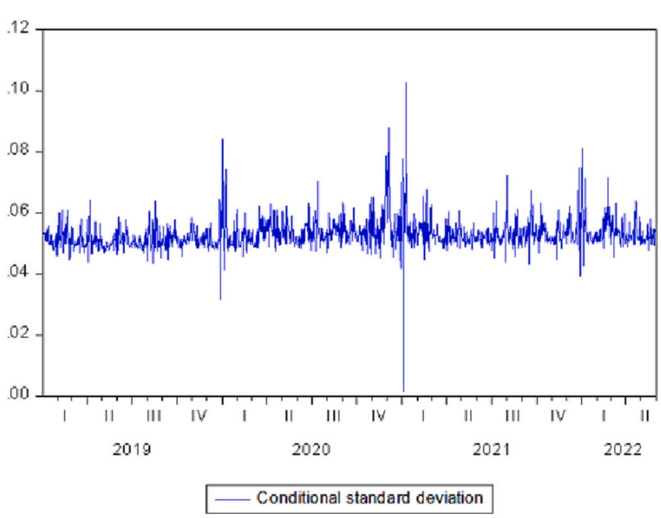

Fig. 1. Conditional standard deviation in carbon emissions for TGARCH model.

we fix ω_1=1, where ω_2 determines the attenuation rate of the influence of low-frequency data on long-term component.

Next, we use the OLS regression analysis to explore the impact of the newly confirmed cases of the COVID-19 epidemic on carbon emissions fluctuation, where carbon emissions volatility in the long- and short-term component is the explained variable, while the newly confirmed cases of COVID-19 epidemic is the explanatory variable. Hence, the benchmark model is as follows

$$Emission_t = \alpha_t + \sum_{i=1}^{7} \beta_{t-i} Covid_{t-i} + \eta_t \tag{12}$$

where α_t is a constant term, β_{t-i} is the coefficient of newly confirmed cases in the lagged period i, η_t is random error term, respectively. In order to observe the continuous impacts of the newly confirmed cases, this benchmark model combines with the daily information to ignore the endogenous difficulty. Then, we divide the newly confirmed cases of COVID-19 epidemic into the long- and short-term component for regression with a lag of 7 periods, which is mainly because the incubation period of COVID-19 epidemic. Next, we discuss whether the newly confirmed cases are an effective variable when adding other control variables, where the extended model is as follows

$$Emission_t = \alpha_t + \sum_{i=1}^{7} \beta_{t-i} Covid_{t-i} + \eta_t \sum_{i=1}^{7} \delta_{t-i} X_{t-i} + \pi_t \tag{13}$$

where X_{t-i} and δ_{t-i} are the corresponding coefficient and set of control variables (Brent oil price, Port congestion level, Port waiting time, Containership idle rate, Port calls level) in the lagged period i, π_t is random error term. From Eq. (13), we try to examine the difference between the newly confirmed case and other control variable.

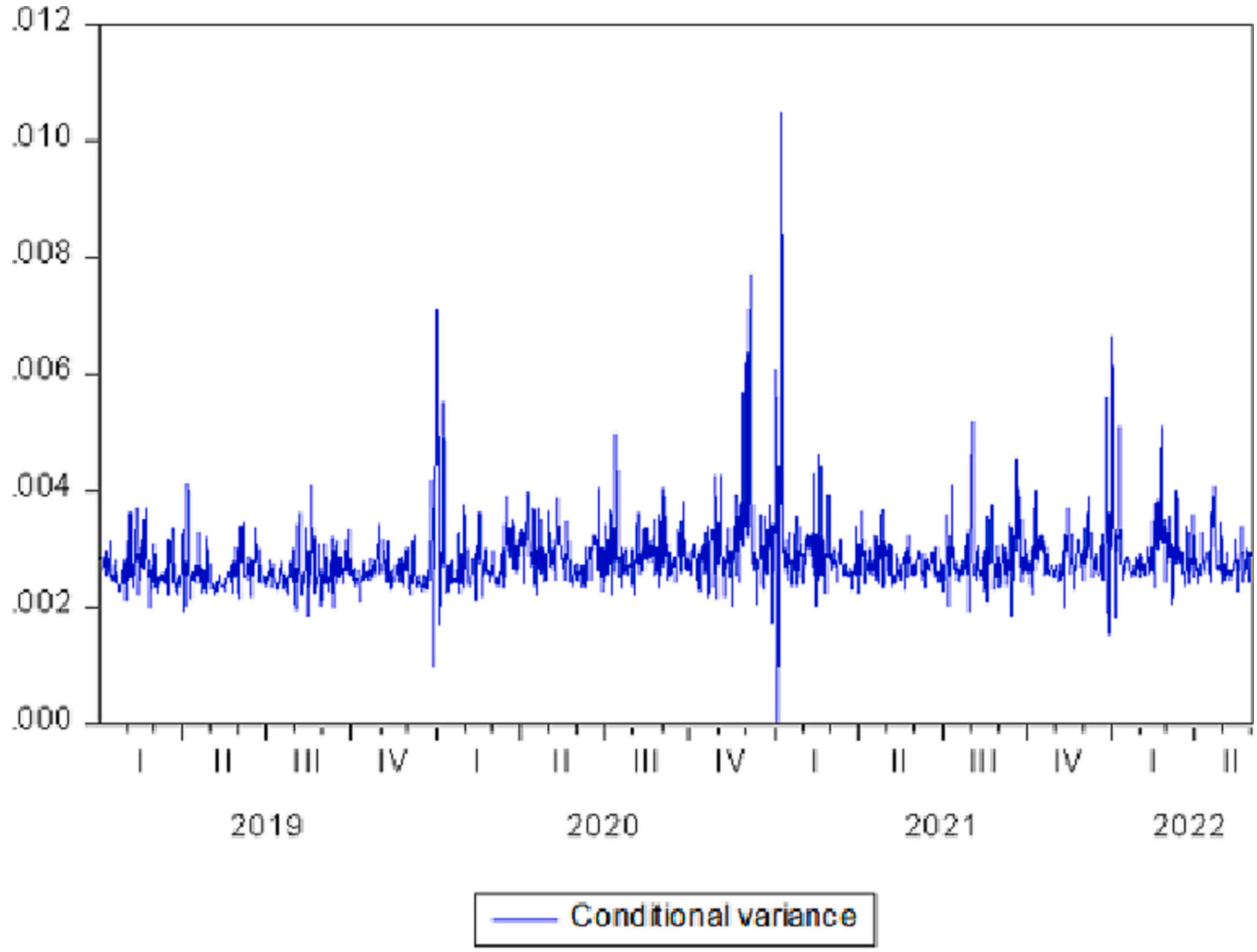

Fig. 2. Conditional variance in carbon emissions for TGARCH model.

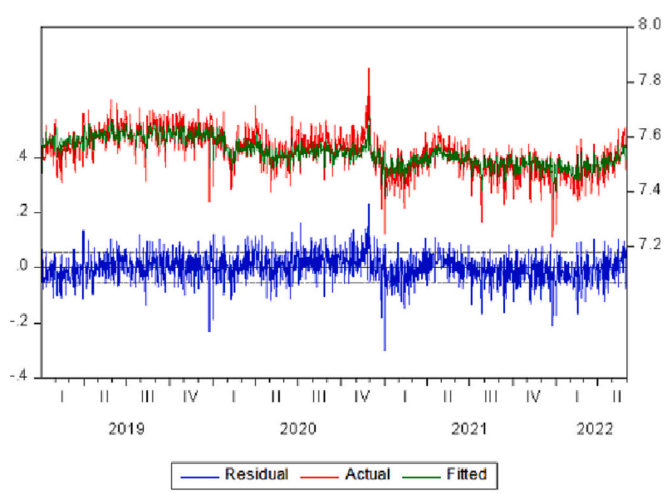

Fig. 3. Residual, actual and fitted values in carbon emissions for TGARCH model.

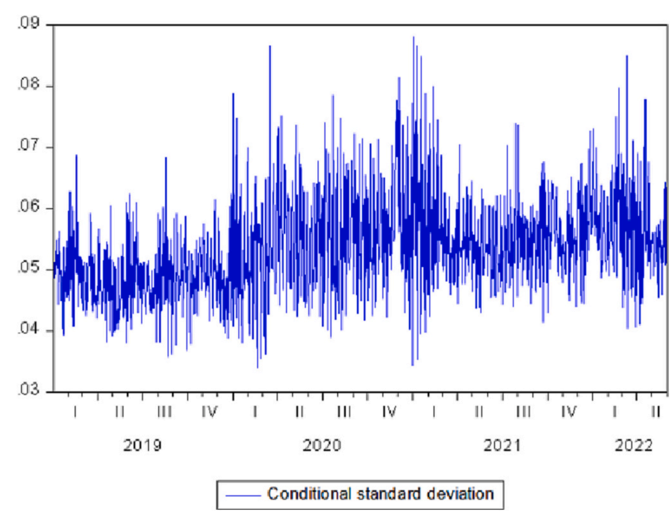

Fig. 4. Conditional standard deviation in carbon emissions for EGARCH model.

In this paper, we extend the traditional model and introduce exogenous variables into the analysis of the fluctuation of carbon emission from international shipping, which puts forward new research ideas. In the TGARCH and EGARCH models, the impact of positive and negative influences on the fluctuation of carbon emission from international shipping under the influence of exogenous variables is explored. Further, using OLS regression and GARCH-MIDAS model, by decomposing fluctuations, we explore whether the COVID-19 epidemic has an impact on short-term component and long-term trend of carbon

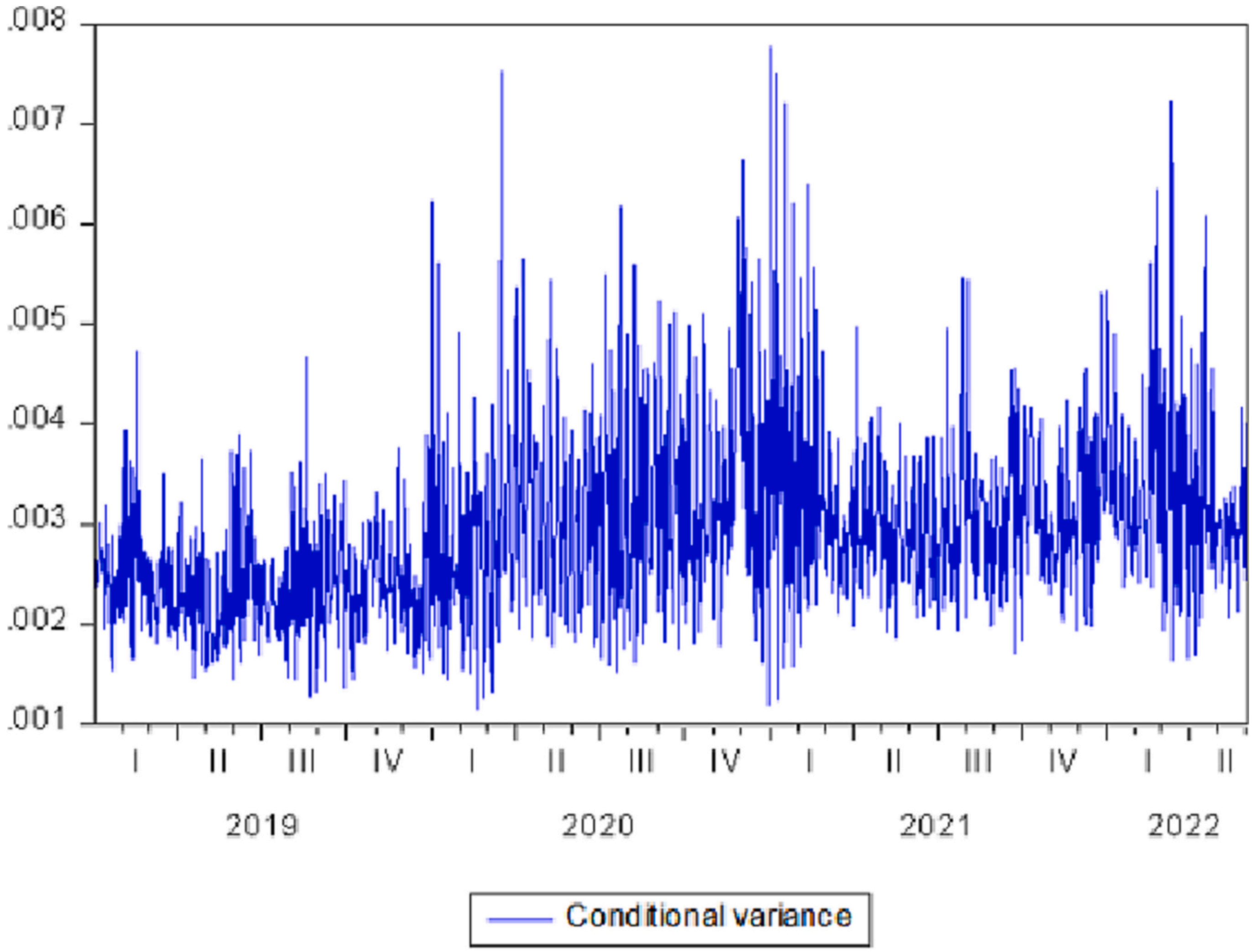

Fig. 5. Conditional variance in carbon emissions for EGARCH model.

emission from international shipping carbon emissions independent of other variables, and further explored the impact of each control variable on international shipping carbon emissions.

3. Data

In order to investigate the influences of COVID-19 epidemic on carbon emissions from international shipping, we consider the daily data of the newly confirmed cases and carbon emissions from January 1, 2019 to May 31, 2022. Additionally, considering the particularity of shipping business, we also introduce the following control variables into the model for analysis: (1) Brent crude oil price. *Brent crude oil price is the benchmark of market oil price and the futures trading variety. Since carbon emissions from international shipping are mainly generated by burning oil during the route, so Brent crude oil price can accurately reflect the direction of carbon emissions.* (2) Port congestion level. *Port congestion is one of the biggest reasons for the increase in carbon emissions of ships berthing. From the outbreak of the epidemic, since the impact of isolation control and other objective reasons (warehouse tension, goods overstock and operation disorder), the carbon emissions of international shipping during berthing have increased.* (3) Port waiting time. *The average waiting time of the port is one of the main objectives of operational efficiency. Although the main engines always stop working, whereas the auxiliary engine will continue to work when the vessels are waiting to enter the ports. Therefore, carbon emissions will increase with the increase of waiting time.* (4) Containership idle rate. *Carbon emissions from shipping are closely related to the number of idle containerships. Since the spread of the COVID-19 epidemic, many shipping lines were cancelled, which broke the new record of the containership idle rate. We can indirectly measure the impact of COVID-19 epidemic on carbon emissions from international shipping.* (5) Port calls level. *Port calls level is crucial to carbon emissions from international shipping. The global supply chain imbalance caused by the COVID-19 epidemic has increased many uncertainties for the future development of shipping industry*. Here, the information of Brent crude oil price is obtained from http://cn.investing.com, and the other information is in https://sin.clarksons.net/. Further, we conduct descriptive statistics on the above variables in Table 1, which includes the mean, median, range, standard deviation, kurtosis, skewness and J-B statistics.

From the outcomes, carbon emissions of international shipping have been fluctuating slightly since the beginning of 2019. Until the outbreak of the COVID-19 epidemic, carbon emissions have declined significantly, and then gradually recovered. During this period, the transportation of medical materials aggravated the increase of carbon emissions. With the slow recovery of global supply chain, carbon emissions reached the maximum value of 2567.02 in the middle of the COVID-19 epidemic, that is, on December 28, 2020. Further, since the spread of Delta virus strain and Omicron virus strain, carbon emission dropped to the minimum value of 1391.68 on December 25, 2021, with a difference of 1175.34 from the maximum value.

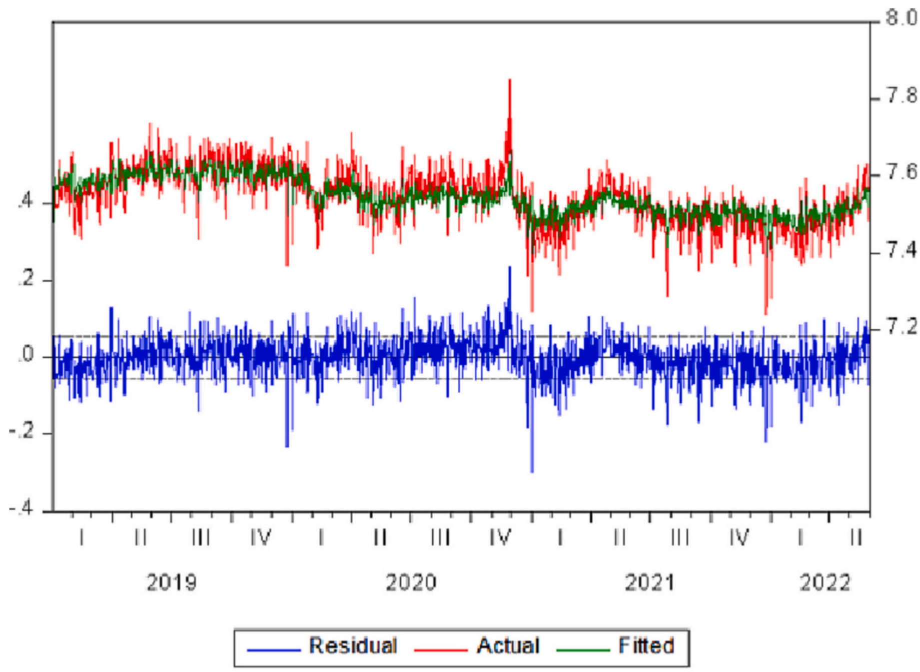

Fig. 6. Residual, actual and fitted values in carbon emissions for EGARCH model.

4. Result and discussion

In this section, we first examine the impact of newly confirmed cases on the volatility estimation of carbon emissions in the TGARCH model and EGARCH model, respectively. On this basis, we add other control variables into the GARCH-MIDAS to take a robustness analysis.

4.1. Volatility estimation of control variables

Before discussing volatility estimations of control variables, we simply regress carbon emissions from international shipping on one lagged value. Notice that all control variables are logarithmic to reduce the errors. Here, we regard the model only considers the newly confirmed cases as the benchmark. As shown in Table 2, we can calculate the value of mean and residuals (RSD) from the AR(1) model, which examines the model whether exists the ARCH effects.

From the residual of carbon emissions, we further examine whether the model exists the ARCH effects. Here, the estimated results from the heteroscedasticity test as shown in Table 3, where we find that the lagged term of squared RSD(−1) has been regressed on the squared RSD and the value of significant coefficient is 0.099 at a 1 % level. Meanwhile, the value of Obs*R^2 is considered as 12.26 at a 1 % level as illustrated by the probability value of Chi-square 0.00. Thus, it exists an ARCH effect on carbon emissions from international shipping during the COVID-19 epidemic.

Based on Table 3, we examine the evidence of high-order ARCH effects that provides an extensive standard of the heteroscedasticity in the seven-order lagged value of squared RSD(−1) according to the previous specification of the ARCH(7) model. From the estimated results of ARCH (7) as shown in Table 4, the first-order and seven-order lagged values of squared RSD(−1) has a high statistical significance at a 1 % level. Additionally, the value of Obs*R^2 reaching 49.10 is even higher than that in the ARCH(1) model, where the outcomes show a highly statistically significance and a substantial rejection. Hence, the ARCH effect is reflected in carbon emissions from international shipping.

Based on Table 4, we obtain the estimated outcomes through calculating the ARCH(1) model; thus, the previous equation is $Emission_t$=2.33[0.00]+(0.69)$Emission_{t-1}$[0.00]+μ_t and σ_t^2=0.0025 [0.00]+0.17μ_{t-1}^2[0.00], where $\mu_t \mid \Omega_t \sim iidN(0,\sigma_t^2)$. Hence, the ARCH(1) model for carbon emissions from international shipping is shown in Table 5.

Since the ARCH effect exists in the fluctuation of carbon emissions from international shipping, then we first use the TGARCH model to explore the asymmetry of positive and negative shock. Here, Table 6 provides the estimated result of the TGARCH model adding the newly confirmed cases of COVID-19 epidemic. In particular, we see that the intercept is 3.87 and the slope is 0.49, where it indicates that the newly confirmed cases is negative and statistically significant at a 1 % level and carbon emissions declines. On the other hand, the variance also indicates the volatility of carbon emissions. Specifically, although RSD2 (−1)*(RESID(−1) < 0) is a positive value, it is not statistically significant, showing that under the impact of the COVID-19 epidemic, the positive and negative effects are symmetrical. But generally speaking, the impact of negative shocks and positive shocks is asymmetric, and negative shocks often result in the higher volatility than positive shocks, which is not consistent with our understanding. This is mainly since the COVID-19 epidemic is a global uncertainty event, where the termination of shipping activity has always decreased carbon emissions for a certain time and the resumption of production promotes carbon emissions to rise again.

Meanwhile, although the result of the TGARCH model indicates carbon emissions are heteroscedasticity during the COVID-19 epidemic, the TGARCH model ignores that the negative variance may have a stronger impact than the positive variance. Hence, this study employs the EGARCH model to illustrate the empirical result in Table 6. Interestingly, we observe the statistical significance levels of coefficients are stronger than those in TGARCH model. The results also indicate the estimated value of mean is roughly the same. Further, carbon emission volatility of is positively correlated with the trend of COVID-19 epidemic, further the positive and negative impacts on carbon emissions are relatively symmetrical.

Further, we observe the exact trend of carbon emission fluctuations from international shipping through the conditional standard deviation and conditional variance as shown in Figs. 1-2. Specially, the conditional standard deviation indicates the deviations from the average value, including positive and negative deviation in the TGARCH model. However, this may provide the unclear information, because most of the time, positive and negative deviations offset each other's impacts; thus,

Table 7
Estimation for Brent crude oil price.

Mean equation	TGARCH				EGARCH			
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	4.42***	0.013	329.37	0.00	4.61***	0.0011	4249.70	0.00
Emission(−1)	0.44***	0.0010	430.72	0.00	0.42***	0.00098	424.77	0.00
Covid	−0.0037***	0.00024	−15.58	0.00	−0.0038***	0.00022	−17.17	0.00
Price	−0.034***	0.0046	−7.29	0.00	−0.039***	0.0016	−24.25	0.00

Variance equation	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0028*	0.0016	1.69	0.090	−30.90***	8.06	−3.83	0.00010
$RSD(-1)^2$	0.011	0.027	0.43	0.67				
$RSD(-1)^2$*(RESID(−1) < 0)	0.051	0.035	1.43	0.15				
$RSD(-2)^2$	0.036	0.026	1.38	0.17				
$RSD(-3)^2$	−0.023	0.022	−1.02	0.31				
$RSD(-4)^2$	0.013	0.029	0.45	0.65				
$RSD(-5)^2$	0.028	0.026	1.10	0.27				
$RSD(-6)^2$	0.022	0.029	0.76	0.45				
$RSD(-7)^2$	0.14***	0.027	5.19	0.00				
GARCH(−1)	−0.22	0.18	−1.21	0.23				
GARCH(−2)	0.34*	0.18	1.85	0.064				
GARCH(−3)	0.0019	0.19	0.010	0.99				
GARCH(−4)	0.15	0.21	0.68	0.49				
GARCH(−5)	−0.18	0.16	−1.11	0.27				
GARCH(−6)	−0.23	0.15	−1.54	0.12				
GARCH(−7)	−0.097	0.15	−0.66	0.51				
ABS(RSD(−1)/SQRT(GARCH(−1)))					0.090	0.057	1.58	0.11
ABS(RSD(−2)/SQRT(GARCH(−2)))					0.17**	0.086	1.99	0.046
ABS(RSD(−3)/SQRT(GARCH(−3)))					0.14**	0.071	2.03	0.043
ABS(RSD(−4)/SQRT(GARCH(−4)))					0.14***	0.054	2.69	0.0071
ABS(RSD(−5)/SQRT(GARCH(−5)))					0.20***	0.068	2.90	0.0037
ABS(RSD(−6)/SQRT(GARCH(−6)))					0.1*	0.085	1.75	0.081
ABS(RSD(−7)/SQRT(GARCH(−7)))					0.17***	0.061	2.78	0.0055
LOG(GARCH(−1))					−1.06***	0.16	−6.62	0.00
LOG(GARCH(−2))					−0.68***	0.23	−2.97	0.0029
LOG(GARCH(−3))					−0.52***	0.19	−2.80	0.0052
LOG(GARCH(−4))					−0.86***	0.15	−5.81	0.00
LOG(GARCH(−5))					−1.02***	0.19	−5.41	0.00
LOG(GARCH(−6))					−0.50**	0.23	−2.19	0.029
LOG(GARCH(−7))					0.32**	0.16	2.00	0.045
Covid	4.65E-05**	2.21E-05	2.11	0.035	0.10***	0.031	3.30	0.0010
Price	−0.000111	0.00035	−0.32	0.75	−0.58	0.49	−1.19	0.23
R-squared	0.48				0.48			
Adjusted R-squared	0.48				0.48			

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

also show a zero deviation from average value, where the conditional variance can overcome this problem. It can be observed that the high variance of carbon emissions is mainly at the beginning of 2020, at the end of 2020 and the beginning of 2022. In addition, Fig. 3 shows the residual value, actual value and fitting variance value of carbon emissions in the TGARCH model under the impact of the COVID-19 epidemic, which is consistent with the response of conditional standard deviation and conditional variance.

Here, the conditional standard deviation and conditional variance of carbon emissions from international shipping are as shown in Figs. 4-5. Based on the result of the EGARCH model, we find that carbon emissions have experienced the significant fluctuations during the research period. However, because of the epidemic uncertainty and response measure, the volatility of carbon emissions is obvious in the early and middle stages of COVID-19 epidemic. Meanwhile, Fig. 6 shows the residual value, actual value and fitting variance value of carbon emissions in the EGARCH model, where are consistent with the response of conditional standard deviation and conditional variance. Next, we add the other control variables into benchmark model to investigate whether they play a significant role in the fluctuation of carbon emissions during the COVID-19 epidemic.

4.2. *Impacts of other control variables*

4.2.1. *Brent crude oil price*

Through adding Brent crude oil price into the benchmark model, the results are shown in Table 7. Here, both the slope and intercept are positive and highly statistically significant, indicating that carbon emissions decrease with the increase of Brent crude oil price. On the other hand, although the value of $RSD^2(-1)$*(RESID(−1) < 0) is positive, it is not statistically significant, which shows that the positive and negative impacts are still symmetrical when adding Brent crude oil price into the benchmark model. Additionally, adding Brent crude oil price significantly intensifies the volatility of carbon emissions. Meanwhile, to ensure the negative effect, we also discuss the EGARCH model in Table 7, which the value of intercept and slop change slightly, both have the statistical significance at the 1 % level. Additionally, the variance also shows that the volatility of carbon emissions is positively correlated with its early volatility when adding Brent crude oil price into the benchmark model.

4.2.2. *Port congestion level*

Next, we further analyze the impact of port congestion level on carbon emission. From Table 8, we find the slope and intercept in the equation of mean value are 0.48 and 4.25, which are a statistically significance at a 1 % level. On the other hand, the value of $RSD^2(-1)$*

Table 8
Estimation for port congestion level.

Mean equation	TGARCH				EGARCH			
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	4.25***	0.11	39.98	0.00	4.34***	0.19	22.38	0.00
Emission(−1)	0.48***	0.020	23.89	0.00	0.45***	0.025	18.42	0.00
Covid	−0.0027***	0.00033	−8.15	0.00	−0.0032***	0.00037	−8.75	0.00
Congestion	−0.059***	0.0099	−5.92	0.00	−0.040*	0.021	−1.86	0.063
Variance equation	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	0.018***	0.00090	19.77	0.00	−2.86	6.92	−0.41	0.68
RSD(−1)^{2}	0.053*	0.029	1.83	0.068				
RSD(−1)2*(RESID(−1) < 0)	−0.027	0.023	−1.16	0.25				
RSD(−2)^{2}	0.0278	0.020	1.42	0.16				
RSD(−3)^{2}	−0.030	0.021	−1.42	0.16				
RSD(−4)^{2}	0.018	0.019	0.98	0.33				
RSD(−5)^{2}	0.026	0.024	1.08	0.28				
RSD(−6)^{2}	0.016	0.024	0.65	0.52				
RSD(−7)^{2}	0.11***	0.023	4.72	0.00				
GARCH(−1)	−0.070	0.24	−0.29	0.77				
GARCH(−2)	0.16*	0.095	1.65	0.099				
GARCH(−3)	−0.22*	0.13	−1.68	0.093				
GARCH(−4)	0.47***	0.11	4.16	0.00				
GARCH(−5)	0.041	0.16	0.25	0.80				
GARCH(−6)	−0.59***	0.040	−14.71	0.00				
GARCH(−7)	−0.26	0.19	−1.37	0.17				
ABS(RSD(−1)/SQRT(GARCH(−1)))					0.098**	0.050	1.96	0.050
ABS(RSD(−2)/SQRT(GARCH(−2)))					0.13*	0.073	1.82	0.069
ABS(RSD(−3)/SQRT(GARCH(−3)))					0.023	0.058	0.40	0.69
ABS(RSD(−4)/SQRT(GARCH(−4)))					0.072*	0.040	1.82	0.069
ABS(RSD(−5)/SQRT(GARCH(−5)))					0.15***	0.054	2.87	0.0041
ABS(RSD(−6)/SQRT(GARCH(−6)))					0.070	0.080	0.87	0.39
ABS(RSD(−7)/SQRT(GARCH(−7)))					0.16***	0.059	2.79	0.0053
LOG(GARCH(−1))					−0.50***	0.14	−3.60	0.00030
LOG(GARCH(−2))					0.13	0.19	0.72	0.47
LOG(GARCH(−3))					0.093	0.12	0.78	0.44
LOG(GARCH(−4))					−0.47***	0.082	−5.69	0.00
LOG(GARCH(−5))					−0.56***	0.14	−4.10	0.00
LOG(GARCH(−6))					0.086	0.18	0.48	0.63
LOG(GARCH(−7))					0.72***	0.13	5.55	0.00
Covid	5.16E-05*	2.64E-05	1.95	0.051	0.040	0.029	1.37	0.17
Congestion	−0.0030***	0.00024	−12.81	0.00	−1.42	1.65	−0.86	0.39
R-squared	0.46				0.46			
Adjusted R-squared	0.46				0.46			

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

(RESID(−1) < 0) is an insignificant coefficient, which means that the positive and negative impacts on carbon emissions are still symmetrical if adding port congestion level as control variable. Additionally, the coefficient of the newly confirmed case is significantly positive, meaning that considering port congestion level increases the volatility of carbon emissions. This is mainly because the outbreak of COVID-19 epidemic results in port congestion and labor shortage. Table 8 also provides the empirical results of the EGARCH model. Like the results of TGARCH model, EGARCH provides the mean and variance equation, where the intercept and slope values are statistically significant at a 1 % level, but the values change slightly. The coefficient of newly confirmed case and port congestion level are significantly negative, indicating that carbon emissions are negatively correlated with newly confirmed case and port congestion level. Additionally, the variance equation shows that the current variance is positively correlated with the previous variance; thus, the volatility of carbon emissions is positively correlated with its early volatility.

4.2.3. Port waiting time

As shown in Table 9, the mean equation shows that the slope and intercept coefficients are both positive, which is highly statistically significant at a 1 % level. Here, the coefficient of port waiting time is significantly negative, indicating carbon emissions decrease with the increase of port waiting time. Meanwhile, the variance equation indicates that all residuals lag behind the square variable, further the value of RSD^{2}(−1)*(RESID(−1) < 0) and coefficient in port waiting time are positive and not statistically significant, indicating that there is no significant asymmetry between positive and negative shocks. Compared with the results in the TGARCH model, that in the EGARCH model shows more significant regardless of the mean equation or variance equation. On the one hand, the slopes of intercept and first-order term are respectively 4.43 and 0.44, which are statistically significant at a 1 % level. On the other hand, the significance and the symbol indicate that the increase of port waiting time has a positive impact on the volatility of carbon emissions. This is mainly due to the impact of the COVID-19 epidemic slowing the navigation speed of vessels and extending the unloading efficiency of port operations, these points results in an increase of carbon emissions.

4.2.4. Containership idle rate

Here, Table 10 indicates the estimated result of the TGARCH model and the EGARCH model adding containership idle rate into the benchmark model. From the outcomes, we easily observe that the slope and intercept are significantly positive at a 1 % level, which the volatility of carbon emissions reduces with the increase of containership idle rate. Further, the variance equation shows that RSD^{2}(−1)*(RESID(−1) < 0) is negative and not statistically significant, indicating there is no significantly asymmetrical between positive and negative shock. Thus, when

Table 9
Estimation for port waiting time.

Mean equation	TGARCH				EGARCH			
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	4.35***	0.44	9.89	0.00	4.43***	0.00071	6253.86	0.00
Emission(−1)	0.47***	0.052	8.93	0.00	0.44***	0.00052	856.74	0.00
Covid	−0.0018**	0.00090	−2.04	0.041	−0.0024***	0.00026	−9.36	0.00
Waiting	−0.084**	0.038	−2.23	0.026	−0.062***	0.0013	−48.47	0.00

Variance equation	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0029	0.013	0.22	0.83	−5.26**	2.57	−2.05	0.040
$RSD(-1)^2$	0.060	0.090	0.67	0.50				
RSD(−1)2*(RESID(−1) < 0)	0.020	0.12	0.16	0.87				
$RSD(-2)^2$	0.020	0.39	0.052	0.96				
$RSD(-3)^2$	0.020	0.31	0.064	0.95				
$RSD(-4)^2$	0.020	0.30	0.067	0.95				
$RSD(-5)^2$	0.020	0.31	0.065	0.94				
$RSD(-6)^2$	0.020	0.27	0.075	0.94				
$RSD(-7)^2$	0.020	0.29	0.068	0.95				
GARCH(−1)	0.24	5.28	0.045	0.96				
GARCH(−2)	0.020	5.26	0.0038	1.00				
GARCH(−3)	0.020	4.98	0.0040	1.00				
GARCH(−4)	0.020	5.14	0.0039	1.00				
GARCH(−5)	0.020	4.70	0.0043	1.00				
GARCH(−6)	0.020	3.89	0.0051	1.00				
GARCH(−7)	0.020	2.34	0.0085	0.99				
ABS(RSD(−1)/SQRT(GARCH(−1)))					0.063	0.043	1.48	0.14
ABS(RSD(−2)/SQRT(GARCH(−2)))					0.15**	0.061	2.40	0.017
ABS(RSD(−3)/SQRT(GARCH(−3)))					0.11**	0.049	2.15	0.031
ABS(RSD(−4)/SQRT(GARCH(−4)))					0.16***	0.035	4.56	0.00
ABS(RSD(−5)/SQRT(GARCH(−5)))					0.16***	0.045	3.68	0.00020
ABS(RSD(−6)/SQRT(GARCH(−6)))					0.072	0.059	1.21	0.23
ABS(RSD(−7)/SQRT(GARCH(−7)))					0.13***	0.049	2.57	0.010
LOG(GARCH(−1))					−0.53***	0.0083	−63.50	0.00
LOG(GARCH(−2))					0.10***	0.030	3.53	0.00
LOG(GARCH(−3))					0.11***	0.020	5.24	0.00
LOG(GARCH(−4))					−0.45***	0.019	−23.37	0.00
LOG(GARCH(−5))					−0.55***	0.021	−26.14	0.00
LOG(GARCH(−6))					0.087***	0.029	2.96	0.0030
LOG(GARCH(−7))					0.75***	0.00071	1053.33	0.00
Covid	0.00	0.00010	0.00	1.00	0.034**	0.017	1.98	0.048
Waiting	0.00	0.00043	0.00	1.00	−1.27*	0.74	−1.71	0.087
R-squared	0.47				0.47			
Adjusted R-squared	0.47				0.47			

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

adding containership idle rate, the positive impact and negative impact with the equal scale have the same impacts. For the outcomes in the EGARCH model, the significance level of intercept and slope are the same as the above result, but only the value fluctuates slightly. At the same time, the equation indicates carbon emissions are positively correlated with the variance, which results in the conclusion that the positive and negative impacts are symmetrical. Taking into account the impacts of containership idle rate, the volatility of carbon emissions is positively correlated with the newly confirmed cases of COVID-19 epidemic.

4.2.5. Port calls level

Table 11 shows that the slope and intercept are significantly positive at a 1 % level, and the coefficient of port calls level is −0.0034, which is also statistically significant level. Then, we find that the lag of square RSD and the coefficient of GARCH term are not significant; thus, $RSD^2(-1)*(RESID(-1) < 0)$ is negative and statistically insignificant, indicating that there is no significant asymmetry between positive and negative shocks. Hence, it is concluded that the positive impact and negative impact can be considered to be symmetrical if adding port call level as the control variable. Further, Table 11 also illustrates the estimated result in the EGARCH model, where the intercept and slope are 4.42 and 0.45 respectively with the statistically significant at a 1 % level. In addition, the coefficient of newly confirmed cases is also negative at a significant level of 1 %, indicating that carbon emissions decrease with the increase of port call level.

4.3. Robustness analysis from GARCH-MIDAS model

Next, we explore the impact of all control variables on the volatility of carbon emissions during the COVID-19 epidemic. After adding five control variables, the impacts of newly confirmed cases on the volatility of carbon emissions is still significant, while it exists some information overlap between carbon emissions and newly confirmed cases. Hence, if other control variables are added simultaneously to the regress, whether the newly confirmed cases can still play an independent and significant role remains to be examined. Therefore, we add the five control variables at the same time into the benchmark model for robustness test. Meanwhile, because too many explanatory variables are easy to have a great impact on the degree of freedom; thus, we only consider that each control variable is added to the regression with a lag of three-order period.

$$Emission_t = \alpha_t + \sum_{i=1}^{3}\beta_{t-i}Covid_{t-i} + \sum_{i=1}^{3}\gamma_{t-i}^{Waiting}Waiting_{t-i} + \sum_{i=1}^{3}\gamma_{t-i}^{Idle}Idle_{t-i} + \sum_{i=1}^{3}\gamma_{t-i}^{Calls}Calls_{t-i} + \sum_{i=1}^{3}\gamma_{t-i}^{Price}Price_{t-i} + \sum_{i=1}^{3}\gamma_{t-i}^{Congestion}Congestion_{t-i} + \lambda_t \tag{14}$$

Table 10
Estimation for containership idle rate.

Mean equation	TGARCH				EGARCH			
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	3.87***	0.20	19.18	0.00	4.24***	0.17	25.19	0.00
Emission(−1)	0.49***	0.027	18.45	0.00	0.44***	0.022	19.97	0.00
Covid	−0.0034***	0.00030	−11.14	0.00	−0.0036***	0.00027	−13.31	0.00
Idle	0.00067	0.0038	0.18	0.86	−0.0026	0.0085	−0.31	0.76

Variance equation	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0024*	0.0013	1.81	0.070	−12.15*	6.23	−1.95	0.051
RSD(−1)^2	0.035	0.033	1.05	0.29				
RSD(−1)2*(RESID(−1) < 0)	−0.0052	0.046	−0.11	0.91				
RSD(−2)^2	0.012	0.026	0.47	0.64				
RSD(−3)^2	−0.038*	0.021	−1.79	0.074				
RSD(−4)^2	0.027	0.033	0.83	0.40				
RSD(−5)^2	0.0054	0.030	0.18	0.86				
RSD(−6)^2	0.011	0.029	0.37	0.71				
RSD(−7)^2	0.088***	0.029	3.07	0.0021				
GARCH(−1)	0.21	0.42	0.50	0.61				
GARCH(−2)	−0.0055	0.39	−0.014	0.99				
GARCH(−3)	−0.012	0.36	−0.032	0.97				
GARCH(−4)	−0.014	0.33	−0.043	0.97				
GARCH(−5)	−0.011	0.38	−0.028	0.98				
GARCH(−6)	−0.016	0.33	−0.048	0.96				
GARCH(−7)	−0.0089	0.27	−0.033	0.97				
ABS(RSD(−1)/SQRT(GARCH(−1)))					0.096*	0.050	1.91	0.057
ABS(RSD(−2)/SQRT(GARCH(−2)))					0.15**	0.072	2.02	0.043
ABS(RSD(−3)/SQRT(GARCH(−3)))					0.036	0.057	0.65	0.52
ABS(RSD(−4)/SQRT(GARCH(−4)))					0.078**	0.038	2.03	0.043
ABS(RSD(−5)/SQRT(GARCH(−5)))					0.16***	0.054	3.07	0.0022
ABS(RSD(−6)/SQRT(GARCH(−6)))					0.075	0.078	0.96	0.34
ABS(RSD(−7)/SQRT(GARCH(−7)))					0.17***	0.058	2.99	0.0028
LOG(GARCH(−1))					−0.54***	0.14	−3.89	0.00010
LOG(GARCH(−2))					0.069	0.19	0.36	0.72
LOG(GARCH(−3))					0.052	0.13	0.41	0.68
LOG(GARCH(−4))					−0.49***	0.084	−5.88	0.00
LOG(GARCH(−5))					−0.60***	0.14	−4.40	0.00
LOG(GARCH(−6))					0.033	0.18	0.18	0.86
LOG(GARCH(−7))					0.67***	0.14	4.86	0.00
Covid	1.50E-05	1.76E-05	0.85	0.39	0.035	0.024	1.47	0.14
Idle	−0.00034	0.00045	−0.76	0.45	0.44	0.42	1.06	0.29
R-squared	0.46				0.46			
Adjusted R-squared	0.46				0.46			

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

where λ_t is the random error term of period t. In order to explore whether it exists coupling effect between the newly confirmed cases and other control variables, the interaction term is added to the regression on Eq. (14), that is

$$\begin{aligned} Emission_t = {} & \alpha_t + \sum_{i=1}^{3}\beta_{t-i}Covid_{t-i} + \sum_{i=1}^{3}\gamma_{t-i}^{Waiting}Waiting_{t-i} + \sum_{i=1}^{3}\gamma_{t-i}^{Idle}Idle_{t-i} \\ & + \sum_{i=1}^{3}\gamma_{t-i}^{Calls}Calls_{t-i} + \sum_{i=1}^{3}\gamma_{t-i}^{Price}Price_{t-i} + \sum_{i=1}^{3}\gamma_{t-i}^{Congestion}Congestion_{t-i} \\ & + \varphi_{t-1}^{Waiting}Covid_{t-1}\bullet Waiting_{t-1} + \varphi_{t-1}^{Idle}Covid_{t-1}\bullet Idle_{t-1} \\ & + \varphi_{t-1}^{Calls}Covid_{t-1}\bullet Calls_{t-1} + \varphi_{t-1}^{Price}Covid_{t-1}\bullet Price_{t-1} \\ & + \varphi_{t-1}^{Congestion}Covid_{t-1}\bullet Congestion_{t-1} + h_t \end{aligned} \tag{15}$$

where $\varphi_{t-1}^{\text{Waiting}}$, $\varphi_{t-1}^{\text{Idle}}$, $\varphi_{t-1}^{\text{Calls}}$, $\varphi_{t-1}^{\text{Price}}$ and $\varphi_{t-1}^{\text{Congestion}}$ are the coefficients of the interaction terms with a lag of one-order period between the newly confirmed case and Brent crude oil price, port congestion level, port waiting time, containership idle rate, port calls level. Further, h_t is the random error term of period t. Hence, the results of regression are shown in Table 12.

From Table 12, after adding the five control variables, the sign and significance of the newly confirmed cases lagged by 1–3 period in the long- and short-term components don't change, where further supports the conclusion the newly confirmed cases are independent of the explanatory variables and has a positive impact on the volatility of carbon emissions. Then, port congestion level in the short-term component is no longer statistically significant, while is also significantly positive in the long-term component, which indicates the impact of port congestion level on carbon emissions is positive. According to the fourth and eighth columns, we find the interaction coefficients in the short-term component of port calls level and Brent crude oil price are statistically significant, while the other control variables aren't at a significant level. On the other hand, only the interaction coefficient between port call level and newly confirmed cases does not have statistical significance, indicating that port call level cannot impact carbon emissions in the post-epidemic era. Note that the different control variables to the impact of carbon emissions have different mechanism in the long- and short-term component. Beyond that, the result also shows the increase in the newly confirmed cases not only has a significant impact on the volatility of carbon emissions in the short-term component, but also has an impact on the long-term component. Therefore, the newly confirmed cases in the GARCH-MIDAS model are directly substituted for the robustness test, where Eq. (16) is

Table 11
Estimation for containership idle rate.

Mean equation	TGARCH				EGARCH			
Variable	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	3.98***	0.34	11.62	0.00	4.42***	4.6E-103	9.5E+102	0.00
Emission(−1)	0.49***	0.036	13.80	0.00	0.45***	4.66E-06	97,283.62	0.00
Covid	−0.0034***	0.00043	−7.98	0.00	−0.0033***	0.00024	−13.52	0.00
Calls	−0.011	0.024	−0.46	0.64	−0.028***	0.00027	−106.69	0.00
Variance equation	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0028	0.0061	0.46	0.65	17.69***	5.70	3.10	0.0019
RSD(−1)^2	0.052	0.050	1.04	0.30				
RSD(−1)2*(RESID(−1) < 0)	−0.035	0.079	−0.44	0.66				
RSD(−2)^2	−1.54E-06	0.075	−2.04E-05	1.00				
RSD(−3)^2	−0.046	0.057	−0.80	0.43				
RSD(−4)^2	0.012	0.11	0.11	0.91				
RSD(−5)^2	−0.0027	0.089	−0.030	0.98				
RSD(−6)^2	−0.0072	0.089	−0.081	0.94				
RSD(−7)^2	0.023	0.070	0.32	0.75				
GARCH(−1)	0.23	1.62	0.14	0.88				
GARCH(−2)	0.017	1.63	0.010	0.99				
GARCH(−3)	0.016	1.65	0.0098	0.99				
GARCH(−4)	0.014	1.41	0.0099	0.99				
GARCH(−5)	0.015	1.02	0.015	0.99				
GARCH(−6)	0.014	1.01	0.014	0.99				
GARCH(−7)	0.0089	0.98	0.0091	0.99				
ABS(RSD(−1)/SQRT(GARCH(−1)))					0.033	0.054	0.61	0.54
ABS(RSD(−2)/SQRT(GARCH(−2)))					0.13*	0.073	1.73	0.084
ABS(RSD(−3)/SQRT(GARCH(−3)))					0.11**	0.046	2.32	0.020
ABS(RSD(−4)/SQRT(GARCH(−4)))					0.12***	0.040	2.95	0.0032
ABS(RSD(−5)/SQRT(GARCH(−5)))					0.19***	0.053	3.64	0.00030
ABS(RSD(−6)/SQRT(GARCH(−6)))					0.078	0.079	0.99	0.32
ABS(RSD(−7)/SQRT(GARCH(−7)))					0.11*	0.064	1.66	0.097
LOG(GARCH(−1))					−0.72***	0.13	−5.55	0.00
LOG(GARCH(−2))					−0.14	0.17	−0.78	0.44
LOG(GARCH(−3))					−0.047	0.12	−0.41	0.68
LOG(GARCH(−4))					−0.55***	0.075	−7.40	0.00
LOG(GARCH(−5))					−0.78***	0.11	−6.91	0.00
LOG(GARCH(−6))					−0.20	0.17	−1.19	0.24
LOG(GARCH(−7))					0.54***	0.13	4.23	0.00
Covid	−3.98E-06	2.62E-05	−0.15	0.88	0.014	0.018	0.73	0.46
Calls	−1.41E-05	0.0010	−0.014	0.99	−3.85***	0.065	−59.00	0.00
R-squared	0.46				0.46			
Adjusted R-squared	0.46				0.46			

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) G_{m-k} \tag{16}$$

where G_{m-k} is the variable set. As shown in Table 13, we analyze the long- and short-term components of carbon emissions from international shipping. Here, θ means the marginal contributions of low-frequency volatility to long-term component and is used to measure the impact of various variables on long-term volatility. It can be observed that if the newly confirmed cases are taken as the control variable, θ is at 10 % statistical significance level, which indicates the increase of newly confirmed cases reduce carbon emissions volatility in the long-term component. Since the 1960s, the outbreak of some crises and wars led to the reduction of carbon emissions from international shipping, including the collapse of the Soviet Union in 1991, the Asian financial crisis in 1997 and the international financial crisis in 2008. However, we observe that those crises only reduced carbon emissions from international shipping in a short period of time. Once the crisis slows down or ends, carbon emissions tended to rebound significantly. Therefore, this study confirms that the impacts of the COVID-19 epidemic are unexpected, that indicates, both long-term term and short-term components have reduced carbon emissions from international shipping. If properly addressed, this crisis may become an opportunity for the reasonable emission reduction measures and promote the low-carbon transformations of the global shipping industry. In addition, when Brent crude oil price is employed as the control variable, we find that Brent crude oil price has a positive correlation with the volatility of carbon emissions; thus, its impact is not obvious in the long-term component. Meanwhile, the coefficients of port congestion level, port waiting time, containership idle rate and port call level are positive, and have statistical significance at the level of 10 %; thus, this means that the above control variable significantly increase the volatility of carbon emissions.

From the outcomes in Fig. 7, it can be seen that the short-term component of carbon emissions is basically the same as that in the long-term component, but there are also some differences. Specifically, the volatility in the short-term component with many peaks, but the volatility of long-term volatility of carbon emissions is relatively stable, indicating that the long-term component of carbon emissions from international shipping can eliminate the noise impact in the short-term component to a certain extent, so it can well reflect the changing trend of international shipping carbon emissions.

5. Conclusions

In this paper, we employ the sample data from January 1, 2019 to May 31, 2022 to discuss the volatility of carbon emissions from international shipping during the COVID-19 epidemic. Based on the TGARCH model and EGARCH model, we examine the impact of each control

Table 12
Regression results for after adding all control variables Long-term component.

	Long-term component				Short-term component			
	Coefficient	Std Dev.	Coefficient	Std Dev.	Coefficient	Std Dev.	Coefficient	Std Dev.
Covid(−1)	−5.21E-05***	7.04E-06	−0.00023	0.00033	−4.09E-05***	3.94E-06	0.182*	0.00024
Covid(−2)	−5.51E-05***	7.09E-06	−1.92E-05	2.32E-05	−4.08E-05***	3.98E-06	4.00E-06	2.03E-05
Covid(−3)	−4.88E-05***	7.11E-06	−1.04E-05	1.68E-05	−4.07E-05***	4.02E-06	2.28E-06	1.48E-05
Waiting(−1)	−13.09***	1.12	−11.48***	1.83	−18.12***	0.70	−23.23***	1.43
Waiting(−2)	−12.62***	1.12	−10.20***	1.70	−17.98***	0.70	−21.15***	1.38
Waiting(−3)	−12.47***	1.13	−9.64***	1.63	−17.84***	0.71	−19.77***	1.35
Idle(−1)	−15.03***	3.82	−26.56***	5.28	−11.25***	2.07	−17.72***	3.34
Idle(−2)	−15.67***	3.84	−25.34***	4.43	−10.61***	2.09	−20.48***	2.56
Idle(−3)	−15.94***	3.85	−25.81***	4.41	−9.96***	2.11	−19.39***	2.58
Calls(−1)	0.026***	0.0066	0.033***	0.0080	0.033***	0.0037	0.032***	0.0045
Calls(−2)	0.023***	0.0066	0.031***	0.0074	0.033***	0.0037	0.030***	0.0040
Calls(−3)	0.021***	0.0066	0.028***	0.0074	0.033***	0.0038	0.031***	0.0040
Price(−1)	−1.54***	0.25	−3.35***	0.35	−1.88***	0.13	−3.76***	0.18
Price(−2)	−1.41***	0.25	−3.10***	0.35	−1.83***	0.14	−3.66***	0.18
Price(−3)	−1.33***	0.25	−2.94***	0.35	−1.77***	0.14	−3.55***	0.18
Congestion(−1)	1.21	0.69	2.03**	0.96	2.88***	0.41	6.50***	0.67
Congestion(−2)	0.81	0.69	1.28	0.87	2.76***	0.41	5.40***	0.63
Congestion(−3)	0.51	0.69	0.78	0.85	2.64***	0.42	4.75***	0.62
Covid(−1)•Waiting(−1)			4.18E-06	3.42E-06			1.76E-05***	2.87E-06
Covid(−1)•Idle(−1)			−1.37E-05	2.02E-05			−4.96E-05***	1.83E-05
Covid(−1)•Calls(−1)			−3.97E-08**	1.92E-08			−1.39E-08	1.45E-08
Covid(−1)•Price(−1)			2.89E-06***	6.12E-07			3.32E-06***	3.67E-07
Covid(−1)•Congestion(−1)			−1.62E-06	2.07E-06			−7.92E-06***	1.47E-06
Constant term	2058.85***	85.08	2049.22***	114.28	1995.43***	47.83	1887.92***	70.46
R^2	0.38		0.42		0.73		0.78	

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

Table 13
Parameter estimation for GARCH-MIDAS model.

	Ln(Covid)	Price	Idle	Congestion	Waiting	Ln(Call)
μ	1819.01*	1826.05*	1829.28*	1831.34*	1827.93*	1819.21*
	(19.36)	(6.42)	(12.40)	(10.85)	(14.97)	(12.63)
α	0.31*	0.30*	0.15*	0.11*	0.19*	0.30*
	(0.07)	(0.06)	(0.05)	(0.03)	(0.06)	(0.05)
β	0.69*	0.06	0.85*	0.89*	0.81*	0.70*
	(0.07)	(0.05)	(0.05)	(0.03)	(0.06)	(0.05)
m	5.57*	7.57*	−527.99*	−9.64	−36.10	−21.41*
	(4.37)	(0.59)	(268.06)	(6.77)	(64.18)	(6.60)
θ	−0.40*	0.44*	57.53*	0.17	0.32*	0.64*
	(0.42)	(0.13)	(29.16)	(0.11)	(0.55)	(0.19)
ω_2	142.09*	2.58*	1.08*	1.00	1.00*	186.37*
	(18.35)	(0.39)	(0.35)	(1.22)	(2.23)	(4.46)
LLF	−4960.06	−4903.73	−4922.53	−4914.32	−4923.95	−4967.80
AIC	7.96	7.87	7.90	7.89	7.91	7.98
BIC	7.99	7.90	7.93	7.92	7.93	8.00

Note: ***, ** and * indicate the rejections of null hypothesis at the 1 %, 5 % and 10 % significance level.

variable on the volatility of carbon emissions during the epidemic. On this basis, we introduce the GARCH-MIDAS model to investigate the coupling effect among all control variables. From the result, we find that the newly confirmed cases and other control variables have a positive impact on the volatility of carbon emissions, while the significant impact of newly confirmed cases is more significant than those of other control variables. Beyond that, whether or not the interaction between each control variable is considered, the information contained in the newly confirmed cases cannot be overwritten, and still affect the volatility of carbon emissions. Additionally, the significances of port congestion level, containership idle rate, port waiting time and port calls level are more obvious than that of Brent crude oil price.

The global real-time data of carbon emissions from international shipping quantifies indirectly the impact of the COVID-19 epidemic on shipping industry, which is the main practical significance for this study. In the post-epidemic era, global economic is recovering. Thus, carbon emissions from international shipping broken by the COVID-19 epidemic are not continuous. The COVID-19 epidemic is the most urgent threat facing the world, while climate change is still the biggest threat facing mankind for a long time. From the empirical outcomes, we can obtain a positive practical guiding significance of carbon emissions from international shipping in the post-epidemic era. Against the backdrop of the reduction of human production and flow caused by the global outbreak of the COVID-19 epidemic, the port should optimize their operating process and improve their operating energy efficiency to ease the congestion and reduce the waiting time. Finally, the cooperation should also be strengthened to further enable shipping company to adjust route and improve multimodal transport to reduce the port deployment, achieve the energy conservation and emission reduction.

In this paper, there are still some points that deserve investigate, where fails to further decompose the carbon emission fluctuations during the epidemic according to the different period. In addition, we consider to introduce more influencing factors related to the change of carbon emissions from international shipping according to the actual cases, and obtain more scientific results, making the study more instructive.

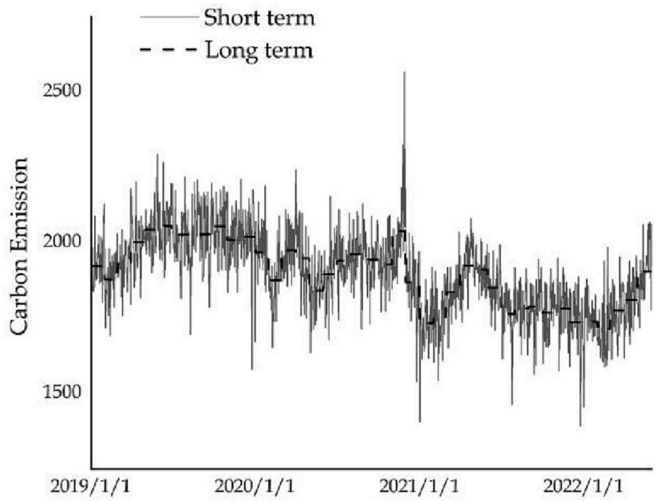

Fig. 7. The volatility of carbon emissions in long- and short-term components.

CRediT authorship contribution statement

Lang Xu: Conceptualization, Methodology, Formal analysis, Investigation. **Zhihui Yang:** Writing – original draft, Visualization. **Jihong Chen:** Writing – review & editing. **Zeyuan Zou:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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