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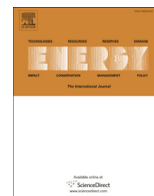
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# Forecasting carbon prices in the Shenzhen market, China: The role of mixed-frequency factors



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## ABSTRACT

In this study, the hybrid of combination-mixed data sampling regression model and back propagation neural network (combination-MIDAS-BP) is proposed to perform real-time forecasting of weekly carbon prices in China's Shenzhen carbon market. In addition to daily energy, economy and weather conditions, environmental factor is introduced into predictive indicators. The empirical results show that the carbon price is more sensitive to coal, temperature and AQI (air quality index) than to other factors. It is also shown that the forecast accuracy of the proposed model is approximately 30% and 40% higher than that of combination-MIDAS models and benchmark models, respectively. Given these forecast results, China's government and enterprises can effectively manage nonlinear, nonstationary, and irregular carbon prices, providing a better investing and managing tool from behavioural economics.

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## 1. Introduction

Over the last few decades, climate change has been considered the most serious environmental problem, raising common concerns for all countries, along with continuous economic development. China, as the largest carbon emitter, has played a major role in global climate change [1], and it has been confronted with increasing pressure to control carbon emissions [2]. In 2013 and 2014, seven national carbon markets were launched in five cities (Beijing, Shanghai, Tianjin, Chongqing and Shenzhen) and two provinces (Guangdong and Hubei) as part of China's commitment to the Kyoto Protocol [3]. The introduction of this market-based approach in China is seen as a major contribution to the achievement of the government's ambitious emissions reduction targets.

The forecasting of carbon prices plays a significant role in understanding China's carbon market dynamics and in making decisions about carbon emissions reductions. Since carbon prices reflect marginal abatement costs, they provide references for policy makers to evaluate climate policies and to alter emissions caps [4].

The forecasting of carbon prices has gained numerous scholars' attention, among which selecting appropriate indicators and models is crucial. Many related studies have confirmed that carbon prices are influenced by multiple variables, such as weather conditions, energy prices, and the economy [5]. Time series models, such as autoregressive integrated moving average model (ARIMA), artificial intelligence models, and the Markov switching model, have been broadly adopted. However, in the current literature, related data employed in forecasting processes emerge at the same frequency and are less prone to fluctuations, possibly resulting in information loss. In China, the carbon market in Shenzhen with the most active trading on carbon allowances is the first centrally approved system at state level [3]. In 2017, the accumulated trading amount of Shenzhen carbon market was up to 180 million tonnes, which has been the indicator of other carbon markets. The carbon price in the Shenzhen carbon market is impacted not only by the internal market but also by external environment heterogeneity [6]. These related data can be published at annually, quarterly, monthly and daily frequencies. Therefore, how to improve the

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forecast accuracy of carbon prices presents a great challenge and has become an urgent issue in China's carbon market.

The aim of this paper is to establish a new method to forecast carbon price with higher accuracy in Shenzhen's carbon market to help the Chinese government to formulate a carbon emissions policy. The main contributions involve three points. First, we construct a more comprehensive factor system, including energy, the economy, weather, and environmental factor. An interesting result is achieved such that the carbon price is more sensitive to coal, temperature and air quality index (AQI). Second, the hybrid of combination-mixed data sampling regression model and back propagation neural network (combination-MIDAS-BP) is presented to perform real-time forecasting of weekly carbon prices using the latest available daily factors. The forecasting of weekly carbon prices is more meaningful for main traders (e.g., electricity generation firms) in the carbon market to optimize their trading strategies over long horizons. Third, compared with the benchmark models, i.e., autoregressive (AR), moving average (MA) and threshold autoregressive conditional heteroskedasticity (TGARCH) models, our proposed method overcomes the error accumulation in these benchmark models and improves the accuracy by approximately 30% and 40% over that of combination-MIDAS models and benchmark models, respectively. The better performance of carbon price forecasting is beneficial for all of the participants in the carbon market.

The remainder of this paper is organized as follows. Section 2 contains a brief literature review. Section 3 introduces the methods used in this paper. The data and empirical results are displayed in Section 4. Section 5 reports the research conclusions.

## 2. Literature review

To forecast carbon prices with greater accuracy, some studies have used the relative factors to forecast, in addition to the carbon price itself. For example, an interesting conclusion is that weather conditions can influence energy demand and have effects on carbon prices. Rickels et al. [5] used temperature as a proxy for weather and identified that temperature has an effect on carbon prices because higher temperature weather creates a great demand of cooling, definitely increasing energy consumption. Alberola et al. [7] concluded that only extreme temperatures influence EUA spot prices, while Lutz et al. [8] indicated that the influence of extreme weather conditions on EUA returns is statistically insignificant.

Energy factors are the most natural determinant of carbon prices because electricity production companies can change their fuel inputs. The existing literature concerning the relationships between carbon price and energy factors has mainly focused on four aspects: coal, oil, natural gas, and electricity. First, coal prices are regarded as a central determinant of carbon prices because coal is a primary source of carbon emissions. Hintermann [9] suggested that coal prices have a negative impact on carbon allowance prices in the EU emissions trading system (EU ETS) market. Zhao et al. [10] demonstrated that carbon prices are significantly impacted by coal prices, although carbon prices vary obviously in different carbon markets in China. Second, oil prices are generally substantiated to have played dominant roles in price change trends among energy markets. Wang and Guo [11] found that the oil market transmits stronger spillover effects on carbon markets than other energy markets. Boersen and Scholtens [12] showed that a shock to oil returns plays positive role in carbon prices. Third, the carbon emissions yielded by gas are only half those produced by coal at the same unit. Therefore, gas is expected to become an important fuel for the power generation industry and plays a significant role in the energy market. Hammoudeh et al. [13] demonstrated that an unexpected increase in the natural gas price could reduce the

European Union Allowances (EUA) price. Fourth, electricity production is a large source of carbon emissions. However, the relationship between the electricity price and the carbon price is not clear. Aatola et al. [4] showed that there are no robust causalities between the EUA price and the electricity price. An alternative explanation is either that the electricity price impacts the carbon price or that the carbon price impacts the electricity price.

Macroeconomic shocks influence the relative demand for goods through incomes and saving, then impacting the prices of goods. When the economy is prosperous, industrials face increasing demand and arrange more production. Then, carbon emissions and the demand for carbon allowances increase as well. Chevallier [14] suggested that carbon prices negatively respond to exogenous shocks that decrease global economic indicators by one standard deviation, using monetary aggregates, price indices, exchange rate, and bond and stock indices. Furthermore, Creti et al. [15] used a stock futures index to represent economic activities and found a cointegrating connection between carbon prices and economic indicators. Moreover, Chevallier [16] used industrial production as a proxy for economic activities and showed that industrial production has a positive impact on EUA prices during periods of economic expansion, while it influence the EUA prices negatively during periods of economic recession.

From the perspective of forecasting models, the artificial intelligence models have been widely applied to forecast carbon prices since they can effectively capture the nonlinear characteristics of carbon prices. Fan et al. [17] used a multi-layer perception neural network prediction model for carbon prices to explain their nonlinearity. However, Anand and Suganthi [18] suggested that a single prediction approach could not produce better performance all the time because of sampling variation, structural changes, and model uncertainty. Therefore, hybrid models have been proposed to overcome the drawbacks of single models to improve the forecast accuracy of carbon prices. Zhu and Wei [19] combined an ARIMA model and least squares support vector machine (LSSVM) to forecast carbon prices and demonstrated greater accuracy than that of single ARIMA, LSSVM, and artificial neural network (ANN). Atsalakis [20] used three computational intelligence techniques to forecast carbon prices and revealed that the novel hybrid neuro-fuzzy controller that forms closed-loop feedback mechanism (PATSON) performs best. Zhu et al. [21] established an empirical mode decomposition-based evolutionary least squares support vector regression multiscale ensemble forecasting model for carbon prices and showed more robust performance. Zhang et al. [22] proposed a hybrid model combined with a complete ensemble empirical mode decomposition (CEEMD), a co-integration model (CIM), generalized autoregressive conditional heteroskedasticity model (GARCH), and a grey neural network (GNN) optimized by ant colony algorithm (ACA) to forecast carbon spot prices and showed remarkably better performance.

However, the above forecasting models require that the relevant drivers be predicted first when forecasting carbon prices. Hence, inaccurate forecasting of the drivers will increase the forecast errors for carbon prices. On the other hand, these forecasting models require that all data be of the same frequency. For example, the equal-weight type method is used to solve all indicators to be the same frequency, which cannot capture the information available in high-frequency variables. Hence, there are information loss and biased forecasts. It is urgent to establish new approaches to manage the problem of mixed frequency to realize more accurate forecasting of carbon prices. To address the limitations shown above, we introduce a MIDAS regression model to predict carbon prices, which uses highly parsimonious lag polynomials to allow data with different frequencies in the model to fully use effective information about the higher-frequency explanatory variables [23].

Different from the traditional individual-MIDAS regression models, this paper proposes combination-forecast pooling with five types of weight schemes to establish a hybrid of a combination-mixed data sampling regression model and a back propagation neural network (combination-MIDAS-BP) to manage the uncertainty. Specifically, we begin by investigating the out-of-sample forecast accuracy of numbers of individual MIDAS regression models by comparing the root mean squared errors (RMSE). Furthermore, the forecast results of combination-MIDAS are obtained based on the forecast results of the best individual MIDAS models. Then, the BP neuron network is applied to correct the forecast error of the combination-MIDAS model to reflect nonlinear patterns of carbon prices. Finally, based on the combination-MIDAS-BP, we can forecast carbon prices with multiple influencing factors. The results show that carbon prices are more sensitive to coal, temperature and air quality index (AQI), indicating the rationality of considering AQI a main driver of carbon prices. This study is an attempt to build a bridge between carbon investment and behaviour economics.

### 3. Methodology

The MIDAS model has the following two advantages over the traditional forecasting models. First, the MIDAS method can enhance forecast accuracy because it can fully utilize high-frequency data without substantial loss of sample information. Second, MIDAS can realize real-time forecasts using the latest published data. This method has been substantiated as useful for various forecasting applications, such as forecasting of financial markets [24,25] and macroeconomic problems, e.g., GDP [26] and inflation [27,28].

#### 3.1. Combination-MIDAS models

In recent years, combination-MIDAS models have been proposed as a simple and effective method to manage the misspecification issues of MIDAS models. This proposed model can obtain forecast results with greater accuracy using forecasts of numbers of individual MIDAS methods, rather than the best one [29]. For example, the combination-MIDAS model has been used to forecast U.S. federal government current expenditures and receipts [30], energy demand in China [31] and carbon price in the EU ETS [32].

There exist several different ways to form combination-MIDAS models, given the forecast results of several individual MIDAS models. Given  $N$  forecast results of individual MIDAS methods with different indicators, the forecast result of a combination-MIDAS regression model is defined as follows:

$$\hat{f}_{N,T+s|T} = \sum_{j=1}^N \hat{w}_{j,T} \hat{y}_{j,T+s|T} \quad (1)$$

where  $\hat{w}_{j,T}$  is the combination weight of the forecast result of the individual MIDAS approach with  $j$ th indicator,  $T$  refers to the last observation of the estimation sample for the individual MIDAS model,  $s = 1, 2, \dots, S$ , and  $\hat{y}_{j,T+s|T}$  suggests the  $s$ th forecast result obtained by the trained individual MIDAS model with the greatest forecast accuracy. This paper considers five types of  $\hat{w}_{j,T}$ , i.e., the mean squared forecast error (MSFE) type, the discounted mean squared forecast error (DMSFE) type, the Akaike information criteria (AIC) type, the Bayesian information criteria (BIC) type and equal-weighted type [29,31,32]. For the details of these five weight types, please see Appendix A.1.

A key problem with the combination-MIDAS regression model is

how to choose the individual MIDAS with the greatest forecast accuracy. To achieve real-time forecasting with the latest available data and to consider the autoregressive effect of  $Y_t$ , the ADL – MIDAS( $m, k, h$ ) model with  $h$ -step-ahead is presented. This model is defined as

$$Y_t = \alpha + \sum_{j=1}^p \gamma_j Y_{t-j} + \beta W(L^{1/m}, \theta) x_{t-h/m}^{(m)} + \varepsilon_t \quad (2)$$

where  $\alpha, \gamma_j$  and  $\beta$  are unknown parameters,  $Y_t$  is the weekly carbon price,  $p$  is the maximum lag order for  $Y_t$ , and  $x_t^{(m)}$  is a daily factor that can be observed  $m$  times from period  $t - 1$  to  $t$ . This paper set  $m = 5, t = 1, 2, \dots, T$ . Here,  $h$  refers to the leads of daily factors. When  $h = 1$ , we can use the daily data before Thursday to forecast carbon prices for this week. Set  $L^{k/m} x_t^{(m)} = x_{t-k/m}^{(m)}$  where  $L^{1/m}$  is a lag operator. When  $k = 0$ ,  $x_{t-k/m}^{(m)}$  refers to the fifth data from week  $t$ ; when  $k = 1$ ,  $x_{t-k/m}^{(m)}$  refers to the fourth data from week  $t$ .  $W(L^{1/m}, \theta)$  is decided by  $L^{1/m}$  and a parameter vector with limited dimension  $\theta$ . Then,  $W(L^{1/m}, \theta)$  can be defined as  $W(L^{1/m}, \theta) = \sum_{k=0}^K w(k; \theta) L^{k/m}$ , where  $w(k; \theta)$  is a polynomial weight, and  $K$  is the maximum lag order of the high-frequency factor.

To reflect the effects of different high-frequency factors on carbon prices, this paper considers the beta polynomial, BetaNN polynomial, exponential Almon lag polynomial, Almon lag polynomial, step function and unrestricted MIDAS (UMIDAS) polynomial [33], as detailed in Appendix A.2, and chooses the most suitable polynomial specification for each factor.

#### 3.2. BP neural network

To simulate the Shenzhen carbon market and to improve the forecast accuracy of combination-MIDAS, the BP neural network is used to correct the forecast error since it can capture the nonlinear characteristics. The advantage of the BP neural network is that it can capture the nonlinear characteristic without a specific model form [34]. Therefore, the proposed combination-MIDAS-BP can utilize the strengths of both combination-MIDAS and the BP neural network.

The BP neural network, featured by back propagation error, is a multi-layer feed forward network and can demonstrate the nonlinear pattern of data. This paper establishes a three-layer BP neural network since it has been theoretically proved that a neural network with three layers can reflect any continuous relationship with desired precision [33]. There are  $n$  neurons in the input layer,  $p$  neurons in the hidden layer, and one neuron in the output layer. The learning step is set to 1000 steps, and the learning rate is 0.01. The target error is 0.001.

Denote  $X(t) = (x_1, x_2, \dots, x_n)$  as the input vector of an input layer. Each neuron in the hidden layer depends on all of the neurons within the input layer. The output of hidden layer is displayed as

$$ho_h = f(hi_h) = f\left(\sum_{i=1}^n w_{ih} x_i(t) - b_h\right) \quad (3)$$

where  $hi_h$  ( $h = 1, 2, \dots, p$ ) is the input of the hidden layer,  $w_{ih}$  is the connection weight between the input layer and hidden layer, and  $b_h$  indicates the threshold value of the neurons in the hidden layer.

The output of the output layer is similarly defined as

$$yo = f(yi) = f\left(\sum_{h=1}^p w_{ho} ho_h - b_o\right) \quad (4)$$

where  $yi$  is the input of the output layer,  $w_{ho}$  is the network weight between the hidden layer and the output layer, and  $b_o$  indicates the

threshold value of the neurons in the output layer.

The error between the actual output and the desired output is given as

$$e = \frac{1}{2}(d - y_o)^2 \quad (5)$$

where  $d$  represents the desired output, and  $y_o$  is the actual output. Therefore, the error of the neural network is the function of the network weights among different layers.

### 3.3. Combination-MIDAS-BP regression models

In this paper, the proposed combination-MIDAS-BP regression model consists of four steps, as shown in Fig. 1. Step 1 refers to establishing an individual MIDAS regression model and chooses the model with the greatest accuracy for each predictor according to its out-of-sample forecast accuracies. The forecast accuracy is represented by the root mean squared errors (RMSE), consistent with the previous literature [35–37], because RMSE is a good indicator for testing the performance of out-of-sample forecasts. Step 2 combines the best individual MIDAS model for each predictor with five weighting schemes and calculates the forecast error of the combination-MIDAS model. Step 3 inputs the error of the combination-MIDAS model into the BP neuron network to forecast and correct the error. Step 4 adds the forecast results gained from the combination-MIDAS and BP neuron network to compute the final forecast of carbon prices.

## 4. Data description and empirical results

### 4.1. Data description

The dataset consists of weekly carbon prices and daily factors selected from energy, economy, weather and environmental aspects. The sample covers the period from January 6, 2014, to June 9, 2017. The period from January 6, 2014, to February 24, 2017, is chosen as the estimation sample to train the proposed models and benchmark models. The period from March 3, 2017, to June 9, 2017, is utilized for the out-sample forecast. The number of out-of-sample observations is determined according to the literature [30,35].

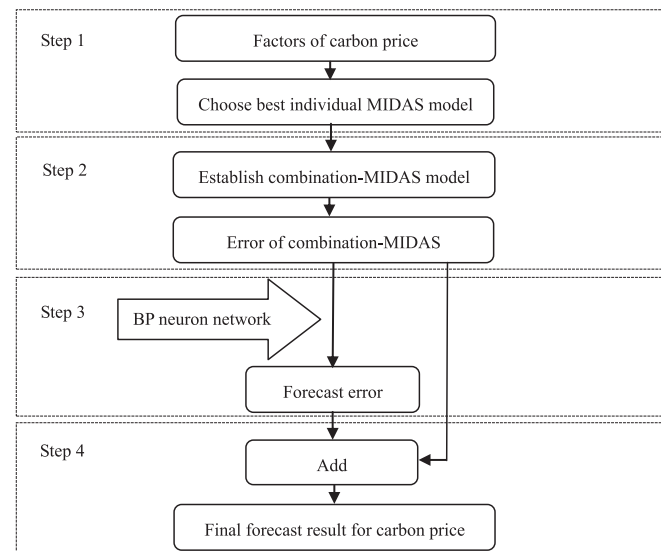


Fig. 1. Flow chart of combination-MIDAS-BP model.

This paper chooses the carbon spot price in Shenzhen because of its representativeness discussed above. The weekly carbon price is defined as the average value of the daily prices in a given week, which can be obtained in the Wind database. Moreover, this paper selects coal and oil prices as proxies for energy factors, which are available in the Wind database. The coal price is defined as the daily continuous coal futures settlement price. The oil price is the Daqing oil price. To proxy economic factors, this paper selects the Shanghai and Shenzhen 300 index (HS300), which is the leading stock index in China and is available in the Wind database. Regarding the weather condition, this paper selects the daily average temperature (Temp) in Shenzhen city, which is available from the National Oceanic and Atmospheric Administration (NOAA). For environmental factors, this paper selects the air quality index (AQI) in Shenzhen, which is available from the Environmental Protection Agency of the People's Republic of China.

To eliminate heteroscedasticity, the factors' growth rates denoted by  $growth_{it}$  are considered in the empirical analysis. They are expressed as

$$growth_{it} = \ln(value_{it}/value_{it-1}) \times 100 \quad (6)$$

where  $i$  is the factor, e.g., carbon price, coal and oil price, HS300 index, temperature (Temp) or AQI. The growth rates of these indicators are plotted in Fig. 2.

### 4.2. Selection of best individual MIDAS models

The individual MIDAS models apply a single predictor to perform the weekly carbon price forecast using the models shown in Section 3.1. As the first step to construct the combination-MIDAS-BP model for weekly carbon forecasts, the selection of the best individual MIDAS model is a key step because it directly influences the accuracy of the final forecast. The best individual MIDAS models are selected by comparing the RMSEs of different MIDAS regression models. The most sensitive predictor of carbon price can also be chosen according to the RMSEs of individual MIDAS regression models.

The optimal lag order and parameters of the daily indicators and weekly carbon price are also determined by comparing the RMSEs of individual MIDAS models with a fixed window method (equation (2) in section 3.1 and equations (11)–(15) in Appendix A.2). To reflect the change trend in the RMSEs, this paper sets the maximum lag orders of daily coal, oil, HS300, Temp, and AQI as 35 and sets the maximum lag orders for weekly carbon price as 5 when considering the 0, 1, 2, and 3 step ahead conditions. This paper considers individual MIDAS regression models without leads based on coal prices as an example to explain the mechanism determining the optimal lag order and parameters. Table 1 shows the RMSEs of individual MIDAS models based on coal prices. When no lag order for carbon price is considered, the best polynomial weight is BetaNN, and the best lag order for coal is 15. When the lag order for carbon price is 1, the best polynomial weight is BetaNN, and the best lag order for coal is 28. When the lag order for carbon price is 2, the best polynomial weight is BetaNN, and the lag order for coal is 15. When the lag order for carbon price is 3, the best polynomial weight is BetaNN and lag order for coal is 28. When the lag order for carbon price is 4, the best polynomial weight is still BetaNN, and lag order for coal is 15. The empirical results show that, with the variation in the lag order for carbon price, the influence of coal on it lasts from 15 to 28 days. At the same time, the BetaNN polynomial weight performs better for all conditions of different lag orders for carbon prices, indicating that this type of weight can better capture the relationship between coal and carbon prices. Furthermore, when the lag orders for carbon prices and coal are 3 and 28, respectively, with BetaNN polynomial weights, namely AR(3)-BetaNN-MIDAS(5,28)

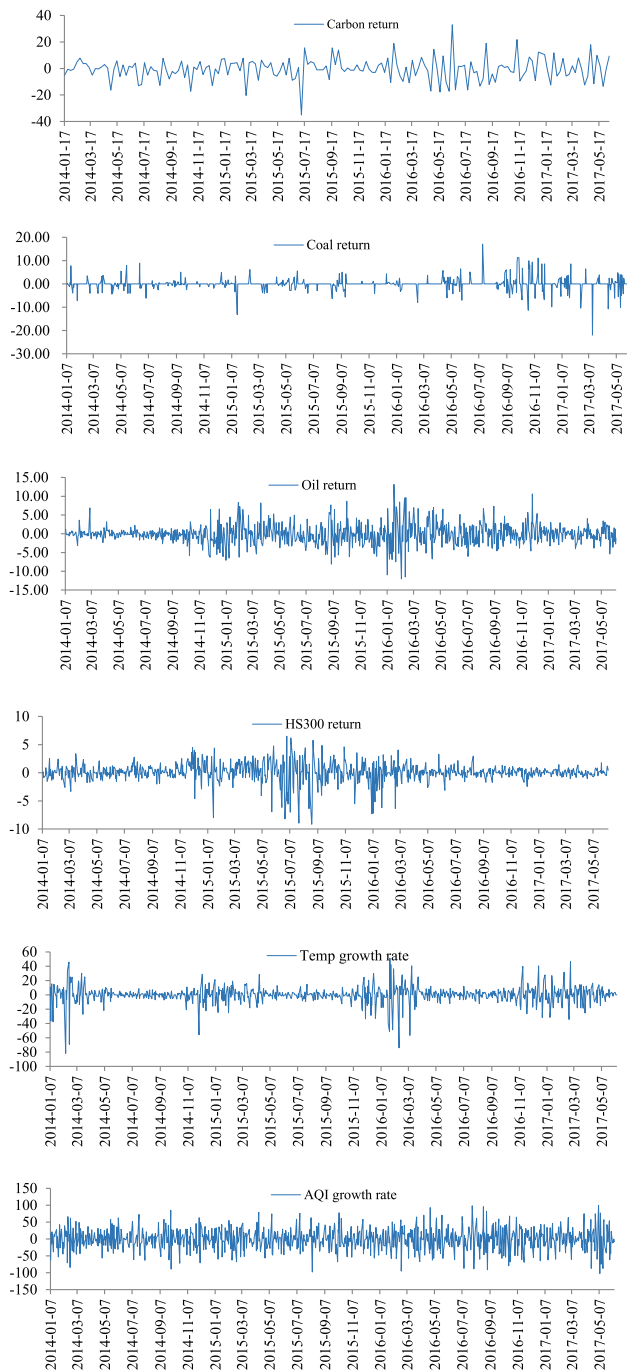


Fig. 2. Growth rates of carbon price, coal price, oil price, HS300 index, Temp, and AQI.

has the highest out-of-sample forecast accuracy.

Considering the different relationships between carbon prices and coal, oil, HS300, Temp, or AQI, this paper applies different polynomial weight types and lag orders for both carbon prices and their factors to decide on the best individual MIDAS model. Using the mechanism shown above, the best individual MIDAS models under all of the conditions are selected. The coefficients in the models are significant. As shown in Table 2, the best individual MIDAS model based on coal for all conditions is still AR(3)-BetaNN-MIDAS(5,28) when the h-step is 0, which has the smallest RMSE. For oil, the individual MIDAS regression model with the greatest accuracy is the one for which the lag orders for carbon price and oil

price are 4 and 31, respectively, with BetaNN polynomial weight when considering 1 step ahead. For HS300, the individual MIDAS regression model with the greatest accuracy is the one that lag orders for carbon prices and HS300 at 4 and 9 with UMIDAS polynomial weights when the h-step is 0. For Temp, the individual MIDAS regression model with the greatest accuracy is the one with lag orders for carbon prices and Temp of 4 and 35 with Step polynomial weights when the h-step is 2. For AQI, the individual MIDAS regression model with the greatest accuracy is the one with lag orders for carbon price and AQI of 4 and 35 with Step polynomial weights when the h-step is 3. At the same time, the effects of coal, oil, Temp, and AQI on carbon prices last longer than the effect of HS300, consistent with the findings of Zhao et al. [32] for carbon prices in EU ETS. However, the best polynomial weight for energy and economic factors are different from the findings of Zhao et al. [32], indicating that the influential processes among carbon prices, energy and economic factors in the Shenzhen market, China, are different from those in the EU ETS. Moreover, in contrast with Zhao et al. [32], carbon prices are significantly auto-correlated in the Shenzhen market of China, lasting for 3 or 4 weeks. Furthermore, when considering 0 or 3 steps ahead, the carbon price is most sensitive to AQI, which indicates the reasonability of including AQI in the indicator set for carbon price. When considering 1 step ahead, carbon price is most sensitive to coal because coal consumption is the largest source of carbon emissions, determining the demand for carbon allowances. When considering 2 steps ahead, carbon price is most sensitive to temperature because it has a significant impact on energy consumption. In general, carbon price is more sensitive to coal, temperature and AQI than to other factors.

#### 4.3. Forecast results of Combination-MIDAS models

The drivers of carbon price considered in this paper have different information sets, which can affect the individual forecasts discussed in Section 4.2. Instead of only utilizing one combination method to determine the weights for each forecast result of the best individual MIDAS models [30], this paper proposes a combination-MIDAS model with five different weight schemes (as shown in equation (1) in Section 3.1 and equations (7)–(10) in Appendix A.1) to address the misspecification biases because it can maintain better performance under structural breaks.

Table 3 shows the out-of-sample forecast accuracy of the combination-MIDAS model. The empirical results suggest that the five weight schemes perform better when considering no steps ahead. Specifically, when considering no steps ahead, AIC and BIC weight schemes have greater forecast accuracy, followed by MSFE weight type. When considering 1 step ahead, MSFE and Equal Weights have greater forecast accuracy, followed by DMSFE weight type. When considering 2 steps ahead, the DMSFE, MSFE, and BIC weight types have greater forecast accuracy than AIC and Equal Weights. When considering 3 steps ahead, MSFE has greater forecast accuracy, followed by DMSFE and Equal Weights. Therefore, MSFE is more robust than the other weight types when forecasting weekly carbon prices.

#### 4.4. Forecast comparison: combination-MIDAS-BP models vs. AR, MA and TGARCH

In this section, the combination-MIDAS-BP model is compared with benchmark models, e.g., AR, MA and TGARCH models. All of the benchmark models are significant at the 1% level. Table 4 represents the forecast accuracy of the combination-MIDAS-BP model. The empirical results demonstrate that the BP neuron network has good performance when correcting forecast errors, similar to the findings of Zhao et al. [33]. The forecast accuracy of combination-

**Table 1**  
RMSEs of individual MIDAS models without leads based on coal price.

Weights	Lag order for coal price					Lag order for coal price				
	6	15	24	28	35	6	15	24	28	35
0 lag orders for carbon price						1 lag order for carbon price				
Beta	8.60	8.60	8.60	8.60	8.60	8.02	8.02	8.02	8.02	8.02
BetaNN	8.80	<b>8.23</b>	8.35	8.66	8.60	8.22	7.75	7.85	<b>7.64</b>	8.05
ExpAlmon	8.60	8.60	8.60	8.60	8.60	8.02	8.02	8.02	8.02	8.02
Almon	8.78	8.40	8.70	8.84	9.33	8.38	8.01	8.16	8.51	8.71
Step	8.59	8.93	9.37	9.94	12.10	7.99	8.31	8.66	8.69	11.38
UMIDAS	8.55	10.62	11.40	11.32	11.03	8.26	10.51	11.77	11.09	11.30
2 lag orders for carbon price						3 lag orders for carbon price				
Beta	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50
BetaNN	7.65	<b>7.23</b>	7.34	7.94	7.68	7.64	7.30	7.34	<b>6.96</b>	7.52
ExpAlmon	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50
Almon	7.85	7.57	7.58	8.12	8.11	7.86	7.61	7.59	8.16	8.12
Step	7.43	7.73	8.03	7.96	10.54	7.43	7.73	8.06	7.94	10.61
UMIDAS	7.58	10.02	11.19	10.45	10.64	7.57	10.24	11.25	10.51	10.69
4 lag orders for carbon price						5 lag orders for carbon price				
Beta	7.44	7.44	7.44	7.44	7.44	7.49	7.49	7.49	7.49	7.49
BetaNN	7.60	<b>7.17</b>	7.30	<b>7.17</b>	7.44	7.69	<b>7.16</b>	7.30	7.66	7.48
ExpAlmon	7.44	7.44	7.44	7.44	7.44	7.49	7.49	7.49	7.49	7.49
Almon	7.78	7.54	7.53	8.11	8.05	7.92	7.62	7.54	8.14	8.06
Step	7.33	7.72	8.08	8.14	10.98	7.40	7.77	8.13	8.24	11.09
UMIDAS	7.54	10.57	11.42	10.91	11.55	7.71	10.59	11.41	10.88	11.42

Notes: The bold values represent the smallest RMSE under the condition of different lag orders for carbon prices.

**Table 2**  
Best individual MIDAS models under all conditions.

H	Model	RMSE
Panel A: Coal		
0	AR(3)-BetaNN-MIDAS(5,28)	<b>6.96</b>
1	AR(4)-BetaNN-MIDAS(5,27)	7.07
2	AR(4)-BetaNN-MIDAS(5,26)	7.04
3	AR(4)-BetaNN-MIDAS(5,25)	7.04
Panel B: Oil		
0	AR(4)-BetaNN-MIDAS(5,19)	7.25
1	AR(4)-BetaNN-MIDAS(5,31)	<b>7.24</b>
2	AR(4)-BetaNN-MIDAS(5,17)	7.26
3	AR(4)-BetaNN-MIDAS(5,29)	7.27
Panel C: HS300		
0	AR(4)-U-MIDAS(5,9)	<b>7.24</b>
1	AR(4)-U-MIDAS(5,8)	7.25
2	AR(4)-U-MIDAS(5,7)	7.26
3	AR(4)-U-MIDAS(5,6)	7.34
Panel D: Temp		
0	AR(4)-ExpAlmon-MIDAS(5,28)	7.11
1	AR(4)-BetaNN-MIDAS(5,27)	7.24
2	AR(4)-Step-MIDAS(5,35)	<b>7.03</b>
3	AR(4)-BetaNN-MIDAS(5,25)	7.23
Panel E: AQI		
0	AR(5)-BetaNN-MIDAS(5,22)	6.89
1	AR(5)-Step-MIDAS(5,34)	7.10
2	AR(5)-BetaNN-MIDAS(5,19)	7.08
3	AR(4)-Step-MIDAS(5,35)	<b>6.86</b>

Notes: The bold values represent the smallest RMSE under the condition of different lag order for carbon price.

**Table 3**  
RMSEs of combination-MIDAS regression models.

Weight	h = 0	h = 1	h = 2	h = 3
MSFE	6.98	<b>7.01</b>	<b>7.00</b>	<b>7.01</b>
DMSFE	6.98	7.02	<b>7.00</b>	7.02
AIC	<b>6.96</b>	7.15	7.24	7.28
BIC	<b>6.96</b>	7.07	<b>7.00</b>	7.04
Equal Weights	6.99	<b>7.01</b>	<b>7.01</b>	7.02

Notes: The bold values represent the smallest RMSE under the condition of different lag orders for carbon prices.

**Table 4**  
RMSEs of combination-MIDAS-BP regression models.

Weight	h = 0	h = 1	h = 2	h = 3
MSFE	4.74	4.71	4.84	4.77
DMSFE	4.79	4.71	4.35	4.82
AIC	4.75	4.85	4.80	4.99
BIC	4.80	4.76	4.81	4.69
Equal Weights	4.71	4.69	4.80	4.75

MIDAS-BP is approximately 30% greater than that of combination-MIDAS models using the BP neuron network to correct the forecast error.

Table 5 demonstrates the RMSE ratios of the combination-MIDAS-BP model to benchmark models and compares their predictive abilities. If the RMSE ratio is smaller than 1, the combination-MIDAS-BP model has greater forecast accuracy than

**Table 5**  
Comparison of the combination-MIDAS-BP models with AR, MA and TGARCH models.

Weight	h = 0	h = 1	h = 2	h = 3
Panel A: AR model				
MSFE	0.58	0.58	0.59	0.59
DMSFE	0.58	0.58	0.53	0.59
AIC	0.58	0.60	0.59	0.61
BIC	0.59	0.58	0.59	0.58
Equal Weights	0.58	0.58	0.59	0.58
Panel B: MA model				
MSFE	0.61	0.61	0.62	0.61
DMSFE	0.61	0.61	0.56	0.62
AIC	0.61	0.62	0.62	0.64
BIC	0.62	0.61	0.62	0.60
Equal Weights	0.61	0.60	0.62	0.61
Panel C: TGARCH model				
MSFE	0.58	0.58	0.59	0.58
DMSFE	0.58	0.58	0.53	0.59
AIC	0.58	0.59	0.59	0.61
BIC	0.59	0.58	0.59	0.57
Equal Weights	0.58	0.57	0.59	0.58

the benchmark models. The results show that combination-MIDAS-BP increases the forecast accuracy by approximately 40% compared with benchmark models, proving that using daily drivers can enhance the forecast accuracy for forecasting weekly carbon prices. These results suggest that the proposed combination-MIDAS-BP model can better take advantage of the strengths of single models, in line with the previous studies [30–33].

## 5. Conclusions

In this paper, we aim to render the method for carbon price forecasting more efficient and effective in the Shenzhen carbon market. Therefore, we propose the combination-MIDAS-BP regression model to overcome the weaknesses of carbon price forecasting. First, individual MIDAS models based on coal, oil, HS300, Temp, and AQI are analysed, and the best individual MIDAS models are selected according to the RMSE index. Second, the best individual MIDAS models are combined with five weight schemes to manage the misspecification biases because they can maintain better performance under structural breaks. Third, this paper uses the BP neuron network to address the uncertainties faced by the combination-MIDAS regression model.

In general, we can draw some conclusions from the empirical analysis results. (1) The effects of coal, oil, Temp, and AQI on carbon prices last longer than the effect of HS300. (2) The carbon price in the Shenzhen market has a significant auto-correlation. (3) Carbon prices are more sensitive to coal, temperature and AQI than to oil and HS300. (4) The MSFE weighting type is more robust as a reference for deciding the weights for the forecast results of the best individual MIDAS models when we establish combination-MIDAS models. (5) The forecast accuracy of the combination-MIDAS-BP model is approximately 30% and 40% greater than that of combination-MIDAS models and benchmark models, respectively. Therefore, the proposed model could provide significant improvements for carbon price prediction and is competitive at predicting nonlinear and irregular carbon prices.

In further research, we aim to choose another forecast model to correct the error of the combination-MIDAS regression model. Furthermore, establishing a more comprehensive factor systems for carbon price forecasting is another challenge because there are other indicators that can influence carbon prices, such as the behaviour of participants in the carbon market.

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## Appendix A

### A.1 Combination weights

#### (i) MSFE-weighted type

The mean squared forecast error (MSFE) is used to combine individual approach. The weight is given as

$$w_{j,T} = m_{j,T}^{-1} / \sum_{j=1}^n m_{j,T}^{-1} \quad (7)$$

where  $m_{j,T} = \sum_{i=T_0}^t (\delta^{i-T_0} (y_{j,T+s} - \hat{y}_{j,T+s|T}))^2 / (t - T_0 + 1)$ . When  $\delta = 1$ ,  $m_{j,T}$  is defined as the MSFE of individual MIDAS model with  $j$ th factor.  $T_0 - t + 1$  is the number of the out-of-sample,  $y_{j,T+s}$  refers to the real observation.

#### (ii) DMSFE-weighted type

When  $\delta = 0.9$  in MSFE-weighted scheme discussed above, it refers to the discounted mean squared forecast error (DMSFE)-weighted type.

#### (iii) AIC-weighted type

AIC refers to the Akaike information criteria (AICs) and is defined as follows:

$$w_{j,T} = \exp(-AIC_j) / \sum_{j=1}^N \exp(-AIC_j) \quad (8)$$

#### (iv) BIC-weighted type

BIC refers to Bayesian information criteria, which is generally applied to combine probability forecasts. BIC-weight scheme is given as follows:

$$w_{j,T} = \exp(-BIC_j) / \sum_{j=1}^N \exp(-BIC_j) \quad (9)$$

#### (v) Equal-weighted type

This kind of weight type plays a special role in the forecast combination literature. The weight is given as

$$w_{j,T} = 1/N \quad (10)$$

### A.2 Polynomial weights

The beta density function is given as

$$w(k; \theta) = w(k; \theta_1, \theta_2, \theta_3) = f(k/K, \theta_1, \theta_2) / \sum_{k=1}^K f(k/K, \theta_1, \theta_2) + \theta_3 \quad (11)$$

where  $f(x_i, \theta_1, \theta_2) = x_i^{\theta_1-1} (1-x_i)^{\theta_2-1} \Gamma(\theta_1 + \theta_2) / \Gamma(\theta_1) \Gamma(\theta_2)$  and  $\Gamma(\theta) = \int_0^1 e^{-x} x^{\theta-1} dx$ . The beta polynomial and BetaNN polynomial are derived from the beta density function according to the values of  $\theta_1, \theta_2, \theta_3$ . When  $\theta_3 = 0$ ,  $w(k; \theta) = w(k; \theta_1, \theta_2) = f(k/K, \theta_1, \theta_2) / \sum_{k=1}^K f(k/K, \theta_1, \theta_2)$ . Here,  $w(k; \theta)$  refers to the beta polynomial. When  $\theta_1 = 1$ ,  $w(k; \theta) = w(k; 1, \theta_2, \theta_3) = f(k/K, 1, \theta_2) / \sum_{k=1}^K f(k/K, 1, \theta_2) + \theta_3$ .  $w(k; \theta)$  refers to the Beta-Non-Zero (BetaNN) polynomial.

The exponential Almon lag polynomial is defined as

$$w(k; \theta) = e^{(\theta_1 k + \theta_2 k^2 + \dots + \theta_p k^p)} / \sum_{k=1}^K e^{(\theta_1 k + \theta_2 k^2 + \dots + \theta_p k^p)} \quad (12)$$

The Almon lag polynomial is displayed as

$$\beta w(k; \theta_0, \theta_1, \theta_2, \theta_3) = \sum_{p=0}^3 \theta_p k^p \quad (13)$$

The polynomial specification of step function is demonstrated as

$$\beta w(k; \theta) = \theta_1 I_{i \in [a_0, a_1]} + \sum_{p=2}^P \theta_p I_{i \in [a_{p-1}, a_p]}, \quad I_{i \in [a_{p-1}, a_p]} = \begin{cases} 1, & a_{p-1} \leq i \leq a_p \\ 0, & \text{otherwise} \end{cases} \quad (14)$$

where  $a_0 = 1 < a_1 < \dots < a_P = K$ .  
UMIDAS generalizes to:

$$Y_T = \alpha + B\left(\beta, L^{1/m}\right) x_t^{(m)} + \varepsilon_t \quad (15)$$

where  $B(\beta, L^{1/m}) = \sum_{k=0}^K \beta_k L^{k/m}$ .

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