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Forecasting the Impact of COVID-19 Epidemic on China Exports using Different Time Series Models

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Abstract

Purpose: The primary objective of this paper is to identify the best forecasting model for China exports, especially during the spread of the COVID-19 pandemic.

Methodology: We used the data of China exports to the United States and different economic regions from January 2014 to January 2021 to compare models using various criteria and selected the best exports forecast model. The hybrid model is employed to conduct the analysis. The combination of the hybrid model consists of six different models: ARIMA, ETS, Theta, NNAR, seasonal and trend decomposition, and TBATS model.

Findings: Our results showed that the hybrid and ANN outperformed the remaining models in forecasting China exports to the world, considering the shock created by the ongoing coronavirus pandemic. This paper underscores the importance of using the specified models in forecasting exports during this period. The results also demonstrate that the magnitude of China exports to all groups decreased and will continue to decline for the next few months.

Practical Implication: Forecasting of the export data is presented for the subsequent nine months, thereby providing insights to all policymakers, governments, and investors to be proactive in designing their strategies to avoid any delay/disruption in the imports from China, which could enhance the smooth flow of raw material and sustain industrial production.

Keywords: COVID-19, Exports, Forecasting, Artificial neural network, Hybrid, Models.

1. Introduction

The coronavirus (COVID-19) pandemic is hitting the world hard from all spheres of life. Its impact on mental health would soon be felt as people are restricted to their homes and social distancing is on the rise to prevent the spread. Stock markets are crashing with stock prices on a downswing, and unemployment is rising as most industries cut their losses by laying off employees whose jobs are relevant only on-site. The ongoing slowdown in economic activities around the globe affected several countries, most of them going into recession and damaging financial stability (Boot, et al., 2020). As a result, researchers, governments, and policymakers became increasingly concerned about the adverse effects of COVID-19 on commercial activities, industrial policies, and the global economy (Amankwah-Amoah, 2020). According to UNCTAD (2020), Chinese manufacturing plays a vital role in several global value chains, implying that any significant disruption in its supply could significantly affect producers around the world (Jiangli, 2020). Considering the uncertainty and magnitude of the impact of the COVID-19 pandemic, we explore the behavior of China's exports before, during, and after the COVID-19 pandemic.

The novel coronavirus (COVID-19) pandemic will exhibit a significant impact on the world economy and society. The widespread dissemination of COVID-19 has been categorized as a public health crisis that poses a severe risk to the macroeconomy through suspension of production activities, disruption of people's mobility, and cut-off of supply chains. Fernandes, (2020) mentioned that service-oriented economies would be seriously affected, thus placing more jobs at risk. In addition, the current crisis is generating spillover impacts throughout supply chains. Therefore, countries highly dependent on foreign trade are more adversely affected. Ozili and Arun, (2020) showed that the increasing number of lockdown days, government policy decisions, and international travel restrictions tremendously affected the level of economic activities, including the closing, opening, lowest, and highest stock market prices (Jordà et al. 2020; Cirillo and Taleb, 2020). Adaptations to combat the virus's risk pushed most countries into deep containment, which resulted in a global recession (Gopinath, 2020a, 2020b).

Predicting the future values of macroeconomic variables with some levels of precision plays a critical role in a government's public policy. The main objective of this paper is to compare the forecast accuracy of China's exports using six different models to the hybrid model (ARIMA, ETS, THETA, ANN, STLM, and TBATS). The second is to determine how likely the COVID-19 pandemic that emanated from China disrupts the flow of goods that China exports to other parts of the world such as the United States, Euro Area, the European Union, BRICS, G7, OECD, and non-OECD countries, all of which are believed to have global economic effects. To the best of the authors' knowledge, this is the first paper in this area that explores China's exports using the best forecasting models. Finally, China's export data are a good source for identifying its economic activities worldwide; thus, one can more precisely identify which groups or countries are primarily affected by disruptions in its exports. A further merit of using export data is that it alleviates the concerns about data quality in developing countries (Jones and Olken, 2010). The justification of using China exports to other parts of the world as the focus is to see whether there is a significant decline in export because of any COVID -19 related issues such as travel restrictions during the initial stage of the pandemic or if any stigma exists in the rejection of China products to other parts of the world as movement restrictions ease.

The structure of this paper is divided into four sections. The first section is the introduction, while section 2 presents the material and methods used in this study. Results and discussion are described in section 3, and section 4 concludes the paper and offers directions for future work.

2. Literature review

The overall impact of the coronavirus on the world economy is devastating, specifically in those parts of the world that have been struggling before the pandemic. Various studies have looked at the impact of COVID-19 on the world economy, but few studies have analyzed the impact of specific significant economies on the world. Hayakawa and Mukunoki, (2020) investigated the impact of COVID-19 on the economies of 186 countries in the first quarter of 2020 from around the world, and they concluded that COVID-19 demonstrated a negative impact on trade among these countries. Fugazza, (2020) showed that commodity exports to China are declining compared to a situation without the COVID-19 crisis, making total commodities exports to China fall by up to US $33.1 billion during 2020. These exports to China constitute a part of raw material used to produce goods that China exports to other countries.

The global growth of the world economy was declining in 2019, and the spread of COVID-19 is fast driving the world economy into a recession (de Vet, et al., 2021). The effects of this recession are severe, leading to historic levels of unemployment and stock prices (Moslehpour et al., 2022). Although strict measures through quarantine, travel restriction, and lockdown were implemented to reduce and contain the outrageous spread of COVID-19 by governments throughout the world, these measures caused a significant decrease in economic activities such as trade, tourism, transportation, banking, and construction (Goolsbee and Syverson, 2020). The reductions in these economic activities exhibit short- and long-term and direct and indirect negative impacts on the economy.

With a rising interest in the study of forecasting the impacts of COVID-19 on trade, various methods have been applied to forecasting and analyzing the spread and effect of COVID-19 on different economic variables. For example, Kumar, et al., (2021) used the exponential smoothing, linear regression model to evaluate the impact of the pandemic on country-driven sectors and recommended some strategies to lessen these impacts on a country's economy. Additionally, Ardabili, et al., (2020) examined an artificial neural network integrated by a grey wolf optimizer for the outbreak of COVID-19 by employing the Global dataset and concluded that the model could be successfully used with the prediction task. In a different light, Gunay, et al., (2020) performed empirical analyses through alternative methods such as ordinary least squares Markov regime-switching (MRS). They mixed data sampling (MIDAS) regressions to examine the impact of the COVID-19 pandemic in comparison to the global financial crisis (GFC) on the Gross Domestic Product (GDP) growth rate of China, they found that the COVID-19 pandemic has had a tremendous inverse effect on China's GDP growth. Furthermore, the forecast accuracy-test statistics showed a superior performance from MIDAS regression than the other alternative models. Furthermore, Al-Qaness, et al., (2020) proposed the use of an improved adaptive neuro-fuzzy inference system (ANFIS) using an enhanced flower pollination algorithm (FPA) by using the salp swarm algorithm (SSA) to forecast the spread of COVID-19 using China and the United States data and indicated that outcomes presented good performances of the model.

Although extensive studies have focused on forecasting methods in general or export forecasting (Winklhofer, et al., 1996), the role of export forecasting using the most accurate models for planning has received limited attention, and exports constitute a significant source of income for most countries (Parteka, 2020, Arezki and Brueckner, 2014). The export base theory of regional growth (Williamson, 1975) postulates that the aggregate economic activity that is relatively open to a large volume of trading transactions with other regions will grow faster or slower concerning changes in the region's export proceeds. That is, increases in its trade revenues from all external sources are the driving force that enhances the regional long-term economic growth. However, a weakness of this theory is that it assumes a perfect elasticity of supply.

Today, approximately one-fourth of total global production is exported. As the primary aim of export forecasting is to decrease uncertainty (Diamantopoulos and Winklhofer, 2003), and export planning is generally characterized by a high level of uncertainty (Diamantopoulos and Winklhofer, 1999, Al-Othman et al., 2008), planning a detailed forecast is critical for countries that depend on exports trade for their survival and economic growth. In forecasting exports, researchers used various models, which resulted in interesting findings. For instance, Alam (2019) and Urrutia et al. (2019) used different ANN and ARIMA models to forecast annual exports and imports of the Kingdom of Saudi Arabia and the Philippines. They demonstrated that both models are reliable for forecasting exports and imports. Scheufele and Grossmann (2019) used the mixed data sampling (MIDAS) model to explain the exports of Germany and

Switzerland and found that monthly indicators based on foreign PMIs strongly correlated with quarterly export growth and performed relatively well with other benchmark models.

Other studies also examined the impact of COVID-19 using single models; however, to our knowledge, our study is the first to describe various approaches to examine exports during the COVID-19 pandemic using seven different forecasting models and evaluate the best model. For instance, Anastassopoulou, et al., (2020) used the mean-field Susceptible-Infected-Recovered-Dead (SIRD) model to demonstrate the magnitude of spread, contagion, and mortality rates COVID-19 in China during the early period of the pandemic. Other studies conducted by Safi and Sanusi (2021), Petropoulos, et al., (2020), and Perrella, et al., (2020) used the exponential smoothing model to forecast the spread and recovery rates of the coronavirus. Their findings indicated a reduction in mortality rates over time, despite increases in the spread. Similarly, Chakraborty and Ghosh, (2020) developed a novel hybrid ARIMA-WBF (wavelet-based forecasting) model to predict the real-time forecasts of daily COVID-19 cases, considering the impact of the broad spectrum of social distancing measures implemented by governments.

While many studies have explored several impacts of COVID-19 on exports, very few have directly studied the best models to forecast China exports, which is a significant source to industries in other countries. Essential activities of manufacturing industries worldwide were interrupted, and the consequent disruptions in the supply chain affected prices around the world (Pierre and David, 2020). The ASEAN nations saw their supply chains being disrupted and experienced economic slowdowns due to the COVID-19 outbreak (Djalante, et al., 2020). In addition to this impact is the falling price of crude oil that emanated from the oil war between Saudi Arabia and Russia, which compounded the economic impact of COVID-19 on the fragile world economy. This event led to an unprecedented uproar of economic activities, such as tightened liquidity situations, the downfall of the financial market, and abnormal outflow of capital from developing nations with tremendous pressure on foreign exchange markets. The situation in developing countries is of significant concern. The spread of COVID-19 in these countries will deteriorate an already delicate macroeconomic condition, where the accumulation of debt has been higher than the government's income even before the crisis (Goodell, 2020).

In addition to the impacts on human life, the novel coronavirus demonstrates the possibility of slowing down the Chinese economy and all economies tied to it. China became the central manufacturing center of several business operations worldwide because of its readily available inexpensive labor and technology (UNCTAD, 2020). Therefore, any interruption of China's output and exports is likely to exhibit consequences and contagious impacts on all its direct and indirect trading partners around the globe. Therefore, the primary objective of this paper is to provide a more accurate and reliable forecasting model for China's exports. In our analysis, we used datasets on the value of China's exports in goods to the world. We used China exports datasets for eight groups in the world, including the United States of America (US), the Organization for Economic Co-operation and Development (OECD), non-OECD, the Group of Seven (G7), BRICS countries, the Group of Twenty (G20), the European Union (EU), and the Euro Zone. The US is the first economy globally and demonstrates a direct and indirect relationship with China in imports and exports. Gros (2021) showed that US goods and services trade with China totaled an estimated $737.1 billion in 2018. Exports were $179.3 billion; imports were $557.9 billion. As a result, the US goods and services trade deficit with China was $378.6 billion in 2018." The OECD is an international organization that works to forge enhanced policies for sustainable living within the member countries. Their goal is to find solutions to various social, economic, and environmental challenges by creating and modifying policies that enhance prosperity, fairness, opportunity, and welfare for all that meet international standards.

The G7 is a forum of the world's seven major developed economies (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) whose leaders meet every year to discuss international monetary and economic policy matters. The primary purpose of this group is to deliberate and help in the resolution of global problems, with specific attention on economic issues (ITD, 2017). In the past, this group deliberated and offered solutions to financial crises, international trade, and world crises such as crude oil shortages. In addition, this group exhibits significant trade ties with China, given the magnitude of China's export to the group. Since 2019, China has exported more than the US $300 billion worth of goods.

BRICS are countries believed to be the future leading suppliers of raw materials (Brazil and Russia), manufactured goods (China and India), and services by 2050 (Beenish, 2016). Although BRICS countries have not put forth formal trade pacts, their leaders regularly attend summits together and often act in accordance with one another's interests (Majaski, 2020). Their growth is a consequence of lower labor and production costs, which are the exploits of their population. BRICS imported more than the US $1,200 billion worth of goods in the final quarter of 2019, making it one of the largest importers of China's goods (OECD Stats, 2020).

The G20 is a group of countries representing civil society, business and labor leaders, scientific and research community, think tanks, women, and youth. The Finance Ministers and Central Bank Governors from the country members meet regularly to discuss trade, health, employment, and agriculture. Population (Australian Government, 2020).

The EU is an economic and political union consisting of 27-member states that perform the obligations and privileges of all members. Each member state is subjected to the union's binding laws within the common legislative and judicial institutions. The trade relation between China and the EU has grown over time, and The members in this group account for 85% of the world economy, 75% of global trade, and two-thirds of the world's in 2019, China was categorized as the third-largest trading partner for EU exports of goods and the most significant partner for EU imports of goods, with a trade deficit in goods of 164 billion Euros (China-EU Statistics, 2021)

The Eurozone is an economic union and the only market without borders for trading and the only currency used by 19 member countries of the zone. It is also a political union that exhibits its parliament and institutions (Fahrholz and Wójcik, 2013). Since 2019, the Eurozone monthly imports from China alone have been more than US $900 billion (OECD Stats, 2020). The member states include Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, The Netherlands, Portugal, Slovakia, Slovenia, and Spain. The Euro area accounts for a relatively limited share of China's exports, although this share increased over time. Exports to China rapidly increased across all Euro area economies over the past decade (Economic bulletin, 2015).

Using different datasets, we forecast China's exports to the abovementioned eight major economic groups of the world using hybrid time series modeling with six component models: including autoregressive integrated moving average model (ARIMA); errors, trend, and seasonal model (ETS); artificial neural network (ANN), a nonseasonal forecasting method to the seasonally adjusted data and re-seasonalizing using the last year of the seasonal component (STLM); exponential smoothing state space model with Box-Cox transformation; ARMA errors; trend and seasonal components (TBATS); and THETA methods.

3. Material and Methods

In this study, we used China exports data of different world groups to compare the models using various forecasting criteria. Data were collected from the OECD database, which can be reached via https://data.oecd.org/, which includes eight groups where China exports a considerable amount of goods and services to its trading partners. This is the total value in dollars for all goods and services from January 2014 to January 2021 and calculated for each group we used in our estimation and prediction. The eight groups considered in our study were the United States, the Euro Area, the European Union (EU), BRICS (Brazil, Russia, India, China, and South Africa), the Group of Seven (G7), the Organization for Economic Co-operation and Development (OECD), and non-OECD countries.

As shown in the time series plots of data in Figure 1, the data are nonlinear, as demonstrated by significant fluctuations. This indicates that caution is needed when using ARIMA models for such data as they may not provide the most accurate forecasts.

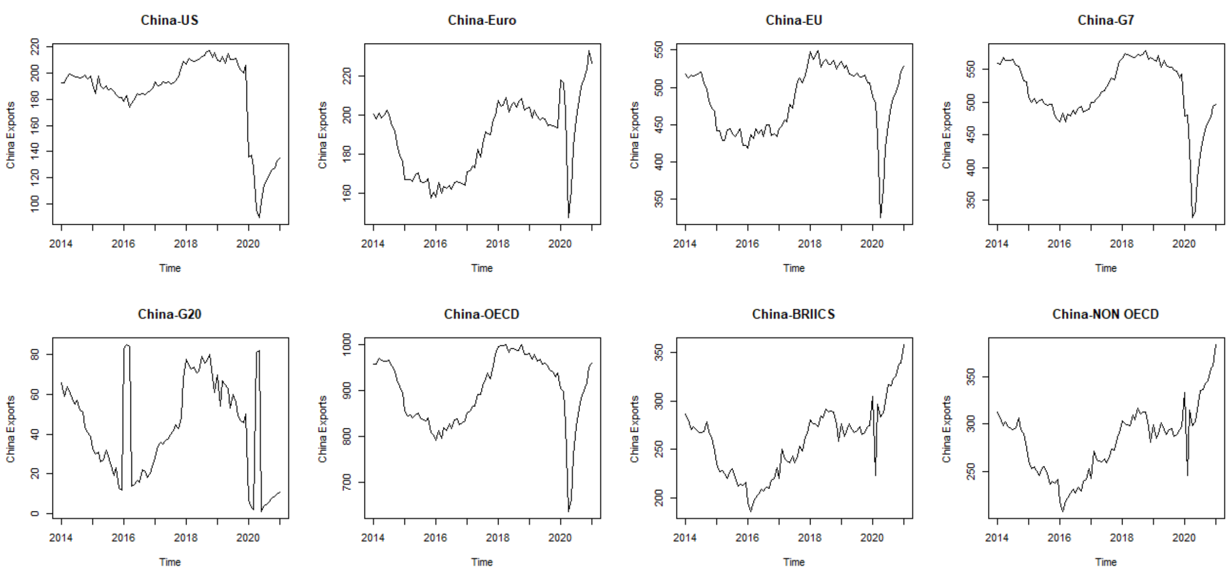

Figure 1: China exports data to different groups from January 2014 to Jan. 2021

3.1 Measures of Forecasting Accuracy

The selection of the best forecasting model is done by adopting the following three forecasting criteria: the MAE (mean absolute error), the RMSE (root mean squared error), and the MAPE (mean absolute percentage error). Either MAE or RMSE is used to compare forecasting methods on a single dataset, whereas MAPE is used to compare the forecasting accuracy on data that exhibit varying time series with different measures. It has been well documented that the RMSE is an appropriate criterion when the data are free of extreme values, whereas the MAE is superior in the presence of outliers (Hyndman & Koehler, 2006).

For example, based on MAE, the efficiency ratio of the proposed forecast model compared to that of benchmark modelΩ is defined as

$$\Omega = \frac{MAE_p}{MAE_b}, \tag{1}$$

where MAE_b and MAE_p are from the benchmark and proposed models, respectively. A ratio smaller than one point indicates that the proposed forecasting model is more efficient than the benchmark model, and when Ω is approximately one, the two forecasting models are roughly equivalent, or the proposed model works poorly (White & Safi, 2016).

3.2 Forecast Models

3.2.1 ARIMA model

The classical ARIMA(p,d,q) model was described by Box G. et al. (2015)

$$\phi(B)\nabla^d Y_i = \theta(B)\varepsilon_i, \tag{2}$$

where $d \geq 1$ is the degree of differencing, $\nabla = 1 - B$ is the differencing operator, the *lag* operator B, is defined as $BY_t = Y_{t-1}$, the operator that gives the previous value of the series. $\phi(B)$ and $\theta(B)$ are the respective polynomials of degrees p and q in B,

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$$

and

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$$

The best fit ARIMA model is selected according to AIC, AICc, or BIC value.

Exponential smoothing methods have been introduced since the 1950s, and currently, they are the most commonly used forecasting techniques in a variety of fields, e.g., economics, business, and others.

Let $Z_1, Z_2, \ldots, Z_n$ be the time series data and $\boldsymbol{x}_t = \left(l_t, b_t, s_t, s_{t-1}, \ldots, s_{t-(m-1)}\right)$, where l_t, b_t, and s_t represent the level, the trend, and the seasonal component, respectively, all at time t. Then, the state space model is

$$Z_t = H\ \boldsymbol{x}_{t-1} + \varepsilon_t \tag{3}$$

$$\boldsymbol{x}_t = F\ \boldsymbol{x}_{t-1} + G\varepsilon_t, \tag{4}$$

Where $\{\varepsilon_t\}$ is the residual at time t, $\varepsilon_t \sim NID\left(0,\sigma^2\right)$. The methodology of the exponential smoothing state-space model is fully automatic by the R-software (Hyndman et al., 2008).

3.2.3 Artificial neural network

The *nnetar* function is used in fitting the ANNs. This function is described as feed-forward neural networks with a single hidden layer and lagged inputs for forecasting univariate time series. This function fits the neural network autoregressive model $\mathrm{NNAR}\left(\mathrm{p},\mathrm{P},\mathrm{k}\right)$. For nonseasonal time series, the default is the optimal number of lags (according to the AIC) for a linear $\mathrm{AR}\left(\mathrm{p}\right)$ model (Hyndman, 2004).

3.2.4 Hybrid model

The hybrid model fits numerous individual model specifications to easily create collective forecasts. The combination of the hybrid model consists of six different models, which are ARIMA, error, trend, and seasonality (ETS), Theta, neural network autoregression (NNAR), seasonal and trend decomposition, and TBATS model (trigonometric seasonal + exponential smoothing method + Box-Cox transformation for heterogeneity + ARMA model for residuals + trend + seasonal (including multiple and noninteger periods).

4. Results and Discussion

This section describes the empirical results of the fitting models for each dataset using seven different approaches, viz., ARIMA, ETS, Theta, ANN, STLM, TBATS, and hybrid models. The forecasting results are presented in the following subsections. Probability plots and the Anderson–Darling normality test were used to determine whether data follow a normal distribution. Results of the Anderson–Darling normality test and the probability plots for each dataset are shown in Table 1 and Figure 1, respectively. The test and plots of normality indicate that the normality assumption is not satisfied. As the data were not normally distributed, we used the ratio of the MAE of the ANN model to that of ARIMA, ETS, Theta, STLM, TBATS, hybrid models in the analysis.

Table 1: Anderson–Darling normality test for each dataset

Groups	Test Value	P value
United States	7.1199	2.2e-16
Euro area	2.3422	5.6e-06
European Union	2.6124	1.2e-06
G7	2.4199	3.6e-06
G20	0.9181	0.0187
OECD	1.9720	4.6e-05
BRIICS	0.9220	0.0183
Non-OECD	0.9409	0.0164

Source: Authors Own Calculations

4.1 Results of All Six Methods

Table 2 presents the complete empirical results for the ratios of RMSE, MAE, and MAPE of ANN to those of ARIMA, ETS, THETA, STLM, TBATS, and HYBRID models for each dataset. These results are based on the ratio of the MAE of the ANN model to that of ARIMA, ETS, Theta, ANN, STLM, TBATS, and HYBRID models.

Table 2: Ratios of RMSE, MAE, and MAPE for ANN to those of ARIMA, ETS, Theta, STLM, TBATS, and HYBRID

Groups	Statistics	ANN/ARIMA	ANN/ETS	ANN/THETA	ANN/STLM	ANN/TBATS	ANN/HYBRID
United States	RMSE	0.1617	0.1618	0.1618	0.1721	0.1618	0.3043
	MAE	0.2178	0.2182	0.2182	0.2290	0.2176	0.3623
	MAPE	0.1657	0.1657	0.1657	0.1726	0.1654	0.2809
Euro area	RMSE	0.3290	0.3289	0.3289	0.3325	0.3395	0.4797
	MAE	0.3379	0.3378	0.3381	0.3474	0.3172	0.4571
	MAPE	0.3306	0.3304	0.3307	0.3404	0.3085	0.4479
European Union	RMSE	0.2553	0.2414	0.2414	0.2401	0.2536	0.4061
	MAE	0.2703	0.2773	0.2773	0.2672	0.2700	0.4108
	MAPE	0.2568	0.2618	0.2618	0.2548	0.2567	0.3896
G7	RMSE	0.2424	0.2282	0.2282	0.2316	0.2339	0.3690
	MAE	0.3145	0.3113	0.3113	0.3120	0.2937	0.4585
	MAPE	0.2821	0.2745	0.2745	0.2759	0.2616	0.4054
G20	RMSE	0.0163	0.0153	0.0153	0.0153	0.0163	0.1594
	MAE	0.0199	0.0241	0.0241	0.0237	0.0233	0.2250
	MAPE	0.0051	0.0054	0.0054	0.0052	0.0053	0.0512
OECD	RMSE	0.1853	0.1686	0.1686	0.1673	0.1774	0.3232
	MAE	0.2184	0.2261	0.2261	0.2228	0.2127	0.3756
	MAPE	0.2081	0.2135	0.2135	0.2114	0.2016	0.3549

BRIICS	RMSE	0.2845	0.2798	0.2656	0.3051	0.2760	0.4349
	MAE	0.3079	0.3222	0.3009	0.3423	0.3015	0.4664
	MAPE	0.3094	0.3270	0.3103	0.3515	0.3051	0.4710
NON-OECD	RMSE	0.3019	0.2942	0.2822	0.3084	0.2931	0.4534
	MAE	0.3221	0.3222	0.3166	0.3460	0.3140	0.4779
	MAPE	0.3237	0.3252	0.3253	0.3572	0.3174	0.4827

Source: Authors Own Calculations

As shown in Table 2, for United states, the relative efficiencies of ANN to ARIMA, ETS, THETA, STLM, TBATS, and Hybrid models equal **Ω** = 0.2178, 0.2182, 0.2182, 0.2290, 0.2176, and 0.3623, respectively. This result indicates that the MAEs for ANN equal 21.78%, 21.82%, 21.82%, 22.90%, 21.76%, and 36.23% of that of ARIMA, ETS, THETA, STLM, TBATS, and hybrid models, respectively. Therefore, this result demonstrates that the ANN model is more superior to ARIMA, ETS, THETA, STLM, TBATS, and HYBRID models in forecasting China exports to all the groups used in the analysis. This indicates that the efficiency of ANN compared to that of the other models is the best in forecasting China's exports. These results are consistent with Alam (2019) and Urrutia et al. (2019) who utilized different forms of ANN and ARIMA models to forecast annual exports and imports of the Kingdom of Saudi Arabia and the Philippines

4.2 Comparison of the Same Method Performance across Different Datasets

The relative efficiencies of ANN to ARIMA for each dataset are **Ω** = 0.1657, 0.3306, 0.2568, 0.2821, 0.0051, 0.2081, 0.3094, and 0.3237, respectively. This result indicates that the MAPEs for ANN equal 16.57%, 33.06%, 25.68%, 28.21%, 0.51%, 20.81%, 30.94%, and 32.37% of those of ARIMA for each dataset, respectively. Therefore, ANN is more superior to ARIMA for each dataset.

In addition, the results for the relative efficiencies of ANN to the forecasting methods ETS, THETA, STLM, TBATS, and HYBRID are like those of the relative efficiencies of ANN to ARIMA.

Using all these approaches, we found that the hybrid and ANN models outperform the remaining models in forecasting China exports to the world, considering the shock created by the ongoing coronavirus pandemic.

4.3 Hybrid Model Forecasting

Table 3 and Figure 2 depict the point forecasts from the ANN model for the next 11 months for China exports to each of the eight groups. Figure 3 presents the 95% confidence interval forecasts using the ANN model for China exports to all groups for the subsequent 9 months. This forecast indicates that the magnitude of export from China to all groups fluctuates but decreases progressively, except for G7 for which it increases relatively. Overall, the magnitude of China's export to all groups decreased since the beginning of the sample forecast period.

Furthermore, Figures A.2–A.9 in Appendix A present the 95% confidence interval forecasts from ARIMA, ETS, Theta, STLM, Tbats, and HYBRID models for the next 11 months for China exports to each of the eight groups.

Table 3: Forecasts from ANN model for all datasets

Date	US	Euro area	EU	G7	G20	OECD	BRIICS	Non-OECD
Feb-21	138.17	182.70	538.11	497.94	10.88	973.53	357.03	389.41
Mar-21	145.18	107.85	556.13	515.81	11.54	1014.59	384.87	413.34
Apr-21	152.67	160.75	546.08	527.05	21.83	958.07	357.85	386.32
May-21	158.73	213.25	560.38	528.66	29.06	1022.46	369.27	396.09
Jun-21	166.03	220.94	555.47	535.28	19.42	1000.81	390.87	413.36
Jul-21	175.94	223.66	533.58	539.12	16.96	1000.69	389.81	434.68
Aug-21	185.07	214.38	529.36	550.43	35.22	999.62	394.42	438.54
Sep-21	193.18	182.23	539.37	557.37	19.88	990.23	387.30	444.24
Oct-21	199.19	140.40	533.60	578.94	24.99	990.22	384.98	445.56
Nov-21	198.35	168.29	534.91	594.43	32.24	991.95	369.98	441.23
Dec-21	202.16	206.15	527.27	573.56	25.93	983.55	374.23	437.61

Source: Authors Own Calculation

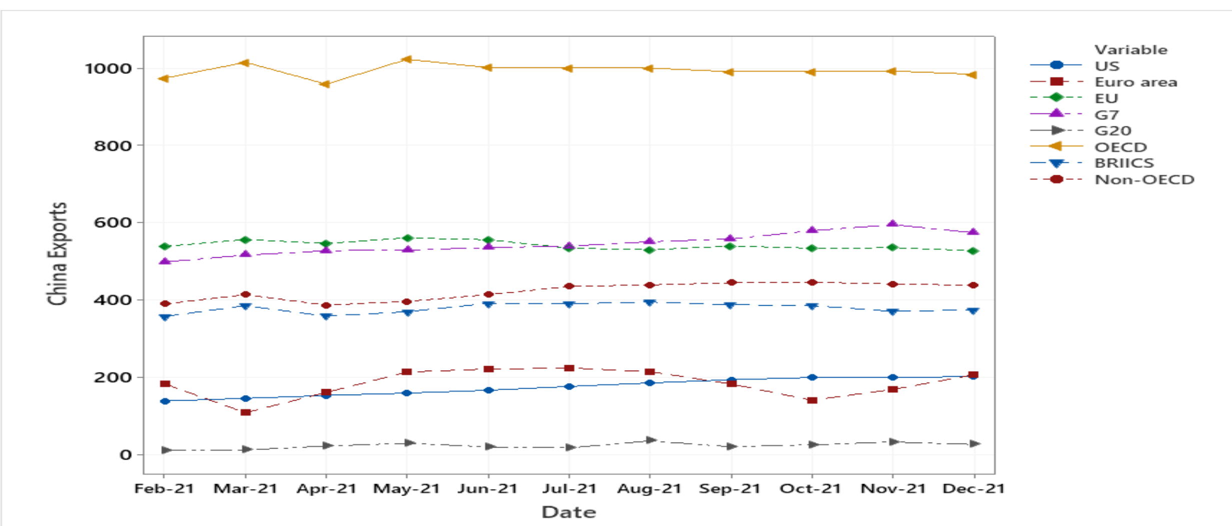

Figure 2: Point forecasts from ANN model for all datasets

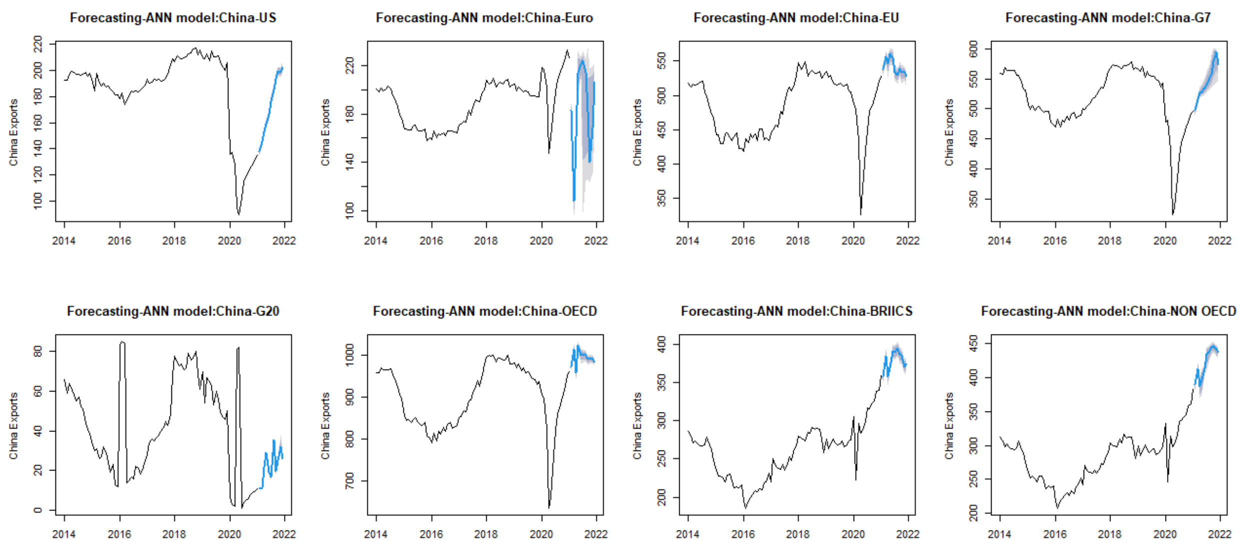

Figure 3: Confidence interval forecasts from ANN model for all datasets

5. Conclusion and Future Research

This study compared forecasting models using various criteria and selected the best exports forecasting model considering the shock generated by the novel coronavirus pandemic. This study underscores the importance of using the specified models in forecasting China exports during this period. According to our analysis, it is safe to say that the ANN model is more superior in forecasting than ARIMA, ETS, THETA, STLM, TBATS, and HYBRID models for forecasting China exports to all the groups. Our suggested model is valuable because it provides a reliable and appropriate forecast for exports, which determines the imports of goods from China from which other countries are dependent, thus representing a valid and objective tool for monitoring China exports. This forecast model indicates that China export to all the groups fluctuates but decreases progressively, except for G7 for which it increases compared with others over time. Overall, the results demonstrate that the number of China's exports to the various groups is unstable and on the decline since the beginning of the sample forecast period.

Considering the impact on the flow of goods to different parts of the world, this research presents insights to policymakers on how to tackle economic activities associated with China exports to various parts of the world. As it affects their imports from China, the magnitude of goods exported to the groups is associated with the COVID-19 pandemic in the current and subsequent waves of the spread. The supply and production of several commodities are affected as China falls short in meeting up the demand for their export of goods. An avenue for future research is to use hybrid models in the context of multivariate time series to forecast multiple time series simultaneously and to study the effectiveness of hybrid models where seasonality is known to exist. Additionally, gathering more steady data on export prices, extensive sample periods over time, or as additional previous data is generated could improve the precision of estimated export models.

Declarations:

Author contributions: *All authors contributed equally to the study from conception and design, material preparation, data collection and analysis to conclusion and policy implication.*

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Conflict of interest: The authors declare that there is no conflict of interest.

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Appendix A:

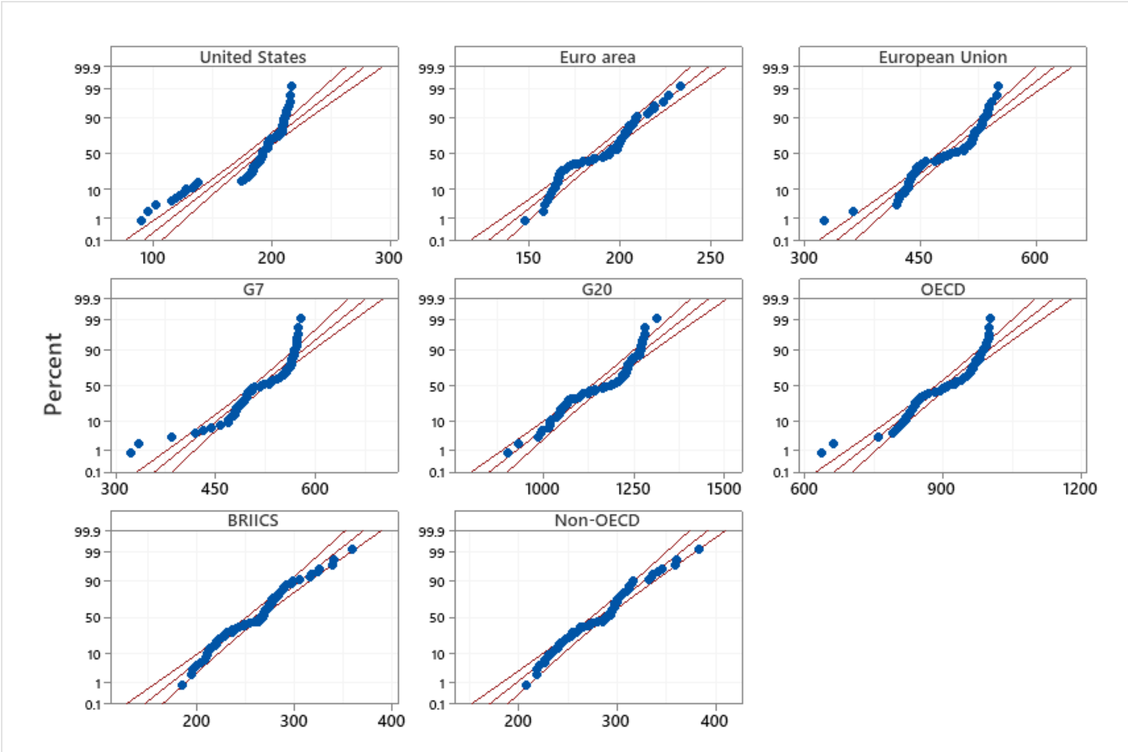

FIGURE A.1: Probability plots for each dataset

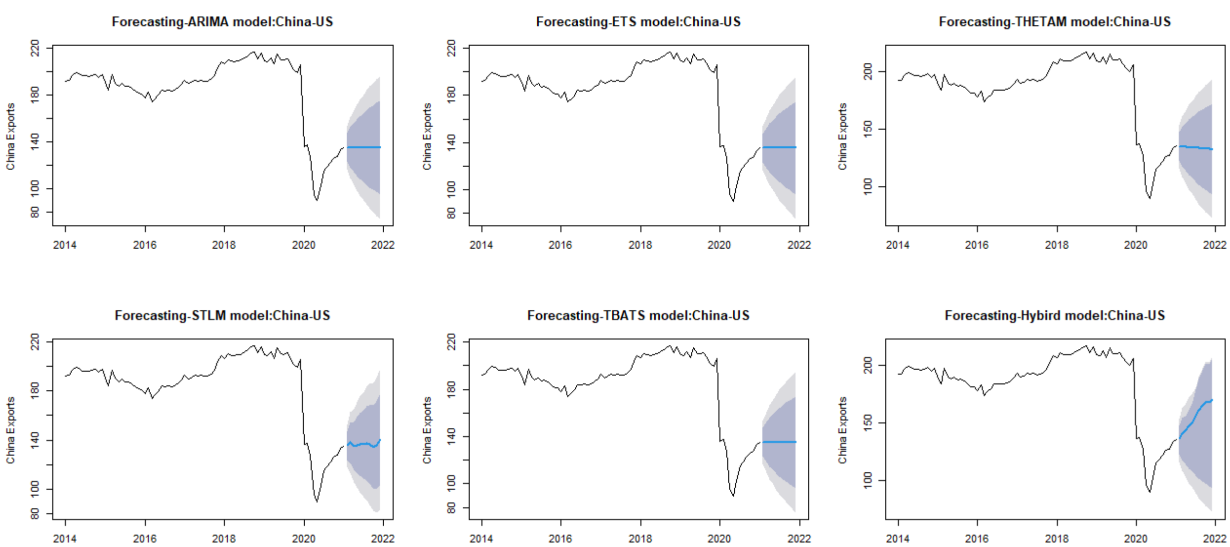

FIGURE A.2
Confidence interval forecasts from all models for China exports to the US

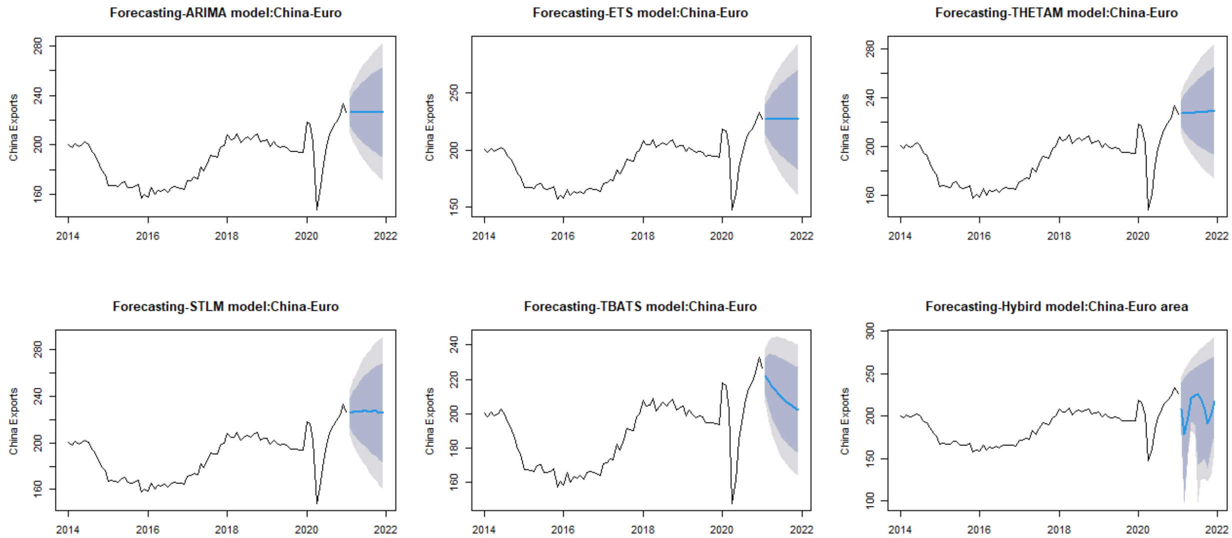

FIGURE A.3
Confidence interval forecasts from all models for China exports to the Euro area

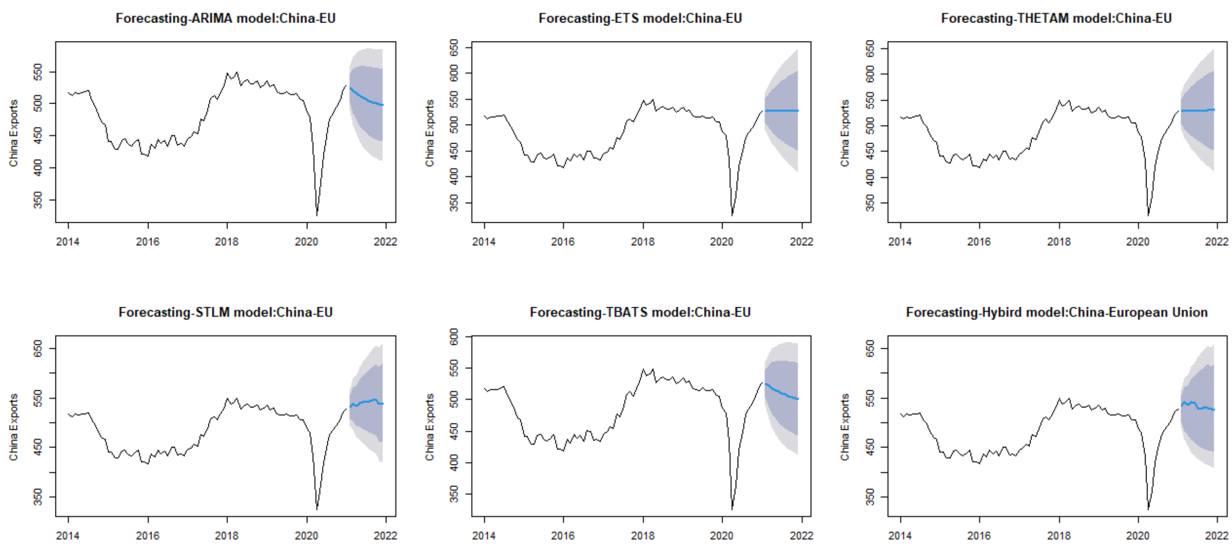

FIGURE A.4
Confidence interval forecasts from all models for China exports to the EU

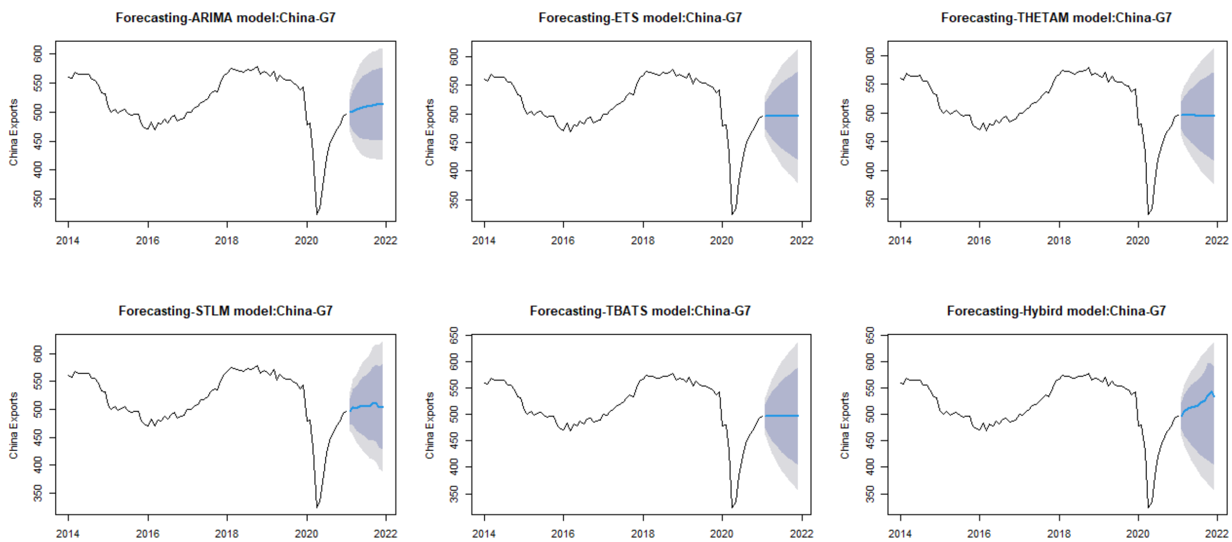

FIGURE A.5
Confidence interval forecasts from all models for China exports to G7

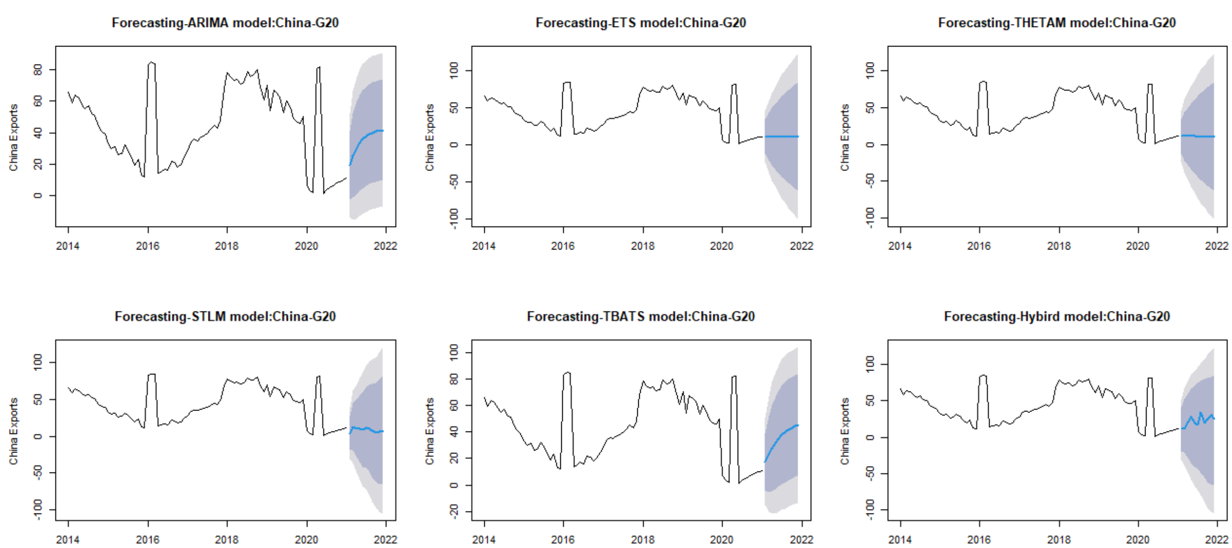

FIGURE A.6
Confidence interval forecasts from all models for China exports to G20

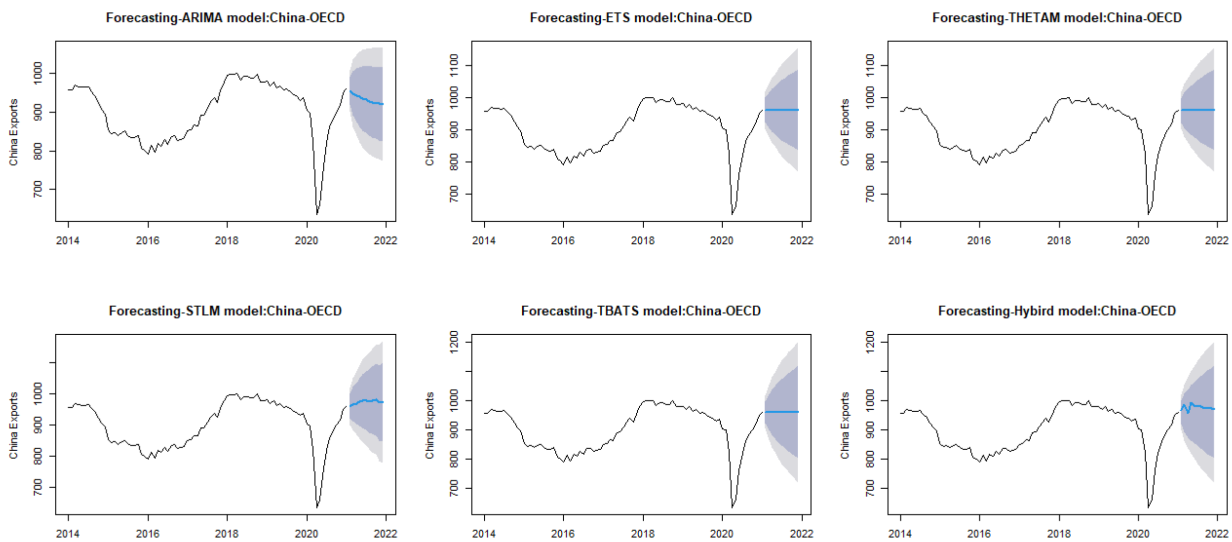

FIGURE A.7
Confidence interval forecasts from all models for China exports to OECD

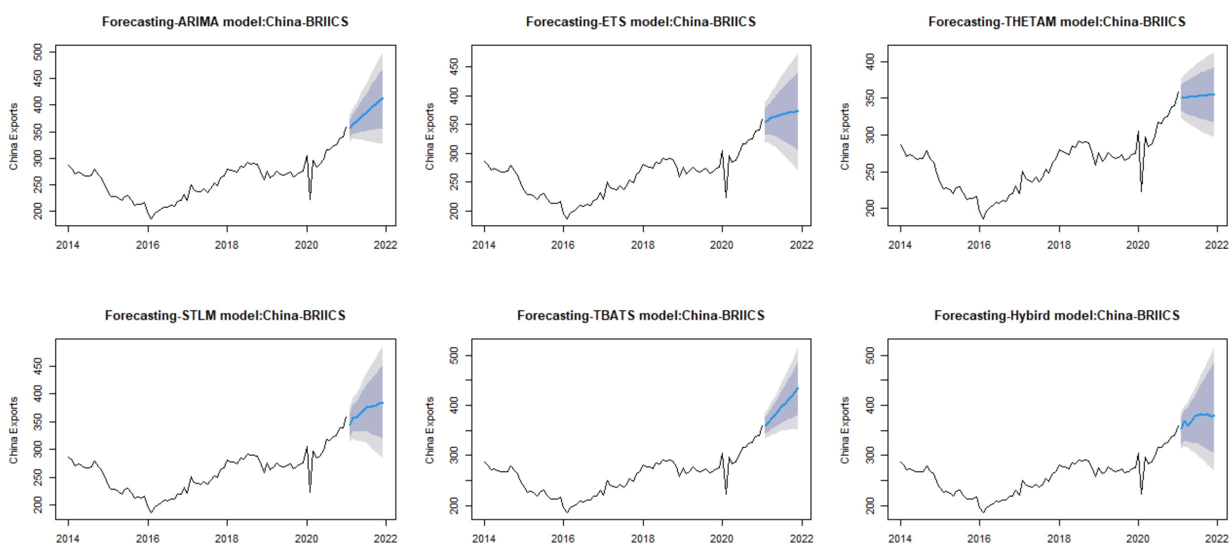

FIGURE A.8
Confidence interval forecasts from all models for China exports to BRICS

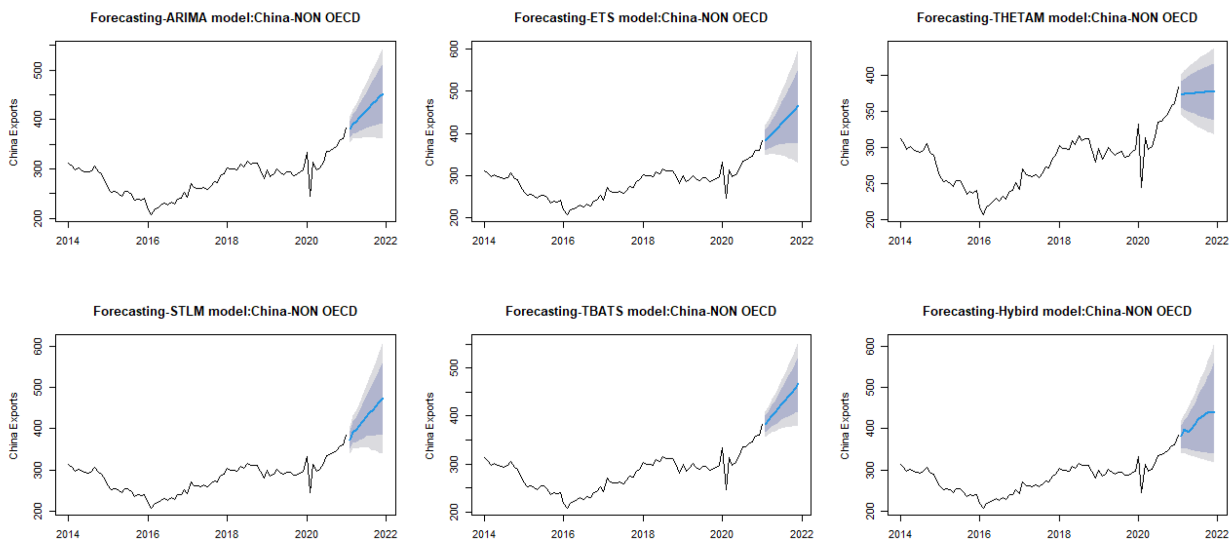

FIGURE A.9
Confidence interval forecasts from all models for China exports to non-OECD