
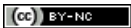


“Forecasting short-term carbon emission futures price volatility: information for hedging carbon emission futures risk”

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Forecasting short-term carbon emission futures price volatility: information for hedging carbon emission futures risk

Abstract

This paper aimed to illustrate how short-term carbon futures speculators might use short-term carbon emission futures data to predict and forecast carbon prices. The paper became apposite given ubiquitous research focussing on long-term carbon futures data, which has left out short-term carbon emission futures speculators with information. Therefore, this paper demonstrated that short-term speculators in carbon futures could indeed use short-term time series data on carbon futures to make a reliable prediction and forecasting of carbon emissions futures price volatility within a short term and thus decide on investment opportunity. The sample data results showed that short-term data could produce a dependable in-sample futures prediction since the in-sample prediction fell within the 95% confidence interval. The demonstration also showed that short-term carbon futures data could assist speculators to conduct a reliable short-term out of sample forecast of carbon futures prices within the closer period. The paper offers practical assistance to carbon futures speculators and is equally important for academic studies for business and economic students on discussions and research bordering on carbon emissions, carbon trading, environmental economics and sustainable development. More carbon short-term forecasting is encouraged – such research should compare short-term forecasting of carbon futures amongst different carbon markets.

Keywords: carbon futures, carbon price, carbon market, emission futures, forecasting, carbon risk, the EU emissions trading system (EU ETS), the clean development mechanism (CDM).

JEL Classification: Q54, G13.

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Introduction

Carbon emission trading has emerged as a global key catalyst, amongst others, for carbon emission reduction and sustainable economic development (Xiong, Shen, Qi, Price, & Ye, 2017; Rannou & Barneto, 2016; Ellerman, Convery, & De Perthuis, 2010). Similar to any other commodity traded in exchanges, carbon emission prices are subject to vagaries posed by systemic (market) events that thus cause fluctuations in the carbon emission futures market (Zhang, 2016). Given this inevitability of attendant volatilities and the potentially inherent risk, carbon emission traders and/or investors need information to reduce the risks that are associated with carbon futures volatility. The use of time series forecasting is one such important tool to provide the enabling forecast information on carbon emission futures either within the short term or long term.

In conventional financial markets, a futures market is a kind of subordinate instrument or monetary contract, in which two traders consent to execute an arrangement of money related instruments or physical wares for future conveyance at a specific cost (Kang, Rouwenhorst, & Tang, 2017). On the

chance that a speculator purchases a futures contract, the trader is fundamentally consenting to purchase something that a trader has not yet delivered at a set cost (Futures-Investor, 2017). The emergence of global carbon emissions markets has also engendered carbon emissions futures system with the carbon trading markets.

Both the purchasers and traders in the carbon emissions futures market business principally go into futures contracts mostly to support normal business risk speculation, which thus makes it that futures engagement resonates as a tool for financial risk hedging (Kang et al., 2017; Futures-Investor, 2017). This thus means that futures marketing deviate slightly from the business mode of spot or cash market, where physical cash is exchanged, hence the need for predicting and forecasting to reduce the risk of loss carbon future trading by carbon price speculators.

The global quest for carbon emission reduction (Clarke, Heinonen, & Ottelin, 2017; Doi, Popov, Barcelona, & Asano, 2011) and mostly the reduction of industrial carbon emission has given rise to the management and speculation of issues in environmental risk management and has thus become part of strategic operational decisions for industries involved in energy intensive processes. Accordingly, carbon futures or contract markets have emerged to provide a unique form of climate financial services, which assists industries and/or traders to hedge their imminent or potential exposure and the attendant mitigation of risks associated with carbon emission compliance (ICE, 2017).

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Whilst many of the research on carbon futures have focused more on long-term forecast of carbon futures, this paper stands out from others by demonstrating that short-term time series could also provide information on the carbon emission futures volatility for the short time carbon emission investors and speculators. This paper thus is important for short time carbon emission futures speculators as it demonstrates a handy non-complicated approach for carbon emission futures speculators who may not be skilled in advanced forecasting approaches. Accordingly, the objective of this paper is to demonstrate the use of short-term time series for forecasting carbon emission futures price and thus provide additional information for short-term carbon emission speculators.

Therefore, the paper has the following structure. After this introduction, the paper presents a brief review of related literature; this is followed by the methodology and results section. The last section of this paper presents the conclusion and recommendation.

1. Theoretical background

The cap and trade of carbon. There is no longer a doubt (except for climate denials) that climate change and the attendant potential catastrophic result for humans is real. This is why the Stern Review warned that, if ignored, climate change would affect humankind globally as scientific evidence alerts. According to Stern Review:

“The scientific evidence points to increasing risks of serious, irreversible impacts from climate change associated with business-as-usual (BAU) paths for emissions” (Stern, 2007, p. 3).

The IPCC (2017) adds that a variety of studies ranging from physiological, ecological and physical add confirmation about the negative implications of climate change on global biological and physical systems.

The warning by scientists triggered action by world bodies, partnerships and conventions such as the Kyoto Protocol, the UN Framework Convention on Climate Change (UNFCCC), the Intergovernmental Panel on Climate Change (IPCC) etcetera. Of these, the Kyoto Protocol stands out as the initiator of guidance on the capping and trading of carbon to alleviate the negative implications of continuous carbon emission in its usual stance.

“The Kyoto Protocol is an international agreement linked to the United Nations Framework Convention on Climate Change, which commits its Parties by setting internationally binding emission reduction targets” (UNFCCC, 2014, p. 1).

Therefore, contemporary trading and pricing of carbon takes a theoretical crux in the Kyoto Protocol; hence, this paper also draws its theoretical foundation on the Kyoto Protocol. This is because, this paper discusses a critical aspects of emission pricing by way of emission futures price forecasting, which is rooted on Kyoto cap and trade. Therefore, this paper contributes to the UN call for collective action to halt unbridled emission of carbon (UNFCCC, 2014).

The Kyoto Protocol gave impetus to three genre of malleable carbon reduction mechanisms, namely the joint implementation, the clean development mechanism and the emission trading (Hepburn, 2007). Emission trading functions through the cap and trade system. The cap system allows the governments to use regulatory initiatives to limit the quantity of carbon assigned or allowed for emission per year; hence, this limit is called the cap. Once a government has determined this cap, it then allocates quotas of this cap to businesses through emission allowance permits. This means that companies that exceed their allowable emission permits would be penalised through payment of carbon tax. In the same vein, businesses that are not able to utilise their assigned emission permit levels may sell such remaining permits to other businesses, such unutilized emission allowances gives rise to buying and selling of carbon emission permits or carbon trading. Since such purchasing and sales occur in a competitive financial market environment, it is open to risks associated with the market, hence forecasting the price risks of carbon emission becomes necessary to assist businesses comply with their countries' commitment to Kyoto Protocol; this forecasting is the focus of this paper. The following section reviews some related literature on carbon futures and forecasting.

2. Related literature

Given the newness of carbon market (Chevallier, 2009), it is not surprised that research bordering on futures market still focusses on conventional commodity markets whilst research about carbon futures is emerging. Despite the newness though, some researchers have begun to carve a new research niche to position carbon market and carbon emission as a new commodity that deserve attention, trading and monitoring using the forecast method.

Byun and Cho (2013) analyzed the instability determining capacities of three methodologies: GARCH approach that utilize carbon prospects prices, a suggested unpredictability from carbon alternatives prices, and the k-closest neighbor approach. In view of the outcomes, they report that

GARCH models perform superior to an inferred instability and the k-closest. This outcome recommends that carbon alternatives have little data about carbon futures because of their low exchanging volume. It has also been found that the price of energy and swapping of carbon trading has volatilities and correlation implication on the price of EU emission trading (Kanamura, 2016). Thus, the fluctuation effect from one market to the other causes risk spill over within and between the energy and carbon markets with the tendencies of implicit risk hedging volatility effect (Balcilar, Demirel, Hammoudeh, & Nguyen, 2016). Accordingly, if risk and fluctuation spill overs do exist between energy and carbon markets (Balcilar et al., 2016), it becomes plausible to expect fluctuations in the carbon futures, but what might be unknown is the angle of fluctuation, which thus necessitates constant research on fluctuation prediction such as in this research. Forecasting the fluctuation in carbon futures constitutes vital information for carbon traders and perhaps for energy traders especially as it provides the ground to nurture and apply suitable hedging strategies (Balcilar et al., 2016) to reduce the risk of loss in carbon trading arising from unplanned fluctuations. A combination of events study with the application of ICSS algorithm approach has been empirically proven to be an efficient tool for detecting and explaining structural breaks in carbon futures (Zhu & Chevallier, 2017). Amongst the findings of causes of carbon futures structural breaks include inter alia, periods of peak in carbon market, the 2008 and 2011 subprime crunch and the EU debt crunch, respectively (Zhu & Chevallier, 2017).

Alberola, Chevallier, and Chèze (2008) studied the day by day value basics of European Union Allowances (EUAs) exchanged from 2005 as a major aspect of the Emissions Trading Scheme (ETS). Two structural fluctuations became apparent on April 2006 and on October 2006 after the European Commission declaration of stricter phase of carbon trading. The outcomes broaden past findings by demonstrating that EUA spot costs respond to price of energy with weak forecasts, as well as to unexpected temperatures changes amid colder occasions. Whilst stressing the importance of multiple forecasting approach on carbon futures, Zhang, Zhang, Xiong, T., and Su (2017) applied the support vector regression approach with a mixture of another important tool, which is the particle swarm optimization to forecast next day's high and low carbon price fluctuations. Their findings indicate significant results, which show that the applied hybrid approach could greatly enhance the forecast of carbon price fluctuation at the interval level.

On the other hand, the likely effect of macroeconomic vagaries on carbon futures has also been receiving research attention (Zeng, Nan, Liu, & Chen, 2017; Chevallier, 2011; Chevallier, 2009), but with conflicting arguments. Some have, based on empirical results, argued that the carbon market is not strongly affected by fluctuations in the macroeconomic environment, but that the carbon market rather has little or slight association with the events in the macroeconomic environment (Chevallier, 2009). Instead, the carbon futures market might have a linkage with energy fluctuations and issues that link with carbon regulations or pronouncements (Baranzini, van den Bergh, Carattini, Howarth, Padilla, & Roca, 2017; Kanamura, 2016).

Since it is important to forecast futures volatility in conventional financial markets, it therefore becomes even more important to forecast the volatility in carbon futures, given the market's newness and the intricacies implicit in the buying and selling of carbon allowances (Smits, 2017; Gao, Smits, Mol, & Wang, 2016). Any news whether real or mere anecdote that flag likely impending and/or imminent carbon meetings and attendant change in policies triggers jittery and/or signals in the carbon futures (Capoor & Ambrosi, 2008). The carbon futures offer a vibrant catalyst to global quest for carbon emission reduction; therefore, market-forecasting tool such as the time series forecast is pertinent to reduce the risk of loss by carbon market participants who might apply the forecast results to hedge systemic risk (Tang, Shen, & Zhao, 2015; MISFD, 2014) in the carbon market. Tang et al. (2015) provide a detailed empirical study about carbon market systematic risk in their analysis of systemic risk inherent in carbon markets such as the EU ETS and the CDM. Their study indicate that whilst the EU ETS might present a systematic risk of about 0.07%, on the contrary, the CDM market tend to present lower or greater systematic risk than the EU ETS depending on the stage of the futures contract (Tang et al., 2015, p. 333). Whilst the previous research on carbon futures forecast have dwelt on long-term time series; this paper uses the following section to demonstrate that short term time series data on carbon futures could provide carbon emission price speculators with reliable prediction and forecasting information on carbon emission price volatility.

3. Method and results

Data used in this carbon futures forecast were collected from the Investing.com carbon futures monthly historical price data (Investing.com, 2017) for the months April 2015 to July 2017. Hence, the data constitutes monthly carbon futures data.

The time series dataset set were entered into the Gretl software, following this, the researcher derived the time trend, which served as the main independent variable; in addition to the time trend, the periodic dummies were also derived and entered into the Gretl software. Following this, a linear regression analysis was conducted (Table 1); thereafter, an in-sample forecast of carbon futures was conducted to estimate the closeness of the prediction to actual emissions price.

First before the forecast, a linear regression was conducted using the monthly carbon price as

the dependent variables, whilst the time trend and periodic dummies served as the independent variables. Thus, the linear regression model is represented as follows:

$$\gamma = \beta_0 + \beta_1\chi_1 + \beta_2\chi_2 + \varepsilon, \quad (1)$$

where γ represents the carbon price;

β_0 represents the regression intercept;

β_1 represents the regression coefficients;

χ_1 represents the time trend;

χ_2 represents the periodic dummies.

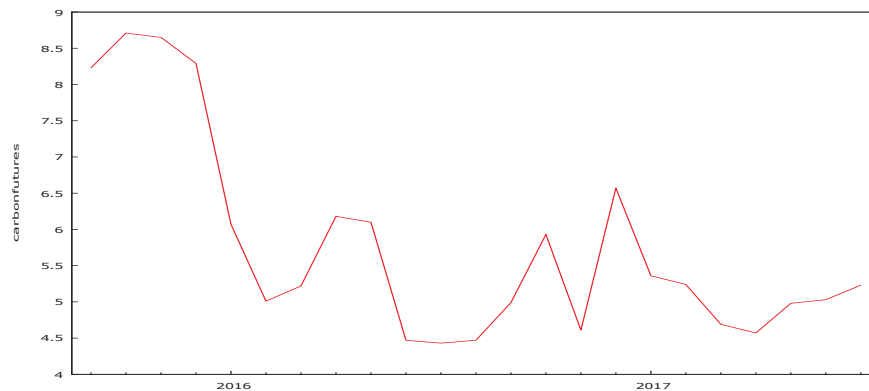


Fig. 1. The spikes of carbon futures in April 2015 to July 2017

In Figure 1, it can be seen that spikes peak up and down, which connotes some elements of seasonality in carbon price. A sharp peak is evident in some months in 2015, 2016 and 2017, all contributing to an uneven downward trend in

carbon price. The sharp peaks make it easier for a carbon speculator to watch out for likely repeats in future periods, hence visualisation of the spikes might also serve as a forecasting apparatus.

Table 1. Linear regression between of carbon futures with time trend as main regressor. Model 5: OLS, using observations September 2015 – July 2017 (T = 23). Dependent variable: carbon price

	Coefficient	Std. Error	T-ratio	P-value	
const	6.895	0.901797	7.6458	0.00002	***
time	-0.107273	0.039661	-2.7047	0.02213	**
dm2	-0.482727	1.11686	-0.4322	0.67476	
dm3	-0.545455	1.11897	-0.4875	0.63644	
dm4	-0.0181818	1.12248	-0.0162	0.98740	
dm5	0.254091	1.12738	0.2254	0.82622	
dm6	-0.428636	1.13364	-0.3781	0.71325	
dm7	-0.241364	1.14124	-0.2115	0.83675	
dm8	-1.13773	1.36759	-0.8319	0.42487	
dm9	0.465909	1.12738	0.4133	0.68813	
dm10	1.28318	1.12248	1.1432	0.27960	
dm11	0.700455	1.11897	0.6260	0.54535	
dm12	1.60773	1.11686	1.4395	0.18057	

Mean dependent var	5.783913	S.D. dependent var	1.396368
Sum squared resid	12.45811	S.E. of regression	1.116159
R-squared	0.709578	Adjusted R-squared	0.361071
F(12, 10)	2.036053	P-value(F)	0.134330
Log-likelihood	-25.58468	Akaike criterion	77.16936
Schwarz criterion	91.93078	Hannan-Quinn	80.88181
rho	0.609406	Durbin-Watson	0.723799

Table 1 indicates that only the time trend is significant at a P-value of 0.02, which is smaller than the alpha level of 0.05; none of the monthly dummies is significant since all the P-values are higher than 0.05.

the negative value of the time coefficient indicate that carbon prices have the tendency to decrease with time (within the sample period), which is a good information for carbon speculators.

Table 2. In-sample prediction September 2015 – July 2016 for 95% confidence intervals, $t(10, 0.025) = 2.228$

Obs	Carbon price	Prediction	Std. Error	95% interval
09 2015	8.23000	7.25364	1.38757	(4.16194, 10.3453)
10 2015	8.71000	7.96364	1.38757	(4.87194, 11.0553)
11 2015	8.65000	7.27364	1.38757	(4.18194, 10.3653)
12 2015	8.29000	8.07364	1.38757	(4.98194, 11.1653)
01 2016	6.07000	6.35864	1.38757	(3.26694, 9.45033)
02 2016	5.01000	5.76864	1.38757	(2.67694, 8.86033)
03 2016	5.22000	5.59864	1.38757	(2.50694, 8.69033)
04 2016:	6.18000	6.01864	1.38757	(2.92694, 9.11033)
05 2016	6.10000	6.18364	1.38757	(3.09194, 9.27533)
06 2016	4.47000	5.39364	1.38757	(2.30194, 8.48533)
07 2016	4.43000	5.47364	1.38757	(2.38194, 8.56533)
08 2016	4.47000	4.47000	1.57849	(0.952911, 7.98709)
09 2016	4.99000	5.96636	1.38757	(2.87467, 9.05806)
10 2016	5.93000	6.67636	1.38757	(3.58467, 9.76806)
11 2016	4.61000	5.98636	1.38757	(2.89467, 9.07806)
12 2016	6.57000	6.78636	1.38757	(3.69467, 9.87806)
01 2017	5.36000	5.07136	1.38757	(1.97967, 8.16306)
02 2017	5.24000	4.48136	1.38757	(1.38967, 7.57306)
03 2017	4.69000	4.31136	1.38757	(1.21967, 7.40306)
04 2017	4.57000	4.73136	1.38757	(1.63967, 7.82306)
05 2017	4.98000	4.89636	1.38757	(1.80467, 7.98806)
06 2017	5.03000	4.10636	1.38757	(1.01467, 7.19806)
07 2017	5.23000	4.18636	1.38757	(1.09467, 7.27806)

Table 2 presents the in-sample prediction, to ascertain how closely time series prediction might help carbon speculators. A visual overview actual carbon price (column 2 from the left) and

the predicted carbon price (column 3 from the left) shows that the predicted price and the actual carbon price are very closely related.

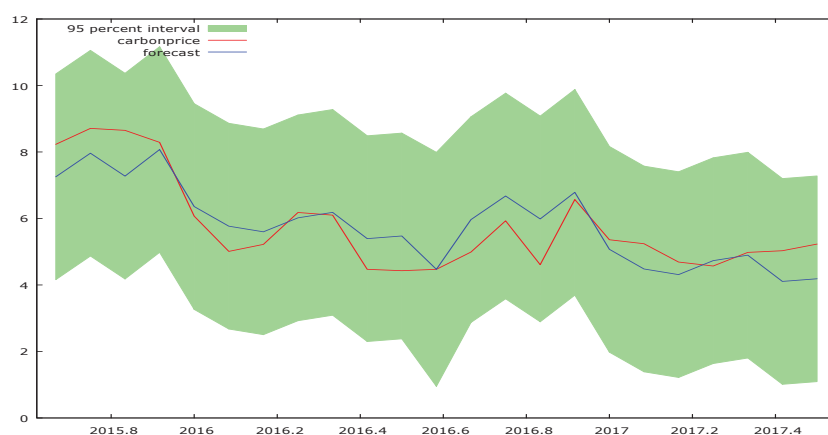


Fig. 2. Lines of in-sample prediction September 2015 – July 2016 and the actual lines

Figure 2 is the line chart of in-sample prediction of carbon price, and it can be seen that the blue line (the forecast or prediction) runs very close to the actual carbon price (red line). The line chart

substantiates the accuracy of the in-sample carbon price forecast since the red and blue lines run close to each other in a steady manners along the trajectory.

Table 3. Out-of-sample forecast for July 2017 – July 2018 For 95% confidence intervals, $t(10, 0.025) = 2.228$

Obs	Carbon price	Prediction	Std. Error	95% interval
08 2017	Undefined	3.18273	1.64868	(-0.490752, 6.85621)
09 2017	Undefined	3.54136	2.04744	(-1.02063, 8.10335)
10 2017	Undefined	4.25136	2.04744	(-0.310626, 8.81335)
11 2017	Undefined	3.56136	2.04744	(-1.00063, 8.12335)
12 2017	Undefined	4.36136	2.04744	(-0.200626, 8.92335)
01 2018	Undefined	2.64636	1.71645	(-1.17814, 6.47086)
02 2018	Undefined	2.05636	2.04744	(-2.50563, 6.61835)
03 2018	Undefined	1.88636	2.04744	(-2.67563, 6.44835)
04 2018	Undefined	2.30636	2.04744	(-2.25563, 6.86835)
05 2018	Undefined	2.47136	2.04744	(-2.09063, 7.03335)
06 2018	Undefined	1.68136	2.04744	(-2.88063, 6.24335)
07 2018	Undefined	1.76136	2.04744	(-2.80063, 6.32335)

Table 3 presents the out of sample forecast. Since there is no actual carbon price in the out of sample forecast to compare with, one could interpret the

accuracy by looking at the probability level, which is 0.025, meaning that the forecast falls within the 95% confidence interval, which is a good forecast.

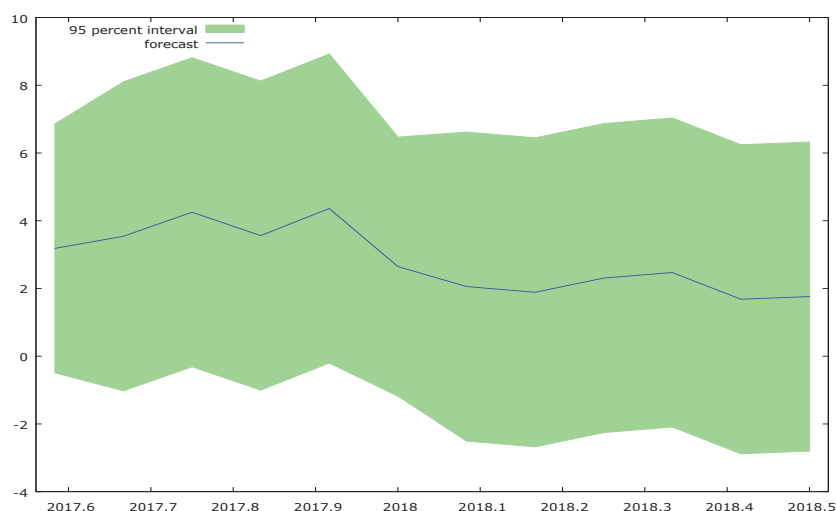


Fig. 3. Out-of-sample forecast and actual lines

Figure 3 presents the line chart for the out of sample forecast. The accuracy of prediction or forecast can be seen from the fact that the blue line (the forecast) lies within or inside the 95 percent confidence interval – an indication of prediction reliability. This can provide a visual picture of the likely future of carbon price for carbon price speculators.

Discussion of results

The carbon futures price was regressed against the time trend, which is the main independent variable (the main regression in this linear regression test). An additional variable, periodic dummies (in this case the different month's data of carbon emission price) were also included, thus giving one dummy for each month within the period covered by the short time series data sample (April 2015 to July

2017). Furthermore, in order to control for seasonality effect, before running the regression, one month dummy was excluded from the periodic dummy variable, which is April 2015. Firstly, a line chart of volatility in Fig. 1, show that indeed carbon futures price is fraught with some volatilities, which is noticeable by the up and down spikes with a gradual descending price trend. Secondly, the linear regression results show that, as the main regressor, time trend does have an influence on carbon futures price volatility at a P-value of 0.02, which is lower than 5% alpha level. This thus shows that time trend has a significant effect on carbon futures price volatility even within the short-term time series and this provides additional information for short-term carbon futures price speculators to consider time trend as a factor in their carbon futures speculation.

However, the monthly periodic dummies were not significant. To demonstrate that short-term time series futures data could assist short-term carbon emission speculators in their carbon futures investment decisions, the in-sample prediction, which appears in Table 2 and Fig. 2 show that short-time carbon futures time series data, can provide a reliable short-term prediction of carbon price. This is evident in Fig. 2, which shows that the prediction line falls within the 95% confidence on the actual carbon price. This in-sample result also provides a carbon emission futures speculator with the confidence to use out-of-sample forecast, which appears in Fig. 3 and which gives a 95% confidence out-of-sample forecast of some months ahead. This demonstration is important given that many investors even in carbon emissions trading engage in short-term period speculation; this genre of investors therefore deserve additional information to assist with their carbon emission price risk reduction strategies. The above illustrations have provided such additional information.

Conclusion

The objective of this paper was to demonstrate that carbon futures price could be reliably predicted with the method of time series forecasting to provide short-term information for carbon price speculators. In order to achieve this objective, the paper used a sample of carbon futures price from April 2015 to July 2017 and used the Gretl software to conduct the time series analysis. The analysis produced an in-sample and out of sample predictions, which showed reliability of forecast at a P-value below the 0.05 significant level or which fell within the 95% confidence level. This shows that short-term carbon price speculators might also benefit from forecasting using short time series, similar to the benefits derivable from long-term time series forecasting.

In an era of growing global concern and campaign for sustainable development, carbon emission reduction has become the prominent focus given scientific evidence of the enormous impact of carbon emission on the ozone layer and the concomitant negative reverberation on climate change. Accordingly, international agreements on carbon policy has galvanized the establishment of

carbon emissions trading and markets to encourage carbon emissions reduction. Similar to other commodity markets, the futures market, which is a contract to exchange a commodity based on a contract price has also become operational in the carbon markets. Therefore, given the newness of carbon emission markets and the implicit systemic risk, carbon emission futures speculators need additional information to assist in speculating risk and to hedge such risks through effective investment planning. This paper thus made an important attempt to provide a demonstration of how short-term carbon futures speculators could use short-term carbon futures time series data to predict and forecast carbon prices within the short time period. This paper stands out from other similar research on carbon emission futures as previous papers have focussed on long-term time series demonstration, thus leaving out short-term speculators with enabling information on whether short-term time series might assist them in predicting and forecasting carbon futures. This paper has demonstrated that short-term speculators in carbon futures could indeed use short-term time series data on carbon futures to predict and forecast futures price volatility within a short term and thus decide on investment opportunity. The sample data results showed that short-term data could produce a reliable in-sample futures prediction since the in-sample prediction fell within the 95% confidence interval. The demonstration also showed that short-term carbon futures data could assist speculators to conduct a reliable short-term out of sample forecast of carbon futures prices within the closer period of some months ahead. Therefore, the paper offers practical assistance to carbon futures speculators and is equally important for academic studies for business and economic students on discussions and research bordering on carbon emissions, carbon trading, environmental economics and sustainable development. More carbon emissions futures short-term forecasting is encouraged – such research should compare short-term forecasting of carbon futures amongst different carbon markets.

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