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A prediction on the impacts of China's national emissions trading scheme on CO_2 emissions from electricity generation

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One of the government policies that can reduce CO_2 emissions is the Emissions Trading Scheme (ETS), which was implemented in the Chinese economy on 16 July 2021. It is the largest ETS in the world, covering 12% of global CO_2 emissions. Since this policy has not been experienced in China, it is necessary to predict its impact on CO_2 emissions in this country. Furthermore, electricity and heat production is the major contributor to total CO_2 emissions from fuel combustion. Therefore, this study attempts to predict the impact of the emissions trading scheme on CO_2 emissions from the combustion of coal, oil and natural gas in electricity generation using annual data from 1985 to 2019. For this purpose, this study first predicts CO_2 emissions from the combustion of coal, oil and natural gas for electricity generation in power plants using ARIMA and structural Vector Autoregression (SVAR) techniques over the 2020–2030 period. It then estimates the short- and long-run impact of the ETS policy on CO_2 emissions from the combustion of coal, oil and natural gas in power plants over the projected period (2020–2030) by employing the ARDL methodology. The results suggest that the ETS policy is effective in reducing the CO_2 emissions from the combustion of all fuels in electricity generation over the long-run. This is because of the increase in CO_2 emissions from the combustion of these fuels in power plants in the long run, which exceed the threshold value. But in the short-run, it has a negative and statistically significant impact only on CO_2 emissions from the natural gas power plants. These results suggest that improving the efficiency of all fuels can significantly reduce CO_2 emissions in electricity generation from coal, oil and natural gas in the short- and long-run. They also enable China's energy policymakers to update the ETS policy in its next phases.

KEYWORDS

emissions trading scheme, CO2 emissions, electricity production, power plants, ARIMA methodology, structural VAR, ARDL model

Abbreviations: CO2, carbon dioxide emissions; SO2, sulfur dioxide; ETS, Emissions Trading Scheme; SVAR, structural Vector Auto-regression; ARIMA, autoregressive integrated moving average; ARDL, Autoregressive distributed lag; GDP, gross domestic product; EEF, energy efficiency; POP, population.

1 Introduction

Environmental degradation due to human activities since industrialization has increased concerns about reducing the negative impacts of this issue on daily life and the speed of degradation. This issue results in externalities or side effects meaning that the activity of economic units affects household consumption and the production of other activities and the benefits of those activities are only for them and do not come into account. Many ways can help to bring externalities into account, such as environmental taxes, direct control, the emissions trading scheme (ETS) and so on. These policies apply to combat climate change, particularly the ETS is the key tool to cost-effectively reduce greenhouse gas emissions. The emissions trading scheme in a country allows firms to sell their excess emission units to firms that are over their targets.

The European emissions trading scheme, as a major pillar of European energy policy, was the first large greenhouse gas emissions trading that was launched in 2005. This policy may lead to three interdependent issues: the allocation approach, the absence of a credible commitment to pursue beyond 2012, and concerns about its impact on the international competitiveness of key sectors (Grubb and Neuhoff, 2010). It has reduced CO_2 emissions by 40–80 million tonnes per year on average (Laing et al., 2014).

Many studies have investigated the various aspects of ETS in China. Some of them have applied difference-in-difference methodology. For example, Peng et al. (2021) showed that this policy reduces carbon emission in those industries that receive allowance. Tang et al. (2021) revealed that the ETS policy through the adjustment of industrial structure and technological innovation decreases carbon emissions. Liu and Sun (2021) showed that the pilot ETS policy has different impact on carbon emissions of provinces in China. Similarly, Ma et al. (2022), using difference-in-difference methodology, demonstrated that this policy beside reducing carbon emissions improves economic performance of enterprises. Other studies employed various methodology to investigate the impacts of ETS policy. Xiao et al. (2021) showed that ETS policy improves total factor productivity in pilot regions in commission with non-pilot regions. Oliveira et al. (2021) using the Economic Projection and Policy Analysis (EPPA) model showed that linking Brazilian ETS policy with China's ETS is less costly because of lower strict targets. Chen et al. (2020) showed that low carbon price in ETS policy provide gain for most of provinces, while those energy rich provinces loss from this policy. This policy may also have an impact on energy efficiency as a result of technological innovation and industrial structure (Liu et al., 2020).

China is one of the top CO_2 emitter countries worldwide. These emissions have resulted from strong economic growth and population growth. China's average annual economic and population growth over the last decade (2010–2021) was 6.95 and 0.50%, respectively. In 2019, the level of CO_2 emissions in this country was 9,919.1 million tonnes of which 53.11% comes from electricity and heat production, 28% from manufacturing, industries and construction, 9.17% from the transport sector and 3.53% from other energy industries own use. Therefore, the Chinese government has attempted to reduce the level of CO_2 emissions through certain environmental policies. For example, the government has committed to reducing carbon intensity by 40–45% during 2005–2020 at the 2009 Copenhagen Summit. To achieve the target in a cost-effective manner, China is signaling strong intentions to establish an emissions trading scheme that in 2013 established pilot studies in seven provinces (Cui et al., 2014). Since the electricity sector is the main contributor to CO_2 emissions in China Jotzo and Löschel (2014) believe that Chinese policymakers need to pay specific attention to the operation of emissions trading in a heavily regulated electricity sector. Dai et al. (2018) found that when the emissions trading scheme policy is implemented in the Chinese economy, the electricity and aviation sectors will be the main buyers of the carbon credits, whereas other sectors will be the main sellers.

China with an annual growth rate of 7% in electricity generation between 2010 and 2018, is one of the top electricity generation countries globally (about 27% of global electricity generation) (IEA, 2021). The growth of electricity consumption also is greater than the global average (about 60-7-0% by 2040) with the majority coming from coal (about 66%) followed by hydropower (about 17%) (IEA, 2021). Therefore, 98% of the emissions from electricity generation came from coal-fired power plants. This means that coal consumption resulted in 4.4 Gt of CO_2 emissions, corresponding to 13% of global CO_2 emissions and 46% of China's emissions from fossil fuel combustion (IEA, 2021). In 2017, China announced the launch of the ETS by the end of 2020 (ICAP, 2020) and operated it by mid-2021 (Verde et al., 2021). Around 2020, the program was expected to be fully operational in the electricity sector and then gradually expand to other industries (Jotzo et al., 2018). Therefore, due to the high contribution of the electricity industry to CO_2 emissions in China (53.11% of total CO_2 emissions), the government has implemented the ETS policy in the electricity industry to reduce CO_2 emissions and to achieve the Copenhagen target in 2021. This policy is a market-based environmental policy aiming at reducing carbon emissions. Therefore, the government and policy makers must pay more attention to its positive impacts. How this policy affects the electricity sector and achieves its target is of great concern for policy makers and potential investors.

Therefore, this study, using different econometric methods, first predicts CO_2 emissions from combustion of coal, natural gas and oil in electricity generation over the next 11 years (2020–2030). It then attempts to investigate the impact of the emissions trading scheme policy on CO_2 emissions from fuel combustion in three types of power plants (i.e., coal, natural gas and oil) in China during 2020–2030. It also estimates the relationship between CO_2 emissions from the combustion of different fuels in power plants and GDP, population and energy efficiency in China. The main contribution of this study is that it is the first study that predicts CO_2 emissions from China's power plants for the next decade. This is because the majority of studies on emission trading scheme policy investigated the impact of pilot policy the selected regions and industries. Another contribution is investigating the impact of the emissions trading scheme at the sectoral level, particularly at the level of three types of power plants for a period which the ETS policy will be implemented in the electricity sector.

This study is organized in the following manner. The next section looks at an overview of the literature on the global and local emissions trading scheme. Methodology and data are outlined in Section 3. Section 4 analyzes the findings of the study and Section 5 deals with the model of the study. Section 6 provides a discussion on results and section 7 presents a conclusion and some policy recommendations.

2 Literature review

In 2011, China, the world's leading carbon emitter, implemented the ETS pilot policy to reduce carbon emissions in seven provinces. Many studies showed that the pilot study is effective in reducing CO_2 emissions in these regions. For example, Wen et al. (2021) showed that overall CO_2 emissions decreased by about 1,165.72 Mt between 2011 and 2015, representing 12.78% of total industrial CO_2 emissions from pilot regions. Zheng et al. (2021) also showed that the ETS pilot policy has played a governance role in China and improved carbon emissions performance.

Chang et al. (2018) found, through co-integration techniques, various impacts of ETS pilot projects in China's provinces, particularly their impacts in the short- and long-run. For example, using the panel data for provinces and industries, Zhang et al. (2019) showed that the ETS has a significant impact on carbon emission intensity in Guangdong and Beijing, while it is not significant in Shanghai, Tianjin, Hubei, and Chongqing. This policy also decreased China's GDP and increased the price of electricity, as indicated by a dynamic recursive Computable General Equilibrium model conducted by Lin and Jia (2019). Similarly, Li et al. (2018) and Zhang et al. (2018) using the CGE methodology found that the ETS policy reduces China's GDP and CO_2 emissions and leads to clean electricity production. Based on the theories and models of equilibrium and system dynamics, Feng et al. (2018) showed that tradable green certificates and carbon emissions trading decline CO_2 emissions in the electric power industry. The emissions trading scheme in the electricity industry will cover around 3 Gt of CO_2 emissions annually, representing about 8% of global CO_2 emissions (Jotzo et al., 2018). Based on non-parametric optimization models Liu et al. (2018) found that the maximum potential gains can be obtained when CO_2-SO_2 emissions trading are combined.

Lu et al. (2021) demonstrated that the carbon trading policy, which has led to additional costs, has less impact on the industrial competitiveness. Zeng et al. (2020) also reported that the emissions trading scheme reduces CO_2 emissions from power plants and can reduce the total abatement costs from 0.37 to 41.5% in China. Tan et al. (2019) using an optimization model found similar results for thermal power generation. Ma et al. (2018) found that both TGC planning and the carbon emissions scheme can jointly adjust the structure of power industries.

The carbon emission trading also affects other sectors. For example, Liu et al. (2021) found that it effectively improves the total asset-liability ratio of enterprises, but decreases the value of the current capital market. Zhang et al. (2022) also showed that carbon emission trading system has a crowding-out effect on R&D investment. However, Liu and Sun (2021) indicated that this policy promotes low-carbon technological innovation.

The review of the above literature shows that many studies have investigated the impact of the pilot study in seven Chinese provinces. They are also focusing on other sectors rather than the electricity sector. No specific studies have predicted the impact of this policy on the CO_2 emissions in electricity production after its implementation. Therefore, this study fills these gaps by predicting the CO_2 emissions from the combustion of coal, oil and natural gas in electricity production and then investigates the impact of the ETS policy on it.

3 Methodology and data

One of the main goals in estimating a regression model is to be able to predict the changes of the endogenous variable with a certain quantity of the exogenous variable. Prediction is the process through which an objective or subjective model can be used to estimate a variable for the past or future. To predict a variable, one must first predict the variable inside the sample, then select the best method. It can then predict the variable based on the best model for the future.

Forecasting is mainly divided into two categories: in-sample forecasting and out-of-sample forecasting. In the in-sample prediction, the variable can be estimated based on a mathematical or qualitative model, then compared with the actual variable. This measures the strength of forecasting models. But the out-of-sample forecast estimates the variable for future or past periods (out of the sample). Mathematical and statistical models are generally used to perform the process of predicting economic variables, that is, the approximate estimation of an economic variable in the future. In other words, the objective method requires the construction of a model.

The quantitative (objective) method is performed using either the econometric or structural method and the time series or non-structural method. In the first method, an econometric model is initially estimated as follows:

$$Y = f(X) \tag{1}$$

Where Y is a dependent variable and X is a vector of independent variables. After the formation of the functions and having the X variables, the Y variable can be estimated or predicted. This is mainly done to predict a variable using changes in other variables.

In the second method, known as the non-structural method, one variable can be predicted based on its own past developments, and does not require another variable. In this method, the most important task is to identify the time series behavior according to its past values. It should be noted that the best way to predict a variable is to use all methods. After forecasting, the two methods will be compared with forecasting scales and the best method will be selected and used for prediction. The two forecasting methods used in this study are described in the following sub-section.

3.1 Vector Autoregression (VAR) model

The VAR methodology is very similar to the simultaneous equation models. But in this method, we are dealing with several endogenous variables and each endogenous variable is explained using its past values and the lagged values of all other endogenous variables of the model. The model generally does not include any exogenous variables. In addition, the VAR model determines the short-term behavior of variables with other variables and the lagged values of the variable itself. The general form of the auto-regression process is as follows:

$$Y_t = A + \sum_{j=1}^{p} B_j Y_{t-j} + \sum_{i=1}^{q} C_i Y_{t-i} + \varepsilon_i \tag{2}$$

Where ε_i is the stochastic term, which in VAR methodology is known as a reaction or stochastic shock.

As noted above, one of the most common time series forecasting methods is the use of the VAR model. Accordingly, in this study, CO_2 emissions from the combustion of coal, oil and natural gas in power plants are estimated within the framework of a structural VAR (SVAR) model, which combines the VAR model and structural regression. In these models, the prediction of a variable, for example Y, is related not only to its previous values, but also to the current and past values of the variables affecting this variable.

Before introducing the primary functional form of the study model, we need to provide some evidence. Mikayilov et al. (2018) and Solaymani (2020) found a positive relationship between CO_2 emissions and gross domestic product (GDP). At the sectoral level, an increase in transport value added stimulates CO_2 emissions from the transport sector (Solaymani, 2022). Evidence has also demonstrated that population is responsible for CO_2 emissions in the economy (Zhang G et al., 2018; Rahman et al., 2020). de Souza Mendonça et al. (2020) argued that an increase of 1% in population increases CO_2 emissions by more than 1%. On the impact of energy efficiency, Razzaq et al. (2021) argued that an improvement of 1% in energy efficiency mitigates CO_2 emissions by less than 0.30% in the short- and long-run. Similarly, Akram et al. (2020) highlighted that energy efficiency reduces carbon emissions in developing economies.

In SVAR models, influential variables can be considered endogenous or exogenous in the model. In this model, based on the above evidence, CO_2 emissions from each power plant are considered as a function of real GDP, population and energy efficiency. Accordingly, the following model is specified:

$$D_t = f(GDP_t, EEF_t, POP_t). \tag{3}$$

Where $C\,O_2$ is CO_2 emissions in millions of tonnes, GDP in billion dollars (at constant 2015 prices) and population (POP) in millions.

3.2 ARIMA model

The autoregressive integrated moving average (ARIMA) process for the variable Y can be represented as the following relationship:

$$\begin{aligned} Y_t &= f(x) + \sum_{i=1}^{p} \beta_i Y_{t-i} \sum_{j=1}^{q} \delta_i u_{t-j} + u_t \\ Yt &= \Delta^d xt = (1-L)^d x_t \end{aligned} \tag{4}$$

Where L is the lag operator. In the ARIMA (p, d, q) process, p, d, and q represent the number of autoregressive lags, the order of differentiation, and the number of moving average sentences, respectively. If d is equal to zero, the ARIMA process becomes the ARMA process. The Box-Jenkins methodology is usually used to estimate the ARIMA and ARMA models, which has three stages of identification, estimation and accurate measurement.

The number of autoregressive sentences and the number of moving average sentences is generally calculated using the autocorrelation and the partial autocorrelation functions based on the Box-Jenkins steps.

3.3 Criteria for measuring the power of predictions

Different criteria were used to compare the forecast power and select the best forecasting method. These criteria include the mean absolute error (MAE), mean squared error (MSE) and mean absolute percentage error (MAPE). These criteria can be formulated as follows.

$$MAE = \frac{\sum_{i=1}^{n}|e_i|}{n} \tag{5}$$

$$MSE = \frac{\sum_{i=1}^{n}e_i^2}{n} \tag{6}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{e_i}{y_i}\right| \tag{7}$$

In these relations n is the number of predictions, e_i is the prediction error obtained from the difference between the predicted values and the actual values, and y_i are the actual values. These criteria will be used to measure predictive power in this study.

In this study, the annual time series from 1985 to 2019 are used to predict CO_2 emissions at each of the power plants. The variables in the study include carbon dioxide (CO_2) emissions from burning coal, natural gas and oil in power plants, real gross domestic product (GDP), Chinese population (POP), and energy efficiency (EEF) for each power plant. The data are collected from the World Bank (World Development Indicators) and the U.S. Energy Information Administration.

3.4 Autoregressive distributed lag (ARDL) model

This study uses an econometric method introduced by Pesaran et al. (2001), known as the ARDL model, to estimate the effect of the emissions trading scheme policy on the CO_2 emissions from the combustion of coal, natural gas and oil in China's power plants. This method is preferable to other traditional methods because it is not necessary that each variable be in its first order. This method is also more efficient for small samples. Under the ARDL method, the maximum level of stationary for all variables must be I (1). Therefore, we use Dickey-Fuller and Phillips-Peron tests to test the stationary of variables in the models. After examining the stationarity of the variables, we need to estimate the relationship between the variables using the following equation.

$$\begin{aligned}\Delta ln CO_{2t} = \alpha_0 + \gamma_1 ln CO_{2t-1} + \gamma_2 ln GDP_{t-1} + \gamma_3 ln POP_{t-1} \\ + \gamma_4 EEF_{t-1} + \gamma_5 DUM_{t-1} + \sum_{i=1}^{p}\delta_1 \Delta ln CO_{2t-i} \\ + \sum_{j=1}^{q}\delta_2 \Delta ln GDP_{t-j} + \sum_{k=1}^{m}\delta_3 \Delta ln POP_{t-k} \\ + \sum_{l=1}^{n}\delta_4 \Delta EEF_{t-l} + \sum_{w=1}^{s}\delta_5 \Delta DUM_{t-w} + u_t\end{aligned} \tag{8}$$

In this equation, the natural logarithmic form is used for the exogenous variables, and Δ shows that the variable is in the first-order difference. CO_2 is the carbon dioxide obtained from electricity generation and is measured in million tonnes of CO_2. GDP is the real gross domestic product (2015 constant prices $US). The EEF indicates the energy efficiency of each power plant. POP is the population (million people), and the DUM is the dummy variable that can be used to examine the impact of the emissions trading scheme policy during the predicted period (2020–2030). t refers to the period 1985–2019 and u_t is the error term.

Before estimating the models, it is necessary to identify the co-integration relationship among variables using the bounds test, to find a high level of confidence in the coefficients of the lagged variables. Simultaneously, this test relies on an F-test consisting of two parts, the upper bound and the lower bound. If the value of F is higher than the upper limit, it is proved that there is a co-integration relation between the variables, and if the value of F is less than the lower limit, the null hypothesis cannot be rejected. If the F-statistic falls between the two limits, the results will not be clear. This test consists of two hypotheses. The H_0 hypotheses shows that all coefficients are zero and the H_1 hypotheses indicates that at least one of the coefficients is not zero. For the F test, we use the critical value developed by Narayan and Smyth, (2005) for small samples. After detecting the establishment of the co-integration relationship, the long-run ARDL model (Equation 9) for calculating the long-run dynamics is estimated as follows:

$$\begin{aligned}lnCO_{2t} = \alpha_0 + \gamma_1 lnCO_{2t-1} + \gamma_2 lnGDP_{t-1} + \gamma_3 lnPOP_{t-1} \\ + \gamma_4 EEF_{t-1} + \gamma_5 DUM_{t-1} + \upsilon_t\end{aligned} \tag{9}$$

In Equation 9, the optimal lag length structure is selected using the Schwartz information criterion. The coefficients measure the long-run effect of each variable of the models on CO_2 emissions. After estimating Equation 9, the residuals will be used as the error correction model (ECM). This model shows how variables quickly return to long-run equilibrium after a shock. The ECM must have a statistical coefficient with a negative sign equal to or less than one. The error correction model of Equation 8 is formulated in the form of Equation 10.

$$\begin{aligned}\Delta ln CO_{2t} = \alpha_0 + \sum_{i=1}^{p}\delta_1 \Delta ln CO_{2t-i} + \sum_{j=1}^{q}\delta_2 \Delta ln GDP_{t-j} \\ + \sum_{k=1}^{m}\delta_3 \Delta ln POP_{t-k} + \sum_{l=1}^{n}\delta_4 \Delta EEF_{t-l} \\ + \sum_{w=1}^{s}\delta_5 \Delta DUM_{t-w} + \theta ECM_{t-1} + \varepsilon_t\end{aligned} \tag{10}$$

For a better understanding of the study methodology, a conceptual framework is presented in the Figure 1.

4 Model estimation

4.1 Determining the optimal lags length

After determining the variable for each model, in the next step, we examine the stationary state of the variables. In this study, the Augmented Dickey-Fuller and the Phillips-Perron tests were used to examine the stationary of variables. The results of these tests are reported in Table 1.

TABLE 1 Result for the unit root test.

Variables	Augmented dickey fuller		Phillips - perron	
	Level	First difference	Level	First difference
*Ln*GDP	0.807	−4.014[a]	0.548	−4.034[a]
*Ln*Pop	−2.146	−2.283	−12.470[a]	−0.641
*Ln*C O 2_C	1.897	−3.593[b]	1.330	−3.593[b]
*Ln*C O 2_G	3.896	−3.002[b]	8.713	−3.070[b]
*Ln*C O 2_O	1.618	−4.649[a]	1.618	−4.661[a]
EEF_C	−0.050	−4.305[a]	−0.730	−4.282[a]
EEF_G	−0.773	−7.441[a]	−2.344	−8.927[a]
EEF_O	−1.397	−4.826[a]	−1.417	−4.778[a]

[a] denotes the variable is significant at 1%
[b] denotes the variable is significant at 5%
Note: _C, _G and _O indicate the variable is for Coal, Gas and Oil power plant, respectively.

TABLE 2 Results for the optimal lag length for each model.

Lag	LogL	LR	FPE	AIC	SC	HQ
	Coal model					
0	−630.524	NA	7.06E+12	40.93704	41.12207	40.99735
1	−312.644	533.2176	24,854.23	21.46092	22.38608[a]	21.7625
2	−289.754	32.48905	16,876.32	21.01641	22.68168	21.55925
3	−266.853	26.59520[a]	12,582.71[a]	20.57115[a]	22.97655	21.35525[a]
4	−254.863	10.82948	22,468.01	20.82988	23.9754	21.85524
	Gas model					
0	−732.59	NA	5.11E+15	47.52192	47.70695	47.58224
1	−453.047	468.9106	2.13E+08	30.51916	31.44431	30.82073
2	−427.877	35.72493	1.25E+08	29.92755	31.59283	30.47039
3	−395.993	37.02712[a]	52,256,486	28.90275	31.30815[a]	29.68685
4	−369.327	24.08505	36,201,720[a]	28.21465[a]	31.36017	29.24001[a]
	Oil model					
0	−657.94	NA	4.14E+13	42.70583	42.89086	42.76614
1	−389.682	449.9818	3.58E+06	26.43109	27.35624[a]	26.73267
2	−367.738	31.14635[a]	2.58E+06	26.04761	27.71288	26.59044
3	−345.501	25.82342	2,011,024[a]	25.64523	28.05063	26.42933[a]
4	−327.991	15.8158	2,514,936	25.54779[a]	28.69331	26.57315

[a]Denotes lag order selected at the 5% level.

Table 2 shows that among the study variables, only the population (POP) is stationary at its level and the other variables are not stationary at their level, but they have been stationary in their first differences. To determine the optimal lag length, we can use the criteria of the likelihood ratio (LR), Akaike (AIC), Schwartz (SC) and Hannan-Quinn (HQ) tests. The results of these tests are reported in Table 2.

According to Table 2, the Schwartz criterion shows one lag for the coal model, three lags for the gas model and one lag for the oil model.

TABLE 3 Results for selection the order of co-integration.

Hypothesis H_0	Hypothesis H_1	Trace statistic	5% Critical value	Max-Eigen statistic	5% Critical value
		Coal model			
r = 0	r ≥ 0	64.04463[a]	47.85613	37.9527[a]	27.58434
r = 1	r ≥ 1	26.09193	29.79707	14.69912	21.13162
r = 2	r ≥ 2	11.39281	15.49471	9.793,107	14.2646
r = 3	r ≥ 3	1.5997	3.841,465	1.5997	3.841,465
		Gas model			
r = 0	r ≥ 0	64.01293[a]	47.85613	39.56543[a]	27.58434
r = 1	r ≥ 1	24.44751	29.79707	19.58731	21.13162
r = 2	r ≥ 2	4.860,201	15.49471	4.615,254	14.2646
r = 3	r ≥ 3	0.244,946	3.841,465	0.244,946	3.841,465
		Oil model			
r = 0[a]	r ≥ 0	55.68548[a]	47.85613	34.52404[a]	27.58434
r = 1	r ≥ 1	21.16145	29.79707	10.90198	21.13162
r = 2	r ≥ 2	10.25947	15.49471	7.89001	14.2646
r = 3	r ≥ 3	2.369,458	3.841,465	2.369,458	3.841,465

[a]Shows H_0 hypothesis reject at 5% level.

4.2 Co-integration test

The purpose of estimating the VAR model is to determine the number of long-run relationships between the model variables. Since the model consists of three variables, it is possible to have at least two long-run relationships between them. To test this problem using the Johansen's method, the maximum eigenvalue and the trace statistics were used. The results of these statistics for each one of the models are presented in Table 3. As can be seen in this table, both the trace statistic and the maximum eigenvalue confirm the existence of at least one long-run relationship between the variables of each one of the models at the 95% confidence level. Therefore, we have estimated a long-run relationship under the Johansen model.

4.3 Johansen model estimation

The Johansen model shows the long-run relationships and is helpful for policymaking. In addition, according to Table 4, the long-run relationships for each model is one, which is stated below. In addition, all variables are considered independent in this regard.

$$\boldsymbol{ln\, CO_2\_C_t = \alpha_1\, ln\, GDP_t + \alpha_2\, ln\, POP_t + \alpha_3 EEF\_C_t} \quad (11)$$

$$\boldsymbol{ln\, CO_2\_G_t = \beta_1\, ln\, GDP_t + \beta_2\, ln\, POP_t + \beta_3 EEF\_G_t} \quad (12)$$

$$\boldsymbol{ln\, CO_2\_O_t = \gamma_1\, ln\, GDP_t + \gamma_2\, ln\, POP_t + \gamma_3 EEF\_O_t} \quad (13)$$

The results show that in the long run, real GDP has a negative and significant relationship with CO_2 emissions for each model. These results also show that, in the long run, there is a significant relationship between population and the CO_2 emissions. This model shows a significant relationship between the energy efficiency of each energy and CO_2 emissions from the combustion of each fuel. This means that their coefficients are reliable at the 1% level of significance, except for the real GDP in the natural gas model.

4.4 ARIMA model's estimation

Another methodology used in this study is the autoregressive integrated moving average (ARIMA) model. The estimation of ARIMA models involves four main steps. The first step is the model's identification. The identification step in estimating ARIMA models is made using the autocorrelation function (ACF) and the partial autocorrelation function (PACF). One of the prerequisites for the ARIMA model is the nonstationary condition of the variable under consideration. The third step in the ARIMA method is the model's evaluation. Normally, at this stage, estimates with higher degrees are made and the best model is selected from them according to Akaike and Schwartz criteria as well as the white noise of the residual terms. The Akaike and Schwartz criteria were used to select the appropriate model, upon which the ARIMA (1,1,4) model, ARIMA (4,1,1) and ARIMA (6,1,10) were selected for coal,

TABLE 4 Results for the Johansen model.

Variable	*Ln*CO_2_C		*Ln*CO_2_G		*Ln*CO_2_O	
	Coefficient (std. err.)	*t*-stat	Coefficient (std. err.)	*t*-stat	Coefficient (std. err.)	*t*-stat
*Ln*GDP	−1.038 (0.004)	259.500	−0.314 (0.185)	1.697	−1.921 (0.066)	29.106
*Ln*POP	0.793 (0.083)	9.554	−26.329 (3.363)	7.829	15.748 (1.255)	12.548
EF_C/G/O	0.384 (0.004)	96.000	0.004 (0.0003)	13.333	0.010 (0.001)	10.000

TABLE 5 Results for the ARIMA model.

Model	Variable	Coefficient	Std. Error	t-Statistic	*p*-value
Coal model	C	126.078	47.752	2.640	0.013
	AR (1)	0.400	0.153	2.619	0.014
	MA (4)	0.245	0.135	1.818	0.079
Gas model	C	2.900	1.830	1.584	0.124
	AR (4)	0.487	0.158	3.091	0.004
	MA (1)	0.428	0.168	2.547	0.016
Oil model	C	3.557	2.954	1.204	0.238
	AR (6)	0.331	0.130	2.539	0.017
	MA (10)	0.564	0.286	1.976	0.057

natural gas and oil models, respectively. However, since the main purpose of estimating these patterns is prediction, the amount of prediction error is more important in selecting the model. Detailed results of the ARIMA estimates are presented in Table 5.

In Table 5, for the coal model, the first-order, AR (1), and the fourth order of the autoregressive sentence, AR (4), are statistically significant. For the natural gas model, the fourth order, AR (4), and the first order, MA (1), are statistically significant and for the oil model, the sixth order, AR (6), and the 10th order, MA (10), are statistically significant.

4.5 Comparing the prediction power of VAR and ARIMA models

In the previous sections, CO_2 emissions from burning coal, natural gas and oil in power plants were estimated using the VAR and ARIMA methods. Based on these methods, the forecasted values of CO_2 emissions and their actual values for each model during 2010–2019 are presented in Tables 6 and 7. In this section, we compare the dual estimates of each model and check which one of them has greater predictive power. To do this, three criteria were used: the sum of squares error (MSE), the mean absolute value of error (MAE) and the mean absolute percentage error (MAPE).

We now turn to the question of which of the two forecasting methods for each model has the least error? To answer this question, we compare the actual data and the predicted values of these two methods over the last 10 years (2010–2019), and determine the one with the least error. Meanwhile, the longer the forecast period, the greater the prediction error because the prediction of each period also contains the sum of the prediction error of the past. To determine the small amount of prediction errors, as mentioned above, the MSE, MAE and MAPE measures were used. The results of these measures are reported in Table 8.

The evaluation of the predictive power of the VAR model and its comparison with the ARIMA model indicates the difference in the accuracy of this model compared to another model. As shown in Table 8, the VAR model has the least error in predicting CO_2 emissions in the oil and natural gas models. However, in the prediction of CO_2 emissions from the coal power plant, the ARIMA model has the least prediction error.

TABLE 6 Actual and residual values of the VAR model.

	Coal model		Gas model		Oil model	
Year	Actual value	Predicted value	Actual value	Predicted value	Actual value	Predicted value
2010	3298.286	3081.626	31.2631	32.97048	59.69654	70.73683
2011	3738.643	3260.812	44.90924	41.97803	59.03182	75.48626
2012	3755.838	3437.098	45.52839	46.92644	68.11364	80.94506
2013	4026.316	3610.376	48.04628	51.68831	83.47544	87.02337
2014	3996.477	3780.464	55.02207	58.13641	93.71664	93.69099
2015	3942.563	3947.14	68.8911	65.36717	108.4021	100.9305
2016	3991.116	4110.158	77.72435	73.16031	123.5707	108.7325
2017	4226.292	4269.263	83.8746	81.55672	120.7689	117.0932
2018	4534.499	4424.203	88.95166	89.9754	128.4015	126.0138
2019	4606.215	4574.732	95.96873	98.07298	143.417	135.499

TABLE 7 Actual and residual values of the ARIMA model.

	Coal model		Gas model		Oil model	
Year	Actual value	Predicted value	Actual value	Predicted value	Actual value	Predicted value
2010	3298.286	3098.594	31.2631	26.21613	59.69654	62.16665
2011	3738.643	3289.894	44.90924	29.14733	59.03182	65.41825
2012	3755.838	3403.149	45.52839	30.9542	68.11364	71.6497
2013	4026.316	3548.166	48.04628	33.29499	83.47544	76.53861
2014	3996.477	3681.818	55.02207	36.18054	93.71664	84.68916
2015	3942.563	3810.925	68.8911	39.09573	108.4021	89.34158
2016	3991.116	3938.214	77.72435	41.46349	123.5707	97.6763
2017	4226.292	4064.777	83.8746	44.09121	120.7689	105.614
2018	4534.499	4191.048	88.95166	46.98417	128.4015	108.4819
2019	4606.215	4317.204	95.96873	49.89155	143.417	114.8871

TABLE 8 Comparing the power of both ARIMA and VAR model in predicting CO_2 emissions.

	Model	RMSE	MAE	MAPE	Smape	Theil U1	Theil U2	Selected model
CO_2 Coal	ARIMA	129.7897	56.27165	1.451,081	1.508,488	0.026986	0.360,476	ARIMA
	VAR	133.7077	55.81578	1.451,521	1.513,455	0.027796	0.371,787	
CO_2 gas	ARIMA	15.79207	7.510,291	10.87788	13.68461	0.266,092	0.352,678	VAR
	VAR	1.516,784	0.752,196	1.296,965	1.294,572	0.020509	0.046997	
CO_2 oil	ARIMA	8.723,121	3.911,894	3.559,546	3.804,302	0.065435	0.544,169	VAR
	VAR	5.148,574	2.291,167	2.82309	2.667,351	0.037203	0.486,747	

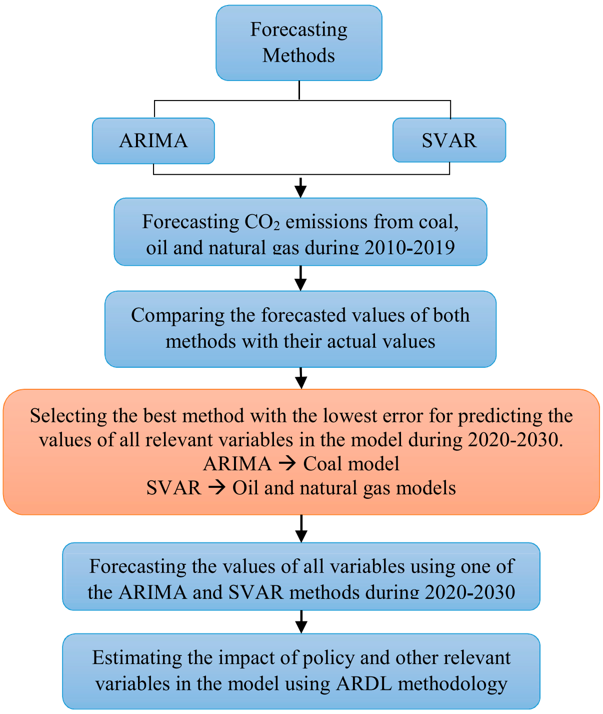

FIGURE 1
Conceptual framework of the study.

4.6 CO_2 emissions forecast

For oil and natural gas models, the prediction criterion is the VAR model and for the coal model, the prediction criterion is the ARIMA model. Therefore, using these methods, we have predicted CO_2 emissions from combustion of coal, oil and natural gas over the 2020–2030 period. The results of these forecasts are presented in Figure 2, which shows that CO_2 emissions have increased over the relevant years.

As Figure 2 shows, CO_2 emissions are increasing for all power plants, but from 2025 the rate of the increase in the coal-fired power plant will be slower. In 2029 and 2030, the gap between CO_2 emissions will be at a minimum, and this could be a promise to reduce CO_2 emissions from power generation in China's coal-fired power plants, which make a very large share of coal-fired electricity generation.

5 Main results of the study

Before estimating the models, we need to find out the long-run relationship between the variables of each model using the bounds test. The value of the F-statistic of this test is compared to the criteria of the Narayan and Smyth (2005) study. If it is above the upper limit of the Narayan and Smyth (2005) criteria, it shows the long-run co-integration relationship between the variables. However, if it falls below the lower limit of the criterion, it does not show any long-run co-integration relationship. Finally, if it falls between the lower and upper limits, the value of the F-statistic will not be definitive. The results of the bounds test of all models in Table 9 show that there exists a long-run co-integration relationship between variables in each model.

After finding a long-run co-integration relationship between the variables within each model, we estimate the short- and long-run impacts of each variable on CO_2 emissions. Table 10 shows

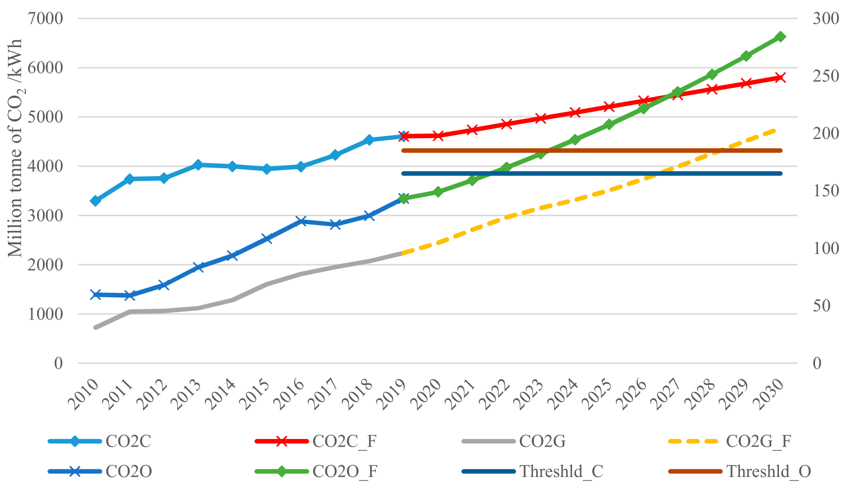

FIGURE 2
Predicted trends of CO_2 emissions created by different power plants during 2020–2030.

TABLE 9 Results for the bounds tests of all three models.

Model	F-value	Result
*Ln*CO2_C = f (*Ln*GDP, *Ln*POP, EEF_C)	30.456	Cointegration
*Ln*CO2_G = f (*Ln*GDP, *Ln*POP, EEF_G)	16.635	Cointegration
*Ln*CO2_O = f (*Ln*GDP, *Ln*POP, EEF_O)	5.032	Cointegration
Critical value bounds		
Level of significant	Lower limit (I(0))	Upper limit (I(1))
10%	2.922	4.061
5%	3.559	4.841
1%	5.064	6.659

the short and long-run results for the coal power plant. The results show that GDP has a positive and significant impact on CO_2 emissions from coal power plants in the short- and long-run. It shows that if real GDP increases by 1%, CO_2 emissions from coal power plants increase by 0.98 and 0.99% respectively in the short- and long-run. The population also has a positive impact on the coal power plant in both the short- and long-run, while its coefficient is not statistically significant. The coefficient of the energy efficiency in the coal power plants shows a negative and statistically significant impact on CO_2 emissions from coal power plants in the short and long run. This means that with an increase of 1% in energy efficiency, CO_2 emissions from coal power plants decline by 0.34 and 0.36% respectively in the short- and long-run. The coefficient of the dummy variable has a negative sign and is statistically significant only in the long run. It shows that the emissions trading scheme can reduce the CO_2 emissions from the coal power plant in the long run.

Table 11 reports the short- and long-run results for the natural gas power plants. The results show that GDP has a positive and statistically significant impact on the CO_2 emissions from the combustion of natural gas in power plants in the short- and long-run. It shows that if real GDP increases by 1%, CO_2 emissions from natural gas power plants increase by 1.53 and 0.76% in the short- and long-run, respectively. The coefficient of the population has a negative impact on natural gas power plants in the short- and long-run, but it is not statistically significant. The coefficient of the energy efficiency in the natural gas power plants shows a negative and statistically significant impact on the CO_2 emissions of natural gas power plants in the short- and long-run. This means that with an increase of 1% in energy efficiency, CO_2 emissions of natural gas power plants decline by 0.003% in the short- and long-run. The coefficient of the dummy variable has a negative sign and is statistically significant in the short and long run. It shows that the

TABLE 10 ARDL results for the Coal power plant (dependent variable = CO2_C).

Variable	Coefficient	Std. Error	t-Statistic	*p*-value
	Long-run			
C	−0.852	9.472	−0.090	0.929
*Ln*GDP	0.981[a]	0.127	7.705	0.000
*Ln*POP	0.134	1.464	0.091	0.928
*Ln*EEF_C	−0.338[a]	0.119	−2.833	0.008
DUM[a](COALF[a]10^9)	-2.39×10^{-13}[a]	5.38×10^{-14}	−4.432	0.000
	Short-run			
D (*Ln*GDP)	0.993[a]	0.019	51.907	0.000
D (*Ln*POP)	0.011	0.124	0.091	0.928
D (*Ln*EEF_C)	−0.363[a]	0.016	−22.703	0.000
DUM[a](COALF[a]10^9)	-3.08×10^{-16}	3.26×10^{-15}	−0.094	0.925
ECT_{t-1}	−0.085[a]	0.006	−14.426	0.000
Diagnostic tests				
Test	**Statistic**	**Value**	**Prob**	
Normality	Jarque-Bera	2.924	0.232	
Serial Correlation	Chi-square (1)	0.008	0.928	
Heteroskedasticity	Chi-square (25)	41.649	0.172	
Functional form	Chi-square (1)	0.555	0.457	
CUSUM test	Stable			
CUSUM of square test	Stable			

[a]denotes level of significance at 1% level.

TABLE 11 ARDL results for the Gas power plant (dependent variable = CO2_G).

Variable	Coefficient	Std. Error	t-Statistic	*p*-value
	Long-run			
C	4.601	11.671	0.394	0.696
*Ln*GDP	1.531[a]	0.159	9.615	0.000
*Ln*POP	−1.992	1.808	−1.102	0.278
*Ln*EEF_G	−0.003[a]	0.000	−10.749	0.000
DUM[a](GASF[a]10^9)	-2.29×10^{-12}[a]	3.42×10^{-13}	−6.692	0.000
	Short-run			
D (*Ln*GDP)	0.758[a]	0.200	3.791	0.001
D (*Ln*POP)	−0.986	0.993	−0.994	0.327
D (*Ln*EEF_G)	−0.003[a]	0.000	−28.307	0.000
DUM[a](GASF[a]10^9)	-1.13×10^{-12}[a]	2.30×10^{-13}	−4.933	0.000
ECT_{t-1}	−0.495[a]	0.047	−10.628	0.000
Diagnostic tests				
Test	**Statistic**	**Value**	**Prob**	
Normality	Jarque-Bera	2.924	0.101	
Serial Correlation	Chi-square (1)	2.634	0.105	
Heteroskedasticity	Chi-square (27)	30.990	0.272	
Functional form	Chi-square (1)	2.61×10^{-5}	0.996	
CUSUM test	Stable			
CUSUM of square test	Stable			

[a]denotes level of significance at 1% level.

emissions trading scheme can reduce the CO_2 emissions from natural power plants in the short and long run.

Table 12 provides the short- and long-run results for the oil power plants. The results show that GDP has a positive and statistically significant impact on the CO_2 emissions from the combustion of oil in power plants in the short- and long-run. It shows that if real GDP increases by 1%, CO_2 emissions from oil power plants will increase by 1.56 and 1.29% in the short- and long-run, respectively. The coefficient of the population has a negative and statistically significant impact on oil power plants in both the short- and long-run. It shows that if the population increases by 1%, CO_2 emissions from oil power plants declines by 9.80 and 4.27% in the short- and long-run, respectively. This may occur due to the increase in the use of more clean energies like natural gas in the combined oil and natural gas power plants. The coefficient of the energy efficiency in the oil power plants shows a negative and statistically significant impact on CO_2 emissions from oil power plants in the short- and long-run. This means that with an increase of 1% in energy efficiency, CO_2 emissions from oil power plants decline by 0.01% in the short- and long-run. The coefficient of the dummy variable has a negative sign and is statistically significant only in the long run. It shows that the emissions trading scheme can only reduce the CO_2 emissions from the oil power plants in the long-run.

6 Discussion

The level of energy consumption cannot be significantly reduced through the increase in energy prices due to the low elasticity of demand for energy. Therefore, economic and population growth are the main contributors to high demand for energy and electricity (Solaymani et al., 2015). Therefore, other policies and motivation methods aimed at increasing energy efficiency and the use of renewable energy sources can help to use fossil fuel power plants in China and other countries.

One of the China's most important sources of CO_2 emissions is its GDP. The results show that GDP positively and significantly increases CO_2 emissions in the short- and long-run. This means that economic growth and its components, such as trade, due to more use of fossil fuels increase CO_2 and other pollutants in the environment. This is consistent with the study conducted by Solaymani (2020), Mohsin et al. (2022) and Solaymani and Shokrinia (2016). The

TABLE 12 ARDL results for the Oil power plant (dependent variable = CO2_O).

Variable	Coefficient	Std. Error	t-Statistic	*p*-value
	Long-run			
C	62.102[a]	8.385	7.407	0.000
GDP	1.558[a]	0.105	14.768	0.000
POP	−9.802[a]	1.287	−7.615	0.000
EF_O	−0.011[a]	0.001	−9.564	0.000
DUM[a](OILF[a]10⁹)	-2.39×10^{-13}	5.38×10^{-14}	−4.431	0.415
	Short-run			
D (GDP)	1.291[a]	0.131	9.862	0.000
D (POP)	−4.265[a]	1.401	−3.044	0.004
D (EF_O)	−0.012[a]	0.001	−20.187	0.000
DUM[a](OILF[a]10⁹)	1.94×10^{-13}	2.35×10^{-13}	0.825	0.415
ECT_{t-1}	−0.085[a]	0.006	−14.426	0.000
Diagnostic tests				
Test	**Statistic**	**Value**	**Prob**	
Normality	Jarque-Bera	4.547	0.103	
Serial Correlation	Chi-square (1)	0.441	0.506	
Heteroskedasticity	Chi-square (19)	23.185	0.229	
Functional form	Chi-square (1)	0.908	0.341	
CUSUM test	Stable			
CUSUM of square test	Stable			

[a]denotes level of significance at 1% level.

population has a negative impact on CO_2 emissions from natural gas power plants. This is because more use of natural gas instead of other fossil fuels in the economy, particularly by households, reduces the level of CO_2 emissions. This is not consistent with the overall finding of studies that have shown that the population increases CO_2 emissions in the overall economy, such as Li and Solaymani (2021). Improving energy efficiency in all power plants reduces CO_2 emissions from the combustion of coal, oil and natural gas in related power plants. Ponce and Khan, (2021) and Mahi et al. (2021) showed that energy efficiency reduces CO_2 emissions significantly. Peng et al. (2021) also showed that energy efficiency improvement reduces CO_2 emissions. Evidence also showed that the emissions trading scheme has a significant and negative impact on CO_2 emissions from the combustion of coal, oil and natural gas in relevant power plants. This finding supports the results of the study conducted by Huang et al. (2021) argued that this policy can reduce CO_2 emissions while it may have a negative impact on the economic performance of China. Mo (2021) also showed that the emission trading scheme (ETS) has been promoted as a cost-effective market-based reduction tool.

7 Conclusion and policy implications

This purpose of this study was to predict the impact of the emissions trading scheme on CO_2 emissions from the combustion of coal, oil and natural gas in electricity generation in power plants using annual data from 1985 to 2019. For this purpose, this study first chooses the best technique between ARIMA and structural Vector Autoregression (SVAR) techniques to predict CO_2 emissions, electricity generation from coal, oil and natural gas, efficiencies of coal, oil and natural gas and other relevant variables over the 2020–2030 period. Then by employing the ARDL methodology and using the predicted values of the study variables, we estimated the short- and long-run impacts of the policy on CO_2 emissions from the combustion of coal, oil and natural gas in electricity generation over the projected period (2020–2030). To estimate the impact of the policy on CO_2 emissions, we used a dummy variable for the forecast period, which is multiplied by the average threshold value of the policy.

The results of this study showed that real GDP has a significant and positive impact on CO_2 emissions from the combustion of all fuels (coal, oil and natural gas) in the short-and long-run. Energy efficiency also has a negative and significant impact on CO_2 emissions from all power plants in the short- and long-run. The results also suggest that the ETS policy is effective in reducing the CO_2 emissions from the combustion of all fuels in electricity production in the long-run. These results suggest that improving the efficiency of all fuels can significantly reduce the level of CO_2 emissions from coal, oil and natural gas in electricity generation in the short- and long-run. This is because of the increase in the level of CO_2 emissions from these power plants in the long-run, which exceed the threshold value. But it has a negative and statistically significant impact only on the CO_2 emissions from the natural gas power plants in the short-run. The results of the study enable Chinese energy policymakers to update the ETS policy in its next phases.

It is recommended that the China's ETS policy needs to be expand to the majority of industries, particularly those with high carbon emissions. Since China has other environmental policies and regulations, a master plan for all need to be prepared and combined. The government's programs for environmental protection must stimulate clean and high-tech industries. The government needs to pay more attention to the differences between industries and regions and prepare effective and appropriate policies and programs for each. The main limitation of the emission trading scheme investigation is the availability of microdata on the amount of emission of major carbon emitting industries and their economic performance. Improvements in the availability of microdata are also recommended.

For future studies, we recommend the use of more appropriate and relevant variables in the modeling to predict the impact of the ETS policy on CO_2 emissions. the use of other econometric methods, such as panel data, is also recommended to predict the impact of the ETS policy on different region or industry.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: The world bank indicators and US Energy Information Administration (EIA).

Author contributions

The author confirms being the sole contributor of this work and has approved it for publication.

Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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