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

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We employ both ex-post and ex-ante approaches to determine the role of speculation in the emissions reduction effect of carbon pricing and its forecasting power in the predictability of climate change. 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 carbon pricing 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.

I. Introduction

Placing a price on carbon emissions (CO₂), notably through the Emission Trading System (ETS), has long been advocated as a necessary and, in theory, cost-effective method of mitigating climate change (Rafatya et al., 2020). The underlying intuition is that higher carbon prices make low-carbon energy more competitive by reducing the demand for carbon-intensive fuels (Martin et al., 2016). 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). However, while carbon allowances, the commodity traded at the ETS, are mostly held by polluting companies that need them to comply with the global goal of emission reductions, investment firms, banks, and brokers have also invested in it primarily for profit's sake. Driven by their profit maximization objective, the financial actors engage in speculation activities that might be detrimental to the functioning of the ETS. This notwithstanding, there has not been any compelling evidence on the extent to which speculation matters in the emissions reduction effect of carbon pricing.

In fact, 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 (see, for example, Bayer & Aklin, 2020; Cui et al., 2021; Green, 2021; Kohlscheen et al., 2021; Rosenbloom et

al., 2020). To bridge this gap, we employ a predictive modelling framework to test whether it is sufficient to rely on a model that captures carbon prices as the sole predictor of climate change compared to a model that controls for the role of speculation in the predictability of climate change.

II. Data and Methodology

A. Data and Preliminary Analysis

This study uses the log of the global atmospheric CO₂ mole fraction per tonne per million (PPM) as a proxy for climate change.¹ The European Allowance (EUA) futures contracts obtained from [investing.com](https://www.investing.com) online database is the measure for carbon prices in this study, while for speculation (SPEC), 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. Using principal component analysis, the resulting search volume variables were combined to arrive at our novel news-based speculative ($SPEC_t$) index, which is further normalised using the following procedure.

$$SPEC_{scaled} = (b - a) \times \frac{SPEC_{unscaled} - \min(SPEC_{unscaled})}{\max(SPEC_{unscaled}) - \min(SPEC_{unscaled})} + a \quad (1)$$

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

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¹ The climate change data was obtained from the National Oceanic and Atmospheric Administration (NOAA)'s National Centres for Environmental Information (NCEI).

Table 1. Preliminary results

Panel 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)						
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***	
Panel 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)	
Panel C: 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	k=5	k=10	k=10
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***
Panel D: 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 syntax ***, ** and * implies the rejection of a null hypothesis at 1%, 5% and 10% levels of significance, respectively.

speculation). The “carbon policy uncertainty (CPU)” index developed by Gavrilidis (2021) is used to proxy for political decisions associated with the operation of the carbon market. Our data collection spans the period from January 2008 to December 2022 overall.

The preliminary results in Table 1 include summary statistics and stochastic properties for each variable of interest. The average carbon allowance price has been well below €20/tCO₂ until recently. It was approximately €14/tCO₂ in Phase II and later declined to €12.4/tCO₂ in Phase III before surging to about €68/tCO₂ in Phase IV. The unprecedented surge in the average prices of carbon allowances coincide with upward trends in the speculation index, which measures the speculation behaviour of emissions non-compliance actors in the ETS. Also presented in the table is evidence of autocorrelation, heteroscedasticity, persistence, and endogeneity in the predictor series.

B. Methodology

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).

$$CO2_t = \alpha + \beta CP_{t-1} + \varepsilon_t \quad (2)$$

Equation (2) is our baseline predictive model, where a higher carbon price is projected to promote decarbonization. To empirically test the hypothesis that speculation could threaten the functioning of the ETS in the future, we extend the predictive model in equation (2) to include the role of speculation, as shown below.

$$CO2_t = \alpha + \beta_1 CP_{t-1} + \beta_2 SPEC_{t-1} + \varepsilon_t \quad (3)$$

Although equation (3) is our extended climate change predictive model, 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 be-

yond reflecting the *SPEC* as a mere additional regressor in the specification to include its interaction with *CP*.

$$CO2_t = \alpha + \beta_1 CP_{t-1} + \beta_2 SPEC_{t-1} + \beta_3 CPI * SPEC_{t-1} + \varepsilon_t \quad (4)$$

Inference from our preliminary results suggests there is likely a tendency towards a correlation between the error term and the predictor series in the above predictive equations. To counter such tendencies, Lewellen (2004) adjusted the OLS estimator to handle the endogeneity issue.

$$CO2_t = \alpha + \beta'_{adj} x_{t-1} + \lambda(x_t - \delta x_{t-1}) + \varepsilon_t \quad (5)$$

The term β_{adj} in equation (5) depict the adjusted OLS estimator, such that; $\beta_{adj} = \hat{\beta} - \lambda(\hat{\delta} - \delta)$, 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 $\hat{\delta}$ 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, Westerlund and Narayan (2015) suggest pre-weighting all of the data by $1/\sigma_v$ and then estimate the resulting equation with OLS. This later approach known as Feasible Quasi Generalized Least Square (FQGLS) is given below.

$$\beta_{adj}^{FQGLS} = \frac{\sum_{t=qm+2}^T \tau_t^2 p_t^d x_{t-1}^d}{\sum_{t=qm+2}^T \tau_t^2 (x_{t-1}^d)^2} \quad (6)$$

where $\hat{\tau}_t = 1/\hat{\sigma}_{v,t}$ is used to weigh all the data in the bias-adjusted predictive model in equation (5), while $p_t^d = p - \sum_{p=2}^T p_t/T$ and $x_t^d = x_t - \sum_{z=2}^T x_t/T$.

We employ single and pairwise methods of evaluating forecast performance to determine which is 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. The Root Mean Square Error (RMSE) and its MSE variant are single model-based forecast performance measures used in this study. To ascertain the robustness of our results, we further complement the single measures with two 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. For detail derivation of each of these approaches to forecast performance evaluation (see Isah & Raheem, 2019; Salisu et al., 2019; Salisu & Isah, 2018).

III. Empirical Results

A look at the predictive regression results in Table 2 shows that the hypothesis of no predictability is significantly rejected both for the restricted and unrestricted predictive models. This confirms the potential of carbon prices and speculation behaviour as accurate predictors of climate change. However, while some previous studies (see Cui et al., 2021; Kohlscheen et al., 2021) confirm the emissions re-

duction effect of carbon pricing, our finding of such emission reduction only becomes evident when the speculation activity of the financial actors in the ETS complements the carbon prices. This is an indication that the speculation may benefit the EST rather than undermine it.

We take a step further to evaluate the forecasting power of the complementing dynamics of carbon prices and speculation on the predictability of climate change. 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. Starting with the single-method forecast performance evaluation measures, presented in Table 3 are the RMSE and MSE values. The lower the RMSE or MSE values, the better the forecast accuracy of a predictive 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, we find the predictive model with the interaction dynamics of carbon prices and speculation as the most accurate to forecast climate change.

We complement the single-method approach to forecast performance evaluation (RMSE and MSE) with a paired method based on the C-T test. 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 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, a look at Table 4 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.

IV. Conclusions

We employ both the ex-post and ex-ante approaches to determine the emissions reduction effect of the ETS and its forecasting power in predicting climate change. We show results that give credence to speculation as capable of enhancing the emissions reduction effect of carbon pricing. This may not be unconnected to the fact that despite their speculation behaviour, the financial actors 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 non-compliance actors in the ETS is inevitable, irrespective of their speculative behaviour.

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Table 2. 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

Table 3. Single-method based forecast performance evaluation results

Predictive model type	In-sample	RMSE			In-sample	MSE		
		Out-of-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.

Table 4. Pairwise-method based forecast performance evaluation results

Predictive model type	In-sample	C-T test			In-sample	C-W test		
		Out-of-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]
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.



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