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Article

Testing the Emissions Reduction Effect of Carbon Pricing: A Predictive Analysis of the Role of Speculation

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Abstract: Despite providing some critical financial services to support the operation of Emissions Trading Systems (ETS), such as increasing market liquidity and price visibility and allowing operators to hedge against future fluctuations, there is growing concern about the potential threat of financial actors' speculation behaviour to the ETS's effectiveness. To confirm or alleviate the fear associated with such concern, we employ both ex-post and ex-ante approaches to determine the role of speculation in the emission reduction effect of the ETS and its forecasting power in predicting climate change. In addition to confirming carbon prices and the speculation behaviour of the emissions non-compliance actors in the ETS as accurate predictors of climate change, we also show that they both matter in the emission reduction effect of the ETS. We use several verifiable econometric approaches to select the Feasible Quasi Generalised Least Squares (FQGLS) as the best estimator for addressing some of the biases in climate change predictability. We demonstrate that a predictive model combining the complementing dynamics of the EST emissions compliance and emissions non-compliance features forecasts climate change more accurately. We demonstrate the robustness of our findings for both in-sample and out-of-sample forecasts and across different forecast horizons by using alternative approaches to evaluate forecast performance.

Keywords: emissions reduction; carbon pricing; ETS; speculation

JEL Code: C53; C58; G14; Q51; Q54

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1. Introduction

Placing a price on carbon emissions (CO2), notably through the Emission Trading System (EST), has long been advocated as a necessary and, in theory, cost-effective method of decreasing emissions and mitigating climate change (Cramton et al., 2017; Rafaty et al., 2020). The underlying intuition is that higher carbon prices make low-carbon energy more competitive, incentivising reducing emissions by reducing demand for carbon-intensive fuels (Arlinghaus, 2015; Martin et al., 2016; OECD, 2021). On this note comes the hypothesis that a strong commitment to higher carbon prices provides incentives for investors to invest in the expansion and development of low-carbon technologies (Kohlscheen et al., 2021; OECD, 2021). Indeed, there is no denying that such a strong commitment to higher carbon prices is in line with the goal of the Paris Agreement to reduce global net anthropogenic CO2 emissions by about 45% from their 2010 level by 2030 and reach net zero by 2050 (UN, 2021). But, despite the recent upward surge in carbon prices, the total global GHG emission level in 2030 has been estimated to be 16% higher than the 2010 level (UN, 2021). This, in particular, contradicts the hypothesis that higher carbon prices induce low-carbon emissions. As a result, there has been continued debate on whether the recent rise in carbon prices is due to commitment to the

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global goal of low carbon or spurred by the growing speculation activities of financial actors in the EST. In order to subject this emerging concern to evidence –based insight, we explore a predictive modelling approach to contribute to literature on emissions reduction effect of carbon pricing on the following grounds.

First, the carbon allowance prices have been validated as mainly driven by demand-side factors, notably energy prices or fuel switching, and economic activity. More importantly, stringent climate change policies, along with some periodic changes in ETS market design, are, by default, the mechanisms often explored to aid the commitment to higher carbon prices, which is crucial for the goal of low carbon emissions. But, in light of the recent substantial increase in carbon allowance prices, particularly in the last two years, the potential role played by speculation has also come into focus. Although there has been little or no tangible evidence suggesting that speculation endangers the effectiveness of the ETS, as speculative behaviour presently only accounts for about 4% of activity in the ETS. However, the increasing participation of emissions non-compliance firms in the ETS has continued to fuel debate that the recent price rally in the carbon market may not necessarily be due to a deliberate policy commitment to higher carbon prices but to increasing interest from emissions non-compliance entities. To test the validity or otherwise of the latter position, we hypothesise that speculation matters in the emission reduction effect of the carbon pricing.

Second, the widely held belief that a higher carbon price is required for the ETS to work as an emissions reduction policy instrument is ad hoc. At the same time, the extant literature on the subject is predominantly based on impact analysis. Whereas there is a growing conviction in the literature that an established impact relationship may not be sufficient to assume the future observation path (see Narayan and Bannigidadmath, 2015). There is also the view that accurate forecasting and predictability of climate change will help implement emissions control policies. Thus, while acknowledging there have been increasing efforts to understand the emissions reduction effect of carbon prices (see, for example, Murray & Maniloff, 2015; Tvinnereim and Mehling, 2018; Bayer & Aklin, 2020; Rosenbloom et al., 2020; Rafaty et al., 2020; Green, 2021; Kohlscheen et al., 2021; Cui et al., 2021), we go beyond the standard ex-post approach and instead employ an ex-ante approach to determine the forecasting power of carbon prices in predicting climate change. Essentially, we employ a number of forecast performance evaluation methods to determine whether it is sufficient to rely on a model that captures carbon prices as the sole accurate predictor of climate change compared to a model that controls for the role of speculation in the predictability of climate change. The essence is to provide the literature with evidence-based insights on whether speculation activity could be considered healthy or detrimental to the functioning of ETS on the pathway to the global goal of low carbon emissions.

2. Data and Preliminary Results

2.1. Data description and source

Of all the greenhouse gases, carbon dioxide (CO2), a major global warming source, remains the workhorse in the literature as a measure of climate change. As a result, this study uses the log of the global atmospheric CO2 mole fraction per tonne per million (PPM) as a proxy for climate change. This, which measures the concentration of CO2 in the atmosphere, was obtained on a monthly basis from the National Oceanic and Atmospheric Administration (NOAA)'s National Centres for Environmental Information (NCEI). [1] Given that the European Union ETS (EU-ETS) is the cornerstone of the world's most ambitious climate strategy, the European Allowance (EAU) futures contracts trading in the Intercontinental Exchange (ICE) measure carbon prices in this study. Our preference for futures contracts over spot is because, in addition to being the most traded, future contracts are relatively less affected by short-run noise (see Koch et al., 2014; Sanni et al., 2015; Segnon et al., 2017; Chung et al., 2018; Batten et al., 2021; Lovcha et al., 2022).

[1] https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/statewide/time-series/3/tavg/all/1/1950-2022?base_prd=true&begbaseyear=1901&endbaseyear=2000

Regarding the measure for the speculation behaviour of the financial actors in the ETS, we extract worldwide Google search volumes relating to different keywords that have become more frequently used in the literature on discussions centred on carbon pricing. The keywords utilised are: “EU ETS”, “EUA price”, “EU ETS price”, “ETS prices”, “ETS carbon price”, “Carbon price”, “Carbon prices”, “Carbon allowance price”, “Carbon market”, “Carbon trading”, “Emissions trading”. Using principal component analysis, the resulting search volume variables were combined to arrive at our novel news-based speculative $\left(SPEC_t\right)$ index, which is further normalised using the following procedure.

$$SPEC_{scaled} = (b-a) \times \frac{SPEC_{unsacled} - min\left(SPEC_{unsacled}\right)}{max\left(SPEC_{unsacled}\right) - min\left(SPEC_{unsacled}\right)} + a$$

The ‘ a ' component of terms $(b-a)$ measures the least values for the index while ' b ’ measures the highest value of the index. Thus, the index takes the values between $a=1$ (the lowest levels of speculation) and $b=1$ (the highest level of speculation). On the measure for changes in political decisions associated with the operation of the carbon market, we use the log of the first difference of the "carbon policy uncertainty (CPU)" index developed by Gavriilidis (2021), following Wu et al.'s (2022) being one of the few notable studies that have also favoured the CPU index of Gavriilidis' (2021) in the literature.

Our data collection spans the period from January 2008 to December 2022 overall. The fact that the carbon price fell to approximately €0.01/tCO2 after October 2006 and that Phase I of the EU-ETS, which covered 2005–2007, was largely considered as the scheme's trial phase. This persistently insignificant value of carbon pricing in the ETS pilot phase explains why our start date starts with Phase II of the EU-ETS.

2.2. Preliminary results

The preliminary results in Table 1 include summary statistics and stochastic properties for each variable of interest. Starting with the mean statistic, we find that carbon dioxide is, on average responsible for 0.04% of the concentration in the atmosphere. We also show that, until the current Phase of trading in the EU-ETS, the average carbon allowance price has been well below €20/tCO2. It was approximately €14/tCO2 in Phase II of the ETS and later declined to €12.4/tCO2 in Phase III before surging higher to about €68/tCO2 in the current trading period (Phase IV of the ETS), which only started in 2021. This period of an unprecedented surge in the average prices of carbon allowances coincides tends to co-move with upward trends in the speculation index, which measures the speculation behaviour of emissions non-compliance actors in the ETS. For instance, while the average speculation index was 53.41 during Phase II of the ETS, it later declined drastically to 11.20 during Phase III of the ETS, only to rise by more than 200% in the current Phase IV of the ETS, where the average monthly speculation index as of December 2022 is 36.83.

Table 1. Descriptive Statistics and Unit Root test.

Table 1(a): Summary Statistics					
	Mean	**Std. Dev.**	**Skewness**	**Kurtosis**	**J-B test**
Climate change (CO2)	400.40	10.31	0.07	1.76	11.71***
Carbon prices (CP)					
CP: ETS-Phase II	13.88	5.22	0.72	3.34	5.45*
CP: ETS-Phase III	12.42	9.09	0.78	1.93	14.37***
CP: ETS-Phase IV	68.36	16.98	-0.57	2.11	2.11
CP: Full-sample	20.36	21.13	1.97	6.03	185.46***
Speculation index (SPEC)					

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SPEC: ETS-Phase II	53.41	21.81	0.26	1.80	4.24
SPEC: ETS-Phase III	11.20	6.16	0.76	4.47	18.01***
SPEC: ETS-Phase IV	36.83	8.92	0.90	4.20	4.65*
SPEC: Full-sample	28.69	23.77	1.06	3.19	33.78***

Table 1(b): ADF Unit Root test

	Augmented Dickey-Fuller (ADF) test		
	Level	**First Difference**	**I(d)**
Climate change (CO2)	-3.7732[b]***	-	I(0)
Carbon price (CP)	-0.7471[b]	-16.0172[b]***	I(1)
Speculation (SPEC)	-2.2346[a]	-11.4095[a]***	I(1)

Note: The syntax ***, ** and * implies the rejection of a null hypothesis at 1%, 5% and 10% levels of significance, respectively.

We also subjected each of the variables to a unit root testing procedure. We find that the null hypothesis of no unit root cannot be rejected in the case of the log of CO2, while the reverse holds for carbon prices (CP) and speculation (SPEC), respectively. However, it is instructive that this stationarity and non-stationarity stochastic behaviour of the predicting and predictor series aligns with the variant predictive models presented in the methodological section, where the variables are defined in a form that exhibits the dynamics of their stochastic properties. To investigate the presence of conditional variance and autocorrelation issues in the variables, we employed the autoregressive conditional heteroscedasticity Lagrange Multiplier (ARCH-LM) test and the Ljung-Box serial correlation test. Presented in the Table 2 is the F-statistic in the case of the ARCH-LM test, and Q-statistic and Q^2-statistic in the case of Ljung-Box autocorrelation test. The null hypothesis for the ARCH-LM is that there is conditional heteroscedasticity, while the null hypothesis for the autocorrelation test is that there is no autocorrelation. Also notable in the Table is evidence of significant persistence and endogeneity in the predictor series. This, among other things, tends to strengthen the appropriateness of our estimation technique as described in the methodological section below.

Table 2. Conditional variance, autocorrelation, persistence and endogeneity test.

	Heteroscedasticity test		**Autocorrelation test**			
	ARCH LM test		**Ljung-Box Q-stat.**		**Ljung-Box Q^2-stat.**	
	k=5	**k=10**	**k=10**	**Q(8)**	**Q^2(4)**	**Q^2(8)**
Climate Change (CO2)	5568.61***	6086.59***	658.26***	1231.0***	530.88***	893.24***
Carbon Price (CP)	4.32***	2.23**	7.75	9.23	17.72***	17.79**
Speculation (SPEC)	106.05***	62.48***	593.20***	1071.3***	380.88***	577.1***

Persistence & Endogeneity tests

	Carbon Price (CP)	**Speculation (SPEC)**
Persistence test	0.99***	0.94***
Endogeneity test	0.9808*** (0.0111)	0.9815*** (0.0191)

Note: The asterisk ***, ** & * implies significance at 1%, 5%, and 10% levels of significance, while the values in parenthesis are the standard error.

3. Methodology

3.1. The predictive model

One of the main innovations of this study is that it uses both the ex-post (impact analysis) and ex-ante (predictive method) approaches to examine the influence of carbon prices on emissions reduction. As a result, our analytical technique begins with Westerlund and Narayan's (2015) bivariate predictive model, which allows us to capture, among other things, some underlying statistical properties of the predicting and predictor series (see Tables 1 and 2). Where there is no such statistical problem, our linear climate change prediction model, as expressed in equation (1), can be considered acceptable, where climate change is the predicting series regressed on carbon pricing (CP).

$$CO2_t = \alpha + \beta CP_{t-1} + \varepsilon_t \tag{1}$$

Equation (1) is our baseline predictive model, where a higher carbon price is projected to promote decarbonization. However, it is intuitive that the bivariate predictive model in equation (1) is restrictive, as the CP is assumed to be driven mainly by emissions compliance activity in the ETS, with stringent climate change policies as the means to committing to higher carbon prices. Whereas restricting the emission reduction effect of CP to mainly the emissions compliance activity of ETS may be inadequate, particularly in the light of the increasing speculation behaviour of emissions non-compliance actors in the ETS. Thus, to empirically test the hypothesis that speculation could threaten the functioning of the ETS in the future, we further extend the predictive model in equation (1) to include the role of speculation, as shown below.

$$CO2_t = \alpha + \beta_1 CP_{t-1} + \beta_2 SPEC_{t-1} + \varepsilon_t \tag{2}$$

Equation (2) is our extended climate change predictive regression, with CO2 simultaneously regressed on emissions compliance and emission non-compliance indicators of activities in the ETS. Given that the innovation herein is to examine the extent to which speculation benefits or undermines the emission reduction effect of carbon prices, we go beyond reflecting the SPEC as a mere additional regressor in the specification to include its interaction with CP, as demonstrated in the following.

$$CO2_t = \alpha + \beta_1 CP_{t-1} + \beta_2 SPEC_{t-1} + \beta_3 CPI * SPEC_{t-1} + \varepsilon_t \tag{3}$$

The aforementioned notwithstanding, inference from our preliminary result suggests there is likely a tendency towards a correlation between the error term and the predictor series in the above predictive equations. Given that such correlation, if it exists, could manifest as endogeneity bias and the potential effect of persistence, the question of what estimator can be considered suitable and appropriate for estimating the models becomes inevitable. The conventional practice would have been to ignore the issues of bias and inefficiency altogether and proceed to assess the predictive models with the standard OLS technique. However, our preliminary analysis suggests the OLS needs to be improved as it lacks the required features to address the said biases when it matters. To counter such tendencies, Lewellen (2004) adjusted the OLS estimator to handle the endogeneity issue.

$$CO2_t = \alpha + \beta'_{adj} x_{t-1} + \lambda(x_t - \delta x_{t-1}) + \varepsilon_t \tag{4}$$

The term β_{adj} in equation (4) depict the adjusted OLS estimator, such that; $\beta_{adj} = \widehat{\beta} - \lambda(\widehat{\delta} - \delta)$, while the probability of endogeneity bias likely to be caused by the correlation of ε_t and x_t is corrected by the inclusion of the additional term $\lambda(\delta - \delta x_{t-1})$ while δ and $\widehat{\delta}$ are fitted coefficients of one period-lagged (x_{t-1}). The term x as used herein is a vector representing carbon price (CP) in our baseline and restricted predictive model, and include speculation (SPEC) and its interaction term with CP in the extended/unrestricted predictive model.

To further account for the probable effect of conditional heteroscedasticity, which is a feature common with time-series data, Narayan and Westerlund (2015) suggest pre-weighting all of the data by $1/\sigma_v$ and then estimate the resulting equation with OLS. This later approach known Feasible Quasi Generalized Least Square (FQGLS) is given as below.

$$\beta_{adj}^{FQGLS} = \frac{\sum_{t-qm+2}^{T} \hat{\tau}_t^2 p_t^d x_{t-1}^d}{\sum_{t-qm+2}^{T} \hat{\tau}_t^2 (x_{t-1}^d)^2} \tag{5}$$

where $\hat{\tau}_t = 1/\hat{\sigma}_{v,t}$ is used to weigh all the data in the bias-adjusted predictive model in equation (6), while $p_t^d = p - \sum_{p=2}^{T} p_t / T$ and $x_t^d = x_t - \sum_{z=2}^{T} x_t / T$.

With FQGLS, one does not need to assume that x_t is stationary, as Lewellen (2004) does with the adjusted OLS, which is quite restrictive. Another feature of the FQGLS is that it contains information in the ARCH structure of the error term often ignored in the adjusted OLS estimator.

3.2. Forecast performance measure

At this juncture, it must be reiterated that this study's focal point is to understand the extent to which speculation enhances or undermines the predicting power of the emission reduction effect of carbon prices. Thus, we employ both the single and pairwise methods of evaluating forecast performance to determine which is the most accurate for the in-sample and out-of-sample forecasts of climate change between the predictive model restricted to the carbon price and the unrestricted predictive model that allows for the role of speculation. Starting with the single model-based forecast performance measure, the Root Mean Square Error (RMSE) is computed for in-sample and out-of-sample forecasts. For instance, if the full-sample period is defined as $t = m+1, \ldots, m+k$, where m the sample period k is the forecast horizon, such that the RMSE for the two forecast periods can be calculated as follows:

In-Sample: $$RMSE = \sqrt{\frac{1}{m} \sum_{t=1}^{m} \left(\hat{CO2}_t - CO2_t \right)^2}$$

(6a)

Out-of-Sample: $$RMSE = \sqrt{\frac{1}{k} \sum_{t=1}^{k} \left(\hat{CO2}_t - CO2_t \right)^2} \tag{6b}$$

To ascertain the robustness of our results, we further complement the RMSE results with a forecast estimate based on Mean Square Error (MSE) - $1/N \sum_{t=1}^{T} \left(\hat{CO2}_t - CO2_t \right)^2$ where N is the number of predictions used in computing the mean. While RMSE and MSE are single model-based forecast performance measures, we are also interested in a pairwise approach to forecast evaluation. We employed the pairwise method to determine the difference between the forecasts of two alternative predictive models. Essentially, we considered two alternative pairwise methods, namely the Campbell and Thompson (C-T, 2008) test and the Clark and West (C-W, 2007) test, both of which are standard forecast measures for nested models which is the case in this study (see Salisu & Isah, 2018; Salisu et al., 2019; Isah & Raheem, 2019).

The C-T test is usually computed as $OOS\_R = 1 - \left(\hat{MSE}_1 / \hat{MSE}_0 \right)$ where $\hat{MSE}_1$ is the mean squared error obtained from Model_4 (which is technically an unrestricted model in this case) and

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$\widehat{MSE}_0$ is the mean square error obtained from the models that ignore the role of speculation (i.e. Model_1 & Model_2), which can be technically referred to as the restricted models. The innovation herein is to determine which is most accurate for forecasting carbon allowance prices: a restricted model that ignores the role of speculation or an unrestricted model that accounts for the role of speculation. Hypothetically, a positive $R^2(OOS\_R)$ statistic such as $R^2(OOS\_R)>0$ this is an indication that the unrestricted model in this case Model_4 is the most appropriate, while the reverse is expected to be the case if the statistic is negative. We further employ the C-W test to complement the C-T test, as it allows us to determine whether there is a significant difference in the errors of two nested competing models. The underlying framework for the C-W test is as follows:

$$\hat{f}_{t+k}=\left(CO2_{t+k}-\widehat{CO2}_{,1,t+k}\right)^2-\left[\left(CO2_{t+k}-\widehat{CO2}_{,2,t+k}\right)^2-\left(\widehat{CO2}_{,1,t+k}-\widehat{CO2}_{,2,t+k}\right),^2\right] \quad (7)$$

where k is the forecast period; $\left(CO2_{t+k}-\widehat{CO2}_{,1,t+k}\right)^2$ is the squared error for the unrestricted multi-factor predictive model; $\left(CO2_{t+k}-\widehat{CO2}_{,2,t+k}\right)^2$ is the squared error for the restricted multi-factor predictive model; while $\left(\widehat{CO2}_{,1,t+k}-\widehat{CO2}_{,2,t+k}\right)^2$ is the adjusted squared error introduced by C-W to correct for any noise associated with the larger model's forecast. Thus, the sample average of $\hat{f}_{t+k}$ can be expressed as: $MSE_0-(MSE_1-\text{adj.})$ and each term is computed as:

$$MSE_0=P^{-1}\sum\left(CO2_{t+k}-\widehat{CO2}_{,1,t+k}\right)^2;$$

$$MSE_1=P^{-1}\sum\left(CO2_{t+k}-\widehat{CO2}_{,2,t+k}\right)^2;\text{ and}$$

$$\text{adj.}=P^{-1}\sum\left(\widehat{CO2}_{,1,t+k}-\widehat{CO2}_{,2,t+k}\right)^2$$

where P is the number of predictions used in competing for these averages? To test for equality of forecast performance between the single-factor-based predictive model and multi-factors-based predictive model, the $\hat{f}_{t+k}$ is regressed on a constant and the resulting t-statistic for a zero coefficient is used to draw an inference. Since the Null hypothesis tests for the equality of MSEs; the alternative hypothesis implies otherwise. The null hypothesis is rejected if the test statistic is greater than +1.282 (for a one-sided 0.10 test) or +1.645 (for a one-sided 0.05 test), respectively.

4. Empirical Result and Discussion of Finding

The empirical results presented in this section are divided into two main parts. In the first part, we present and discuss the predictive regressions obtained from the estimation of the restricted and unrestricted predictive models considered in the predictability of climate change. In the second part, we explore a number of single and pairwise approaches to determine which is the most accurate between the restricted and unrestricted predictive models in the predictability of climate change. Given that the accuracy of in-sample forecasts is insufficient to assume out-of-sample forecasts gain, the forecast performance evaluation is considered not only for the in-sample estimates but also for out-of-sample forecasts. More importantly, we utilize the rolling window approach in the case of the latter to report results for different forecast horizons (h), such as; h-4 for four months period ahead forecast, h=8 for eight months period ahead forecast, and h=12 for twelve months period ahead forecast.

4.1. Predictability testing results

We begin our empirical analysis by presenting the predictability results, and the essence is to determine the validity of the predictor series under consideration as an accurate predictor of climate

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change. A look at the predictive regression results in Table 3 shows that the hypothesis of no predictability is significantly rejected for the restricted and unrestricted predictive models. This confirms the potential of carbon prices and speculation behaviour as accurate predictors of climate change. However, quite an interesting observation in the regression results is the fact that complementing the carbon prices (CP), a measure of emission compliance in the ETS, with speculation (SPEC), a measure of speculative behaviour in the EST, appears to benefit the emission reduction effect of the EST more. On the one hand, our finding of a positive sign on the coefficient for carbon prices contradicts the hypothesis that a higher carbon price is crucial to the emission reduction effect of ETS.

Table 3. Predictive regression results.

Predictive model type	Predictors					
	Carbon Prices **(CP)**	Carbon Prices (CP) and Speculation (SPEC)		Carbon Prices (CP)/Speculation (SPEC) with their interaction term		
		CP	**SPEC**	**CP**	**SPEC**	**CP*SPEC**
Restricted model	1.8968*** (0.0092)					
Unrestricted model [1]		1.8392*** (0.0056)	0.0146*** (0.0001)			
Unrestricted model [2]				1.2069*** (0.0045)	0.1733*** (0.0009)	-0.0642*** (0.0006)

Note: The values in the parenthesis are the standard error, while ***, **, and * imply significance at 1%, 5%, and 10% levels of significance, respectively.

While acknowledging that some previous studies (see Cui et al., 2021; Kohlscheen et al., 2021) confirm the direct emission reduction effect of carbon pricing in their findings, our finding of such emission reduction only becomes evident when the carbon price is complimented with the speculation activity in the EST. This, in particular, is an indication the emission non-compliance firms may benefit the EST rather than undermine it. For instance, despite the growing fear about the potential threat of the speculation behaviour of financial actors to the functioning of the ETS, the fact that they render some essential services to the ETS-affected companies, such as assisting with the establishment of more market liquidity and price visibility, as well as allowing operators to hedge against future fluctuations, means their participation in the ETS is inevitable. It is, therefore, not surprising that the speculation complements the functioning of the ETS in the pathway to the global goal of reducing carbon emissions.

4.2. In-sample and out-of-sample forecasts results

However, while the mentioned previous studies are mainly based on impact analysis (ex-post), we take a step further to evaluate the forecasting power of the complementing dynamics of carbon prices and speculation in the predictability of climate change. The goal is not to simulate but to determine whether an unrestricted predictive model that simultaneously captures emissions compliance and the emissions non-compliance dynamics of the ETS is the most accurate framework for forecasting climate change. To establish the validity of this hypothesis for in-sample and out-of-sample forecasts, we used 90% of our total sample period for the in-sample forecasts. Then we used the remaining 10% of the data scope to implement the out-of-sample forecast. This has been a common practice in the literature, particularly when the goal is to determine the relative accuracy of alternative predictive models. Indeed, there is no rule of thumb on what sample percentage can be considered most appropriate. Researchers in the literature have used 25%, 50%, and 75% (see Narayan & Gupta, 2015). Still, the choice is usually boiled down to data scope and to ensure sufficient data scope to allow for the out-of-sample forecast of different periods ahead of forecast horizons.

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Starting with the single-method forecast performance evaluation measures, presented in Table 4 are the RMSE and MSE values. The lower the RMSE or MSE values, the better the forecast accuracy of a predictive model.

Table 4. Single-method based forecast performance evaluation results.

Predictive model type	**RMSE**				**MSE**			
	In-sample	Out-of-sample			In-sample	Out-of-sample		
		h=4	**h=8**	**h=12**		**h=4**	**h=8**	**h=12**
Restricted model	1.8608	1.8570	1.8674	1.8797	3.4626	3.4488	3.4875	3.5335
Unrestricted model [1]	1.7725	1.7775	1.8011	1.8301	3.1417	3.1598	3.2440	3.3492
Unrestricted model [2]	1.0405	1.0291	1.0258	1.0493	1.0826	1.0592	1.0524	1.1011

Note: The smaller the values of RMSE and MSE, the better the forecast accuracy of a predictor or model.

In conformity with our earlier finding that the complementing dynamics of carbon prices and speculation are the most effective for enhancing the emission reduction effect of the ETS, a look at Table 4 also shows that the predictive model with the interaction dynamics of carbon prices and speculation is the most accurate to forecast climate change. Compared to the restricted and unrestricted model [1], for example, we find the RMSE and MSE relatively lower for the unrestricted predictive model [2]. The consistency of this finding holds for both the in-sample and out-of-sample forecasts and across the different forecast horizons considered. This suggests that both emission compliance and the emission non-compliance dynamics of the ETS matter for enhancing the accuracy of climate change forecasts, mainly when they are explored from a complementary perspective rather than just their forecasting power.

We supplement the single-method approach to forecast performance evaluation (RMSE and MSE) with a paired method based on the C-T test. The C-T statistic makes it considerably easier to compare the performance of two competing predictive models since it involves a pairwise comparison of forecasts based on two alternative models that are nested in nature. A positive C-T statistic suggests that the unrestricted model [2] is more accurate at forecasting climate change than the restricted or unrestricted models [1]. We can see how the C-T statistic in Table 5 reinforces the preceding inference obtained from the RMSE and MSE values. We then use the Clark and West (2007) [C-W] test to determine the validity of the C-T statistic. While the null hypothesis for the C-W test is that two competing predictive models have identical forecast accuracy, Table 5 shows an overwhelming rejection of the null at the 1% level of significance in favour of the unrestricted model [1] as the most accurate to forecast climate change. Given the robustness of our finding across alternative measures of forecast performance and the consistency of the results both in-sample and out-sample, it is both statistically and practically valid to infer that both the emissions compliance and the emissions non-compliance dynamics of the carbon market matter in the emission reduction effect of the ETS as well as in the predictability of climate change.

Table 5. Pairwise-method based forecast performance evaluation results.

Predictive model type	**C-T test**				**C-W test**			
	In-sample	Out-of-sample			In-sample	Out-of-sample		
		h=4	**h=8**	**h=12**		**h=4**	**h=8**	**h=12**
Restricted Vs Unrestricted [2]	0.6553	0.6647	0.6755	0.6712	3.4498*** [12.42]	3.5599*** [12.82]	3.8764*** [12.14]	4.3571*** [10.99]

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Unrestricted [1] Vs Unrestricted [2]	0.6873	0.6928	0.6982	0.6883	3.9288*** [12.36]	3.9776*** [12.77]	4.1942*** [12.89]	4.5229*** [12.62]

Note: A positive C-T value implies that the preferred predictive model (unrestricted model [2]) outperforms the restricted or unrestricted model [1] and the reverse holds if the statistic is negative. The C-W test t-statistic is based on the critical values of 1.28, 1.64, and 2.00 for 10%, 5% and 1% levels of significance, respectively.

5. Conclusions

We employ both the ex-post and ex-ante approaches to empirical analysis to determine the emission reduction effect of the ETS and its forecasting power in predicting climate change. In addition to confirming carbon prices and the speculation behaviour of the emissions non-compliance actors in the ETS as accurate predictors of climate change, we also show that they both matter in the emission reduction effect of the ETS. We offer that a predictive model with the complementary dynamics of the EST emissions compliance and emissions non-compliance features is more accurate at forecasting climate change. We demonstrate the robustness of our findings for both in-sample and out-of-sample forecasts and across different forecast horizons using alternative approaches to evaluate forecast performance. Thus, despite the growing fear about the potential threat of the speculation behaviour of financial actors to the functioning of the ETS, our finding of the speculation as capable of enhancing the emissions reduction effect of carbon pricing may not be unconnected to the fact that the financial actors despite their speculation behaviour also render some essential services to the ETS-affected companies. Such services, which include assisting with establishing more market liquidity and price visibility and allowing operators to hedge against future fluctuations, mean the participation of the emissions non-compliance actors in the ETS is inevitable irrespective of their speculation behaviour.

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