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Analysis of the Dynamics of Carbon Pricing: The Role of Speculation in the Emissions Trading System (ETS)

By

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THESIS CERTIFICATION

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DEDICATION

This thesis project is dedicated to the memory of the late Dr. Abdulkader Cassim Mahomedy, under whose supervision I defended my proposal for this thesis before his demise. May Allah forgive all his shortcomings and grant him Aljanah Fridaus.

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All praise and thanks belong to Almighty Allah (S.W.T.), for my existence and capacity to accomplish this feat are entirely due to His magnificence.

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Too obvious to ignore are my beloved wife, Aminat Aminu, and my lovely children, Fu'ad Omeiza Isah and Fahkrijahan Oiza Isah, for patiently standing by me with their heart-warming support, love, and understanding.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ADP	Ad Hoc Working Group on the Durban Platform for Enhanced Action
AIC	Akaike Information Criteria
AOLS	Adjusted Ordinary Least Square
AR	Autoregressive
ARMA	Autoregressive and Moving Average
CPU	Carbon Policy Uncertainty
CDM	Clean Development Mechanism
COP	Conference of Parties
ECFs	Emissions Compliance Firms
ENCFs	Emissions Non-compliance Firms
ETS	Emissions Trading System
EC	European Commission
EUAs	European Emission Allowances
EEX	European Energy Exchange
EU	European Union
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GFC	Global Financial Crisis
GISS	Goddard Institute for Space Studies
GHG	Greenhouse Gases
HA	Historical Average
IPCC	Intergovernmental Panel on Climate Change
MSR	Market Stability Reserve
MIDAS	Mixed-Data Sampling
MSE	Mean Square Error
NASA	National Aeronautics and Space Administration
OLS	Ordinary Least Square
RMSE	Root Mean Square Error
SIC	Schwarz Information Criteria
TTF	Tile Transfer Facility
UNEP	United Nations Environment Programme
UNFCCC	United Nations Framework Convention on Climate Change
UN	United Nations
WMO	World Meteorological Organization

ABSTRACT

Purpose – To align with the global goal of keeping the temperature rise to well below 2 degrees Celsius, a market-based policy initiative, the "Emissions Trading System (ETS)," is to mitigate climate change. However, the carbon allowances traded at the ETS are held and traded not only by polluting companies, but also emissions non-compliance financial firms. These financial firms though engage in speculation, there has not been any compelling evidence of the extent to which speculation matters in carbon pricing. To bridge this gap, this study is premised on three separate but related essays to: (i) determine the accurate framework for modelling the dynamics of carbon pricing; (ii) determine the extent to which speculation matters in the predictability of carbon pricing; and (iii) determine whether speculation undermines or benefits the emission reduction effect of carbon pricing.

Methodology –We employ the GARCH-MIDAS econometric technique to test the hypothesis that an all-inclusive framework that reflects the emission compliance and emissions non-compliance dynamics of the ETS is the most accurate approach to modeling carbon prices. We also employ some verifiable econometric procedures to arrive at the Feasible Quasi Generalised Least Square (FQGLS) as the most appropriate estimator to address some of the biases in the predictability of carbon prices.

Findings – A modeling framework that captures both emissions compliance and emissions non-compliance dynamics of the ETS is the most accurate to modeling carbon prices. We find that speculation is a good predictor of carbon prices. We find that both emission compliance and emission non-compliance dynamics of the carbon market matter for the emissions reduction effect of the ETS and for enhancing the accuracy of climate change forecasts.

Research Contribution – The literature on emission trading has continued to ignore the speculative behavior of the emissions non-compliance firms in the ETS. As a result, we construct a composite news-based speculation index to simultaneously capture the emissions compliance and emissions non-compliance dynamics of the ETS in a single framework. We provide the literature with a data-driven framework upon which the predictive power of speculation is examined both in the predictability of carbon pricing and in the forecast of emission reductions.

Keywords: Carbon pricing; Speculation; ETS; Modelling framework; Predictability

LIST OF ARTICLES SUBMITTED FOR PUBLICATION

1. Experimenting with the forecasting power of speculation in the predictability of carbon prices (Published in Emerging Markets Finance and Trade) https://doi.org/10.1080/1540496X.2024.2324194

2. Testing the emissions reduction effect of carbon pricing: A predictive analysis of the role of speculation (Accepted for publication in Energy RESEARCH LETTERS)

3. Revisiting the framework for modelling carbon allowances: Does speculation matter?
4. (Submitted to Journal of Empirical Economics)

CHAPTER ONE
INTRODUCTION

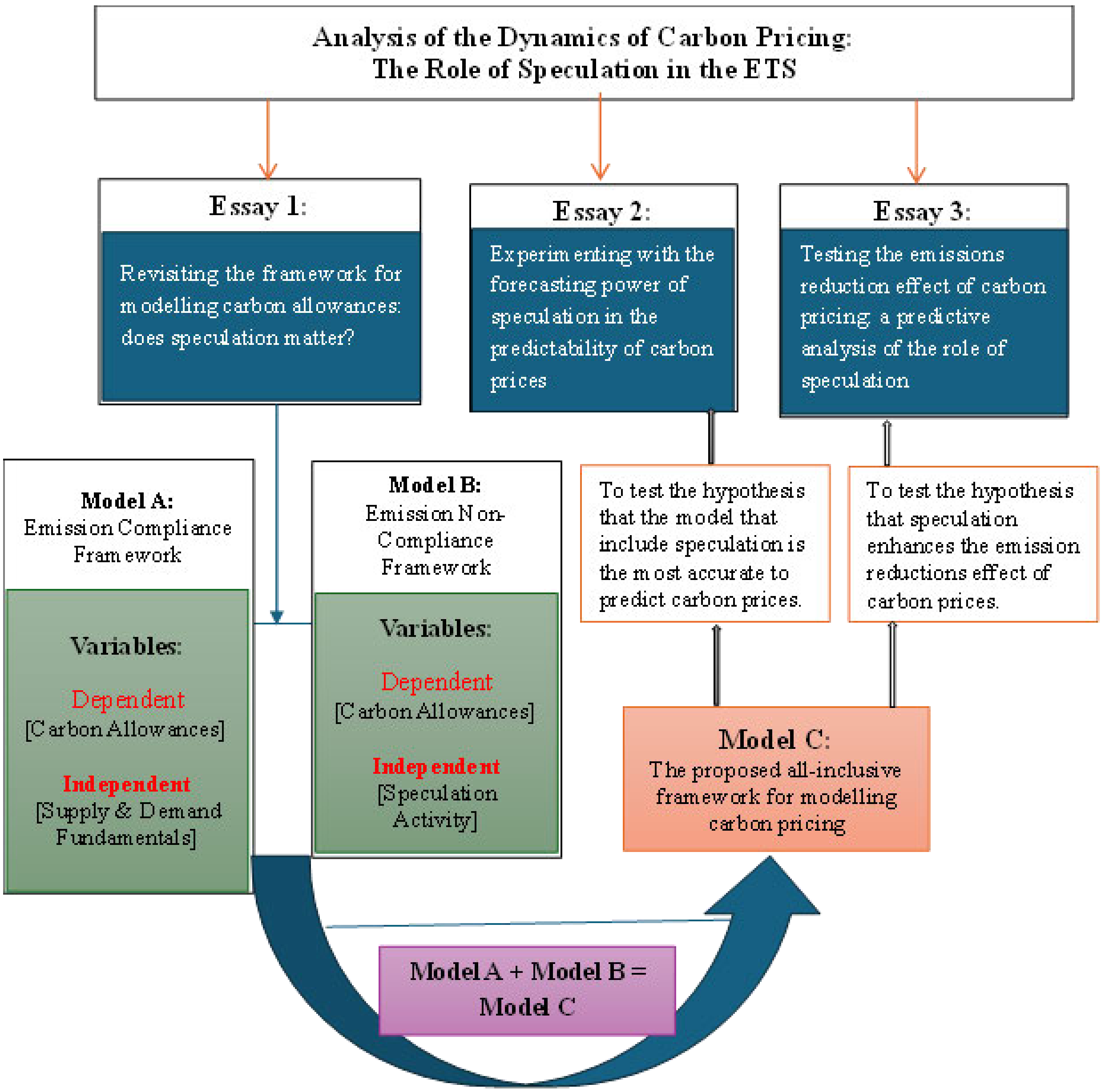
1.0 Context of the Study

The World Economic Forum (2006) rates failure to mitigate climate change as the most likely impactful risk for the coming decades in their assessment of global risks. Indeed, the phenomenon of "climate change," which often manifests in the form of changes in precipitation patterns, rising sea levels, storms, wildfires, and heatwaves, among others, has been the most debated global issue of the twenty-first century. In comparison to non-climate-change scenarios, unabated climate change is expected to hurt the global economy by lowering labour productivity (Adom & Amoani, 2021), disrupting supply chains, leading to higher food prices, and increasing food insecurity (Faccia et al., 2021). It does become inevitable to keep the global temperature, a source of climate change, well below 2 degrees Celsius. The "Emissions Trading System (ETS)" has been developed as a market-based policy initiative to mitigate climate change. A well-designed ETS can reduce carbon emissions at low economic and social costs (Baranzini et al., 2017). However, the carbon allowances traded at the ETS have increasingly evolved into a financial asset, making them vulnerable to events that have little to do with some of the structural fundamentals that serve as the workhorse of existing theories for explaining the dynamics of carbon allowances. For example, while carbon allowances are mostly held and traded by polluting companies that need them to comply with the global goal of emission reductions, investment firms, banks, and brokers have also invested in them primarily for profit's sake (see Quemin & Pahle, 2023).

Motivated by their profit maximization objective, the financial actors engage in "speculation," which might be detrimental to the functioning of the ETS. Despite this portending the possibility of the activity of the financial actors undermining the environmental goal of ETS, the fundamentals predominant in the literature as drivers of carbon pricing are carbon allowance supply and factors that influence the demand for carbon allowances. To this end, there hasn't been any compelling evidence on the extent to which the speculation activity of financial actors matters in the dynamics of carbon pricing. To bridge this gap, we developed an all-inclusive carbon pricing framework that accommodates not only the emission compliance activity of the

ETS but also the speculation activity of the financial actors in the market. The goal is to reduce the unexplained component of the ETS with the hypothesis that speculation matters in the dynamics and forecasting power of carbon pricing, particularly in the predictability of the future path of climate change. These objectives formed the fulcrum of this thesis in three separate but related essays. Depicted in Figure 1.1 is a conceptual framework showing the mechanism of the linkages among the three essays and the variables of interest.

Figure 1: Conceptual Framework



Source: The conceptual framework figure is plotted by the author

In the first essay, we rest on the increasingly vulnerable nature of the carbon markets to the emissions non-compliance activity of the financial actors to hypothesize that the continuous confinement of the dynamics of carbon pricing to demand and supply market fundamentals might not be accurate after all. For instance, the recent surge in the prices of carbon allowances has been attributed mainly to the growing speculation activity of the financial actors in the carbon markets (see Roques et al., 2022). In other words, there has been growing concern about the likelihood of the increasing speculation activity of financial actors overwhelming or undermining the emissions reduction role of the ETS (see Berta et al., 2017). Given this, there is a need for a review of the framework for modelling carbon allowances. As a result, we modified the framework for modelling carbon allowances to accommodate the growing commentaries linking the trend of excessive changes and volatility in carbon prices to speculation. Covering Phase II, Phase III, and Phase IV of the EU Emission Trading System (EU-ETS), we construct a news-based speculation index drawing from the extensive data archive of Google Trends to validate the accuracy of our proposed all-inclusive framework as a more comprehensive approach to modelling carbon prices using the GARCH-MIDAS econometric technique.

A well-behaved ETS with a reasonable carbon price is required for the ETS to fulfil its function as an emission reduction policy tool. However, such a well-behaved ETS can only exist with accurate and reliable carbon allowance price forecasts. According to Wang et al. (2022), a precise carbon price forecast can influence the benefits and costs of carbon market participants as well as the carbon emission quote setting, which is crucial for the stability and prosperity of the emission trading program (Dutta, 2018; Zhu et al., 2018; Hao & Tan, 2020). However, the fundamentals commonly acknowledged in the literature as predictors of carbon prices are mostly factors related to emissions compliance activity in the market, particularly those associated with the demand and supply dynamics of carbon pricing. Meanwhile, substantial speculative activity in the carbon futures markets has the potential to significantly alter futures prices from those supported by supply and demand fundamentals (Lucia et al., 2015). To this end, we further test the validity of our proposed all-inclusive framework in terms of the predictability of carbon pricing in the second essay of this study. We augment the fundamentals that are, in theory, widely recognized as predictors of carbon prices to include speculation in the quest to improve the forecast accuracy of carbon allowance prices.

Finally, despite the fact that the ETS is essentially a market for polluting enterprises that need allowances to comply with ETS requirements, financial actors as earlier listed have continued to participate. In doing so, they provide a critical service to ETS-affected enterprises, contributing to the establishment of more market liquidity and price visibility, as well as allowing operators to hedge against future swings. Thus, notwithstanding the widespread assertion of the potential threat of the growing presence of financial actors to the emissions reduction goal of the ETS, it is undeniable that some of the services they render to the ETS are equally inevitable. To this end, having a data-driven estimate on the extent to which speculation benefits or undermines the emissions reduction functioning of the ETS will provide policymakers with evidence-based insight into whether and to what extent speculation activity in the ETS should be restricted. As a result, we employ both ex-post and ex-ante approaches to empirical analysis to determine the extent to which speculation matters in the emission reduction effects of the ETS and the predictability of climate change.

1.1 Motivation for the Study

The seminal paper by Salant and Henderson (1987) theoretically motivates the appeal to determine and develop an all-inclusive framework to accommodate emissions compliance and emissions non-compliance dynamics of carbon prices in the ETS. Carbon allowance supply and factors influencing demand for carbon permits are traditionally the fundamentals that, in theory, determine carbon pricing. But, because allowance supply is constant in any given year, the literature has continued to emphasise factors affecting demand for carbon allowances in carbon pricing models. However, operational experience with ETS shows that the allowance supply schedule is dynamic and is subject to potential policy changes. In this regard, we are guided by the central assumption of Salant and Henderson's (1987) Hotelling-type anticipation model, which predicts that news becomes a critical component of expectation formation if market participants are exposed to ongoing regulatory intervention that significantly impacts prices.

In applying the above theoretical position to an essential prediction in the ETS context, Salant (2016) and Koch et al. (2016) believe that any announcement that affects the market's estimate of the likelihood of a cap revision will cause sharp price jumps regardless of whether the proposed change occurs. For example, the early-2018 upward trend in carbon allowance prices is attributed to the implementation of increasingly stringent climate change policies in the European Union (EU) and various changes in ETS market design (ECB, 2022). The European Commission's announcement of the European Green Deal in late 2019, combined with the European Council's approval of a new EU-wide emission reduction target in late 2020, has also been suspected of being responsible for the recent trends in the prices of EU allowances (EUA). The EUA prices hit an all-time high of €98.49/tCO2e, marking an increase of around 130% over prices in early 2021 and more than a 200% increase since early 2020.[1] This is combined with an increase in EUA price volatility, culminating in a price variation of more than 10% in early March 2022.

Even though the recent spike in carbon prices and its volatility is widely attributed to a crisis in the European energy markets and uncertainty regarding the scope and ambition of the EU ETS's ongoing reform, the increasing activities of financial actors in the carbon markets have also sparked discussion about the role and potential effects of speculation in the ETS. In light of this, among other things, a fundamental question relevant to this study is whether it is sufficient to continue relying on the existing emission compliance-based framework for analysing the dynamics of carbon pricing. To validate or refute this concern, we extend the traditional emission compliance-based model to account for the uncertainty in the ETS cap-setting process and the speculation activity of the emissions non-compliance actors in the market. That is, while the ETS's ability to reduce emissions largely depends on the flexibility and certainty with which a carbon price is established, events in the ETS have continued to suggest that mere speculation about the political commitment to the indicated cumulative cap influences the dynamics of carbon pricing. Based on these and other insights, this study's main and specific objectives are as stated below.

1.2 Overall Objective and Specific Aims of the Study

This study aims to develop a framework capable of accommodating both emissions compliance and emissions non-compliance dynamics of carbon pricing. More specifically, the study sets out to achieve the following:

[1] See Figure 2.5.

i. Determine a modelling framework that can be considered the most accurate for analysing the dynamics of carbon pricing.
ii. Determine the relative accuracy of emission compliance and emission non-compliance predictors in predicting carbon pricing.
iii. Determine whether speculation is detrimental or beneficial to the emissions reduction effect of carbon pricing.

1.3 Contribution of the Thesis to Literature

Although carbon allowances and permits in the ETS are mostly held and traded by polluting companies (i.e., emissions compliance firms) that need them to comply with the global goal of emission reductions, firms that has nothing to with the emission compliance goal of the EST also participate in the market. The latter are considered emission non-compliance firms as they are mainly responsible for providing necessary financial services to ETS-affected companies, such as increasing market liquidity and price visibility and allowing operators to hedge against future price fluctuations. This implies that, in addition to compliance firms, a portion of the carbon allowances traded in the ETS are owned by financial actors (emissions non-compliance firms) who have nothing to do with the ETS but have invested in it primarily for profit. In the quest to actualize their primary goal of profit maximisation, the emissions non-compliance firms often engage in "speculation" activity, which could be detrimental to the functioning of the ETS depending on how much of the overall market activity is driven by speculation. Despite this, among other things, the fundamentals that in theory determine carbon pricing remain carbon allowance supply and the factors that influence the demand for carbon permits.

Essentially, the literature on emission trading has continued to ignore the speculation activity of emissions non-compliance firms in the carbon market. To bridge this important gap, the contribution of this study to the literature on carbon pricing is threefold. First, we go beyond the norm of the ETS emissions compliance-based framework to develop an all-inclusive carbon pricing modelling framework that accommodates not only the regulatory agent but also the speculation activity of the emission non-compliance firms. Notwithstanding the few notable extant studies where volume and open interest data were utilised to capture the role of speculation in the carbon market (see Lucia et al., 2015), our study is the first, at least to the best of our knowledge, to have innovatively created a composite news-based speculation index to capture simultaneously the emissions compliance and emissions non-compliance dynamics of ETS in a single framework. Second, we subject the proposed all-inclusive framework to both in-sample and out-of-sample predictability tests, and the essence is to determine the extent to which speculation matters for enhancing the forecast accuracy of carbon prices. Finally, we employ both ex-post and ex-ante approaches to empirical analysis to determine the extent to which speculation matters in the emission reduction effects of the ETS as well as in the predictability of climate change.

1.4 Significance of the Study

It's interesting to understand the dynamics of carbon pricing in the ETS setting for various reasons. First, by creating a market and a CO2 price, the carbon permit scheme through the ETS gives businesses a reason to shift to being less reliant on fossil fuels. Second, price information is required by both emissions compliance firms and emissions non-compliance firms (speculators) to manage and hedge their portfolios. As a result, they need daily updates on market price movements and a thorough understanding of the underlying factors. Third, the analysis of carbon pricing will provide policymakers with evidence-based insights into the mechanisms that will promote carbon pricing flexibility and certainty in an emission trading system. Finally, having a data-driven estimate on the role of speculation in the emission reduction effect of ETS as well as on the extent to which speculation matters in the predictability of climate change, will provide policymakers with evidence-based insight into whether and to what extent emissions non-compliance firms (financial actors) is beneficial or detrimental to ETS.

1.5 Structure of the Study

Structured into six chapters, the first chapter (Chapter 1) of this thesis introduces the study by illustrating its rationale and purpose(s), as well as providing information on the three distinct related objectives that form the three essays that constitute the fulcrum of this thesis. Background and trends in climate change, ETS's evolution, and its fundamentals are in Chapter 2.

In the first essay presented in Chapter 3 of this thesis, a novel dataset, "the news-based speculation index," was constructed. The essence is to test the hypothesis that an all-inclusive framework that accommodates both emission compliance and emissions non-compliance activities of the ETS is the most appropriate to model the dynamics of carbon pricing.

Using relevant model performance evaluation techniques, we tested the accuracy or otherwise of the proposed framework against a number of existing alternative frameworks. The second essay, presented in Chapter 4, examined the forecasting power of the preferred model in the predictability of carbon prices.

In the third essay housed in Chapter 5, we experiment with both ex-post and ex-ante approaches to empirical analysis to determine the extent to which speculation matters in the emission reduction effects of the ETS and the predictability of climate change. The final concludes the thesis and offers recommendations based on the thesis finding.

CHAPTER TWO
BACKGROUND ANALYSIS AND STYLIZED FACTS

2.0 Introduction

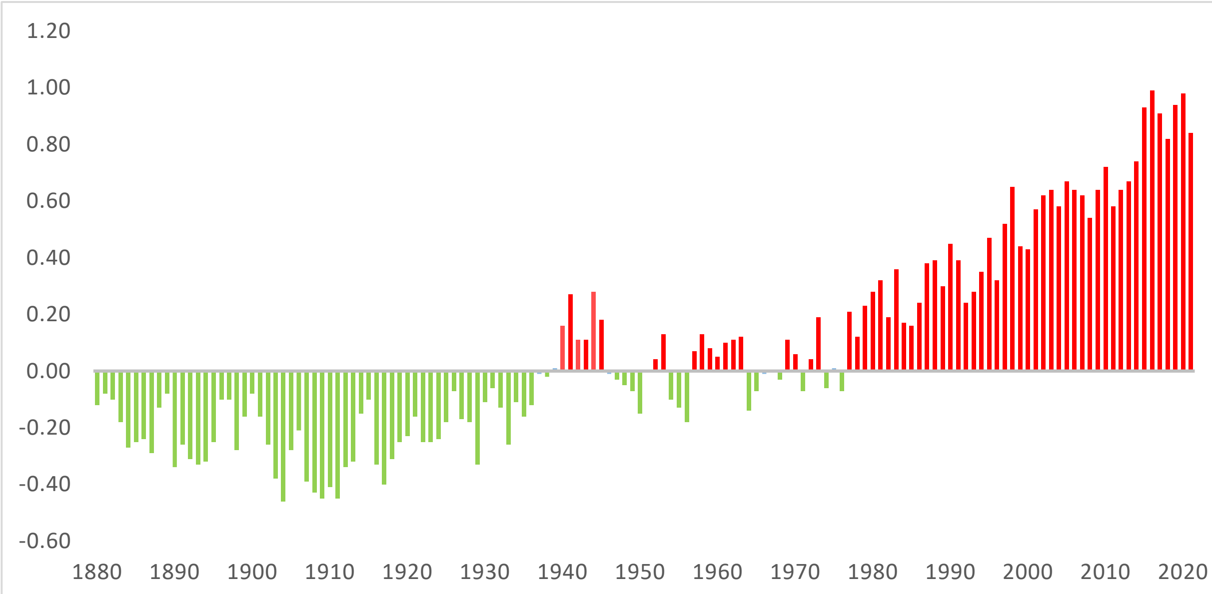
This Chapter offers an evidence-based background analysis of the ETS and its fundamentals. In the first section of the Chapter, we provide background information on the physical and economic implications of climate change in order to emphasise the need for emissions control measures to achieve the global goal of low carbon emissions. In the second section, we highlight the evolution and operation of carbon pricing globally. In the concluding part of the Chapter, we present some stylized facts about ETS and its fundamentals.

2.1 Background Literature on the Consequences of Climate Change

The phenomenon of "climate change" has likely been the most widely debated topic on the planet. Although the recent COVID-19 outbreak makes it seem impossible to focus on anything other than the pandemic, the threat of climate change has continued to dominate the global agenda. For example, the human-caused emissions of greenhouse gases (GHG) widely regarded as the main driver of climate change, have since the start of the industrialization in 1750 increased from about 277 parts per million (ppm) to about 409.89 ppm as at 2019 (Joos & Spahni, 2008; Dlugokencky & Tans, 2020). The release of greenhouse gases has the potential to accelerate global warming and, as a result, raise the earth's average surface temperature to levels not seen in millions of years (IPPC, 2013).[2] Scientists have also cautioned against the possibility of hitting climate tipping points, which would have disastrous effects on the planet's ability to support life (Wunderling et al., 2021). Figure 2.1, for example, is global and ocean surface temperature, where the average temperature across the worldwide surface as of 2021 was 0.84oC, above the 20th-century average. To put it another way, the nine years from 2013 to 2021 are among the ten warmest on record. Since 1880, the average yearly global temperature increase has been +0.08°C each decade; however, since 1981, the average annual increase rate has grown by more than twice that amount. Essentially, the year 2021 marks the 45th year in a row in which the global temperature has been at least nominally higher than the norm for the 20th century.

[2] Intergovernmental Panel on Climate Change (IPCC)

Figure 2-1: Global Average Temperature Changes (1880-2021) [3]



Source: Figure is plotted by the author based on data from National Centres for Environmental Information (NCEI).
Note: The green bars indicate cooler-than-average year, while the red bars show warmer-than-average year.

If the growing trends in average global temperature depicted in the graph above continue, such changes in climate conditions are projected to increase global warming by about 4°C relative to pre-industrial levels. According to the IPCC (2013), this has the potential to significantly raise the average temperature on the Earth's surface. Warming to 2 degrees Celsius rather than 1.5 degrees Celsius is anticipated to increase the number of people exposed to climate-related risks and poverty by hundreds of millions by 2050 (Xu et al., 2019). Climate change has the potential to cause displacement, disrupt food chains, jeopardise livelihoods, and exacerbate conflict stress (IPCC, 2019). In other words, in addition to the obvious physical repercussions of climate change, such as significant changes in precipitation patterns, rising sea levels, hurricanes, wildfires, and heatwaves, the steady rise in average world temperature is expected to harm macroeconomic forecasts. As temperatures rise due to global warming, worker productivity is anticipated to reduce as a result of rising rates of death and sickness, as well as a general decline in efficiency (Adom & Amoani, 2021). Furthermore, natural disasters that interrupt the supply chain are likely to have an impact on certain pricing, particularly the price of agricultural items.

[3] https://www.ncei.noaa.gov/access/monitoring/global-temperature-anomalies/anomalies

Although global warming may positively impact some cold developed countries, such as Canada and Russia, for a time, the opposite is likely to be true in hotter regions. Bangladesh, whose 70% of the total area is less than one metre above sea level, is an excellent example of the latter. Despite only being responsible for 0.3% of global emissions, the country is still largely vulnerable to the consequences of climate change (Gardiner, 2014). In other words, the distribution of harmful effects of climate change is not uniform worldwide. However, while the worst warming effects are likely to be concentrated in hotter regions, it is instructive that no country can claim to be immune to the negative consequences of climate change. Given the growing threat of global warming to human survival and the entire Earth's surface, there is growing international agreement on the need for immediate GHS reductions (see Hu et al., 2020). Policymakers at national, regional, and international levels have put forward proposals to respond to the climate challenge (see Copper and Ambrosi, 2009). Thus, the following offers some stylized facts on the evolution of some of the policy options and carbon emissions mitigation initiatives that have emerged on the path to the global goal of low carbon emissions.

2.2 An Overview of Emission Reduction Policies

Despite the Stern (2007) review suggesting that the benefits of strong and early actions on climate change far outweigh the costs of not acting, it is instructive that the importance and appropriateness of generalising the implementation of emission control policies across the globe remain contentious, given that different economies characterised by varying economic structures differ in their shares of contribution to CO2 emissions. Prior to the industrial revolution in the 1800s, the inflows of GHGs associated with animals and sediment were naturally balanced, as were the outflows of carbon absorbed by the ocean and plants. Human activities, such as the combustion of fossil fuels, upset the balance, leading carbon dioxide emissions from fossil fuels to increase by more than 3% per year on average in the 2000s (Garnaut, 2011). Indeed, in its 2013 assessment, the IPCC found that human activities are responsible for nearly 95% of global warming. Recognising the negative externalities and repercussions of GHG emissions, the world has grown increasingly concerned about environmental issues, with an increased effort to regulate CO2 emissions produced by human activities. The World Meteorological Organisation (WMO) began to express alarm about rising carbon dioxide emissions generated by human activity in the late 1970s.

Scientific concerns about global warming began translating into political ones in 1988 due to severe heat waves and droughts in North America. In this context, the WMO and the United Nations Environment Programme (UNEP) established the International Panel on Climate Change (IPCC). The primary objective of the IPCC is to examine and report on scientific evidence of climate change as well as viable responses to it. Since then, the IPCC has played a key role in following discussions and procedures relating to the development of climate change policies. The first assessment report of the IPCC, released in 1990, and subsequent reports inspired the establishment of the United Nations Framework Convention on Climate Change (UNFCCC) in 1991. Following this was the 1992 Rio Earth Summit, at which 166 countries ratified the United Nations Framework Convention on Climate Change, which went into force in 1994. Even though the UNFCCC does not set a precise national or worldwide objective for lowering GHG emissions, it does incorporate essential concepts and principles that have served as the foundation for subsequent international climate change debates and processes. In summary, the UNFCCC establishes the following:

i. To stabilise the climate within a time frame that allows natural systems to adapt without causing significant damage to food systems and economic development.
ii. Countries must keep track of and reduce their GHG emissions, and different national limitations must consider the various responsibilities and capacities of the various countries.
iii. To give keen attention to developing economies, particularly those deemed most vulnerable to the adverse effects of climate change.

While it is true that the UNFCCC falls short of many environmentalists' expectations due to the lack of specific emission reduction targets, it is instructive that it is still an important step in establishing foundational principles that will later guide subsequent negotiations on national GHG emission reductions. The UNFCCC, for example, eventually resulted in a Conference of Parties (COP) conference in Kyoto, Japan, in 1997, where 37 industrialised countries and the European Union committed to decrease greenhouse gas emissions. However, a look at Table 2.1 reveals that the route to the Kyoto Protocol began even before 1997, in Berlin, Germany, in

1995, with COP1, where the focal purpose was to examine the success of the Convention's commitments in combatting climate change.

Table 2.1: Summary of United Nation Climate Conference (COP1-27)

Year	COP Type	Remarks
1995	COP1	To assess the effectiveness of the Convention's accords in mitigating climate change. The review's results indicated the need for a legally enforceable protocol, rather than voluntary commitments under the Convention, with new national emission reduction objectives and a specific time limit.
1996	COP2	Adoption of the Intergovernmental Panel on Climate Change's second assessment report, which warned of a discernible human influence on global climate change. The meeting emphasised the critical need for a blinding protocol to address GHG emission issues.
1997	COP3	Adoption of the Kyoto Protocol on Climate Change, a binding agreement that mandates industrialised nations reduce GHG emissions by 5.2% by 2012 (first commitment phase: 2008–2012) compared to 1990 levels (22.7 billion metric tons).
1998	COP4	At the very least, agreement on the detailed structure of the Kyoto Protocol by the sixth meeting of the COP. The summit was marked by informal conversations about the importance of poor countries committing to decreasing GHG emissions.
1999	COP5	Monitoring commitments and the architecture of the Kyoto procedures, particularly the Clean Development Mechanism (CDM), were discussed, and criteria for industrialised nations' national emissions reporting were developed.
2000	COP6-1	Attempted to clarify the provisions of the Kyoto Protocol but failed to gain agreement among the umbrella group, which includes the United States, Australia, Canada, Japan, and Russia, developing countries, and the European Union. The main points of disagreement were natural forests' temporary carbon storage role and their inclusion in the CDM, as well as the need for binding standards for reduction promises.
2001	COP6-2	Reached an agreement on the Kyoto Protocol's principal unsolved concerns, which led to the passage of the Bonn Agreements on international climate policy, which provided the conditions for ratifying and implementing the Kyoto Protocol.
2001	COP7	The Marrakesh Accords were a set of fifteen decisions on how to structure and implement the Kyoto Protocol. This included a mechanism for monitoring compliance, the use of carbon sinks credit under the Kyoto Protocol, and the encouragement of climate action in underdeveloped nations. The acceptance of the Accords prepared the stage for the entrance into effect of the Kyoto Protocol.
2002	COP8	Negotiations on the terms of the Kyoto Protocol were praised. The design of the CDM and the utilisation of monies contributed by developed nations for climate action in poor countries were decided. A work programme was launched to raise awareness of climate challenges and integrate them into the educational activities of the Parties.

2003	COP9	The two-year negotiations on the rules for afforestation and reforestation initiatives in developing countries were successfully concluded, bridging the last gap in the Kyoto Protocol rules of implementation.
2004	COP10	The summit discussed funding, institutional change, capacity training, and technology transfer to support UNFCCC adoption in underdeveloped nations.
2005	COP11	Adoption of the Montreal Action Plan, a road map for the international climate regime after 2012. The Kyoto Protocol was completely implemented, and its organisational structure was fortified with a rigorous review regime and greater finance.
2006	COP12	The meeting focused on African concerns such as capacity building, aid in the development of concrete projects, and participation in the CDM.
2007	COP13	Adoption of the Bali Action Plan, which entailed parties negotiating concrete promises and contributions to carbon reductions (including deforestation reductions), adaptation, technology, and financing through 2012 and beyond.
2008	COP14	The key features of a new climate regime were examined, with a focus on the necessary national GHG reduction objectives and financial support for climate action in developing countries.
2009	COP15	The Copenhagen Accord was drafted, which established certain key components of future international climate policy, and 1.5 degrees Celsius or 2.0 degree C" limit emission norm was agreed upon by a wide group of developed and developing countries. In addition, from 2010 to 2012, developed countries pledged up to $30 billion towards climate action in underdeveloped countries. A technology Mechanism and a REDD+ Mechanism were considered to assist poor nations with technology projects and to reduce emissions from deforestation and forest degradation.
2010	COP16	With the adoption of the Cancun accords, the accords established in Copenhagen were formalised, expanded upon, and operationalized. These include governmental recognition of the two-degree target, forest conservation (REDD+ Mechanism), technology cooperation, and developing-country capacity-building. Industrialised countries have offered $100 billion per year by 2020 to fund developing countries' climate change efforts.
2011	COP17	The Kyoto Protocol will be extended for a second time beginning in 2013. The meeting also approved the Green Climate Fund, which would provide financial assistance to both developed and developing countries in their efforts to combat climate change. The ADP created a deadline for creating a new international pact to replace the Kyoto Protocol when it expires in 2012.
2012	COP18	The submitter spearheaded more immediate climate efforts required to reach the Copenhagen Accord's 2 degrees Celsius objective. Amendment to the Kyoto Protocol requires a reduction in GHG emissions of at least 18% below 1990 levels by 2020 (second commitment phase: 2013-20).

2013	COP19	Initiated negotiations for a global climate deal in advance of the 2015 Climate Change Conference in Paris on themes such as mitigation, adaptation, financing, technology, transparency, and capacity building.
2014	COP20	The framework was laid for negotiations on a new global climate agreement to be agreed upon at the 2015 climate change conference in Paris.
2015	COP21	Adoption of the Paris Agreement, which aims to strengthen the international response to the threat posed by climate change by limiting the rise in global temperature this century to well below 2 degrees Celsius. Parties to the conference also agreed to accelerate and intensify the actions and investments required for a sustainable low-carbon future.
2016	COP22	The key objective is to continue building the global response to the issue of climate change and keeping the momentum for climate action going.
2017	COP23	The primary goal is to accelerate climate action to complete the work timetable established by the Paris Climate Change Agreement.
2018	COP24	To complete the Paris Rulebook, a set of regulations will enable the 197 parties to the Convention to fully execute the Paris Agreement's goal of keeping global warming well below 2 degrees Celsius and ideally 1.5 degrees Celsius by the end of the century.
2019	COP25	To formalise the regulations for implementing the Paris accords and to speed steps to accomplish the decarburization pledges made in the agreement.
2021	COP26	The main goal was to achieve worldwide net zero emissions by mid-century and limit warming to 1.5 degrees Celsius.
2022	COP27	The initiative aims to unite, coordinate, and guide the actions of all stakeholders across the built environment value chain. The goal is to bring the government together to accelerate global efforts to confront the climate crisis.

Source: The author constructed the table using historical reports from the various Conferences in Paris (COP) that have occurred to date.

A detailed examination of Table 2.1 reveals that the Kyoto Protocol, often known as the "Marrakesh Accords," was adopted for implementation at the COP7 in Marrakesh, Morocco in 2001. Several countries, including the United States and Australia, initially refused to ratify the Kyoto Protocol, citing the requirement that developing economies restrict their emissions as well. Significant public disputes questioned the scientific foundation for climate change prediction, and the oil sector invested significantly in contesting or rejecting climate change. Thus, despite widespread recognition of the challenges posed by climate change, governments continue to dispute on the equal distribution of GHG emission limits and reductions. These manifest in many national objectives about justice, ethics, and development issues.

Developing guidelines for agreement on appropriate and reasonable national emission objectives faces continuing technological and political obstacles. These objectives entail creating, approving, implementing, and overseeing systems to achieve them. They cover key topics such as financing adaptation and mitigation in poor countries, as well as providing developing countries with access to climate-friendly technology. These, among other difficulties, were the focus of COPs in Copenhagen in 2009, Cancun in 2010 (COP16), and Durban in 2011 (COP17), when discussions were underway to create a legally enforceable convention for the years after 2012, the end of the Kyoto Protocol's first commitment period.

In contrast to Copenhagen, Cancun generated the Cancun Agreements, which laid the groundwork for a number of major agreements, including the Green Climate Fund, the Technology Mechanism, the Cancun Adaptation Framework, and Forest Management Reference Levels. Many people expected Durban to result in a settlement for the phase after 2012. Regrettably, it was determined that any international legally binding pact for emission reductions will be drafted by 2015 and implemented by 2020. The Durban Platform for Enhanced Action was established to support discussions on a new global agreement that would take effect in 2020. However, NGOs, scientists, and certain countries criticise the delay in international action to combat climate change by over ten years, from 2012 to 2020. As a result, the Kyoto Protocol's second commitment period began in 2013 with the UNFCCC's 21st COP (i.e., COP21), which was later held in Paris in 2015 and resulted in what is now known as the Paris Agreement.

The Paris Agreement seeks to strengthen and replace the Kyoto Protocol, a previous international deal aimed at reducing greenhouse gas emissions. The Paris Agreement intends to significantly reduce global greenhouse gas emissions in order to limit the rise in global temperatures this century to 2 degrees Celsius over preindustrial levels, while also seeking ways to restrict the increase to 1.5 degrees. As part of the agreement, all big polluters have promised to cut their climate pollution and to strengthen those pledges over time. The agreement sets a framework for transparent monitoring, reporting, and raising individual and collective climate targets for countries. It also provides a way for wealthier countries to assist underdeveloped countries with climate mitigation and adaptation measures.

The Paris Agreement was open for signatures from April 22 to April 21, 2017. According to Article 21(1), it entered into force on November 4, 2016, and as of January 20, 2021, it had been signed by 195 countries and ratified by 190. Thus, the adoption of the Kyoto Protocol, which culminated in the Paris Agreement, represents a watershed moment in international climate politics over the last two decades. By delivering global binding emission reduction targets, the Protocol and, consequently, the Paris Agreement paved the way for a carbon emission trading system (ETS). In this context and in the quest to understand the dynamics and fundamentals of the leading instrument in the carbon market (i.e., carbon pricing), we proceed, as shown in the following sections, to provide comprehensive background information on the goal, mechanism, and operation of carbon emission trading.

2.2.1 Emissions Control Instruments

To cut emissions and maintain global temperatures below 2 degrees Celsius, various alternative policy solutions have been created and implemented (see Perman et al., 2013). Institutional techniques to enable emissions abatement targets through socialisation and education programmes emphasising social duties are examples of such policy choices. We also have the command-and-control option, which entails placing constraints or norms on inputs, outputs, manufacturing processes, or even activity location. However, in comparison to institutional approaches and command and control instruments, market-based instruments have maintained scholarly attention and discussion. Indeed, market-based mechanisms such as taxes or carbon trading are judged more acceptable in economic theory than command-and-control regulation.

The underlying assumption is that market-based mechanisms, also known as "carbon pricing," have the potential to ensure both environmental effectiveness and economic efficiency, allowing emission reduction targets to be met at the lowest possible cost. However, the fact that a portion of the carbon allowances traded in carbon markets are owned by financial players calls for concern. This is because the financial actors have nothing to do with the ETS but invested in it mainly for profit. To maximise their profits, they frequently participate in "speculation" activities, making the ETS relatively complex, as it is clear whether the speculation is destructive or advantageous to the ETS. Therefore, the background information on the various instruments of carbon pricing is explored in a manner that takes cognizance of speculation activity in the EST.

2.2.1.1 Market –based instrument: Carbon Pricing

The literature mostly described the pollution produced by people and firms that participate in carbon-emitting activities as a "negative externality", given the detrimental side consequences of such pollution, particularly with regard to global warming, Thus, when policymakers prefer market-based instruments in the pathway to the worldwide goal of emission reductions, the underlying intuition is to effectively correct such a negative externality (i.e., market failure). The concept is straightforward: by placing a price on carbon, polluters are compelled to absorb the costs that their emissions place on society, motivating them to cut emissions and convert to sustainable energy sources. A policy that places a price on CO2 emissions to alter behaviour and reduce overall emissions is known as carbon pricing. In other words, carbon pricing is a technique used to account for the external costs and consequences of carbon emissions. The harm from emissions, such as pollution and negative health effects, is connected to the sources by assigning a value to the CO2 released. Emission trading systems (ETS) and carbon taxes (CT) are the two methods for pricing carbon.

a) Carbon tax (CT)

By putting a direct price on GHG emissions, the carbon tax is a market-based policy instrument that directly taxes economic players for each tonne of carbon pollution they release. According to this strategy, the government serves as the regulator and determines how much emitters must pay for each tonne of emissions they are accountable for.[4] To avoid paying the tax, it is hoped that enterprises and consumers will reduce their emissions. In this instance, cheaper taxes result from less pollution. Either emissions taxes or commodities taxes are used to describe carbon taxes. A CO_2 emissions tax is calculated according to how much CO_2 an entity emits. A goods tax, on the other hand, concentrates on products or services that are typically GHG-intensive, like aviation and petrol. Both strategies offer high levels of price certainty due to the set cost per tonne of pollution, but they are less predictable as to how much emissions will be cut.

b) Emission Trading Systems (ETSs)

The ETS, a cap-and-trade system, is an allocation scheme that allows carbon market participants to buy and sell allowances with a set emission limit. It is a method of controlling carbon dioxide (CO_2) emissions in which a central authority establishes a limit or cap on the amount of carbon that can be emitted (Marcus, 2006). Because the carbon market is similar to other financial markets (Brohe et al., 2009), most existing studies on the carbon market have assumed that the market, in its statistical characteristics, closely resembles conventional financial products such as shares, stocks, bonds, and foreign exchange. In contrast to these traditional financial market products, the commodity traded in carbon markets is gas and CO_2, affecting the climate and doubling as a global public good. Furthermore, carbon markets differ from traditional financial markets because they can be regulated (compliance markets) and voluntary.

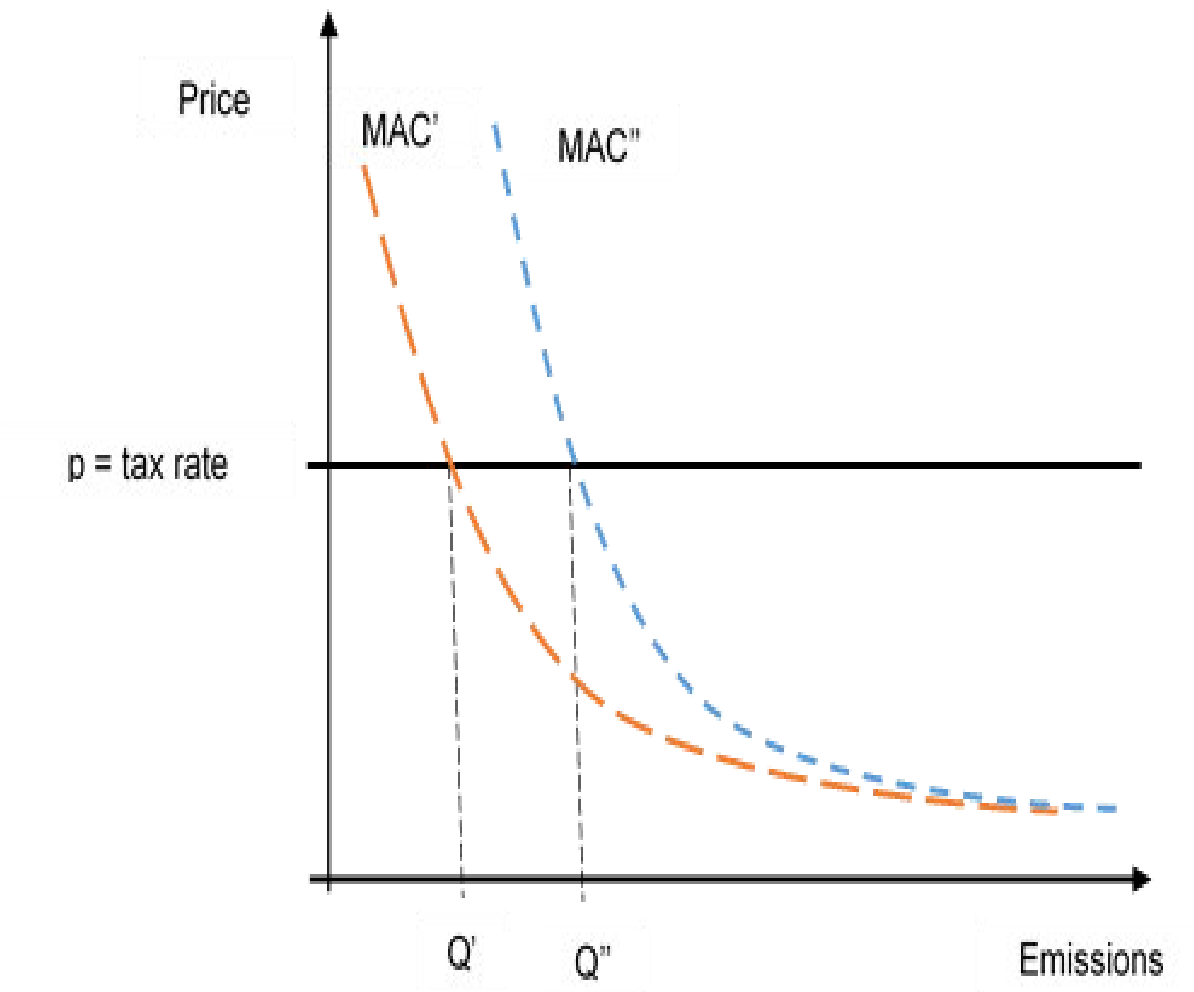
Obligatory national, regional, or international carbon reduction initiatives shape and govern the compliance markets. In most cases, it takes the shape of a cap-and-trade system, which establishes a ceiling (or "cap") on all direct GHG emissions from a given sector and creates a market where the emission rights (in the form of carbon permits or allowances) are traded. Allowances are distributed to participants based on the set emissions targets. Since each actor will be driven to produce less than or equal to the GHG emissions target or cap, this should theoretically result in a decrease in the sector's overall emissions. Businesses can decide how to use their funds for new technology and other improvements to reduce emissions while bearing in mind that the cost of doing so will increase as the cap tightens.

[4] Center for Climate and Energy Solutions. (2009). Carbon Tax Basics. https://www.c2es.org/content/carbon-tax-basics/%206

2.2.1.2 Carbon Tax (CT) *vs* Emission Trading System (ETS)

The ETS and carbon taxes are two alternative methods of pricing carbon. For instance, in the case of a carbon tax, the regulator sets the price of CO2 emissions while abatement efforts dictate the quantity of emissions. The Figure below (Figure 2.2) illustrates this viewpoint by fixing the price of carbon emissions while varying the level of emissions in accordance with the cost curves for abatement. Emissions are modified under the carbon tax until the tax rate is equal to marginal abatement costs.

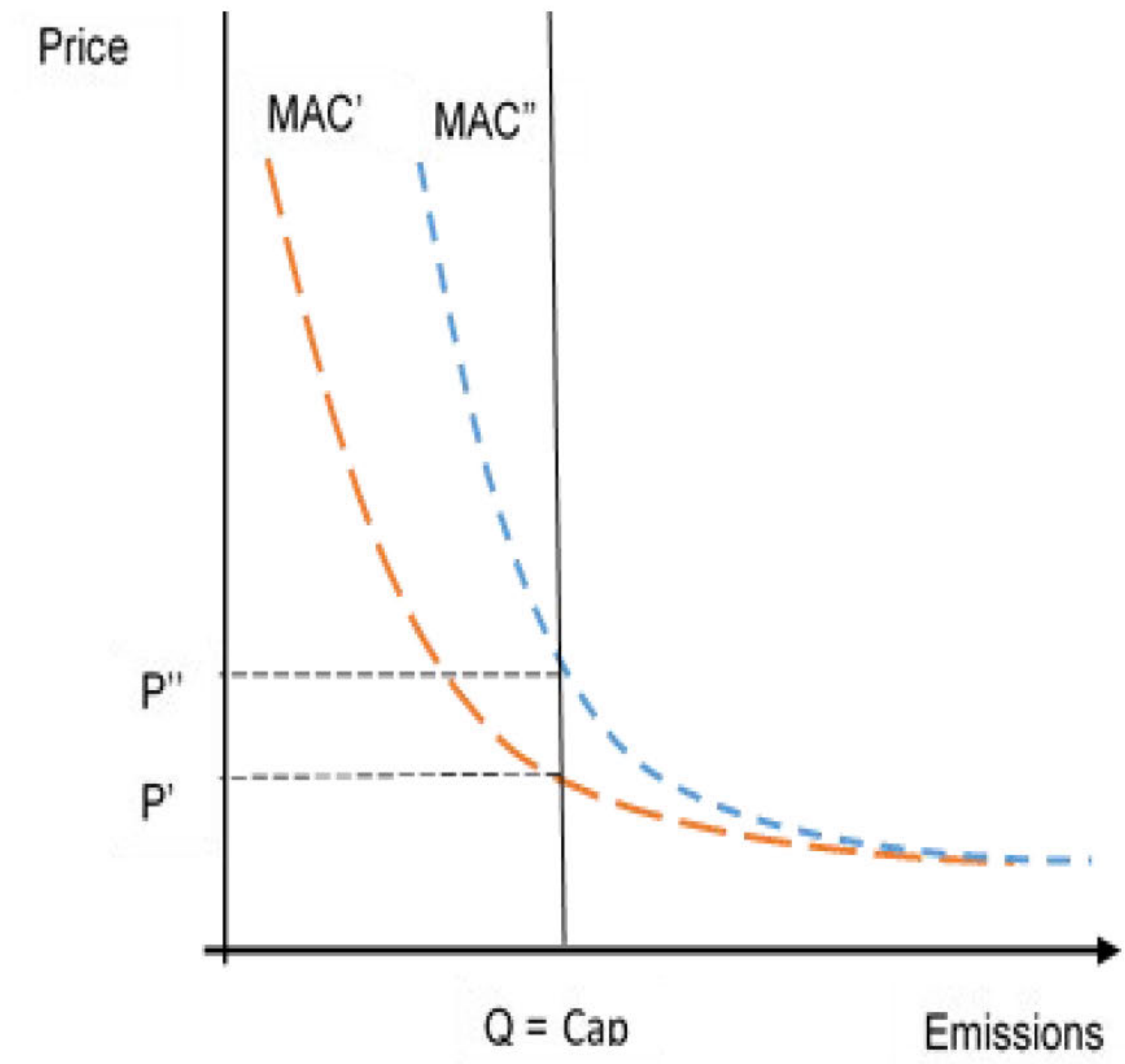
Figure 2-2: Carbon tax –based market instrument for emission reductions



Source: The Figure is plotted by the author as seen in the study by Kettner (2013, pp. 5)

In the case of the emission trading system (ETS), the regulator controls the quantity of emissions but not their price. Instead, as illustrated in Figure 2.3, the market forces of supply and demand for emission permits determine the price of emissions. The supply in this case is determined by the total emissions cap, whereas the demand is determined by the enterprises' individual marginal abatement cost functions (see Metcalf, 2009).

Figure 2-3: ETS –based market instrument for emission reductions



Source: The Figure is plotted by the author as seen in the study by Kettner (2013, pp. 5)

The curved, coloured dotted lines in Figures 2.2 and 2.3 represent different marginal abatement cost curves; for example, MAC' stands for less expensive abatement, while MAC" stands for more expensive abatement. The carbon price for the two possible policies is shown in each figure as a black dotted line. The resulting emission level and price are determined by where the curves in each figure connect.

Although carbon taxes (CT) and emissions trading (ET) are thought to have a similar marginal incentive to reduce emissions (ET), in practice, these instruments have different costs and benefits that accrue at different times and on different geographical scales (He & Lin, 2018). This and other relative advantages and disadvantages of either instrument have fuelled debate in the literature about which of these alternative carbon pricing instruments works best at mitigating emissions.

Weitzman (1974) has shown that under uncertainty of marginal abatement costs and marginal benefits, the outcomes of taxes and permits are not equivalent. Furthermore, the relative slopes of the curves determine the ultimate outcomes of the policy. Hence, it has been established that both market-based instruments, namely, carbon taxes and ETS, have advantages and disadvantages, but which choice should be considered the most appropriate will depend on which of the uncertainty about prices and uncertainty about quantity constitutes the more significant burden to society (Murray & Dey, 2009). For clarity, we summarise some similarities and dissimilarities between carbon taxes and ETS in the following (see Table 2.2).

Table 2.2: Carbon Taxes vs ETS

Characteristics	**Carbon Taxes (C-T)**	**Emission Trading Systems (ETS)**
Certainty of Prices	Businesses can predict the price of carbon emissions as they are certain about it.	The price of emission is unpredictable as it is not constant, and businesses are not certain about it.
Level of Emissions	The level of emissions is not constant.	The level of emissions is constant because the level of emissions is fixed.
Mode of Control	The amount of carbon emitted is fixed per ton, which is translated into an oil, electricity, or natural gas tax.	Emissions are limited by issuing licenses for each tone of carbon dioxide produced.

Source: Table constructed by the author with excerpt from Parry et al. (2022)

In other words, under a carbon tax, firms can be certain of the cost of carbon emissions, whereas under an emission trading plan, the price of emissions can fluctuate and is not permanently fixed. Furthermore, carbon tax modifications are dependent on emissions levels, whereas an emissions trading plan includes a predetermined cap on overall emissions. While neither the carbon tax nor the ETS are immune to ambiguity, the latter can help to reduce uncertainty about benefits (Kettner, 2011). For example, it is well understood that the benefit of carbon reduction is proportional to the rise in global temperature, which is proportional to CO2 emissions. As a result, it is informative that the ETS has the capability of determining the permissible amount of emissions and the consequent advantages. For example, we have yet to evaluate the impact of any specific carbon tax level on emissions and, hence, expected benefits.

The ETS has been widely preferred by a number of countries and regions as the most appropriate carbon pricing instrument to reduce carbon emissions on the pathway to the global goal of limiting global temperature and avoiding the negative effects of climate change, partly due to its relative advantage in terms of certainty of quantitative emission reduction targets. For instance, as part of their commitment to the global goal of low carbon emissions, some 46 national jurisdictions and 35 cities, states, and regions, accounting for close to a quarter of global GHG emissions, are currently putting a price on carbon. Many of these jurisdictions are dealing with carbon price through developing and implementing ETS. The ETSs were reportedly covering more than 40% of the world's GDP as of 2021, functioning in 38 nations, 18 states or provinces, and six cities, according to the World Bank Group's 2021 study, "Emissions Trading in Practise," with further systems reportedly in the works.

The International Carbon Action Partnership (ICAP, 2022) highlights in its status report how ETS innovations are expanding and gathering up speed around the world, with a rising number of systems. According to the paper, there are already 25 emissions trading systems (ETSs) in place, accounting for 17% of worldwide GHG emissions. The European Union Emissions Trading System (EU-ETS), the United Kingdom ETS, the German National ETS, the Swiss ETS, the California Cap-and-Trade Programme, the US Regional Greenhouse Gas Initiative, the Massachusetts Limits on Emissions from Electricity Generators, the Quebec Cap-and-Trade System, the Nova Scotia Cap and Trade Programme, Mexico's ETS, the Kazakhstan ETS, the

New Zealand ETS, the Chinese National ETS, the Korean ETS, and the Japanese GX ETS. About 22 ETSs are currently being constructed or studied, especially in South America and Southeast Asia. At the time of writing, approximately one-third of the world's population is subject to an active ETS (see ICAP, 2022).

It is essential to emphasise that to be environmentally beneficial, a trading system must successfully cut emissions. This, in turn, is dependent on the strictness of the cap and the program's capacity to provide consistent legal safeguards and financial incentives. Many nations throughout the world are altering their ETS to fit with net-zero goals, and existing systems are evolving and becoming more resilient to external shocks. Carbon prices have risen practically everywhere because of the anticipation of stricter emissions limits in the future. However, there is rising evidence of variations in emission price trends (see Kettner, 2011; Lucia et al., 2015; Ye & Xue, 2021), which provides a difficulty for firms when selecting whether to engage in pollution reduction-based investment. To put it another way, rising volatility in emission prices do not provide a clear investment signal and tend to make decision-making and planning harder for businesses.

As a result, stable emissions price has been prioritised in the emission trading system to ensure environmental efficacy and cost-efficiency, as well as to provide investment and innovation incentives for low-carbon technology. This, however, requires a full grasp of the fundamentals underlying the underlying sources of carbon price changes. For example, the EU-ETS is the carbon price reference point to date, and if the EU-ETS is to be used as a template for understanding the dynamics of carbon pricing around the world, the starting point, as demonstrated in the following, is to be familiar with some stylised facts and trends in EU-ETS emission prices.

2.3 Some Stylized Facts and Trends in EU-ETS

It makes no difference where emission reductions are implemented; the environmental impact of emission reductions is the same regardless of where they are implemented, particularly in terms of physical location. More crucially, the reason for carbon trading is that it permits reductions to be made where the cost of reduction is lowest, cutting the overall cost of tackling climate change.

The European Union's Emissions Trading System (EU-ETS), which went into effect in 2005, was not only the first attempt to create a mandatory carbon market to reduce emissions in high-intensity carbon-emitting industries, but it is also the most extensive cap-and-trade programme and the cornerstone of the world's ambitious climate strategy. The EU-ETS operates on a "cap-and-trade" approach, in which all system participants agree to a "cap" or limit on total greenhouse gas (GHG) emissions, which is then translated into marketable emission allowances. The EU-ETS allocates tradable emission allowances to market players through free allocation and actions. A single allowance permits the bearer to emit one tonne of CO_2 equivalent. Participants subject to the EU-ETS are required to monitor, report, and surrender enough emission allowances to cover their annual emissions on an annual basis. Participants who expect to emit more than their authorised quantity can lower their emissions or purchase additional allowances on the secondary market from businesses with excess allowances or through Member State-run auctions.

The EU-ETS tracks CO_2 emissions from around 11,500 businesses across 31 EU countries (the 28 EU countries plus Iceland, Liechtenstein, and Norway). With EU-ETS members currently accounting for 45% of Europe's GHG emissions (Wang & Zhao, 2019), the European Commission has proposed expanding the ETS to additional sectors including as road transport and shipping. According to Yang and Luo (2020), the EU-ETS carbon pricing effort accounts for around 3.9% of worldwide GHG emissions, valued at $31.76 billion (Zhou, 2018). Due to its magnitude, the EU-ETS has grown over the last sixteen years and is now widely considered as a model for a coordinated global approach to carbon pricing, covering approximately 75% of international emission allowance trading. The EU-ETS is divided into two trading eras, the first from January 2005 to December 2007, and the second from January 2008 to December 2012. The EU-ETS trading period's third phase went from January 2013 to December 2020, and the programme is now in its fourth phase, which will run from 2021 to 2030. While certain recent price hikes and volatility in carbon allowances have been linked to market fundamentals, economic activity, and regulatory rules in the carbon market's operation, the potential impact of excessive speculation has also been highlighted. This has now sparked debate about whether financial transactions have a greater influence on prices than supply and demand fundamentals.

Thus, Figures 2.4 and 2.5 show carbon price patterns covering significant events that may have influenced the various trading periods.

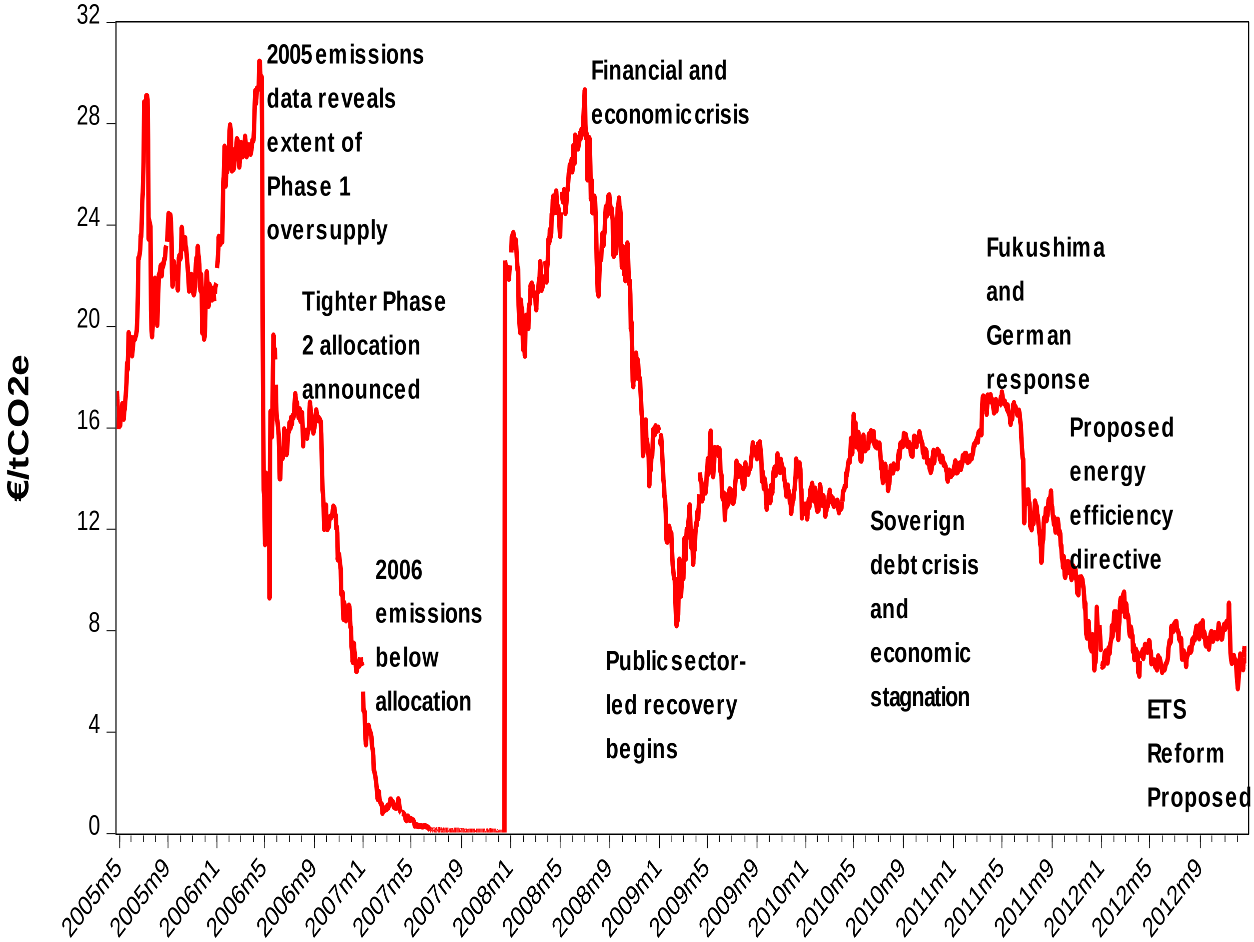
2.3.1 Phase I and Phase II of the EU-ETS

Figure 4.4 depicts a visual examination of EUA prices over the first two stages of the EU emissions trading periods, as well as significant economic and non-economic factors that may have altered the dynamics of carbon pricing within the framework of emission trading systems. Almost all allowances were given away for free and were mostly based on past emissions. This technique, known as "grandfathering," occurred during the pilot phase of the project. Furthermore, CO_2 emissions from power plants and energy-intensive industries such as iron, steel, cement, and oil refining were covered during the EU-ETS trading period (Borghesi & Montini, 2016). Despite being considered the scheme's testing phase, this initial phase established a price for EU allowances such that the penalty imposed on enterprises for noncompliance was 40 Euros per tonne of CO_2 (i.e., €40/tCO_2). There is little doubt that some of the initiatives saw during the ETS trial phase resulted in some spectacular successes. The decrease of 200 million metric tonnes of CO_2, or 3% of total verified emissions, is one remarkable achievement.

A quick glance at Figure 2.4 reveals that EUA prices fluctuated dramatically during the pilot phase, peaking at roughly €40/tCO_2 in early 2006 and hovering around €15/tCO_2 for the most of 2006 before beginning a slow fall to a negligible price for the duration of the pilot phase. While it is obvious that an oversupply of permissions resulted in the eventual price collapse, the desire to understand the factors that led to the aforementioned "excess supply" of allowances became a matter of academic interest at the time with the increasing range of possibilities. One such scenario is that enterprises continued to operate as normal with an excessive number of freely grandfathered permits (over-allocation). It's also possible that emission reductions (abatement) were significantly easier and less expensive than expected. These departures from predicted emission levels may have decreased demand for allowances, causing a price fall. In theory, either of them might have caused the EUA price fall seen during the EU-ETS test phase.

With the advent of real-world emissions data, however, there has been increasing data-based evidence supporting the fact that the oversupply of allowances is due to many allowances being allocated to businesses. To validate or refute this position, Anderson, and Maria (2010) used historical industrial emissions data in their study of abatement and allocation in the EU-ETS pilot phase to investigate the level of abatement and over-allocation that occurred. The analysis discovers that there is over-allocation and abatement, as well as under-allocation and emission inflation. To put it differently, the analysis estimates that allowances will be over-allocated by 280 million during the three trading years of the trial phase, with a total abatement of 247 million tonnes of CO_2.

Figure 2-4: Trends in EUA prices and major events in the Phase I (2005-2007) and Phase II (2008-2012) trading periods



Source: Figure is plotted by the author using the ICE Endex EUA Futures obtained from https://www.investing.com/commodities/carbon-emissions

Because the second phase of the EU-ETS coincided with the first commitment period of the Kyoto Protocol, the EU imposed a tighter emission cap by reducing the total number of EU allowances (EUAs) by 6.5% from 2005. The addition of Iceland, Norway, and Liechtenstein as new Member States during Phase II of the plan was a significant achievement. The scope has also been expanded to include nitrous oxide produced in certain Member States during the production of nitric acid. Unlike the pilot phase, when all allowances were freely allocated, Member States could auction off up to 10% of the allowances in phase II, rather than free allocation.

Throughout phase II of the programme, businesses were permitted to use credits from the Kyoto Protocol's Clean Development Mechanism (CDM) and Joint Implementation (JI), apart from nuclear plants, agricultural, and forestry operations. There are presently 1.4 billion metric tonnes of CO2 equivalent credits on the market (European Commission, 2014). The purpose was to provide low-cost mitigation options to businesses, which led to the EU-ETS becoming the primary driver of the international carbon market. However, the additional credits, in conjunction with the 2008 global financial crisis, reduced emissions from EU firms while creating a large surplus of EUAs, causing EUA prices to fall from €30 per tCO2 to less than €7 per tCO2.

A closer examination of Figure 2.4 reveals that EUA prices fluctuated during the second phase of the EU-ETS trading period and consistently fell to zero, particularly during the peak of the 2008 economic crisis. While this suggests that phases I and II of the scheme are typified by substantial price volatility (Borghesi & Montini, 2016), the fundamental source(s) of the volatility differ for phase I versus phase II. The severe economic crisis has been largely blamed for the extreme volatility of EUA prices in the second phase. Koch et al. (2014) find that the economic recession is a robust explanatory variable for observed prices in their empirical analysis of the drivers of fluctuations in EUA prices in the second phase of the EU-ETS, whereas renewable policies and the use of international credits have only moderate effects on EUA prices, according to the authors.

Regardless of the supposed unique drivers of EUA pricing volatility in phases I and II, allowance over-allocation is most visible in phase I. Nonetheless, it has been claimed that the second phase was over-allocated. Indeed, it is believed that the presence of an unduly decentralised system, as well as too generic national cap restrictions, aggravated the overstock problem in both phases I and II of the EU-ETS trading periods. As a result, price volatility occurred during both the first and second stages of the trading session. This volatility raises uncertainty among EU-ETS users, prompting some to postpone costly investments in low-carbon technologies (see Gronwald & Ketterer, 2012; Gronwald & Hintermann, 2015).

The "governance problem" is also regarded to have significantly impacted the effectiveness of the EU-ETS market during its first two phases. According to Frunza et al. (2011), the governance issue manifested itself in the form of political pressure on the government from interest groups requesting further subsidies, as well as poor monitoring and transparency issues. According to Borghesi and Montini (2014), permit swaps in the carbon market were prompted mostly by illegal behaviour in the absence of proper regulation, resulting in concerns with poor monitoring and transparency.

Considering the aforementioned, one concrete example was Holcim's claim in 2010 that 1.6 million emission allowances had vanished from their Romanian registration account. In a similar example, Blackstone Global Ventures announced in January 2011 that 475,000 emissions allowances had mysteriously gone from its Czech Republic account, resulting in a loss of around 7 million euros. Due to different governments suspending their carbon trading registries, including Austria, the Czech Republic, Estonia, Greece, and Poland, the European Commission was compelled to cease 75% of the ETS market until January 26, 2011. To address some of the issues that have significantly hampered the operation of the EU-ETS market, the EU revised its directive and implemented new anti-fraud measures, as well as new registration legislation, such as the replacement of national registries with a Union registration maintained centrally by the European Commission. Nonetheless, numerous concerns connected to an excess of emission allowances have persisted and continue to impair the scheme's operation and efficacy, according to Borghesi and Montini (2016).

2.3.2 Phase III and Phase IV of the EU-ETS

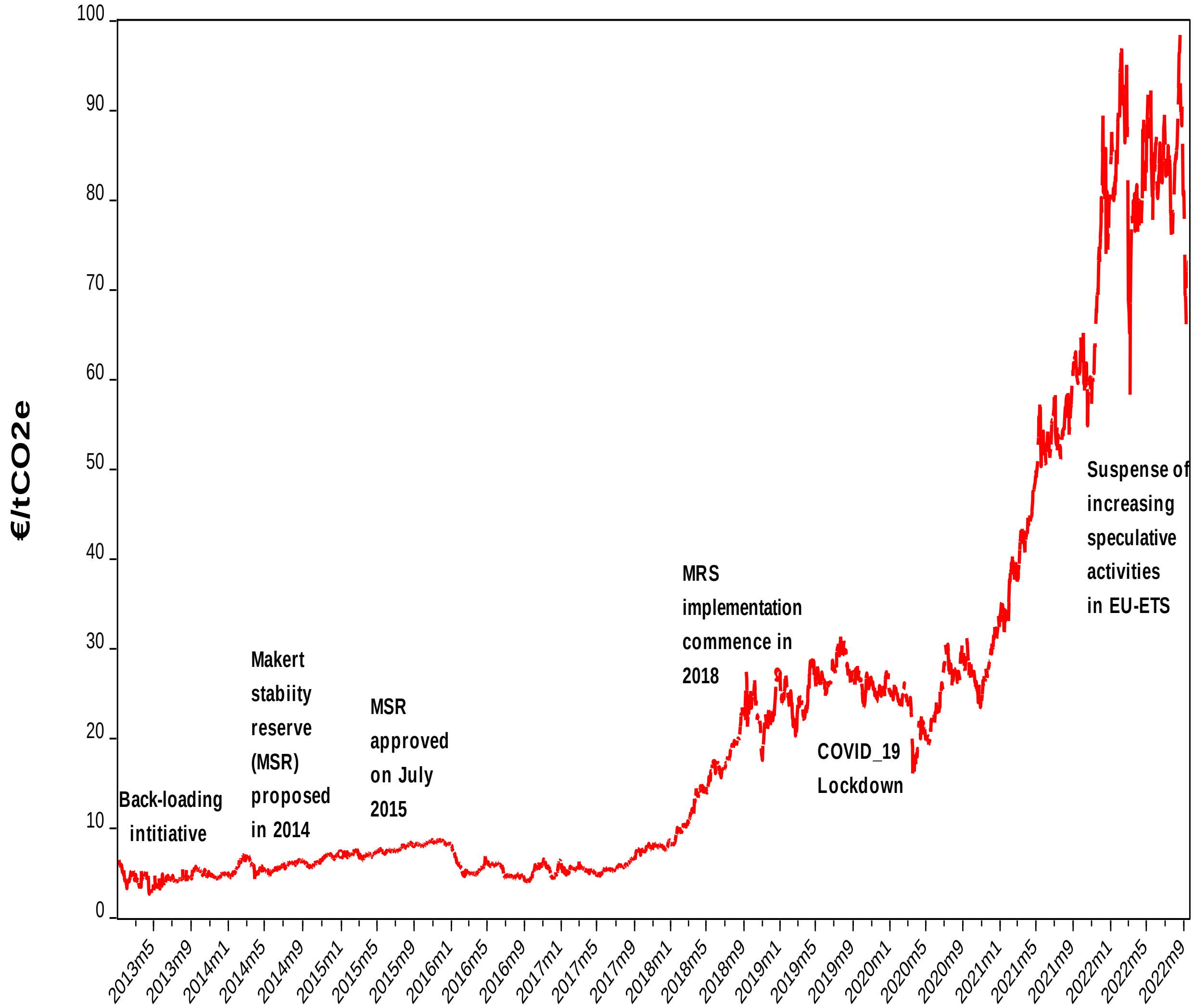
As previously indicated, phase III of the EU-ETS runs from January 2013 to December 2020, while phase IV begins in January 2021 and runs through December 2030. Figure 2.5 depicts a visual study of the patterns in EUA pricing across the many economic and non-economic variables thought to have shaped EU-ETS operations in the third and fourth phases of the scheme. The enormous surplus of emission allowances that typified the programme's second phase was carried over to phase III of the scheme, which was one of the key issues experienced in the early phases of the third phase of the EU-ETS. In other words, due to the exceptional decline in carbon prices over the first two phases of the EU-ETS trading period, about 2 billion allowances were carried over from phase II to phase II of the EU-ETS. As illustrated in the graph below, average EUA prices between January 2013 and December 2013 were only around €1/tCO2 to €5/tCO2, which could be attributed to the carryover of the oversupply challenge from phase II to phase III.

As a result of the above issues, one of the measures recommended by the European Commission at the beginning of the third phase of the EU-ETS was the proposal for back-loading, which was agreed by the Council and the Parliament in 2013. The purpose of this project was to postpone auctions for 900 million allowances anticipated from 2014 to 2016 to rebalance supply and demand in the EU-ETS and reduce price volatility.[5] Back-loading, however, was only intended to be a short-term solution for the period of the EU's third ETS phase, which lasts through 2020. To achieve this, the European Commission declared from the start that a more thorough structural reform of the EU-ETS was necessary for an effective reduction of the emission allowance surplus and to prevent adverse effects on the functioning of the EU-ETS (de Perthuis & Trotignon, 2014; Caton et al., 2015). As a result, in 2014, the European Commission suggested creating a market stability reserve (MSR).[6]

[5] See the European Parliament and Council's Decision No. 1359/2013/EU of December 17, 2013, which amends Directive 2003/87/EC and clarifies provisions regarding the timing of greenhouse gas auctions. To establish the volume of greenhouse gas emission permits to be auctioned in 2013–2020, see also Commission Regulation (EU) No. 176/2014 of February 25, 2014, amending Regulation (EU) No. 1031/2010.

[6] See COM (2014) for detail on proposal for the establishment and operation of market stability reserve (MSR) for the EU-ETS.

Figure 2-5: Trends in EUA prices and major events in the Phase III (2013-2020) and Phase IV (2021-2030) trading periods



Source: Figure is plotted by the author using the ICE Endex EUA Futures obtained from https://www.investing.com/commodities/carbon-emissions

The MSR proposal was made public at the same time as the EU Communication on "A Policy Framework for Climate and Energy from 2020 to 2030." There are two goals for the MSR. Handling and managing the surplus and overallocation of emission allowances is the first stage. By adjusting the number of allowances to be auctioned based on market conditions, the second tries to make the European framework more resilient. The MSR is intended to operate "automatically" in accordance with pre-established standards and requirements, thereby reducing the Commission's discretionary power during implementation and increasing the overall efficacy and transparency of the EU-ETS.

The MSR was approved by the European Parliament in July 2015 and the Council in October 2015, as can be seen in the graphic above. The deposit of allowances in reserves commenced in January 2019 following the formation of the MSR in 2018. However, the principal allocation process was amended as early as 2013 to satisfy some of the MSR's objectives, with allowances for more than 40% of all confirmed emissions auctioned out. This suggests that, beginning in 2013, the concept of allocation of emission allowances switched dramatically from grandfathering to auctioning, with some free allocation based on benchmarks (BMs). The EU-ETS Auctioning Regulation keeps an eye on the auctioning procedure to make sure it is free from bias and open, transparent, uniform, and harmonised. According to the revised EU-ETS Directive (European Commission, 2014), auctions must satisfy standards for predictability, cost-efficiency, fair access to auctions, and simultaneous access to crucial information for all operators.

The fact that a BM bases the number of free permits on the output (or input) of the installation is instructive. In light of this, it is not unexpected that industrial facilities other than those that generate electricity using BMs have not yet received free distribution of allowances. Each product has a BM, for instance, whether it is steel, cement, or lime. The institutions were given 80% of what they would have received under the BM allotment in allowances. Throughout phase III of EU-ETS trading, industries at risk of carbon leakage are anticipated to receive 100% of the BM allocation, even if this allocation amount is anticipated to decrease annually to 30% in 2020.

Figure 2.5 also shows a fascinating trend in which the EU-ETS appears to have been unusually resilient in the face of the recent COVID-19-induced economic shock. The 'Great Lockdown' connected with the advent of the COVID-19 pandemic, like the 2008 global financial crisis (GFC), has had an impact on economic activity, cutting emissions and demand for emissions permits. In comparison to the GFC, however, the carbon markets reacted more rationally to the economic shock linked with COVID-19. During COVID-19, for example, EUA prices initially decreased but quickly stabilised following a period of volatility, with prices recovering to pre-pandemic levels. More notably, since the later part of phase III of the EU-ETS trading period, EUA prices have been on a constant recovery trend, climbing from €25/tCO2 on October 21, 2020, to roughly €57/tCO2 on May 14, 2021.

EUA prices reached a new high of €97/tCO2 on February 8, 2022, marking a price rise of more than 120% since early 2021 and more than 200% since early 2020. On August 19, 2022, the price reached an all-time high, approaching €100/tCO2. This unusual surge in EUA prices can be ascribed to regulatory changes such as the development and implementation of MSR in 2018-2019, as well as the EU's heightened aspirations to decrease GHG emissions to at least 55% below 1990 levels by 2030. This target will put the EU on pace to reach climate neutrality by 2050. This target will put the EU on pace to reach climate neutrality by 2050. However, this will demand a more ambitious EU-ETS, which is why the EU has advocated for the EU-ETS's scope to be enlarged to encompass additional sectors such as maritime transport and maybe heating and transportation.

The much-increased carbon prices are not without worry, even while recognising the severity of climate change necessitates restricting the supply of emission permits to guarantee that carbon pricing (EUA prices) is successful in sufficiently decreasing carbon emissions. Not only have EUA prices in the EU-ETS almost tripled recently as compared to the first two trading phases and the beginning of the third trading period, but the upward trends in EUA prices also seem to have sparked unprecedented volatility levels (see Roques et al., 2022).

According to Roques et al. (2022), the surge in EUA prices and volatility occurs in the context of a European energy market crisis, a sharp increase in commodity prices, and uncertainty about the scope and ambition of the ongoing EU-ETS reform. However, as shown in Figure 2.5, there is growing concern about increased speculation activity in carbon markets, which many commentators attribute to the recent ETS price rally. However, there needs to be more verifiable evidence on whether such speculation activities threaten the ETS's operation on the path to the global goal of low carbon emissions. As a result, in the following chapter, we developed a novel framework to provide evidence-based insight into whether speculation matters in the dynamics of carbon prices.

CHAPTER THREE

REVISITING THE FRAMEWORK FOR MODELLING CARBON ALLOWANCES: DOES SPECULATION MATTER?

3.0 Introduction

To align with the global goal of keeping temperature rise well below 2°C, a market-based phenomenon called "carbon pricing" has been widely acknowledged as the most crucial policy instrument to address climate change (Kettner, 2011). Compared to the "command-and-control" regulatory approach, carbon pricing has the dual potential of ensuring environmental effectiveness and economic efficiency, respectively, which tend to manifest in emission reductions at the lowest costs (Baranzini et al., 2017). Carbon pricing is usually in the form of taxes on polluters (carbon taxes, CT) or a "cap-and-trade" emissions trading system (ETS). While the former directly places a price on carbon by defining an explicit tax rate on carbon emissions, the latter is a system where emitters can trade emission units to meet their emission targets (Marcus, 2006). A well-designed ETS is assumed to be capable of reducing emissions at low economic and social costs. However, carbon allowances (permits), traded as commodities under the ETS, have evolved into a financial instrument (Quemin & Pahle, 2023). As a result, they tend to be vulnerable to events that have nothing to do with some of the fundamentals that serve as the core of existing theories for explaining carbon price dynamics. For instance, while polluting organisations (i.e., emissions compliance firms [ECFs]) in the ETS hold and trade carbon permits to meet the global aim of emission reductions, developers of projects require access to a deep pool of capital to fund their emission reduction activities. As a result, besides compliance firms, non-compliance firms such as banks, among others, have continued to participate in the market to provide a necessary service to the companies affected by the ETS, helping to establish more market liquidity and price visibility, and allowing operators to hedge against future price fluctuations.

The preceding suggests that, besides compliance firms, a portion of the carbon allowances traded in the carbon markets are owned by financial actors (emissions non-compliance firms [ENCFs]). However, it is instructive that the ENCFs have nothing to do with the emission reduction goal of the ETS but have invested in it primarily for profit. To achieve their primary goal of profit maximisation, the ENCFs frequently participate in "speculation" activity. Although there is a view that the speculation activity is likely to undermine the ETS's operation, undeniable is the fact that speculators can trade carbon allowances to increase liquidity while bridging gaps in supply and demand. Therefore, the extent to which speculation undermines or benefits the emission reduction goal of the EST depends on how much of the overall market activity is driven by speculation. Despite this, the fundamentals predominantly acknowledged in the literature as drivers of carbon pricing are carbon allowance supply, which is typically measured in terms of political decisions and changes in the ETS's regulatory framework (see Benz & Truck, 2009; Mansanet-Bataller & Pardo, 2009; Mansanet-Bataller & Sanin, 2014; Hitzemann et al., 2015; Koch et al., 2016; Deeney et al., 2016; Salant, 2016; Fan et al., 2017; Friedrich et al., 2020) and factors that influence the demand for carbon allowances, such as energy prices, weather condition, and economic activity (see Christiansen et al., 2005; Mansanet-Bataller et al., 2007; Alberola et al., 2008; Delarue et al., 2008; Carraro & Favero, 2009; Wei et al., 2010; Hintermann, 2010; Koch et al., 2014; Hammoudeh et al., 2014; Zhu & Chevallier, 2017; Segnon et al., 2017; Chung et al., 2018; Zhang et al., 2018; Ji et al., 2018; Wu et al., 2020; Wang & Zhao, 2021; Adhurim & Mario, 2021; Dong et al., 2021; Li et al., 2021). In other words, the literature on emission trading has continued to ignore the speculation activity of the ENCFs in the carbon markets.

Nonetheless the lack of compelling evidence on the extent to which speculation matters in the dynamics of carbon prices, many commentators and financial experts have continued to attribute the recent surge in carbon allowance prices to the increasing speculation activity of economic actors in the carbon markets (see Roques et al., 2022). Thus, the fear that the growing movement of financial actors in the carbon market may overwhelm and undermine the environmental goal of carbon pricing (see Berta et al., 2017) suggests the need for a review of the framework for modelling carbon allowances. Given this, we go beyond the norm of restricting the dynamics of carbon pricing to a market fundamentals-based framework to develop an all-inclusive carbon pricing modelling framework that accommodates not only the emission compliance activities in the ETS but also the speculation activity of the ENCFs. The innovation herein is to reduce the unexplained component of the dynamics of carbon pricing with the hypothesis that speculation matters in the framework for modelling the dynamics of carbon allowances.

There are no denying a few notable instances where volume and open interest data have been used to capture the role of speculation in the carbon market (see Lucia et al., 2015). The innovation in the context of this study, however, rests on developing a novel composite news-based speculation index to capture the speculation activity of the ENCFs in the carbon market. Also, the ETS was created through political decisions and has continued to be implemented through regulatory and operating guidelines. Therefore, specific characteristics of the ETS, such as its inelastic supply of allowances, a lack of long-term policy commitment to achieving climate targets, and regulatory uncertainty about the scope and ambition of reforms in the carbon markets, have been posited as likely to induce future speculation with consequences such as market destabilisation due to increased price volatility, price bubbles, or manipulation (Sockin & Xiong, 2015; Koch et al., 2016; Salant, 2016).

Given the preceding, it will be interesting to see how regulatory events associated with the operation of the ETS influence the extent to which speculation matters in the dynamics of carbon pricing. However, the extant literature has continued to discuss the link between carbon pricing and regulatory events separately (Koch et al., 2016; Deeney et al., 2016) and between carbon pricing and speculation (Lucia et al., 2015; Friedrich et al., 2020; Roques et al., 2022). To bridge this gap, we augment the prominent market fundamentals approach to modelling carbon pricing to include not just speculation but also the role of regulatory events as the probable underlying source of the speculation. This idea is entirely conceivable given that it has been suggested that changes in policies, market structure, and perceived commitment to achieving climate targets may be able to induce a variety of price expectations, favouring self-realised expectations, in which speculators attempt to predict the strategies of other speculators rather than relying on market fundamentals to form expectations (see Roques et al., 2022).

It must be pointed out at this juncture, however, that while carbon allowances are traded daily, political decisions guiding the operations of the ETS are not pronounced daily, hence our methodological bias towards an econometric technique that allows for the cohabitation of such variables of interest with mixed frequencies. We favour the GARCH-MIDAS model as this study's most appropriate econometric technique. More importantly, the choice of the GARCH-MIDAS not only enables us to capture both the returns and volatility dynamics of carbon allowance prices but also affords us the ability to overcome the hurdle of information loss that is common with the practice of data aggregation at uniform frequencies (i.e., data splicing). In addition to the increasing prominence and application of GARCH-MIDAS in the literature (see Salisu et al., 2020; Liu et al., 2021; Oloko et al., 2022, among others), the outcome of our preliminary analysis, which includes evidence of conditional heteroscedasticity and serial correlation, also offers strong support for its suitability in this study.

The remaining sections of this Chapter are structured as follows: Section 3.1 further motivates the study by considering the possibility of speculation in the dynamics of carbon pricing. Section 3.2 presents our proposed all-inclusive framework, where we extend the standard market fundamentals approach to modelling carbon pricing to include the role of speculation. Section 3.3 discusses the data and offers some preliminary results. Section 3.4 presents the methodology, while Section 3.5 discusses our findings. Section 3.6 summarises the Chapter.

3.1 Motivation for the role of speculation in the dynamics of carbon pricing

One of the most frequently asked questions about carbon allowance prices is what the underlying drivers of price changes have been and how much of an impact different potential drivers have had on the overall dynamics of the market. The common practice in the literature has been to model the prices of emission allowances as a function of theoretically motivated fundamental drivers of abatement costs (see Friedrich et al., 2020, for a detailed literature review on the underlying drivers of price changes in the carbon market). But, while some recent episodes of price increases and volatility in carbon allowances have been attributed to market fundamentals such as fuel switching (Hintermann, 2010; Koch et al., 2014; Segnon et al., 2017), economic activity (Ji et al., 2018; Zhang et al., 2018; Yang et al., 2018; Li et al., 2021), and regulatory guidelines in the operation of the carbon market (Mansanet-Bataller & Sanin, 2014; Hitzemann et al., 2015; Koch et al., 2016; Fan et al., 2017), the potential role of excessive speculation has also come into focus. This portends that the underlying sources of changes and volatility in carbon allowance prices are far from exhaustive, so continuous confinement of the dynamics of carbon pricing to demand and supply market fundamentals might not be accurate after all. As earlier demonstrated in Figure 2.5, two price spikes, in 2017/2018 and 2020/2021, that caused the carbon price to soar from €5/tCO2 to a peak of €90/tCO2 not only occurred at the same time that more stringent emission reduction targets were anticipated but coincided with mostly anecdotal evidence about the massive market entry of new financial actors and investors. This has since triggered debate over whether financial transactions influence prices more than supply and demand fundamentals (Roques et al., 2022). There is no denying that financial institutions have been responsible for carrying out some essential tasks in the carbon market, policymakers and scholars are nevertheless concerned about the possibility that excessive speculation could undermine the functioning and emission reduction goal of the carbon market (Koch et al., 2016; Salant, 2016). More importantly, while the concept of speculation is not new, particularly from the viewpoint of traditional financial literature, it is expected to be relatively more complex in politically created markets such as ETS, where the asset value is crucially dependent on political support and legitimacy rather than being intrinsically (material) valued (de Perthuis & Trotignon, 2014; Grosjean et al., 2016; Koch et al., 2016; Salant, 2016). Despite this, the probable role of speculation in the dynamics of carbon pricing has been largely left unexplored. This may not be unconnected to the fact that tools to assess the extent to which speculation matters in the dynamic of carbon pricing are urgently needed but still need to be created.

Inspired by the lack of verifiable evidence on whether speculation poses a threat to the ETS's operation on the path to the global goal of low carbon, we broaden the standard carbon pricing modelling framework, which confines the dynamics of carbon prices to demand and supply market fundamentals, to include the speculation activity of the emissions non-compliance actors in carbon markets. We created a novel speculation dataset to provide evidence-based insights into the debate over speculation's role and potential impact on carbon prices. To the best of our knowledge, this is the first study to have explored an all-inclusive cap-and-trade framework comprising emissions compliance and emissions non-compliance activity of the ETS to model the dynamics of carbon pricing.

3.2 Theoretical Framework

Structured markets for reaching the global goal of net-zero emissions via buying and selling allowances at a certain emission limit have sprouted up in several countries worldwide (Lin &

Jia, 2020).[7] The European Union ETS (EU-ETS) remains the most extensive cap-and-trade programme and the cornerstone of the world's most ambitious climate strategy. As a result, we follow the standard practice in the literature to develop our all-inclusive framework for modelling carbon allowances around the EU-ETS, which is widely regarded as a global reference point for carbon pricing. The ETS anywhere in the world operates as follows: A central regulatory authority establishes an annual cap on aggregate emissions, measured in tonnes of carbon dioxide equivalent (tCO2e). Companies and facilities participating in the system must hold allowances issued by the regulator (i.e., the government) for each tCO2e emitted in a calendar year.

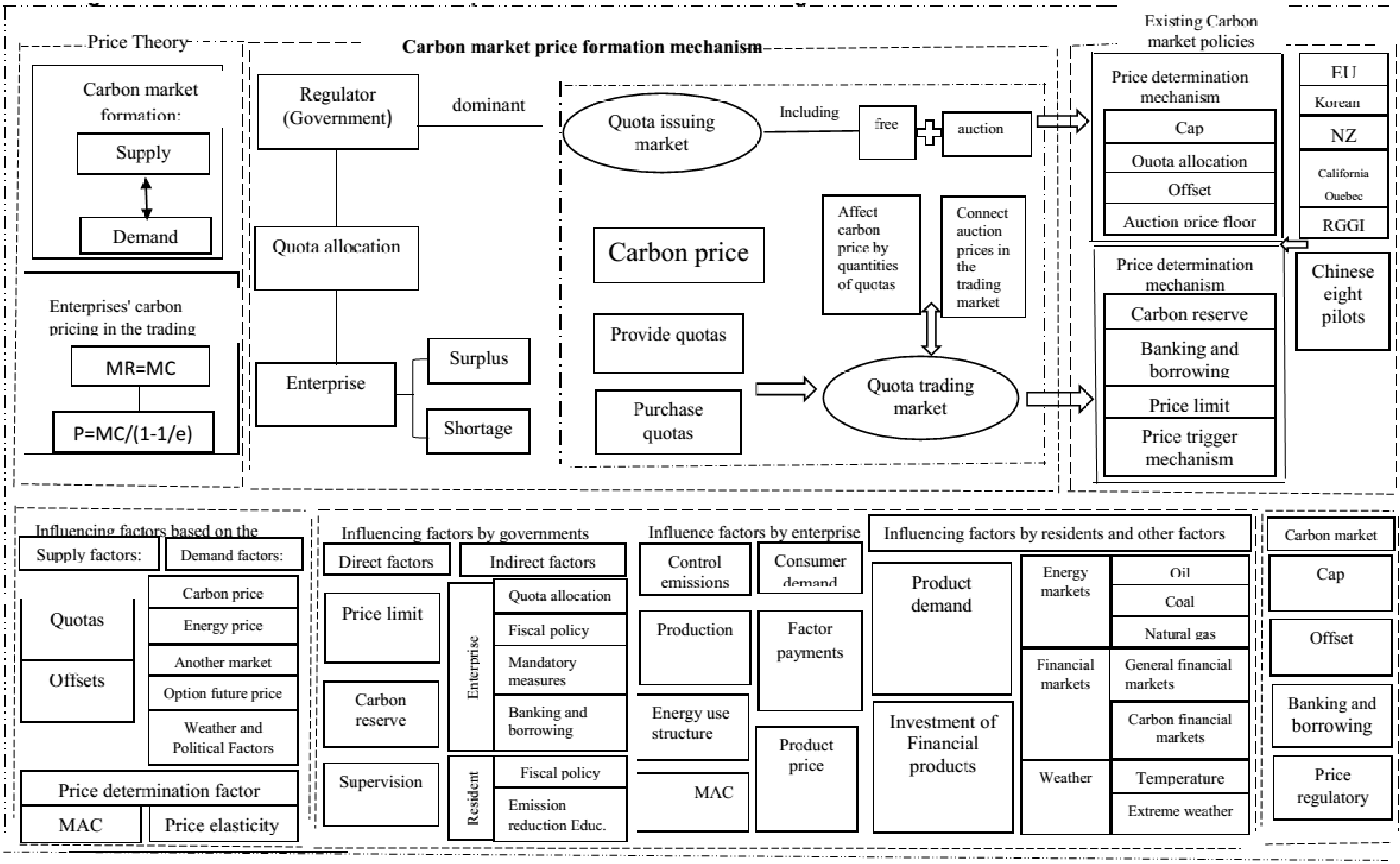
Companies and facilities receive the allowances at the beginning of the compliance period, have sufficient allowances to cover their polluted emissions during the trading period, and have to surrender them at the compliance deadline. If a company fails to submit enough allowances by the deadline, it must pay a penalty for each tonne of CO2 uncovered. However, because the cap may have been set at the start of the compliance period, no additional carbon permits can be created in the system. As a result, if total emission allowances are insufficient, companies will only have two options for ensuring compliance. They can either reduce their emissions or purchase them on the market to avoid penalties. In this sense, the ETS mechanism helps create market demand for allowances and thus determines a carbon price. In other words, the ETS does not set the price of a permit; instead, it is determined by the trading activities of firms in the permit market (allowances). Figure 3.1 summarises the principles of carbon price generation, transmission mechanisms, and influencing factors.

Essentially, we begin our all-inclusive approach to modelling the dynamics of carbon pricing with the classic market fundamentals approach, which is based on price determination theory, as shown in the Figure. However, while the illustration in the Figure begins with the general price theory and then proceeds to the specific term "carbon market price formation," of particular interest herein is the latter, where both government and enterprise are vital agents in the

[7]The European Union ETS (EU-ETS), the United Kingdom ETS, the German National ETS, the Swiss ETS, the Massachusetts Limits on Emissions from Electricity Generators, the Quebec Cap-and-Trade System, the Nova Scotia Cap and Trade Programme, Mexico's ETS, the Kazakhstan ETS, the New Zealand ETS, the Chinese National ETS, the Korean ETS, and Japan's Saitama target are all ETSs in use today.

formation of prices in the carbon market. Given that the EU-ETS is a model for other ETSs worldwide, the "regulatory agent" in the context of this study refers to the European Commission (EC), which is responsible for issuing emission permits in the EU-ETS carbon market. On the other hand, the enterprise comprises polluting companies that require allowances to comply with carbon market regulations.

Figure 3-1: Formation of carbon market price mechanism and influencing factors[8]



Source: The Figure is plotted by the author as seen in the study by Ji et al. (2018, pp. 4).

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[8] Note: MC is marginal cost, MR is marginal revenue, MAC is marginal abatement cost, and the term e represents the price elasticity of demand

Theoretically, the enterprise's pricing is generally driven by two factors: its marginal cost (MC) and the price elasticity of demand on the market. On the one hand, marginal cost is expected to positively impact price, whereas demand elasticity is expected to have a negative impact. What summarises this position in Figure 3.1 is the term $P = MC / (1-1/e)$ "on the assumption that the price elasticity of demand is infinite if the market is perfectly competitive." By applying general price theory to the development of the carbon market price, the firm will evaluate its marginal abatement cost (MAC) and the price elasticity of demand for carbon emissions permits when determining the carbon price in the trading market. The lower the MAC, the lower the price; conversely, the higher the elasticity, the lower the price.

In general, the equilibrium between the supply and demand from businesses engaged in emissions reduction is what determines the price of carbon. In the quota allocation market, the government either gives away or sells quotas to businesses. The supply and demand in the quota trading market are determined by how close or far the actual emissions of the firms come to matching the quotas. Based on their respective MAC prices and price elasticity of demand in the carbon market, each party will submit a price offer. The price will then be matched through a series of consultations to produce the transaction price, which is the carbon price (see Figure 3.2).

Given that supply and demand determine the price of carbon, the "market fundamental" serves as the backbone of the framework for simulating the dynamics of carbon pricing, as indicated in equation (3.1).

$$P_{CO_2} = f\left(D_{CO_2}, \bar{Q}\right) \tag{3.1}$$

where P_{CO_2} denoting carbon price is a function of the need for permits (D_{CO_2}) and $\bar{Q}$ reflecting the total number of permits/allowances issued by the government, for instance, the European Commission (EC) in a particular year. The need for permits, on the other hand, is influenced by activity in the power generation and industrial processing sectors of the economy, although the number of permits remains constant over the course of a year. Following the Lovcha et al. (2022)

approach, we split as show in equation (3.2) the demand for permits between the two main sectors—electricity generation and industrial processes.

$$D_{CO_2} = D_{CO_2}^{ELE} + D_{CO_2}^{IND} \tag{3.2}$$

where D_{CO2} as earlier defined is demand for permit and split between the demand for permit in the electricity generation sector $D_{CO_2}^{ELE}$ and demand for permit in the industrial processes sector $D_{CO_2}^{IND}$.

Electricity plays an essential role in our model. Although electricity consumption does not generate emissions, but electricity production does. Electricity demand does not influence permit demand directly as firms that consume electricity do not buy permits. Electricity generation may emit more or less CO2, depending on the share of fossil fuel energy sources used for power generation. The emission cost in electricity generation is transferred to the price and paid by the electricity consumers (see Fabra and Reguant, 40). Natural gas and coal are the primary fossil fuels used for electricity generation particularly in the EU. So, the total demand for permits generated by the electricity sector can be represented as follows:

$$D_{CO_2}^{ELE} = \alpha_{gas} * D_{gas}^{ELE} + \alpha_{coal} * D_{coal}^{ELE}, \tag{3.3}$$

where α_{gas} and α_{coal} are measures for CO_2 emission intensities of natural gas and coal, while D_{gas}^{ELE} and D_{coal}^{ELE} stand for the total demand for these fossil fuels for power generation. Multiplying equation (3.3) by the total demand for fossil fuels for electricity generation, D_{FF}^{ELE}, and by electricity demand, D_{ELE}, we arrived at equation (3.4).

$$D_{CO_2}^{ELE} = \frac{D_{FF}^{ELE}}{D_{ELE}} \left(\alpha_{gas} * \frac{D_{gas}^{ELE}}{D_{FF}^{ELE}} + \alpha_{coal} * \frac{D_{gas}^{ELE}}{D_{FF}^{ELE}} \right) * D_{ELE} = S_{FF} * \alpha_{FF}^{ELE} * D_{ELE} \tag{3.4}$$

Strictly speaking, D_{ELE} is the energy demand (fossil fuels and clean energy) for electricity production. However, given that electricity production is a way to transform energy, we can assume that the energy demand here is equal to the electricity supply and, in its turn, electricity supply is equal to the electricity demand at a given price. The term S_{FF} is ratio of fossil used for power generation and α_{FF}^{ELE} the weighted average emission intensity of fossil fuels used for electricity production. Thereafter, the total CO2 emissions generated by industrial production are expressed below:

$$D_{CO_2}^{IND} = \alpha_{gas} * D_{gas}^{IND} + \alpha_{coal} * D_{gas}^{IND} + \alpha_{oil} * D_{oil}^{IND} \tag{3.5}$$

At this point, renewable energy consumption for industrial processes is not included in the framework because it is minimal in the EU, whose ETS serves as a model for other ETS worldwide. Coal, natural gas, oil products, and electricity account for approximately 90% of the EU's industrial energy consumption (see Lovcha et al., 2022).

To get the total demand for CO_2 permits/allowances, we combined equations (3.4) and (3.5) as follows:

$$D_{CO_2} = \alpha_{gas} * D_{gas}^{IND} + \alpha_{coal} * D_{gas}^{IND} + \alpha_{oil} * D_{oil}^{IND} + s_{FF} * \alpha_{FF}^{ELE} * D_{ELE} \tag{3.6}$$

We further assume that the demand for any fuel type in equation (3.6) depends, among other things, on the economy's production level (*Y*), reflecting the need for industrial production or consumption of manufactured goods. Other factors are the prices of this fuel, its substitutes, and the carbon price. Following Alberola et al. (2008), we consider a weather index based on a weighted average deviation from historical temperature (TMP). The economic rationale for including this index for weather conditions hinges on the fact that extremely high and extremely low temperatures increase energy demand (for air conditioning or heating) and carbon prices (Sanin et al. 2015). To accommodate this latter assumption, the demand for CO2 permits/allowances can be rewritten as follows:

$$D_{CO_2} = f\,(P_{gas},\, P_{coal},\, P_{oil},\, P_{ele},\, P_{CO_2}, S_{FF}, Y,\, TMP) \tag{3.7}$$

A log-linear approximation can be used to reduce Equation (7) to a linear function, where the log demand for permits is defined by the sum of variables weighted by a factor expressing their relevance in the equation.

$$\begin{aligned} \ln D_{CO_2} = {} & \lambda_1 \ln P_{gas} + \lambda_2 \ln P_{coal} + \lambda_3 \ln P_{oil} + \lambda_4 \ln P_{ele} + \lambda_5 \ln P^{R}_{CO_2} + \lambda_6 \ln S_{FF} + \\ & \lambda_7 \ln Y + \lambda_8 TMP \end{aligned} \tag{3.8}$$

The same transmission from equation (3.8) can also be applied to the price of permits/allowances in equation (1) as follows:

$$\ln P_{CO_2} = \eta_d \ln D_{CO_2} + \ln \bar{Q} \tag{3.9}$$

where the η_d parameter account for the relative importance of the demand for permits (D_{CO_2}) in price-setting. To complete the framework, we subsume equation (3.8) within (3.9) and arrived at the following estimable carbon price model.

$$\begin{aligned} \ln P_{CO_{2,t}} = {} & \lambda_1 \ln P_{gas,t} + \lambda_2 \ln P_{coal,t} + \lambda_3 \ln P_{oil,t} + \lambda_4 \ln P_{ele,t} + \lambda_5 \ln S_{FF,t} + \\ & \lambda_6 \ln Y_t + \lambda_7 TMP_t + \lambda_8 \bar{Q}_t + \varepsilon_t \end{aligned} \tag{3.10}$$

According to equation (3.10), the fundamentals that, in theory, determine carbon pricing include factors influencing the demand for carbon permits/allowances and carbon allowance supply. Because carbon allowance supply is constant in any given year, the literature has continued emphasising factors that affect demand for carbon allowances in the carbon pricing model. As a result, the standard practice in the literature has been to suppress the supply-side component of the model. However, operational experience with ETS shows that the allowance supply schedule is dynamic in the real sense but subjective to changes in regulation and policy announcements.

Thus, rather than limiting the dynamics of carbon pricing in equation (3.10) to mainly demand-side market fundamentals, we instead equate the supply-side component of the model (i.e. $\bar{Q}$) to policy variables on the assumption that changes in policy directives in the carbon market are a possible source of uncertainty in the dynamics of carbon pricing, such that; $\bar{Q} = CPU$ .The term "CPU" denoting carbon policy uncertainty measures changes in carbon policy, usually in terms of announcements of changes in emissions policy in the forms of "cap updating," "backloading," "National Allocation Plans (NAPs)," and other related "policy events (see Koch et al., 2016; Friedrich et al., 2020)." However, it is instructive that the mentioned studies rely primarily on a sample event approach using a dummy variable modelling process that assigns one (1) to periods that coincide with verified emissions announcement events on carbon pricing and zero (0) otherwise. One of the shortcomings of this approach is that it only demonstrates the constant impact of specific events, whereas what tends to fuel the amber of volatility in the dynamics of carbon pricing is the political uncertainty inherent in the ETS cap-setting process. Therefore, the global carbon policy uncertainty (CPU) index recently developed by Gavriilidis (2021) was preferred in the context of this study as the measure for changes in carbon policy (see Wu et al., 2022). Thus, substituting for $\bar{Q}$ in equation (3.10) will yield the following:

$$\begin{aligned} \ln P_{CO_{2},t} = \lambda_1 \ln P_{gas,t} + \lambda_2 \ln P_{coal,t} + \lambda_3 \ln P_{oil,t} + \lambda_4 \ln P_{ele,t} + \lambda_5 \ln S_{FF,t} + \\ \lambda_6 \ln Y_t + \lambda_7 TMP_t + \lambda_8 CPU_t + \varepsilon_t \end{aligned} \quad (3.11)$$

The specification in equation (3.11) expresses the carbon price as a function of factors that affect the demand for carbon permits and changes in carbon policy, which is consistent with market fundamentals and regulatory modelling frameworks for analysing the dynamics of carbon prices. That said, it is instructive that the fuel prices in equations (3.11) are only captured implicitly. In contrast, they can also be explicitly represented via an abatement method known as fuel-switching price. A theoretical price can help find an equilibrium price level to describe the exchange from coal to gas-based power production. The logic behind the fuel-switching method is that the composition of power generation will dictate the need for emission allowances by determining fuel and EUA prices.

The "merit order," which is defined by fuel prices and the added cost of emission allowances, determines which technology (coal or gas plants) gets implemented first (Bertrand, 2014). Because of the structure of Europe's energy sector, fuel switching is likely to occur mostly between coal and gas. In other words, coal's relative cost compared to natural gas is a short-term benchmark for the electricity and heat industries to engage in CO2 reduction strategies. As a result, switching from coal-fired to gas-fired power generation will be Europe's most cost-effective choice, requiring less than half the allowances required by coal-fired power generation to produce the same quantity of electricity.

To put it another way, the importance of the fuel-switching approach, particularly in the context of this study, is based on the fact that the majority of the sectors covered by EU-ETS can switch between different fuels in their manufacturing process (see Hintermann, 2010; Creti et al., 2012). As a result, we rewrite the carbon price model in equation (3.11) to allow for explicit analysis of the switching impacts of fuel prices on the carbon price, as shown below.

$$\begin{aligned} \ln P_{CO_{2},t} &= \lambda_1 Fswitch_t + \lambda_2 \ln P_{ele,t} + \lambda_3 \ln S_{FF,t} + \lambda_4 \ln Y_t + \\ &\quad \lambda_5 TMP_t + \lambda_6 CPU_t + \varepsilon_t \end{aligned} \tag{3.12}$$

Using the IEA[9] 2019-2021 EU marginal coal- and gas-fired power generation costs, the fuel-switching price denoted as *Switch* in equation (3.12) is calculated as follows:

$$Fswitch = \frac{\left(P_{gas}/0.50\right) - \left(P_{coal}/0.38\right)}{0.96 - 0.41} \tag{3.13}$$

While the terms P_{gas} and P_{coal} remain as earlier defined, the coal-fired power plant efficiency rate is put at 0.38 while the emission intensity factor is 0.96 tCO2/MWh, while the rate for a natural gas-fired power plant is put at 0.50 and its associated emission intensity factor is 0.41

[9] https://www.iea.org/data-and-statistics/charts/european-union-marginal-coal-and-gas-fired-power-generation-costs-2018-2021

tCO2/MWh. Thus, the main difference between Equations (3.11) and (3.12) is that the latter explicitly analyses the switching effects of fuel prices. In contrast, the former implicitly captures the effects via price changes in oil, coal, and gas.

Because coal and oil are both large emitters, their prices are projected to have a negative impact on allowance prices. In other words, we anticipate falling EUA prices when coal and oil prices rise since rising coal or oil prices restrict coal-fired electricity output in favour of less CO2-intensive power plants. Conversely, when gas costs rise, we predict rising EUA prices. The difference between gas and coal prices is seen as the abatement cost to reduce CO2. The greater the gap, the fewer sources will switch to burning gas, resulting in increased CO2 emissions and an increase in the price of carbon allowances.

However, the omission of weather variables in the specifications can be compensated for with the introduction of the switching price effects, particularly in equation (3.12)[10], we have yet to take cognizance of the possible omission of other factors with the potential of influencing the carbon price but are unobservable. For example, the carbon allowances have since grown into a financial instrument, such that the price dynamics are influenced by events that have little to do with the activities of emissions compliance agents in the market (for example, the speculation activity of the emissions non-compliance agents). There have been particularly growing commentaries attributing the current trends of volatility and instability in EUA prices to the financial trading activities of emissions non-compliance agents.

It was asserted that some characteristics of the EU-ETS market are likely to fuel the development of further speculation activity in the future, which is expected to harm both the carbon price's short- and long-term stability. This, among other things, has created further complexity in the framework for modelling the dynamics of carbon pricing. For example, the growing speculation and financial trading activity of non-compliance agents in the carbon market have fuelled doubts about whether it is theoretically sufficient to limit the modelling framework to fundamentals that

[10] Extreme rain, for example, will cause the price of CO2 emission allowances to fall. Rainfall, for example, will influence the proportion of power generated from non-CO2 sources. High precipitation levels will increase the possibilities of producing hydroelectricity and will allow energy production to shift to less-polluting sources (Mansanet et al., 2007).

are mainly influenced by the activities of emissions compliance and regulatory agents in the market.

Although it is difficult to evidence empirically the extent to which the speculation, as mentioned above, activity of ENCFs in carbon markets matters in the dynamics of carbon pricing, rather than assuming such as another omitted factor captured by the error terms, this present study innovatively decomposed the error term (ε_t) in equations (3.11) and (3.12) into two unobserved components: $\varepsilon = \varepsilon_{spec} + \varepsilon_{CO_2}$, as shown below.

$$\ln P_{CO_{2,t}} = \lambda_1 \ln P_{gas,t} + \lambda_2 \ln P_{coal,t} + \lambda_3 \ln P_{oil,t} + \lambda_4 \ln P_{ele,t} + \lambda_5 \ln S_{FF,t} + \lambda_6 \ln Y_t + \lambda_7 TMP_t + \lambda_8 CPU_t + \varepsilon_{spec,t} + \varepsilon_{CO_{2,t}} \tag{3.14}$$

$$\ln P_{CO_{2,t}} = \lambda_1 Fswitch_t + \lambda_2 \ln P_{ele,t} + \lambda_3 \ln S_{FF,t} + \lambda_4 \ln Y_t + \lambda_5 TMP_t + \lambda_6 CPU_t + \varepsilon_{spec,t} + \varepsilon_{CO_{2,t}} \tag{3.15}$$

where ε_{spec} on the one hand denotes unexpected carbon market shocks related to speculation activity of the non-compliance agents in the carbon market, while the latter, for example (ε_{CO_2}), remains the conventional error terms as it captures the unexpected changes in omitted factors that influence carbon prices.

Both equations (3.14) and (3.15) are the starting point of our all-inclusive modelling framework for analysing the dynamics of carbon pricing, with the implicit and explicit expressions of the fuel prices being the only difference. We modified and extended the traditional market fundamentals and regulatory modelling approach to accommodate the growing speculation activity of the ENCFs in the carbon market.

However, rather than merely decomposing the error term into two components that only reflect the speculation activity of the ENCFs as an additional unobservable term, we re-represented the element of the error term to capture the speculation activity of the ENCFs in an observable form, as shown below.

$$\ln P_{CO_{2,t}} = \lambda_1 \ln P_{gas,t} + \lambda_2 \ln P_{coal,t} + \lambda_3 \ln P_{oil,t} + \lambda_4 \ln P_{ele,t} + \lambda_5 \ln S_{FF,t} + \lambda_6 \ln Y_t + \lambda_7 TMP_t + \lambda_8 CPU_t + \lambda_9 SPEC_t + \varepsilon_{CO_{2,t}} \quad (3.16)$$

$$\ln P_{CO_{2,t}} = \lambda_1 Fswitch_t + \lambda_2 \ln P_{ele,t} + \lambda_3 \ln S_{FF,t} + \lambda_4 \ln Y_t + \lambda_5 TMP_t + \lambda_6 CPU_t + \lambda_7 SPEC_t + \varepsilon_{CO_{2,t}} \quad (3.17)$$

The specification in equations (3.16) and (3.17) completes our modification and extension of the standard market fundamentals-based framework to an all-inclusive variant comprising emissions compliance and non-emissions compliance activities in the carbon market. Essentially, we hypothesized that our proposed all-inclusive framework is the most appropriate to model the dynamics of carbon pricing compared to the traditional framework, largely restricted to market fundamentals associated with the activities of emissions compliance agents only.

3.3 Data and Preliminary Analysis

3.3.1 Data description and source

The carbon price variable is measured in terms of the European Allowance (EUA) futures contract traded on the Intercontinental Exchange (ICE), the leading EU-ETS trading platform in the world. We prefer futures contracts over spot because they are said to be less affected by short-run noise and are more actively traded (see Koch et al., 2014; Sanni et al., 2015; Segnon et al., 2017; Chung et al., 2018; Batten et al., 2020; Lovcha et al., 2022). That said, we compute the continuously compounded returns of the EUA prices as the first difference of the log of the EUA price series: $rEUA_t = 100 * \left[\ln(P_{CO,t}) - \ln(P_{CO,t-1})\right]$, where $P_{CO,t}$ denoting EUA price at period t remains as earlier defined.

Moving forward, we take insights from the previous literature on the subject matter (Mansanet-Bataller et al., 2007; Alberola et al., 2008; Mansanent-Bataller & Keppler, 2010; Creti et al., 2012; Sanni et al., 2015; Batten et al., 2021; Lovcha et al., 2022) to reckon with some fundamentals as significant for explaining the dynamics of carbon pricing. Starting with fuels and/or energy prices, for example, we employ the first monthly futures of publicly traded contracts, namely; the Rotterdam coal contracts as a proxy for coal prices (P_{coal}), the Tile

Transfer Facility (TTF) gas contract as a proxy for gas prices (P_{coal}), the Brent crude oil contract as a proxy for oil prices (P_{oil}), while the German electricity base contract is used as a proxy for European electricity price (P_{ele}). While we recognize that data for these variables are equally available daily, we chose monthly because the highest accessible frequency for other variables of interest is monthly.

Regarding the fuel-switching variable, it remains as earlier defined, while our measure for economic activity (ECO), for instance, the EU Stoxx 600, was inspired by Lovcha et al. (2022). The variable for the weather condition is measured in terms of temperature anomalies (TMP). Our carbon policy variable, meant to capture changes in the political decisions associated with the operation of the carbon market, was obtained via the carbon policy uncertainty (CPU) index developed by Gavriilidis (2021). Some of the recent studies on carbon pricing, such as Yan and Cheung's (2023) for the case of China and Wu et al.'s (2022) for the case of EU-ETS, have also controlled for the policy variable using the CPU index of Gavriilidis' (2021).

Finally, while the daily carbon prices and the variant energy prices considered were sourced from the European Energy Exchange (EEX) via Thomson Reuters DataStream, the EU Stoxx 600, a measure of economic activity, and the temperature anomalies that proxy for weather conditions was obtained from investing.com[11] and the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies (GISS)[12], respectively.

3.3.2 Approach to constructing the speculation (SPEC) index

In this study, we construct a new index for measuring the activity of emissions non-compliance firms in the carbon market. The new index is a news-based composite index that seek to measure speculation in terms of the volume of search and accessibility of information on trading activity in the carbon market. Thus, the news-based speculation collected from the big data archive of Google Trends. 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 and/or phrases utilized to extract the index are: "EU ETS", "EUA price", "EU ETS

[11] https://www.investing.com/indices/stoxx-600
[12] https://data.giss.nasa.gov/gistemp/

price", "ETS prices", "ETS carbon price", "Carbon price", "Carbon prices", "Carbon allowance price", "Carbon market", "Carbon trading", "Emissions trading". This approach is similar to the one used in Salisu et al. (2021) to generate news-based uncertainty index induced by COVID-19 (see also, Olubusoye et al., 2020). Using principal component analysis, the resulting search volume variables were combined to arrive at our novel news-based speculative index ($SPEC_{index,t}$), which is further normalized using the following procedure.

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

The *‘a’* component of terms (*a* – *b*) 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* = 100 (the highest level of speculation). This approach to assigning weight also find support in Olubusoye et al. (2020) and Salisu et al. (2021).

3.3.3 Preliminary Results

Table 3.1 presents the mean statistic for the daily EUA prices for both the level and returns. The average daily EUA prices are about €20.20/tCO2, while the latter show that the average return on carbon prices is about 0.03 for the period under consideration. The fact that the return on the EUA prices is positive may be appealing to both the existing and potential investors in the carbon market. What is, however, of concern is whether the average price of EUA at €20 is sufficient to stimulate the EST goal of emission reductions. With respect to the standard deviation statistics, it measures on average the dispersion of EUA prices and its returns from the mean level. The relatively large values of the standard deviation statistic as reported in Table 3.1 is an indication of probable high volatility, particularly in the returns of the EUA prices. The implication of such high volatility includes investment risk, the need for portfolio diversification, adjustments to trading strategies, and the importance of effective market regulation.

The EUA price return is also negatively skewed and exhibits heavy tails. The latter, which implies leptokurtic distribution, is often called excess kurtosis. This, among other things, suggests the possibility of the EU-ETS being susceptible to risk, which, according to Adediran and Swaray (2023), is in line with the position of Dou et al. (2022). Regarding other variables of interest whose summary statistics were also represented in the table, we find the monthly mean values of the energy prices relatively higher for coal prices. At the same time, electricity has the lowest average monthly prices. The large values of the standard deviation statistic associated with each of the energy prices, all of which have been widely acknowledged as the fundamental drivers of carbon prices, yet again confirm the likelihood of volatility in the dynamics of carbon pricing. A further look at Table 3.1 shows that the mean statistic for the speculation (SPEC) variable is 28.50, which is an indication of low speculation activity in the ETS since the SPEC index, as earlier demonstrated, ranges between 1 and 100 as the lowest and highest speculation activity in the carbon market. Same as every other variable of interest under consideration, the values of the standard deviation statistic are also large for SPEC.

Table 3.1: Preliminary Results

	Daily EUA Prices		Monthly Energy Prices and Fuel-Switching					ECO	TMP	CPU	SPEC
	Actual	**Returns**	**COAL**	**GAS**	**OIL**	**ELE**	**Fswitch**				
Table 1a: Summary statistics											
Mean	20.195	0.032	99.917	27.494	78.216	19.982	-77.583	335.258	0.072	140.771	28.504
Std. Dev.	20.812	3.076	63.593	30.066	25.851	24.636	43.799	70.399	0.172	72.607	23.705
Skewness	2.012	-0.808	2.632	3.675	0.186	1.710	-2.457	-0.130	0.063	1.295	1.079
Kurtosis	6.303	17.643	10.220	17.484	1.876	4.444	10.305	2.273	2.609	4.332	3.259
No. Obs.	3913	3912	180	180	180	180	180	180	180	180	180
Frequency	Daily		Monthly								
Start	2/01/2008		January, 2008								
End	30/12/2022		December, 2022								
Table 1b: Conditional Heteroscedasticity & Autocorrelation tests											
ARCH(10)	47092.5***	15.564***	50.531***	2.704***	1.589	1.094	69.010***	1.423	6.215***	1.529	46.583***
ARCH(20)	23867.9***	14.072***	22.605***	3.409***	0.855	1.240	104.57***	1.439	3.931***	1.008	32.784***
ARCH(30)	16183.2***	9.615***	12.202***	3.799***	0.521	0.814	75.371***	1.045	2.520***	0.915	5.575***
Q(10)	38230.0***	36.592***	1436.5***	17.161*	17.623*	15.097	470.99***	16.100*	725.95***	34.331***	1262.3***
Q(20)	75014.0***	104.23***	2126.6***	24.673	25.982	31.982**	483.59***	22.134	982.66***	67.468***	1983.6***
Q(30)	11062.0***	132.40***	2288.2***	38.934	38.424	44.848**	502.16***	32.317	1066.9***	77.720***	2246.8***
$Q^2(10)$	36702.0***	239.98***	782.51***	32.918***	12.628	12.459	187.72***	21.355**	96.715***	16.173*	621.73***
$Q^2(20)$	69635.0***	511.55***	867.52***	57.399***	14.174	29.790*	187.87***	24.214	155.40***	22.397	836.77***
$Q^2(30)$	10026.0***	511.55***	876.28***	84.774***	15.886	31.061	188.00***	28.642	224.05***	29.095	855.62***

Note: The letter r next to the EUA prices and the various energy and fuel costs under consideration indicates that these prices were stated as returns and are measured as the log of the first difference between their respective values. Other variables in the table, particularly summary statistics, remain computed. 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. We presented F-statistics in the former example and Q-statistic and Q^2-statistic in the latter. The null hypothesis for the ARCH-LM is that there is conditional heteroscedasticity, whereas the null hypothesis for the autocorrelation test is that there is no conditional heteroscedasticity. The asterisk ***, ** & * implies significance at 1%, 5%, and 10% levels of significance, respectively.

The additional preliminary results presented in the second part of Table 3.1, namely, the autoregressive conditional heteroscedasticity (ARCH) test and the Ljung-Box autocorrelation test (Q-stat. and Q2-stat.), are of particular importance to our choice of estimation technique in this study. Although these tests were performed at varying lag lengths, we find the rejection of the null hypothesis of no ARCH and autocorrelation effects evident in all variables. There is overwhelming evidence of conditional variance and autocorrelation problems in each variable under consideration. The consistency of these results across different lag lengths further confirms, in particular, our earlier suspense about volatility in the dynamics of carbon pricing. Thus, in addition to the mixed frequency nature of the variables of interest, which is daily for the EUA prices and monthly for SPEC and other variables, what further informs the choice of our estimation technique, as demonstrated in the following immediate section, is the finding of the presence of volatility in the variables.

3.4 The Econometric Framework

Given that the carbon allowances (permits) traded in the ETS are characterised with statistical features that are comparable to those of conventional financial products, namely, shares, bonds, and foreign exchange, we chose an econometric technique that has the potential to capture the carbon price expected returns and volatility dynamics. Motivated by the mixed frequencies of the variables under consideration, we prefer the GARCH-MIDAS model as the most suitable for analysing the volatility dynamics of carbon allowance price returns. One of the merits of the GARCH-MIDAS is that it helps overcome the challenges of information loss familiar with data aggregation into a uniform frequency. Thus, rather than resulting in data splicing, which is the popular technique for aggregating data into a uniform frequency, the GARCH-MIDAS instead helps us to retain the natural features of our variables of interest, such that our dependent variable ($rEUA$), has a higher (daily) frequency. In contrast, the exogenous factors captured singly in terms of the individual indicators of energy prices, economic activity, weather condition, CPU, and speculation, which in particular related to the primary objective of this study, has a lower (monthly) frequency. Consequently, our GARCH-MIDAS-X model for the carbon market measured in terms of carbon allowance price returns is as follows:

$$rEUA_{i,t} = \mu + \sqrt{\tau_t \times h_{i,t}\, \varepsilon_{i,t},} \quad \varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N(0,1), \quad \forall\, i = 1, \ldots, N_t \tag{3.18}$$

$$h_{i,t} = (1 - \alpha - \beta) + \frac{(r_{i-1,t} - \mu)^2}{\tau_i} + \beta h_{i-1,t} \tag{3.19}$$

$$\tau_i^{(r\omega)} = m^{(r\omega)} + \theta^{(r\omega)} \sum_{k=1}^{K} \phi_k\left(\omega_{1,}\omega_{1,}\right) X_{i-k}^{(r\omega)} \tag{3.20}$$

The conditional mean component of the GARCH-MIDAS framework is defined by equation (3.18) while the conditional variances are defined by equations (3.19) and (3.20) for the short- and long-run components of the GARCH-MIDAS model. In terms of the parameters associated with each equation, μ equation (3.18) captures the unconditional mean of the return series while the short-run component of the variable with high-frequency data in equation (3.19) is h_{it} following a GARCH (1,1) process where α and β are ARCH and GARCH terms, respectively, which are conditioned to be positive and/or at least zero $(\alpha > 0 \text{ and } \beta \geq 0)$ and summing to less than unit $(\alpha + \beta < 1)$.

The term τ_t describes the long-run element that incorporates the exogenous series (or realized volatility in the absence of an exogenous series) and requires repeating the annual value over the months in that year. The phrase (8) describes the long-term element that includes the exogenous series (or realised volatility in the absence of an exogenous series) and requires repeating the annual value over the course of the year's months. Superscript $(r\omega)$ in equation (3.20) stands for the adoption of a rolling-window framework, which allows the secular long-run component to fluctuate monthly with *m* denoting the long-run component intercept.

Quite of interest and a focal point of our analysis is the MIDAS slope coefficient (θ), which incorporates the predicting power of say speculation or the exogenous predictor X_{i-k} in the predictability of carbon allowance price returns, where $\phi_k(\omega_1,\omega_2) \geq 0, k = 1,...,K,$ is the weighting scheme that must sum to one for the parameters of the model to be identified.

3.5 Empirical Results

The main goal of this study is to determine the most appropriate framework for modelling the dynamics of carbon pricing. Thus, we rest on the increasing speculation activity of the financial actors in the ETS to hypothesize that speculation matters in the dynamics of carbon pricing. To achieve this, we go beyond the norm of restricting the dynamic of carbon prices to a market fundamentals-based framework to an all-inclusive carbon pricing framework that accommodates not only the emission compliance activity of the ETS but also the speculation activity of the ENCFs. As theoretically demonstrated in Section 3 of this study, our proposed all-inclusive framework (the unrestricted model) is an augmented variant of the traditional market fundamental approach (the restricted framework) to modelling carbon prices. We arrived at our proposed all-inclusive framework (unrestricted model) by innovatively reducing the unexplained component of the dynamics of carbon pricing. To test the validity of our all-inclusive framework as the most appropriate for modelling carbon pricing compared to the traditional restricted approach, we developed a novel composite news-based speculation index to empirically evaluate the importance of speculation in the dynamics of carbon pricing.

Table 3.2: GARCH-MIDAS –based regression results

GARCH-MIDAS Model Type	μ	α	β	θ	w	m	Model Selection Criteria			Rank
							Log-LL	***AIC***	***SIB***	
GARCH-MIDAS model with realized volatility (RV) based on the fixed window										
GARCH-MIDAS-RV	0.0010*** (0.0003)	0.1421*** (0.0100)	0.7882*** (0.0193)	0.0362*** (0.0029)	6.3262*** (1.2759)	0.0002*** (0.0000)	8051.1	-16090.1	-16052.5	**15th**
GARCH-MIDAS-X										
GARCH-MIDAS-COAL	0.0009*** (0.0003)	0.1146*** (0.0063)	0.8786*** (0.0064)	0.1287*** (0.0472)	1.4426*** (0.1156)	0.0015*** (0.0005)	8438.7	-16865.4	16827.8	**4th**
GARCH-MIDAS-GAS	0.0009*** (0.0003)	0.1144*** (0.0063)	0.8745*** (0.0067)	0.0404*** (0.0120)	1.6447*** (0.5950)	0.0009*** (0.0002)	8435.8	-16859.7	-16822.1	**6th**
GARCH-MIDAS-OIL	0.0009*** (0.0003)	0.1126*** (0.0062)	0.8764*** (0.0066)	0.0226* (0.0133)	5.8861 (4.5880)	0.0013*** (0.0002)	8433.2	-16854.5	-16816.9	**10th**
GARCH-MIDAS-ELE	0.0009** (0.0003)	0.0947*** (0.0052)	0.8945*** (0.0056)	0.0174*** (0.0105)	10.417 (7.9835)	0.0008*** (0.0001)	8431.8	-16851.6	-16814.0	**13th**
GARCH-MIDAS-X1: (X1 = Composite index of the energy prices)										
	0.0009*** (0.0003)	0.1173*** (0.0065)	0.8731*** (0.0067)	0.0546*** (0.0201)	1.0270*** (0.1473)	0.0011*** (0.0003)	8433.8	-16855.7	-16818.1	**9th**
GARCH-MIDAS-FSwitch	0.0009*** (0.0003)	0.1143*** (0.0063)	0.8744*** (0.0066)	0.1180** (0.0058)	5.5173 (3.8152)	0.0010*** (0.0002)	8434.7	16857.4	16819.8	**8th**
GARCH-MIDAS-ECO	0.0009*** (0.0003)	0.1139*** (0.0062)	0.8734*** (0.0067)	0.1019* (0.0571)	9.7415** (4.2333)	0.0010*** (0.0002)	8432.2	-16852.3	-16814.7	**12th**
GARCH-MIDAS-TMP	0.0009*** (0.0003)	0.1161*** (0.0064)	0.8750*** (0.0066)	0.7675** (0.3987)	1.0042*** (0.3122)	0.0010*** (0.0002)	8432.6	-16853.1	-16815.5	**11th**
GARCH-MIDAS-X2: **(**X2 = Composite index of ECO and TMP)										
	0.0009*** (0.0003)	0.1141*** (0.0062)	0.8736*** (0.0067)	0.0912 (0.0825)	10.150 (8.6457)	0.0010*** (0.0002)	8431.5	-16851.0	-16813.4	**14th**
GARCH-MIDAX-X3: (X3 = Composite index of X1 & X2)										
	0.0010*** (0.0003)	0.1132*** (0.0062)	0.8763*** (0.0066)	0.1138*** (0.0276)	1.4927*** (0.1573)	0.0011*** (0.0002)	8439.0	-16866.0	-16828.4	**2nd**
GARCH-MIDAS-X4										
GRACH-MIDAS-CPU	0.0009*** (0.0003)	0.1117*** (0.0061)	0.8767*** (0.0065)	-0.0169*** (0.0059)	25.980* (14.993)	0.0013*** (0.0002)	8436.2	-16860.3	-16822.7	**5th**
GARCH-MIDAS-X5: (X5 = Composite index of X3 & X4)										
	0.0010***	0.1135***	0.8752***	0.1145***	1.5931***	0.0011***	8439.0	-16856.9	-16828.3	**3rd**

	(0.0003)	(0.0062)	(0.0066)	(0.0254)	(0.1458)	(0.0002)				
GARCH-MIDAS-X6										
GARCH-MIDAS-SPEC	0.0009*** (0.0003)	0.1144*** (0.0063)	0.8771*** (0.0065)	0.0249** (0.0108)	8.9450 (6.7086)	0.0016*** (0.0004)	8435.0	-16857.9	-16820.4	**7th**
GARCH-MIDAS-X7: (X7 = Composite index of X5 & X6)										
	0.0011*** (0.0003)	0.1145*** (0.0063)	0.8743*** (0.0067)	0.1011*** (0.0237)	1.4179*** (0.1692)	0.0012*** (0.0002)	8439.0	-16866.0	-16828.4	**1st**

Source: Authors' own creation/work

Note: Log-LL, AIC, and BIC denote log-likelihood, Akaike Information Criterion, and Bayesian Information Criterion, respectively. The values in parenthesis are the standard error, while ***, **, and * imply significance at 1%, 5%, and 10% levels of significance. The model with the largest log-likelihood and the least AIC and BIS is ranked the best.

The empirical estimates presented in Table 3.2 were based on the various competing carbon price models specified in Section 3.2 using the GARCH-MIDAS technique. GARCH-MIDAS has a feature to accommodate the mixed frequency of the variables and our preliminary findings of the inherent volatility in the variables, which, if ignored, is likely to undermine the accuracy of the estimates. The variants of the GARCH-MIDAS models considered are GARCH-MIDAS-RV and GARCH-MIDA-X, respectively. The term RV in the former implies realized volatility inherent in the EUA price returns. The X term in the latter denotes exogenous regressors captured singly for each of the fundamentals considered potential underlying sources of volatility in the EUA price returns.

The biggest lag order (K) of MIDAS of the GARCH-MIDAS-RV and GARCH-MIDAS-X models is set to 11 at the point where we obtained maximum logarithm likelihood as optimal for a particular GARCH-MIDAS model. To empirically validate the relative accuracy of our proposed all-inclusive framework, we compared the GARCH-MIDAS-X estimates obtained from it to those obtained from the alternative frameworks. To determine the best fit among the competing models, we ranked the individual models based on their respective log-likelihood ratios and the AIC and SIB statistics, respectively. The model with the largest log-LL, with least AIC and SIB values is judged as the best-fit model and the most preferred framework for modelling the dynamics of carbon pricing. However, irrespective of the variant of the GARCH-MIDAS model that is under consideration, the parameters of interest are: μ, α, β, θ, w and m.

The parameter μ, for example, captures the unconditional mean of EUA price returns, and the value is positive both for the realized volatility–based GARCH-MIDAS and across all the variants of the GARCH-MIDAS-X models considered. It is also evident in the table that the coefficients on ARCH (α) and the GARCH (β) terms are positive and statistically significant. More importantly, the volatility persistence coefficient measure in terms of the sum of the ARCH and GARCH terms (i.e., $\alpha + \beta$) is close to one irrespective of the variants of the GARCH-MIDAS models estimated. This is an indication that the short-term EUA price returns have the highest level of persistent volatility. The fact that this finding is consistent and robust across both GARCH-MIDAS-RV and GARCH-MIDAS-X models not only conforms to our preliminary result of the inherent volatility in EUA price returns but also finds support in Wu et al. (2022), whose study also confirms the persistence of volatility in EUA price returns across different types of GARCH-MIDAS models.

Regarding the slope coefficient, we find the coefficient on the parameter θ statistically significant both for the realized volatility (RV) in GARCH-MIDAS-RV and the exogenous regressors (Xs) in GARCH-MIDAS-X. The fact that the RV has a positive effect on the long-term EUA returns is an indication that the bigger the fluctuation in the RV, the bigger the long-term volatility in the EUA price returns. In addition, the various exogenous factors, namely, energy prices, economic activity, weather conditions, climate policy uncertainty (CPU), and the speculation activity of the financial actors, are all important in the volatility dynamics of the EUA price returns. In sum, all the individual exogenous regressors and the composite index exhibit the potential of causing higher long-term EUA volatility with CPU the only notable exception.

However, while acknowledging that Aotola et al. (2013), Tan and Wang (2017), Ji et al. (2018), Wang and Zhao (2021), and Li et al. (2021) have all proven the significance of energy prices and economic activity as the main drivers of carbon prices, the theoretical and empirical validity of speculation having a significant influence on the volatility dynamics of EUA price returns is considered largely innovative in the context of this study. Saying it differently, the fact that the coefficient on the parameter θ is positive when the GARCH-MIDAS-X model is estimated as GARCH-MIDAS-SPEC suggests that the higher value of the speculation could forecast higher long-term volatility in the EUA price returns. The underlying intuition in this regard is that, with the increasing participation of financial actors in the ETS, speculation activity in the ETS would wildly fluctuate, leading to increased volatility in the returns of the EUA prices.

But, unlike speculation, the parameter θ is negative when the GARCH-MIDAS-X model is estimated as GARCH-MIDAS-CPU, which, on the other hand, is an indication that a higher value of uncertainty in the regulatory framework of the ETS is likely to foster lower-term volatility in the EUA price returns. This could explain the position of Wu et al. (2022), that with a drastic climate change, EUA prices would fluctuate, and the government would respond by publishing some regulations. The published regulations are meant to mitigate volatility resulting from carbon reaching its peak. The fact that some of the regulations are published with the goal of price stabilization should explain why the CPU can cause declining volatility in EUA prices.

Finally, at the heart of this study is the question of which framework is the most appropriate or the best fit for modelling the dynamics of carbon prices. Thus, while the GARCH-MIDAS-RV is our benchmark model, we then proceed on to test if expressing the X component of the GARCH-MIDAS-X in a composite form, is more appropriate compared to expressing the X singly for each of the regressors, as demonstrated so far. Using the principal component analysis (PCA) technique, our first composite form of the GARCH-MIDAS-X model is GARCH-MIDAS-X1, where X1 is the composite index of all the energy prices (coal, gas, oil, and electricity). For GARCH-MIDAS-X2, X2 is the composite index of economic activity (ECO) and weather conditions measured in terms of temperature (TEMP) anomalies. The X3 in the Garch-Midas-X3 is the composite index of the X1 and X2. By extending the composite index of X3 to include the CPU (X4), we arrived at another extended composite index in GARCH-MIDAS-X5, where X5 is a combination of X3 and X4.

Defining our proposed all-inclusive framework for modelling carbon prices is GARCH-MIDAS-X7, where X7 is the all-encompassing composite index that accommodates all the indicators of emission compliance activities and, by extension, the non-emission compliance activities in the EU-ETS. We find the GARCH-MIDAS-X model with the X captured in composite form ranked among the best three fits for modelling carbon prices. As expected, the GARCH-MIDAS-RV ranked last regarding the most appropriate framework for modelling the volatility dynamics of carbon price returns. This is particularly in line with our earlier submission that each exogenous factor is relevant to the volatility dynamics of carbon price returns. More importantly, using alternatives model selection criteria, namely log-LL, AIC, and BIC, the GARCH-MIDAS-X7 is consistently revealed and ranked as the best-fit model. This, among other things, validates our hypothesis that an all-inclusive framework encompassing the ETS's emission and non-emission compliance activities is the most appropriate for modelling carbon prices. In other words, ignoring the growing speculation activity of the financial actors in the ETS, particularly where it matters, is likely to undermine the accuracy of the inference drawn from the dynamics of carbon pricing.

3.6 Summary of the Chapter

In this Chapter, we examine the role of speculation in the dynamics of carbon pricing, covering Phase II, III, and IV of the trading period of carbon allowances in the EU-ETS. Motivated by the assertion that if left unchecked, the increasing speculation activity of the financial actors is likely to overwhelm or undermine the environmental goal of the ETS, we modified the framework for modelling carbon allowances to accommodate the growing commentaries linking the trend of excessive changes and volatility in the EUA prices to speculation. We hypothesized that an all-inclusive framework that accommodates both the ECFs and ENCFs activities of the ETS is the most accurate for ensuring the adequacy of the inference drawn on the dynamics of carbon pricing. We innovatively reduce the unexplained component of the dynamics of carbon pricing by developing a composite news-based speculation index that enables us to empirically evaluate the hypothesis that speculation matters in the dynamics of carbon prices. However, in addition to our preliminary finding of evidence of inherent volatility in the EUA prices in particular, the variables of interest are also of mixed frequency. Rather than forcing the data to be of uniform frequency, we employ the GARCH-MIDAS econometric technique, which has been proven not only suitable for addressing the volatility dynamics of the dataset but also capable of accommodating the variables at their "natural" mixed frequencies.

Given the above, among other things, we go beyond the norm of restricting the dynamics of carbon pricing to a market fundamentals-based framework to develop an all-inclusive carbon pricing modelling framework that accommodates not only the emission compliance activity in the ETS but also the speculation activity of the ENCFs in the market. We developed a novel composite news-based speculation index, and using the GARCH-MIDAS framework, we show that the speculation activity of the financial actors is relevant to the volatility dynamics of carbon prices. Our finding suggests that higher speculation values spur long-term volatility in EUA price returns. We employ alternatives model selection criteria where the outcomes from each consistently and uniformly rank the GARCH-MIDAS-X framework that accommodates emissions compliance and non-emissions compliance in the ETS as the best fit for modelling the dynamics of carbon pricing.

Thus, compared to the standard carbon pricing modelling framework, which confines the dynamics of carbon prices to demand and supply market fundamentals, we show that our all-inclusive framework provides a more comprehensive approach to modelling carbon prices. However, the global goal of low carbon emissions requires a well-behaved ETS, which is crucial for the stability and prosperity of the emission trading programme to fulfil its function as an emission reduction policy tool. Given that such a well-behaved ETS cannot exist in isolation from accurate and reliable carbon allowance price forecasts, it thus becomes inevitable to test further the viability of our all-inclusive framework for modelling carbon pricing from the perspective of in-sample and out-of-sample forecasts for the predictability of carbon prices. According to Wang et al. (2022), an accurate carbon price forecast matters for the benefits and costs of carbon market participants and the carbon emission quote set. Motivated by this, among other things, the predictability and viability of our proposed all-inclusive framework are further tested in our second essay. The goal is to determine the appropriate framework to provide the market with accurate carbon price signals.

CHAPTER FOUR

EXPERIMENTING WITH THE FORECASTING POWER OF SPECULATION IN THE PREDICTABILITY OF CARBON PRICES

4.0 Introduction

The ETS must have a reasonable carbon price to fulfil its function as an emission reduction policy tool. A low carbon price is predicted to weaken the confidence of market participants and consequently undermine the efficiency of the ETS (Liu et al., 2021). On the other hand, however, a high carbon price is predicted to spur the development of innovative green technologies and, by extension, improve the efficiency of the ETS (Li et al., 2021). A well-designed ETS has the potential to induce emissions reductions at minimal economic and social costs (Zhu & Chevallier, 2017; Dong et al., 2022). However, such a well-behaved ETS can only exist with accurate and reliable carbon allowance price forecasts. According to Wang et al. (2022), a precise carbon price forecast can influence the benefits and costs of carbon market participants as well as the carbon emission quote setting, which is crucial for the stability and prosperity of the emission trading programme (Dutta, 2018; Zhu et al., 2018; Hao & Tan, 2020).

Based on the preceding, this research aims to improve the forecast accuracy and predictability of carbon allowance prices. There is no denying that there have been growing efforts in the literature to understand the operation of the ETS and its future values through adequate forecast analysis (see Zhao et al., 2018; Hao & Tian, 2020; Adekoya, 2020). However, while inference drawn from the immediately preceding Chapter suggests both ECFs and ENCFs contribute decisively to the functioning of the ETS, the fundamentals commonly acknowledged in the literature as predictors of carbon prices are mostly factors that influence the activities of the ECFs, particularly those associated with the demand and supply dynamics of carbon pricing. Notable in this regard are energy prices, economic activity, and weather conditions. These fundamentals are not only prominent in literature as drivers of carbon prices but also taunted as predictors of their future path.[13] Meanwhile, substantial speculative activity in the carbon futures

[13] Christiansen et al. (2005), Mansanet-Bataller et al. (2007), Alberola et al. (2008), Delarue et al. (2008), Carraro and Favero (2009), Wei et al. (2010), Hintermann (2010), Koch et al. (2014), Hammoudeh et al. (2014), Zhu and Chevallier (2017), Segnon et al. (2017), Chung et al. (2018), Zhang et al. (2018), Ji et al. (2018), Adhurim and

markets has the potential to significantly alter futures prices from those supported by supply and demand fundamentals (Lucia et al., 2015).

Moreover, if the vast majority of carbon allowances traded in the ETS occur on the derivatives market, then market participants, carbon exchanges, and the regulatory body will all be interested in a framework that can provide them with reliable insight into the role of speculation in the future path of the market. Yet, to the best of our knowledge, the methodology for modelling carbon prices currently mainly rests on fundamentals associated with the emission compliance dynamic of the ETS. Thus, the innovation in the context of this study is to explore an all-encompassing multi-factor-based prediction model that incorporates not only market fundamentals related to the emissions compliance dynamic of the ETS but also the speculation activity of the emissions non-compliance firms. We hypothesised that speculation matters for the predictability of carbon prices.

There are two main modelling approaches to forecasting carbon prices in the literature: statistical models and factor-based predictive regression. In the former, the forecastability of carbon prices rests on their past value (see Byun & Cho, 2013), while in the latter it is predicated on a set of fundamentals thought to be the driving forces behind carbon pricing (see Alberola et al., 2008; Creti et al., 2012). Although the latter considered as an improvement over the former, it still tends to suffer from over-parameterisation problems, in which regression techniques fit well in-sample but perform poorly out-of-sample forecasting. As a result, the research on the prediction of carbon prices is moving away from predictive models based on actual data and towards models based on synthetic data. Simultaneity issues in data-based multi-factor predictive models may also explain why artificially based models are becoming more popular for forecasting carbon prices.

Carbon prices are however vulnerable to the whims of systemic (market) events, just like any traditional commodity traded on an exchange, and this is what causes volatility in the market for carbon emission futures (Zhang, 2016). More so, statistical, and artificial data-based models

Mario (2021), Dong et al. (2021), among others, are some of the studies that have established the significant impact of energy prices namely, coal prices, gas prices, oil prices and electricity prices on carbon prices.

cannot deal with the nonlinearity, trend, heteroscedasticity, persistence, and structural shifts inherent in carbon prices. If left unaddressed, the probable inherent nature of these statistical features in the predictor series can undermine their forecasting power in the predictability of carbon prices. As a result, we employ the Feasible Quasi Generalised Least Squares (FQGLS) estimator developed by Westerlund & Narayan (2015), which can capture endogeneity, persistence, and conditional heteroscedasticity biases in a predictive regression (see Westerlund & Narayan, 2012, 2015; Narayan & Gupta, 2015; Salisu et al., 2019; Isah & Raheem, 2019). To the best of our knowledge, Adekoya (2020) remains the only notable exception to have shown that adjusting an estimator to account for inherent statistics in the predictors matters for enhancing the forecast accuracy of carbon prices. However, the innovation in this study is to evaluate the predictability of carbon prices both from the viewpoint of the forecasting power of a predictor as well as the choice of the estimator.

More importantly, the carbon market is an initiative of political legislation, and as such, regulatory uncertainty about the scope and operation of the market is capable of fueling future speculation in the market (see Sockin & Xiong, 2015; Koch et al., 2016; Salant, 2016). The intuition here is that changes in policies, market design, and perceived commitment to meeting climate targets induce diverse price anticipations, in which speculators try to anticipate the strategies of other speculators rather than relying on market fundamentals to form expectations (see Roques et al., 2022). As a result, it will be an intriguing experiment to investigate how regulatory events associated with the ETS's operation affect the forecasting power of speculation on the predictability of carbon prices. On this note, we further subject our hypothesis that speculation matters in the predictability of carbon prices to a robustness check or sensitive test by controlling for the role of political decisions associated with ETS operations.

The remaining sections of this Chapter are as follows: Section 4.1 presents the predictive models. Section 4.2 explains the data and also offers some preliminary analysis. Section 4.3 presents the methodology. Section 4.4 presents and discusses the results, while Section 4.5 summarises the Chapter.

4.1 The Predictive Model

For clarity, the various indicators included in our predictive model as potential predictors of carbon prices stem from the various fundamentals earlier identified in theoretical framework in section 3.2. Thus, we follow the linear multi-predictor set-up by Makin et al. (2014) to begin our predictive framework, where carbon allowance price $\left(P_{CO}\right)$ is the predicting series regressed on economic activity and weather variations.

$$P_{CO,t} = \alpha_0 + \beta_1 eco_{t-1} + \beta_2 tmp_{t-1} + \varepsilon_t \tag{4.1}$$

Equation (4.1) is our baseline multi-factor predictive model named "Model_1" for convenience. It is a prototypical form of predictive regression widely used in the literature (see Rapach et al., 2010; Westerlund and Narayan, 2012, 2015; Isah and Raheem, 2019; Salisu et al., 2020, 2021; Isah et al., 2022). The term $P_{CO2,_t}$ represents carbon prices, eco_t denotes economic activity, while tmp_t is the temperature anomalies which proxies for weather variation. The term α_0 is the intercept, while β_1 and β_2 are the coefficients of the one-period lagged value of the predictor series.

Motivated by the increasing evidence of the fuel-switching price, a proxy for marginal abatement costs and fundamental associated with the emissions compliance activities of firms in the carbon market, we extend the predictive model in equation (4.1) to include the probable forecasting power of the fuel-switching price in the predictability of carbon prices.

$$P_{CO,t} = \alpha_0 + \beta_1 eco_{t-1} + \beta_2 tmp_{t-1} + \beta_3 fswitch_{t-1} + \varepsilon_t \tag{4.2}$$

Equation (4.2) is our extended multi-factor predictive model named "Model_2", where the fuel-switching price variable remains as earlier defined equation (3.13).

Indeed, while equation (4.2) is an extensive variant of the multi-factor predictive model in equation (4.1), it still restricts the predictability of carbon prices to emission compliance activities in the carbon market. However, firms that has little or no consideration for the emission reduction target of the ETS have also continued to participate in the market with their sole motive of profit maximisation rather than the global goal of emissions reductions, fuelling speculation activities in the carbon market. Therefore, we yet again modified the predictive model in equation (4.2) to enable us further to experiment with the extent to which the speculation activity of the emissions non-compliance firms matters in the predictability of carbon prices.

$$P_{CO,t} = \alpha_0 + \beta_1 eco_{t-1} + \beta_2 tmp_{t-1} + \beta_3 fswitch_{t-1} + \beta_4 spec_{t-1} + \varepsilon_t \qquad (4.3)$$

Equation (4.3) is our all-inclusive multi-factor predictive model, where emissions compliance and non-emissions compliance dynamics of the ETS are captured jointly in a single predictive framework named "Model_3". While all the predictor series in equation (4.3) remain as earlier defined, $spec_t$ represent the speculation index which is a proxy for the activities of the emissions non-compliance firms in the market.

Furthermore, because the carbon market is a product of political decisions, Sockin and Xiong (2015), Koch et al. (2016), and Salant (2016), among others, believe that regulatory uncertainty regarding the scope and ambition of the ETS is a source of future speculation in the carbon market. As a result, in our proposed all-inclusive multi-factor prediction model, we further control for carbon policy uncertainty (CPU), as illustrated below.

$$\begin{aligned} P_{CO,t} = {} & \alpha_0 + \beta_1 eco_{t-1} + \beta_2 tmp_{t-1} + \beta_3 fswitch_{t-1} + \beta_4 spec_{t-1} + \\ & \beta_5 cpu_{t-1} + \beta_6 spec * cpu_{t-1} + \varepsilon_t \end{aligned} \qquad (4.4)$$

With the introduction of CPU in equation (4.4), we can experiment with the hypothesis that changes in political decisions related to the operation of the ETS enhance the forecasting power of speculation in the predictability of carbon prices. To allow for consistency in our procedure, equation (4.4) is named "Model_4" in this study.

4.2 Data and Preliminary Analysis

4.2.1 Data description and sources

The European Union ETS (EU-ETS) is the cornerstone of the world's most ambitious climate strategy. Consequently, carbon prices (*PCO*) in this study are measured in terms of the European Allowance (EUA) futures contracts traded in the Intercontinental Exchange (ICE). We compute continuously compounded returns of the EUA prices as the first difference of the log of the EUA price series, such that; $PCO_t = 100 * [\ln(EUA_t) - \ln(EUA_{t-1})]$. The first difference of the log of the EU Stoxx 600 is used to proxy for economic activity (*ECO*), while the weather condition is measured in terms of the global temperature anomalies ($TEMP$). Regarding the fuel prices, we employ the first monthly futures of publicly traded contracts, namely; the Rotterdam coal contracts as a proxy for coal prices (P_{coal}), while the Tile Transfer Facility (TTF) gas contract is used to proxy for gas prices (P_{coal}). However, unlike Adekoya (2020) where these fuel prices are implicitly captured individually as predictors of carbon prices, we follow the fuel-switching technique in equation (3.13) to capture the fuel prices explicitly. 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 to construct the speculation (SPEC) index used in this study. 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 $(SPEC_t)$ index, which is further normalised using the following procedure.

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

The *‘a’* component of terms (*a* – *b*) 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* = 100 (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 "climate policy uncertainty (CPU)" index developed by Gavriilidis (2021) to proxy for the role of uncertainty.

With respect to the sources of the data, both carbon and energy prices are obtained from the European Energy Exchange (EEX), with the EU Stoxx 600 which proxies for ECO obtained from investing.com, while the temperature anomalies are sourced from the Goddard Institute for Space Studies (GISS) of the National Aeronautics and Space Administration (NASA). Given that the Phase I of the EU-ETS, which covered 2005–2007, was widely regarded as the experimental phase of the scheme, our data set covers from January 2008 to December 2022. More importantly, the highest accessible frequency for CPU, TEMP and ECO is monthly, thus explain why we restrict other variables of interest to monthly frequency even though some are available on daily frequency.

4.2.2 Preliminary results

The preliminary analysis results for this Chapter are presented in three parts (see Table 4.1). The first part presents summary statistics for each variable, such as the mean, standard deviation (Std. Dev.), skewness, kurtosis, and Jarque-Bera (JB) statistics. The second part includes the results of the conditional heteroscedasticity and autocorrelation tests performed on each variable. The final section of the table contains results from persistence and endogeneity tests. More importantly, in all these statistical tests, the carbon allowance prices, and other variables of interest are expressed in returns and percentiles, with the speculation (SPEC) index being the only exception that remains as earlier defined. A cursory look at the first part of Table 4.1 shows that the monthly carbon price return is 0.80%, which is commendable as it attracts investors into the market and enhances the emission reduction goal. In another development, the mean statistic for SPEC is 28.5, implying low speculation activity in the ETS, given that the SPEC index, as earlier measured, ranges between 1 and 100 as the lowest and highest speculation activity in the carbon market.

The standard deviation statistic of 14.36% reported for carbon price return suggests that the series is volatile, which conforms to the increasing evidence of volatility in the dynamics of carbon prices (see Ibrahim & Kalaitzoglo, 2015; Dong et al., 2022). Except for the TMP, all the variables are leptokurtic, while the skewness statistic, on the other hand, is mixed as it is positive for some variables but negative for others. The JB test statistic rejects the null hypothesis of the normal distribution of the series except TMP and CPU. A further look at the second part of the table is overwhelming evidence of conditional heteroscedasticity and autocorrelation effects, respectively. The table concludes with persistence data produced by regressing each predictor series on its initial lag using the OLS estimator. The endogeneity test findings, which are likewise presented in the table's last section, follow a three-step approach.

To begin with, we estimate a predictive model with OLS the estimator: $P_{CO,t} = \alpha + \beta z_{t-1} + \varepsilon_t$, where $P_{CO,t}$ denotes carbon allowance price returns and z_{t-1} is the lag of the predictor variable. In the second stage, we use the Westerlund and Narayan (2015) technique to model the predictor series $z_t = \lambda(1-\gamma) + \gamma z_{t-1} + \varepsilon_t$. In the final step, the relationship between the predicting and predictor error terms ($\varepsilon_{P_{CO,t}}$ and $\varepsilon_{z,t}$) is captured using the following regression: $\varepsilon_{P_{CO,t}} = \rho \varepsilon_{z,t} + \eta_t$. If the coefficient ρ is statistically different from zero; then, the predictor variable is endogenous; and if otherwise, it is exogenous. However, while we find considerable evidence of persistence in all the predictor series, the endogeneity results reveal the predictors as strictly exogenous.

We extend our preliminary analysis to illustrate a co-movement between carbon allowance price returns and the speculation index. A cursory look at Figure 4.1 shows that the two variables are trending in the opposite direction in the early part of Phase II of trading in the carbon market but otherwise in Phase III and Phase IV. To validate or refute this illustration, we subject our preliminary results to a more technical and analytical procedure, as demonstrated in the empirical results section of the paper.

Table 4.1: Preliminary Results

Table 4.1(a): Summary statistics

	Mean	**Std. Dev.**	**Skewness**	**Kurtosis**	**JB-Stat.**
P_{CO}	0.80	14.36	-0.95	5.71	81.65***
ECO	0.15	4.47	-0.56	4.31	22.35***
TMP	0.07	0.17	0.06	2.61	1.26
$Fswitch$	0.01	0.40	0.54	5.24	46.06***
$SPEC$	28.50	23.70	1.08	3.26	35.25**
CPU	0.76	35.82	0.11	3.43	1.69

Table 4.1(b): Conditional Heteroscedasticity and Autocorrelation tests

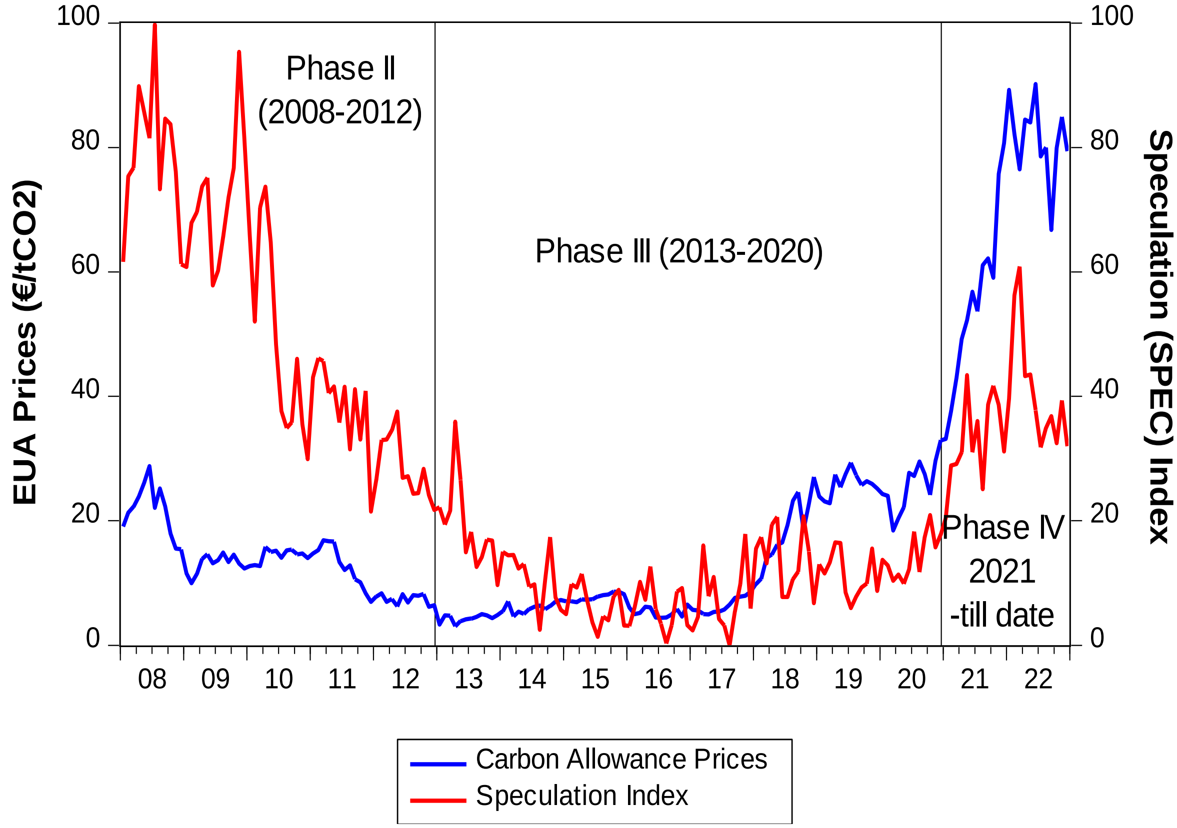
	ARCH LM test			**Ljung-Box test**					
	ARCH(4)	**ARCH(8)**	**ARCH(12)**	**Q(4)**	**Q(8)**	**Q(12)**	**$Q^2(4)$**	**$Q^2(8)$**	**$Q^2(12)$**
P_{CO}	4.32***	2.23**	1.63*	7.75	9.23	11.302	17.72***	17.79**	20.16*
ECO	2.59**	2.62***	1.42	8.92*	13.18	17.93	11.46**	19.01**	22.44**
TMP	17.23***	7.90***	5.19***	381.13***	627.16***	804.50***	84.85***	95.89***	96.86***
$Fswitch$	12.14***	7.63***	5.93***	11.17**	17.96**	24.79**	39.67***	54.24***	66.35***
$SPEC$	106.05***	62.48***	41.98***	593.20***	1071.3***	1442.0***	380.88***	577.1***	669.6***
CPU	3.66***	1.93*	1.24	29.22***	30.72***	47.71***	14.04***	16.07***	16.24

Table 4.1(c): Persistence and Endogeneity tests

	ECO	TMP	$Fswitch$	$SPEC$	CPU
Persistence test	0.1016 (0.0751)	0.8073*** (0.0423)	0.2397*** (0.0757)	0.9460*** (0.0230)	0.3788*** (0.0697)
Endogeneity test	0.0220 (0.2420)	8.1047 (11.0186)	0.4243 (2.8159)	0.2064 (0.1463)	-0.0006 (0.0323)

Note: We consider three different lag lengths (4, 8, and 12) for both the ARCH and autocorrelation tests, and the essence is to demonstrate some level of consistency and robustness of our results. The asyteric ***, **, and * denote significance at the 1%, 5%, and 10% levels of significance in each of the tests.

Figure 4-1: Trends in EUA Prices and Speculation Index



Source: Authors' own creation/work

4.3 Methodological Framework

4.3.1 The estimation techniques

In each of the variants of multi-factor predictive models specified in equations (4.1), (4.2), (4.3), and (4.4), there is likely a tendency towards a correlation between the error term and predictor series, which could lead to endogeneity bias and the potential effect of persistence, as evidenced by our preliminary results. As a result, how to estimate each of these predictive models arises. The typical approach would have been to run OLS while ignoring the issues of bias and inefficiency. However, our first findings indicate that our variables have some statistical characteristics that make the OLS approach inappropriate for some of the biases that may occur. To address one of these biases, Lewellen (2004) created a bias-adjusted estimator that addresses the endogeneity issue in particular. As a result, equation (4.5) represents the updated variant of our predictive models.

$$P_{CO,t} = \alpha_0 + \beta'_{adj} z_{t-1} + \delta(z_t - \rho z_{t-1}) + \varepsilon_t \tag{4.5}$$

where z_t is a vector representing the multi-predictor series, the composition of which depends on which variants of the multi-factor predictor models is under consideration. The OLS estimator adjusted for potential bias in equation (4.5) is denoted as $\beta_{adj} = \hat{\beta} - \delta(\hat{\rho} - \rho)$, while the endogeneity bias caused by the correlation of ε_t and z_t is corrected by the inclusion of the additional term $\delta(z_t - \rho z_{t-1})$ while ρ and $\hat{\rho}$ are fitted coefficients of one period-lagged (z_{t-1}). 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. Hence, the Feasible Quasi Generalized Least Square (FQGLS) is as given below.

$$\beta_{adj}^{FQGLS} = \frac{\sum_{t-qm+2}^{T} \hat{\tau}_t^2 p_t^d z_{t-1}^d}{\sum_{t-qm+2}^{T} \hat{\tau}_t^2 (z_{t-1}^d)^2} \tag{4.6}$$

where $\hat{\tau}_t = 1/\hat{\sigma}_{v,t}$ is used to weigh all the data in the bias-adjusted predictive model in equation (4.6), while $p_t^d = p - \sum_{p=2}^{T} p_t / T$ and $z_t^d = z_t - \sum_{z=2}^{T} z_t / T$.

With FQGLS, one does not need to assume that z_t is stationary, as Lewellen (2004) does with the adjusted OLS (AOLS), 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 AOLS estimator. However, rather than arbitrarily settling for a particular estimator as the most appropriate, we employ AIC and SIC model selection criteria to scientifically arrive at the best estimator among the alternatives, namely, the standard OLS, the adjusted-OLS (AOLS), and the FQGLS.

4.3.2 Forecast evaluation technique

In our forecast performance study, we evaluated both single and paired approaches to establish the most effective prediction framework for the predictability of carbon pricing. We selected 75% of our entire sample period to allow for both in-sample and out-of-sample forecast studies, as is usual practice in the literature when predicting with a time-series sample. Although there is no fixed rule for determining what percentage of a sample is adequate for predicting analysis, researchers in literature have utilised 25%, 50%, and 75% (see Narayan & Gupta, 2015). Given the scope of data, we used 75% of the sample for in-sample estimation while the balance of 25% falling outside the 75% scope enabled us to estimate the out-of-sample forecasts. Following the tried-and-true procedure. A recursive window technique that allows us to account for the time-varying behaviour of carbon price returns in the predictive models is used to construct our forecast estimations, following the standard but established procedure in the literature (Devpura et al., 2018).

The single model-based forecast measure, for instance, Root Mean Square Error (RMSE) for both in-sample and out-of-sample forecasts can be computed as follows:

In-Sample: $$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m}\left(r\widehat{P}_{CO,t} - rP_{CO,t}\right)^2} \tag{4.7a}$$

Out-of-Sample: $$RMSE = \sqrt{\frac{1}{k}\sum_{t=1}^{k}\left(\widehat{P}_{CO,t} - P_{CO,t}\right)^2} \tag{4.7b}$$

Here, the full-sample period is defined as $t = m+1,\ldots,m+k$, such that; m is the sample period, k is the forecast horizon.

To ascertain the robustness of our results, we further complement the RMSE results with a forecast estimate based on Mean Square Error (MSE) - $1/N\sum_{t=1}^{T}\left(\widehat{P}_{CO,t} - P_{CO,t}\right)^2$ 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 alternatives 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 $OOS\_R = 1 - \left(M\widehat{S}E_1 / M\widehat{S}E_0 \right)$ where $M\widehat{S}E_1$ is the mean squared error obtained from Model_4 (which is technically an unrestricted model in this case) and $M\widehat{S}E_0$ 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. A positive $R^2\left(OOS\_R\right)$ statistic such as $R^2\left(OOS\_R\right) > 0$ 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. In addition to the C-T test, we use the C-W test to assess whether there is a substantial difference in the errors of two nested competing models. The following is the basic framework for the C-W test:

$$\hat{f}_{t+k} = \left(P_{CO,t+k} - \widehat{P}_{CO,1,t+k} \right)^2 - \left[\left(P_{CO,t+k} - r\widehat{P}_{CO,2,t+k} \right)^2 - \left(\widehat{P}_{CO,1,t+k} - \widehat{P}_{CO,2,t+k} \right),^2 \right] \qquad (4.8)$$

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

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

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

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

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 t-statistic obtained for a zero coefficient is utilised to make a conclusion. The alternative hypothesis indicates the reverse because the Null hypothesis tests for MSE equivalency. 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).

4.4 Empirical Result Presentation and Discussion of Finding

One of the main contributions of this study to the literature on the predictability of carbon prices is the hypothesis that an all-inclusive predictive model that includes not only the emissions compliance activity of the ETS but also the emission non-compliance activity is the most appropriate for enhancing the accuracy of carbon price forecasts. More so, we experimented with some alternative estimators to determine whether the choice of estimator also matters in the predictability of carbon pricing. We also control for the role of carbon policy uncertainty and test whether it matters in speculation's forecasting power and carbon prices' predictability. Finally, we test the robustness of our preferred predictive model for the predictability of carbon prices by embarking on a comparative evaluation of its in-sample and out-of-sample forecasts relative to carbon price forecasts based on statistical predictive models. We grouped our results presentation and discussion of findings into four subsections. Section 4.4.1 presents the predictability testing results, where the findings help us to ascertain the significance of speculation and other variables of interest as potential predictors of carbon prices. The predictability testing results also enable us to determine the most appropriate estimator among the many alternatives in the predictability of carbon prices. Section 4.4.2 presents the in-sample and out-of-sample forecasts using the preferred estimator. Section 4.4.3 examines the extent to which the CPU's role as the underlying source of speculation in the ETS also matters in the predictability of carbon prices. Section 4.4.4

offers some robustness checks and presents additional results. Section 4.4.4 provides some robustness checks and presents additional results.

4.4.1 Predictive regression results

To facilitate the compression of the analyses discussed herein as they relate to our predictability regression results presented in Table 4.2, we begin this section with a cursory reminder of the previous sections. We experiment with four variants of multi-factor theory-based predictive models defined as Model_1, Model_2, Model_3, and Model_4 in the predictability of carbon prices across different estimators (OLS, AOLS, and FQGLS). Our first task, therefore, is to determine which is most appropriate among these alternative estimators and whether their accuracy varies for the different predictive models under consideration. Thus, for each variant of the multi-factor-based predictive models, the AIC and SIC model selection criteria were used to arrive at the preferred estimator. The smaller the AIC or SIC values, the better the model fits and the estimator under consideration. Where there is a conflict between the results of AIC and SIC, the latter is usually given preference because it assigns a higher penalty to too many parameters in the model (see Salisu & Oloko, 2015).

The analysis and discussion of the regression results in Table 4.2 are based on the estimates obtained via the preferred estimator, whose choice we arrived at systematically using the mentioned model selection criteria. For example, we use the AIC and SIC model selection measures, and we find that the FQGLS estimator consistently outperforms the OLS and AOLS estimators, regardless of the variant of the multi-factor-based predictive model under consideration. For instance, the AIC and SIC values are, in relative terms, uniformly and consistently lower for predictive models estimated via FQGLS compared to those estimated via OLS and AOLS, respectively. Thus, in addition to adjusting the OLS estimator to account for endogeneity bias and the effect of persistence, also accounting for conditional heteroscedasticity via the application of FQGLS by pre-weighting the data is the most appropriate approach to predicting carbon price returns. Therefore, the null hypothesis of no predictability in this is evaluated based on predictive regressions obtained via FQGLS.

Table 4.2: Predictive regression results based on different estimators

Model & Estimator	Predictors					Model Selection Criteria	
	ECO	*TMP*	*Fswitch*	*SPEC*	*SPEC*CPU*	*AIC*	*SIC*
Model_1							
OLS	0.4583*** (0.0114)	-0.3681 (0.3536)				2.4444	2.4804
AOLS	0.4599*** (0.0115)	-0.4673 (0.3756)				2.4595	2.5307
FQGLS	0.4832*** (0.0023)	-0.2112 (0.1375)				1.5359	1.6605
Model_2							
OLS	0.4577*** (0.0116)	-0.3440 (0.3627)	0.0155 (0.1586)			2.4611	2.5147
AOLS	0.4591*** (0.0118)	-0.4315 (0.3879)	0.0750 (0.2551)			2.4865	2.5938
FQGLS	0.4813*** (0.0022)	-0.2208* (0.1169)	-0.1398* (0.0741)			1.5331	1.6939
Model_3							
OLS	0.3560*** (0.0197)	1.0781*** (0.4039)	-0.0190 (0.1445)	0.0172*** (0.0028)		2.2780	2.3495
AOLS	0.3503*** (0.0208)	1.1816*** (0.4416)	0.1248 (0.2325)	0.0181*** (0.0029)		2.3095	2.4525
FQGLS	0.0628*** (0.0112)	-0.1483 (0.1732)	-0.0898 (0.0704)	0.0295*** (0.0010)		0.5194	0.7339
Model_4							
OLS	0.3325*** (0.0151)	0.9362*** (0.3079)	-0.0970 (0.1103)	-0.1392*** (0.0140)	0.0337*** (0.0039)	1.7393	1.8287
AOLS	0.3182*** (0.0144)	0.9993*** (0.3044)	-0.1714 (0.1610)	-0.1742*** (0.0140)	0.0415*** (0.0029)	1.5660	1.7448
FQGLS	0.0488*** (0.0165)	-0.2327 (0.1681)	-0.0924 (0.0577)	0.0415*** (0.0117)	-0.0024 (0.0023)	0.5167	0.7669

Note: The estimator (i.e., OLS, AOLS, and FQGLS) with the lowest AIC and SIC for each of the various models under evaluation is the best. The values in parenthesis represent the standard error, whereas ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Starting with our baseline predictive model, where the predictors are restricted to business as usual (BAU) emissions, we find the null hypothesis of no predictability significantly rejected when the predictor is economic activity. The fact that the sign on the coefficient on ECO is positive is both theoretically and empirically reasonable, given that increasing economic activity has the potential to induce carbon emissions, and the only way to counter such increasing carbon emissions is to increase the cost of abatement, in this case rising carbon prices. The fact that this finding is consistent across each of the alternative predictive models considered finds support in the extant literature, where increasing economic activity has been proven to lead to emissions of CO2, causing a shortage of carbon allowances and consequently manifesting into an increasing carbon price in the ETS (see Zhang et al., 2018; Ji et al., 2021; Wang & Zhao, 2021).

However, the null hypothesis of no predictability, especially when the predictor is temperature (TMP) anomalies, is only statistically rejected in Model 2, where the coefficient on TMP is negative. The extent to which weather conditions matter in the dynamics of carbon pricing depends on whether the temperature anomalies skew more towards extreme coldness or extreme heat, hence our earlier position that the impact of TMP on carbon pricing can be positive or negative. Also, the significance of the fuel-switching price as a measure of abatement cost and a potential predictor of a carbon price is only statistically viable in Model 2. However, the fact that the coefficient on Fswitch is consistently negative in each of the predictive models where it features (i.e., Models 2, 3, and 4) has been both theoretically and empirically validated in the literature (see Delarue et al., 2008; Hintermann, 2010; Koch et al., 2014; Segnon et al., 2017).

Conforming to our hypothesis that the speculation activity of the emissions non-compliance firms (ENCFs) matters in the dynamics of carbon pricing, the coefficient on SPEC in Model_3 is positive and statistically significant, showing that speculation is a good predictor of carbon pricing. That is, in contrast to the view that speculation undermines the emissions reduction goal of the ETS, our finding reveals SPEC as capable of impacting the ETS positively and making it attractive to investors. On the hypothesis that changes in political decisions related to the operation of the carbon market are the underlying source of speculation in the market, we find that the CPU played little or no significant role in the extent to which speculation matters in the dynamics of carbon prices.

4.4.2 In-sample and out-of-sample forecasts using the preferred estimator (FQGLS)

Following our validation of SPEC and other variables of interest as potential predictors of carbon prices, the next step is to determine the in-sample and out-of-sample forecasting power of the predictors in predicting carbon prices using the preferred estimator (i.e., FQGLS). Starting with the in-sample forecast results in Table 4.3, we find the RMSE and MSE values consistently lower for Model_3 than those RMSE and MSE values obtained for Model_1 and Model_2, respectively. Thus, in addition to accounting for endogeneity, persistence, and ARCH effects biases, an all-inclusive framework encompassing both emissions compliance and emissions non-compliance activities of the ETS is the most appropriate for the in-sample forecasts of carbon pricing. Strengthening our findings in this regard are the C-T results, whose statistics are positive in both scenarios being considered, suggesting that the in-sample forecasts of carbon price returns based on Model_3 are relatively more accurate when compared to those obtained based on Model_1 and Model_2, respectively. More importantly, the t-statistics reported at 12.46, and 12.44 is an overwhelming confirmation of Model_3 as the most accurate for the in-sample forecasts of carbon prices compared to Mode_1 and Model_2, respectively.

Table 4.3: In-sample forecast results

	Model_1	**Model_2**	**Model_3**	**Model_3 *vs* Mode_1**	**Model_3 *vs* Mode_2**
RMSE	0.7395	0.7036	0.3842		
MSE	0.5469	0.5429	0.1476		
C-T test				0.7300	0.7280
C-W test				0.7191*** [12.4625]	0.7064*** [12.4414]

Note: The lower the RMSE and MSE values, the more accurate the predictor or model's forecast. A positive C-T statistic suggests that Model_3 outperforms the other prediction models (Model_1 or Model_2), whereas a negative value indicates the opposite. Finally, the critical values for the C-W test t-statistics are 1.28, 1.64, and 2.00 for significant levels of 10%, 5%, and 1%, respectively.

Further depicted in Figure 4.2 is the visual representation of our in-sample forecast results across the three competing multi-factor predictive models considered. Consistent with our findings thus far, a figure shows that the predicted carbon price return series can track the actual carbon price returns more. This further attests to the superior performance of our proposed all-inclusive multi-factor-based predictive model, for instance, Model_3, compared to Model_1 and Model_2.

Figure 4-2: Graphical illustrations of in-sample forecasts performance

Figure 2.1: In-sample forecast of carbon allowance price returns with a baseline model (Model_1) without the role of speculation

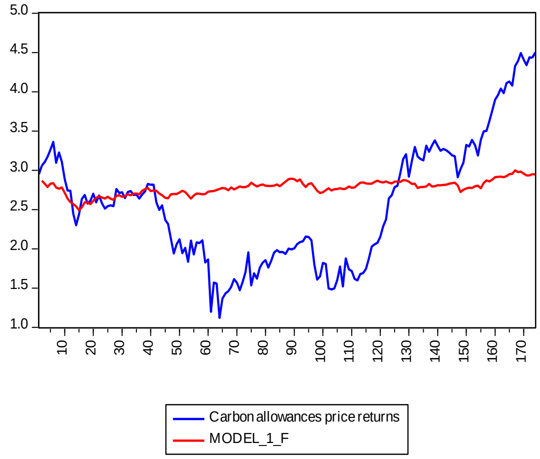


Figure 2.2: In-sample forecast of carbon allowance price returns with an extended model (Model_2) without the role of speculation

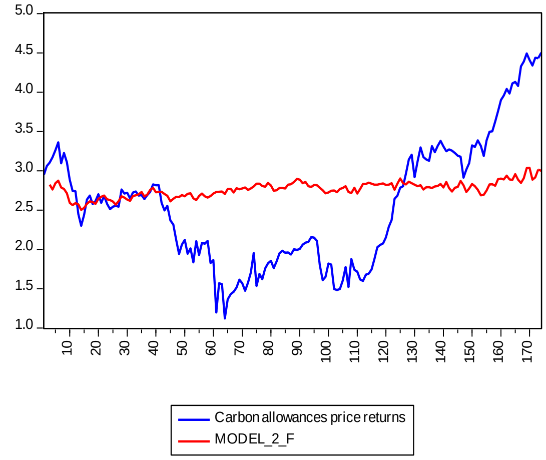
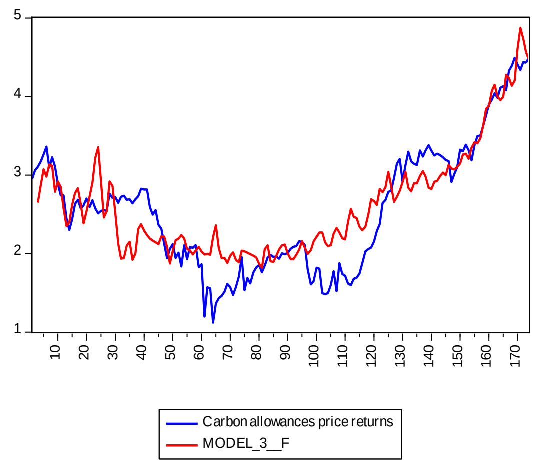


Figure 2.3: In-sample forecast of carbon allowance price returns with an extended model (Model_3) with the role of speculation



One widely held belief in the literature is that in-sample data is insufficient to predict out-of-sample forecast gain. As a result, we expand our predictability study to incorporate out-of-sample forecasts. The rolling window strategy, as shown in Table 4.4, yields a prediction horizon (h) of 4 for a four-month forecast, 8 for an eight-month forecast, and 12 for a twelve-month forecast. We compared the out-of-sample forecast of carbon pricing based on Model_3 to the out-of-sample forecast estimates generated from Model_1 and Model_2, respectively, using the same technique as in the case of the in-sample study. The out-of-sample forecast results show that Model 3 has the lowest RMSE and MSE values when compared to Models 1 and 2. We supplement these findings with those obtained using the paired approach to predict performance evaluation. C-T and C-W statistics continuously demonstrate that Model 3 is the most accurate prediction framework for assuring a credible out-of-sample carbon pricing estimate. This result's robustness is visible across the alternative forecast horizons considered.

Table 4.4: Out-of-sample forecast results

	RMSE			**MSE**		
	h=4	**h=8**	**h=12**	**h=4**	**h=8**	**h=12**
Model_1	0.7518	0.7746	0.7982	0.5652	0.6001	0.6372
Model_2	0.7505	0.7745	0.7977	0.5632	0.5998	0.6364
Model_3	0.3801	0.3771	0.3758	0.1445	0.1422	0.1412
	C-T test			**C-W test**		
	h=4	**h=8**	**h=12**	**h=4**	**h=8**	**h=12**
Model_3 *vs* Model_1	0.7442	0.7629	0.7783	0.7638*** [12.6110]	0.8352*** [12.0562]	0.9339 [11.1720]
Model_3 *vs* Model_2	0.7434	0.7628	0.7780	0.7551 [12.4664]	0.8293*** [11.8912]	0.9268*** [11.0519]

Note: The lower the RMSE and MSE values, the more accurate the predictor or model's forecast. A positive C-T statistic suggests that Model_3 outperforms the other prediction models (Model_1 or Model_2), whereas a negative value indicates the opposite. Finally, the critical values for the C-W test t-statistics are 1.28, 1.64, and 2.00 for significance levels of 10%, 5%, and 1%, respectively.

4.4.3 Does CPU matter in the SPEC predictability of carbon prices?

Unlike the conventional commodity markets, the carbon market is a creation of political decisions, with the commodities traded in the market proven to be vulnerable to changes in political decisions related to the operational framework of the ETS. More importantly, the uncertainty regarding the political framework of the ETS is posited as capable of fueling rising future speculation in the market (see Kettner et al., 2011). By adjusting for carbon policy uncertainty (CPU) as the underlying source of speculation (SPEC) in the ETS, we further scrutinise our findings. We investigate the impact of CPU sensitivity on SPEC's forecasting power and the significance of that for carbon price predictability.

Table 4.5: In-sample and out-of-sample forecasts with the role of CPU

	Model_4		Model_4 *vs* Model_3	
	RMSE	**MSE**	**C-T test**	**C-W test**
In-sample	0.3867	0.1495	-0.0130	-0.0009 [-0.4960]
h=4	0.3826	0.1464	-0.0131	-0.0008 [-0.4522]
h=8	0.3793	0.1439	-0.0119	-0.0018 [-0.3581]
h=12	0.3780	0.1428	-0.0116	-0.0006 [-0.3321]

Note: The lower the RMSE and MSE values, the more accurate the predictor or model's forecast. A positive C-T statistic suggests that Model_4 outperforms Model_3, whereas a negative value indicates the opposite. Finally, the critical values for the C-W test t-statistics are 1.28, 1.64, and 2.00 for significance levels of 10%, 5%, and 1%, respectively.

Compared to the RMSE and MSE statistics in Tables 4.3 and 4.4, the statistics are higher in Table 4.5, indicating that the CPU undermines the forecasting power of SPEC in the predictability of carbon price returns. The fact that the C-T statistics are all negative also suggests that the all-inclusive multi-factor-based predictive model (Model_3) that includes speculation (SPEC) without controlling for CPU remains the most accurate framework for predicting carbon prices. The consistency of this finding is evident in both the in-sample and out-of-sample forecasts and across the different forecast horizons considered. Even though the C-W test results appear to suggest there is no difference in the relative accuracy of Model_4 compared to Model_3 in the predictability of carbon pricing, we rest on the dominance of the evidence that favours Model_3 to declare it the most appropriate for enhancing the predictability of carbon pricing.

4.4.4 Robustness check and additional results

In this section, we assess the robustness of our preferred theory-based multi-factor predictive model by comparing its in-sample and out-of-sample forecast performance to that of conventional time-series models. Presented in Table 6 are additional in-sample and out-of-sample forecast results, where all the alternative forecast performance measures are employed to confirm the robustness of our proposed all-inclusive multi-factor-based predictive model as the most accurate in the predictability of carbon prices. For instance, the RMSE and MSE values reported for Model_3 in Tables 4.3 and 4.4 are significantly lower than those reported in Table 6 for each of the alternative traditional time-series predictive models considered, namely the Historical Average (HA) model, Autoregressive (AR) model, Autoregressive and Moving Average (ARMA) model, and Frictionally Autoregressive Moving Averages (ARFIMA). Both C-T and C-W tests also confirmed the robustness of our findings in each of these time-series predictive models, and the evidence holds consistently for in-sample and out-of-sample forecasts.

Table 4.6: Out-of-sample forecast results (Statistical models vs the preferred multi-factor predictive model)

	RMSE				MSE			
	In-sample	**h=4**	**h=8**	**h=12**	**In-sample**	**h=4**	**h=8**	**h=12**
HA	0.6897	0.7179	0.7604	0.8001	0.4656	0.5154	0.5783	0.6402
AR	0.9105	0.9120	0.9230	0.9341	0.8291	0.8318	0.8520	0.8520
ARMA	1.4305	1.4136	1.3967	1.3804	2.0465	1.9983	1.9509	1.9056
ARF	0.9576	0.9576	0.9668	0.9761	0.9170	0.9171	0.9347	0.9528
	C-T test				**C-W test**			
		h=4	**h=8**	**h=12**	**In-sample**	**h=4**	**h=8**	**h=12**
Model_3 *vs* HA	0.6896	0.7195	0.7540	0.7793	0.6028*** [11.1998]	0.6902*** [10.1179]	0.8162*** [8.9071]	0.9683*** [8.2703]
Model_3 *vs* AR	0.8219	0.8262	0.8330	0.8342	1.2432*** [13.3628]	1.2578*** [13.8061]	1.3011*** [14.1936]	1.3654*** [14.3604]
Model_3 *vs* ARMA	0.9278	0.9276	0.9270	0.9258	3.5518*** [17.8295]	3.4687*** [17.4610]	3.3859*** [17.0833]	3.3072*** [16.7472]
Model_3 *vs* ARF	0.8390	0.8424	0.8478	0.8517	1.4167*** [14.0612]	1.4261*** [14.4853]	1.4643*** [14.9233]	1.5238*** [15.1908]

Note: The lower the RMSE and MSE values, the higher the predictor or model's forecast accuracy. A positive C-T number indicates that Model_3 outperforms the alternative prediction model (i.e., Model_1 or Model_2), whereas a negative statistic indicates the opposite. Finally, the C-W test t-statistics are based on critical values of 1.28, 1.64, and 2.00 for significance levels of 10%, 5%, and 1%, respectively.

4.5 Summary of the Chapter

In this Chapter, we experiment with a number of theory-based multi-factor predictive models to understand the extent to which the speculation activity of the emissions non-compliance firms (ENCFs) matters in the future path of carbon pricing, which in turn matters for the global goal of emissions reductions. We hypothesis that an all-inclusive multi-factor predictive framework reflecting the emissions compliance and non-emissions compliance dimensions of the ETS simultaneously is the most accurate in predicting carbon prices. We control for the role of the CPU as the underlying source of speculation in the ETS and then evaluate whether the CPU matters in ETS's forecasting power and carbon pricing's predictability. We compared the accuracy of our proposed and preferred theory-based multi-factor predictive model in the predictability of carbon pricing with those of the conventional time-series/statistical model approach to forecasting. Using AIC and SIC model selection criteria, we arrived at the Feasible Quasi Generalised Least Square (FQGLS) developed by Westerlund and Narayan (2015) as this study's most appropriate and preferred estimator.

Empirically, inferences from predictive regression results validate the significance of the predictor series under consideration as a potential predictor of the in-sample and out-of-sample forecasts of carbon pricing. Of particular interest in this regard is the rejection of the null hypothesis of no predictability, particularly concerning the impact of SPEC on carbon price returns. However, the CPU plays little or no significant role to the extent to which speculation matters in the dynamics of carbon prices. Consolidating on our gains from the overwhelming evidence of speculation (SPEC) as a good predictor of carbon pricing, we employ single and pairwise approaches to forecast performance evaluation to show that speculation matters for enhancing the accuracy of carbon price forests. We find the in-sample and out-of-sample forecasts obtained from the all-inclusive theory-based multi-factor predictive model more accurate when compared to those obtained from statistical models such as AR, ARMA, AFRIMA, and HA. We find the robustness of the results evident for both in-sample and out-of-sample forecasts across the different forecast horizons considered.

It must be pointed out herein that the fact that the coefficient on SPEC is positive is an indication that the speculation activity is capable of increasing carbon price returns. This portends that, in contrast to the view that the increasing speculation activity of the financial actors undermines the ETS goal of emissions reductions, the speculation activity may yet enhance the effectiveness of the ETS. To test the validity or otherwise of this assertion, we employ both ex-post and ex-ante approaches to empirical analysis to determine the extent to which speculation matters in the emission reduction effects of the ETS and the predictability of climate change.

CHAPTER FIVE

TESTING THE EMISSIONS REDUCTION EFFECT OF CARBON PRICING: A PREDICTIVE ANALYSIS OF THE ROLE OF SPECULATION

5.0 Introduction

Carbon emissions (CO_2) have long been touted as a required and, in theory, cost-effective strategy of reducing emissions and mitigating climate change (Cramton et al., 2017; Rafaty et al., 2020). Higher carbon prices, the fundamental intuition goes, make low-carbon energy more competitive, incentivizing emissions reductions by reducing demand for carbon-intensive fuels (Arlinghaus, 2015; Martin et al., 2016; OECD, 2021). On that basis, the idea that a strong commitment to increased carbon prices creates incentives for investors to participate in the extension and development of low-carbon technologies (Kohlscheen et al., 2021; OECD, 2021) is advanced. Indeed, such a strong commitment to increased carbon prices is consistent with the Paris Agreement's target of reducing global net anthropogenic CO_2 emissions by around 45% from their 2010 level by 2030 and reaching net zero by 2050 (UN, 2021). To put it another way, the objective of limiting global warming to 2^{o}C assumes that CO_2 levels must fall by around 25% from 2010 levels by 2030 and reach net zero by 2050 or around 2070.

However, 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 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 global goal of low carbon or spurred by the speculation activity of the emissions non-compliance actors in the carbon markets. As previously established in Chapters 3 and 4 of this thesis, the growing activities of financial actors in the ETS continue to raise a concern about the role and potential effect of speculation on the functioning of the ETS (Roques et al., 2022). More importantly, this concern has revived the debate on the measures to stabilise carbon prices, which is crucial for the effectiveness of carbon pricing on the pathway to the global goal of low-carbon emissions. In this context, this Chapter aims to determine whether and to what extent the participation of financial actors' matter in the emissions reduction effect of carbon pricing. Essentially, we employ a predictive modelling approach to contribute to the literature on the emissions reduction effect of carbon pricing in two ways:

To begin with, 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.

Secondly, a recent report by Ampudia et al. (2022) contained the fact that the price of emissions allowances traded on the EU-ETS has increased from below 10 Euros per tonne of CO2 (€10/tCO2) to above €90/tCO2 since the beginning of 2018. Fundamentally, 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, considering 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, 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. As a result, we hypothesise that speculation matters in the forecasting prowess of carbon prices and the predictability of climate change. To validate or refute this position, 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.

5.1 Data and Preliminary Results

5.1.1 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).[14] However, the carbon prices (CP) and speculation index (SPEC) remain as earlier defined in the data section of the previous Chapters. Since the start date for carbon prices is 2008, we also restrict the start date for other variables to 2008. Hence, our sample coverage spans from January 2008 to December 2022.

5.1.2 Preliminary results

The preliminary results in Table 5.1 include summary statistics and stochastic properties for each variable of interest. Starting with the mean statistic, we find that for the period under consideration, on average, of every million air particles, about a million are carbon dioxide molecules, which is also the same thing as saying 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

[14] 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

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. Quite an interesting finding herein is that this period of an unprecedented surge in the average prices of carbon allowances coincides with an indication of 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 5.1: Descriptive Statistics and Unit Root test

Table 5.1(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)					
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 5.1(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 equations (5.1) and (5.2), so the variant predictive models, as represented in the following methodological section, are correctly specified. In other words, the variables are defined in a form that exhibits the dynamics of their stochastic properties.

Table 5.2: 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.

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 5.2 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 5.2 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.

5.2 Methodology

5.2.1 Predictive model

One of the study's primary features 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 predictor series, in this case, carbon pricing. Where there is no such statistical problem, our linear climate change prediction model, as expressed in equation (5.1), can be considered acceptable, where climate change is the predicting series regressed on carbon pricing (CP).

$$CO2_t = \alpha + \beta CP_{t-1} + \varepsilon_t \tag{5.1}$$

Equation (5.1) 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 (5.1) is restrictive, as the CP is assumed to be driven by emissions compliance activity in the ETS, with stringent climate change policies as the means to commit to higher carbon prices. Whereas restricting the emission reduction effect of CP to 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 (5.1) to include the role of speculation, as shown below.

$$CO2_t = \alpha + \beta_1 CP_{t-1} + \beta_2 SPEC_{t-1} + \varepsilon_t \tag{5.2}$$

Equation (5.2) is our extended climate change predictive regression, with CO2 simultaneously regressed on emissions compliance and emission non-compliance indicators of activities in the ETS. However, given that the innovation herein examines 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.

$$CO2_t = \alpha + \beta_1 CP_{t-1} + \beta_2 SPEC_{t-1} + \beta_3 CP_{t-1} * SPEC_{t-1} + \varepsilon_t \tag{5.3}$$

Notwithstanding the aforementioned, 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.

$$TMP_t = \alpha + \beta'_{adj} x_{t-1} + \lambda(x_t - \delta x_{t-1}) + \varepsilon_t \tag{5.4}$$

The term β_{adj} in equation (5.4) 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$\left(x_{t-1}\right)$. 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 as Feasible Quasi Generalized Least Square (FQGLS) is given below.

$$\beta_{adj}^{FQGLS} = \frac{\sum_{t-qm+2}^{T} \widehat{\tau}_t^2 p_t^d x_{t-1}^d}{\sum_{t-qm+2}^{T} \widehat{\tau}_t^2 (x_{t-1}^d)^2} \tag{5.5}$$

where $\hat{\tau}_t = 1/\hat{\sigma}_{v,t}$ is used to weigh all the data in the bias-adjusted predictive model in equation (5.5), while $p_t^d = p - \sum_{p=2}^{T} p_t / T$ and $x_t^d = x_t - \sum_{z=2}^{T} x_t / T$.

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.

5.2.2 Forecast performance measure

Now, 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: $$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m}\left(C\hat{O}2_t - CO2_t\right)^2} \qquad (5.6a)$$

Out-of-Sample: $$RMSE = \sqrt{\frac{1}{k}\sum_{t=1}^{k}\left(C\hat{O}2_t - CO2_t\right)^2} \qquad (5.6b)$$

To ascertain the robustness of our results, we further complement the RMSE results with a forecast estimate based on Mean Square Error (MSE) - $1/N\sum_{t=1}^{T}\left(C\hat{O}2_t - CO2_t\right)^2$ 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 alternatives 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 $OOS\_R = 1 - \left(M\widehat{SE}_1 / M\widehat{SE}_0 \right)$ where $M\widehat{SE}_1$ is the mean squared error obtained from Model_4 (which is technically an unrestricted model in this case) and $M\widehat{SE}_0$ 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. A positive $R^2\left(OOS\_R\right)$ statistic such as $R^2\left(OOS\_R\right) > 0$ 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:

$$\hat{f}_{t+k} = \left(CO2_{t+k} - C\widehat{O}2_{,1,t+k} \right)^2 - \left[\left(CO2_{t+k} - C\widehat{O}2_{,2,t+k} \right)^2 - \left(C\widehat{O}2_{,1,t+k} - C\widehat{O}2_{,2,t+k} \right),^2 \right] \quad (5.7)$$

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

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

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

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

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.

5.3 Empirical Result and Discussion of Finding

The empirical results presented in this section are divided into two main parts, in line with the various specific objectives of this study. In the first part, we present and discuss the predictive regressions obtained from the estimation of the restricted and variant 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.

5.3.1 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 change. A look at the predictive regression results in Table 5.2 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 ETS, appears to benefit the emission reduction effect of the ETS more.

Table 5.2: 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

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. 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 ETS. This, in particular, further confirms our earlier position in the previous chapters that the speculation behaviour of the emission non-compliance firms may benefit the ETS 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.

5.3.2 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. Starting with the single-method forecast performance evaluation measures, presented in Table 5.3 are the RMSE and MSE values. The lower the RMSE or MSE values, the better the forecast accuracy of a predictive model.

Table 5.3: 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 5.3 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 models [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.

Table 5.4: 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]
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.

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 5.4 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 5.4 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. 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.

5.4 Summary of the Chapter

In this Chapter, we employ both the ex-post and ex-ante approaches 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 show that a predictive model with the complementary dynamics of the emissions compliance and emissions non-compliance features of the ETS 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.

CHAPTER SIX

SUMMARY, CONCLUSION AND RECOMMEMDATION

6.0 Summary of Finding

Covering Phase II, III, and IV of the trading period of carbon allowances in the EU-ETS, this study examines the role of speculation in the dynamics of carbon pricing. The ETS is primarily a market for polluting companies that require allowances to comply with ETS regulations. Still, emission non-compliance entities have also continued to participate in the market. Thus, there has been a growing number of commentaries attributing the recent trends of price rallies in the ETS to the speculation activity of financial actors. Motivated by the assertion that if left unchecked, speculation activity is likely to overwhelm or undermine the environmental goal of the ETS, we modified the framework for modelling carbon allowances to accommodate the growing commentaries linking the trend of excessive changes and volatility in carbon prices to speculation. Essentially, an all-inclusive framework that accommodates both the ECFs and ENCFs activities of the ETS is the most accurate for ensuring the adequacy of the inference drawn on the dynamics of carbon pricing. Employing a GARCH-MIDAS econometric technique, we show that the speculation activity of the financial actors is relevant to the volatility dynamics of carbon prices as it offers insights beyond what is readily contained in the realised volatility of the EU-ETS. We also experiment with a number of theory-based multi-factor predictive models to understand, in particular, the extent to which speculation matters in the future path of carbon pricing. We find an all-inclusive, multi-factor-based predictive model that includes the role of speculation as the most accurate framework for ensuring the accuracy of carbon prices. Both the in-sample and out-of-sample forecasts obtained from our all-inclusive theory-based multi-factor predictive model are relatively more accurate when compared to those obtained from statistical models such as AR, ARMA, AFRIMA, and HA. Finally, we find the complementary dynamics of carbon price and speculation relevant to the ETS emissions reduction effect and climate change predictability.

6.1 Conclusions

Despite the widespread assertion of the potential threat of the growing presence of financial actors and their speculation behaviour to the emissions reduction goal of the ETS, the complimentary dynamics of carbon prices and speculation tend to benefit the emission reduction functioning of the ETS and enhance the accuracy of climate change forecasts. This may not be unconnected to the fact that, aside from their speculation behaviour, the emissions non-compliance firms, in particular the financial actors, offer some services that are crucial to the functioning of the ETS, such as assisting with the establishment of more market liquidity and price visibility, as well as allowing operators to hedge against future fluctuations. Therefore, it is not surprising that the emissions non-compliance firms complement the functioning of the ETS on the pathway to the global goal of reducing carbon emissions. More importantly, an all-inclusive framework reflecting both emissions compliance and the emissions non-compliance dynamics of the ETS offers a more comprehensive approach to predicting carbon price signals than the standard carbon pricing modelling framework, which confines the dynamics of carbon prices to demand and supply market fundamentals.

6.2 The Implication of the Finding and Recommendations

For the ETS to work as an emission reduction policy tool, it must be well-behaved and have a reasonable carbon price. As a result, the findings of this thesis provide several pathways that can be useful in the pursuit of such a well-behaved carbon market. For example, having a data-driven model that accommodates emission compliance and non-compliance features of the ETS should be a prerequisite upon which the regulatory authority in the ETS bases its decisions on which dimensions of the activity in the ETS are likely to benefit or undermine the emissions reduction functioning of the ETS. Both emissions compliance firms and emissions non-compliance enterprises (speculators) require adequate and reliable price information to manage and hedge their portfolios. This, however, must be taken in collaboration with accurate and trustworthy price information. Given our discovery that speculation is a good predictor of carbon pricing and climate change, any act that limits the predictability of carbon pricing to fundamentals related to ETS emissions compliance activity may jeopardise the accuracy of carbon price forecasts, which are critical for the stability and prosperity of the emission trading programme. In sum, there is a need for incentive-based carbon pricing research of this nature to provide policymakers with evidence-based insights into the mechanisms that will improve carbon pricing flexibility and certainty in an emission trading system.

6.3 Suggestion for Future Research

Even with the gains from the role of speculation in the operation of ETS, as established in the context of this study, it is instructive that it may not be sufficient to ignore the growing concern that increasing speculation activity in the ETS may undermine its emissions reduction effectiveness. Therefore, there is a need for further studies to help provide the literature with viable insights on the degree of speculation that can be considered excessive and detrimental to the emission reduction function of the ETS. Therefore, future research could consider the following as some of the gaps that can be bridge.

i. Utilising a simulation technique to experiment with different scenarios of projection of the possible implications of various degrees of speculation behaviour in the ETS.
ii. Consider how the Social Costs of Carbon (SCC) could be factored into the carbon pricing. This will assist in responding to the current Just Transition narratives, where economic and social costs must be considered.
iii. A further investigation of the effectiveness and efficiency of different carbon pricing mechanisms – especially given the number of countries the candidate identified as embracing carbon pricing. By tracking these global carbon pricing mechanisms/instruments, various aspects linked to carbon pricing can be investigated.
iv. The disadvantages of profit-seeking investment firms, banks, and brokers (Emission noncompliance group) have been noted. Are there any positive externalities associated with having these actors in the carbon markets?

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APPENDIX A

PROGRAMME CODES FOR THE FIRST ESSAY

Appendix A1: Pre –estimation programme codes

Series Transformation

```
series reua=100*log(eua/eua(-1))
series rcoal=100*log(coal/eua(-1))
series rgas=100*log(gas/gas(-1))
series roil=100*log(brent/brent(-1))
series rele=100*log(ele/ele(-1))
series geco=100*log(eco/eco(-1))
series gcpu=100*log(cpu/cpu(-1))
```

Descriptive Statistics

```
'Group all series
group stat_series eua reua coal gas brent ele fs eco tmp  spec cpu

'Descriptive Stat
freeze(descriptive_stat) stat_series.stats
```

Serial Correlation test

```
'Carbon prices
equation serial_eq_eua.ls eua c
freeze(qstat11_eua) serial_eq_eua.correl(10)
freeze(qstat21_eua) serial_eq_eua.correlsq(10)
freeze(qstat12_eua) serial_eq_eua.correl(20)
freeze(qstat22_eua) serial_eq_eua.correlsq(20)
freeze(qstat13_eua) serial_eq_eua.correl(30)
freeze(qstat23_eua) serial_eq_eua.correlsq(30)

'Carbon prices returns
equation serial_eq_reua.ls reua c
freeze(qstat11_reua) serial_eq_reua.correl(10)
freeze(qstat21_reua) serial_eq_reua.correlsq(10)
freeze(qstat12_reua) serial_eq_reua.correl(20)
freeze(qstat22_reua) serial_eq_reua.correlsq(20)
freeze(qstat13_reua) serial_eq_reua.correl(30)
freeze(qstat23_reua) serial_eq_reua.correlsq(30)
```

```
'Coal prices
equation serial_eq_rcoal.ls rcoal c
freeze(qstat11_rcoal) serial_eq_rcoal.correl(10)
freeze(qstat21_rcoal) serial_eq_rcoal.correlsq(10)
freeze(qstat12_rcoal) serial_eq_rcoal.correl(20)
freeze(qstat22_rcoal) serial_eq_rcoal.correlsq(20)
freeze(qstat13_rcoal) serial_eq_rcoal.correl(30)
freeze(qstat23_rcoal) serial_eq_rcoal.correlsq(30)

'Gas prices
equation serial_eq_rgas.ls rgas c
freeze(qstat11_rgas) serial_eq_rgas.correl(10)
freeze(qstat21_rgas) serial_eq_rgas.correlsq(10)
freeze(qstat12_rgas) serial_eq_rgas.correl(20)
freeze(qstat22_rgas) serial_eq_rgas.correlsq(20)
freeze(qstat13_rgas) serial_eq_rgas.correl(30)
freeze(qstat23_rgas) serial_eq_rgas.correlsq(30)

'Oil prices
equation serial_eq_roil.ls roil c
freeze(qstat11_roil) serial_eq_roil.correl(10)
freeze(qstat21_roil) serial_eq_roil.correlsq(10)
freeze(qstat12_roil) serial_eq_roil.correl(20)
freeze(qstat22_roil) serial_eq_roil.correlsq(20)
freeze(qstat13_roil) serial_eq_roil.correl(30)
freeze(qstat23_roil) serial_eq_roil.correlsq(30)

'Electricity prices
equation serial_eq_rele.ls rele c
freeze(qstat11_rele) serial_eq_rele.correl(10)
freeze(qstat21_rele) serial_eq_rele.correlsq(10)
freeze(qstat12_rele) serial_eq_rele.correl(20)
freeze(qstat22_rele) serial_eq_rele.correlsq(20)
freeze(qstat13_rele) serial_eq_rele.correl(30)
freeze(qstat23_rele) serial_eq_rele.correlsq(30)

'Fuel Switching
equation serial_eq_fs.ls fs c
freeze(qstat11_fs) serial_eq_fs.correl(10)
freeze(qstat21_fs) serial_eq_fs.correlsq(10)
freeze(qstat12_fs) serial_eq_fs.correl(20)
freeze(qstat22_fs) serial_eq_fs.correlsq(20)
freeze(qstat13_fs) serial_eq_fs.correl(30)
freeze(qstat23_fs) serial_eq_fs.correlsq(30)
```

```
'Economic activity
equation serial_eq_geco.ls geco c
freeze(qstat11_geco) serial_eq_geco.correl(10)
freeze(qstat21_geco) serial_eq_geco.correlsq(10)
freeze(qstat12_geco) serial_eq_geco.correl(20)
freeze(qstat22_geco) serial_eq_geco.correlsq(20)
freeze(qstat13_geco) serial_eq_geco.correl(30)
freeze(qstat23_geco) serial_eq_geco.correlsq(30)

'Weather condition
equation serial_eq_tmp.ls tmp c
freeze(qstat11_tmp) serial_eq_tmp.correl(10)
freeze(qstat21_tmp) serial_eq_tmp.correlsq(10)
freeze(qstat12_tmp) serial_eq_tmp.correl(20)
freeze(qstat22_tmp) serial_eq_tmp.correlsq(20)
freeze(qstat13_tmp) serial_eq_tmp.correl(30)
freeze(qstat23_tmp) serial_eq_tmp.correlsq(30)

'Speculation
equation serial_eq_spec.ls spec c
freeze(qstat11_spec) serial_eq_spec.correl(10)
freeze(qstat21_spec) serial_eq_spec.correlsq(10)
freeze(qstat12_spec) serial_eq_spec.correl(20)
freeze(qstat22_spec) serial_eq_spec.correlsq(20)
freeze(qstat13_spec) serial_eq_spec.correl(30)
freeze(qstat23_spec) serial_eq_spec.correlsq(30)

'CPU
equation serial_eq_gcpu.ls gcpu c
freeze(qstat11_gcpu) serial_eq_gcpu.correl(10)
freeze(qstat21_gcpu) serial_eq_gcpu.correlsq(10)
freeze(qstat12_gcpu) serial_eq_gcpu.correl(20)
freeze(qstat22_gcpu) serial_eq_gcpu.correlsq(20)
freeze(qstat13_gcpu) serial_eq_gcpu.correl(30)
freeze(qstat23_gcpu) serial_eq_gcpu.correlsq(30)
```

Conditional Heteroscedasticity test

```
'Carbon prices
freeze(arch_eua_10) serial_eq_eua.archtest(10)
freeze(arch_eua_20) serial_eq_eua.archtest(20)
freeze(arch_eua_30) serial_eq_eua.archtest(30)
```

```
'Carbon price returns
freeze(arch_reua_10) serial_eq_reua.archtest(10)
freeze(arch_reua_20) serial_eq_reua.archtest(20)
freeze(arch_reua_30) serial_eq_reua.archtest(30)

'Coal prices
freeze(arch_rcoal_10) serial_eq_rcoal.archtest(10)
freeze(arch_rcoal_20) serial_eq_rcoal.archtest(20)
freeze(arch_rcoal_30) serial_eq_rcoal.archtest(30)

'Gas prices
freeze(arch_rgas_10) serial_eq_rgas.archtest(10)
freeze(arch_rgas_20) serial_eq_rgas.archtest(20)
freeze(arch_rgas_30) serial_eq_rgas.archtest(30)

'Oil prices
freeze(arch_roil_10) serial_eq_roil.archtest(10)
freeze(arch_roil_20) serial_eq_roil.archtest(20)
freeze(arch_roil_30) serial_eq_roil.archtest(30)

'Electricity prices
freeze(arch_rele_10) serial_eq_rele.archtest(10)
freeze(arch_rele_20) serial_eq_rele.archtest(20)
freeze(arch_rele_30) serial_eq_rele.archtest(30)

'Fuel Switch
freeze(arch_fs_10) serial_eq_fs.archtest(10)
freeze(arch_fs_20) serial_eq_fs.archtest(20)
freeze(arch_fs_30) serial_eq_fs.archtest(30)

'Economic activity
freeze(arch_geco_10) serial_eq_geco.archtest(10)
freeze(arch_geco_20) serial_eq_geco.archtest(20)
freeze(arch_geco_30) serial_eq_geco.archtest(30)

'Weather condition
freeze(arch_tmp_10) serial_eq_tmp.archtest(10)
freeze(arch_tmp_20) serial_eq_tmp.archtest(20)
freeze(arch_tmp_30) serial_eq_tmp.archtest(30)

'Speculation
freeze(arch_spec_10) serial_eq_spec.archtest(10)
freeze(arch_spec_20) serial_eq_spec.archtest(20)
freeze(arch_spec_30) serial_eq_spec.archtest(30)
```

```
'CPU
freeze(arch_gcpu_10) serial_eq_gcpu.archtest(10)
freeze(arch_gcpu_20) serial_eq_gcpu.archtest(20)
freeze(arch_gcpu_30) serial_eq_gcpu.archtest(30)

''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
```

Appendix A2: Main estimation programme codes

```
%%%%%%% GARCH-MIDAS %%%%%%%%%%%%%
clear % used to clear/delete the variables created in Workspace.
clc % used to clear the Command Window (where we execute MATLAB commands).
clear;
clc;
```

In-sample predictability

```
**************************************************************************
Carbonp = xlsread ('PhD_Data_Full.xlsx', 'Daily', 'B14:B3904')./100; % Daily Series
period = 22;
num Lags = 11;

% GARCH-Model with realized volatility based on fixed window
[estParams,~,Variance, Long Run Var] =
 GarchMidas (Carbonp, 'Period', period, 'NumLags', numLags, 'RollWindow', 1,'ThetaM', 1).
% [estParams, EstParam Cov, Variance, Long Run Var] =
GarchMidas (Carbonp, 'Period', 22, 'NumLags', 11).

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% GARCH-MIDAS_Model Using an exogenous variable [X]
clear;
clc;

% EUA price return data
Carbonp = xlsread ('PhD_Data_Full.xlsx', 'Daily', 'B14:B3904')./100;

% Period and Number of Lags
period = 12;
numLags = 6;

% X variable
xMonth1 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'B3:B181')./100 ;         % Monthly Series
(Coal)
xMonth2 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'C3:C181')./100 ;         % Monthly Series
(Gas)
```

```
xMonth3 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'D3:D181')./100 ;         % Monthly Series
(Oil)
xMonth4 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'E3:E181')./100 ;         % Monthly Series
(ELE)
xMonth5 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'F3:F181')./100 ;         % Monthly Series
(X1)
xMonth6 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'G3:G181')./100 ;         % Monthly Series
(FS)
xMonth7 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'H3:H181')./100 ;         % Monthly Series
(ECO)
xMonth8 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'I3:I181')./100 ;         % Monthly Series
(TMP)
xMonth9 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'J3:J181')./100 ;      % Monthly Series (X2)
xMonth10 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'K3:K181')./100 ;       % Monthly Series
(X3)
xMonth11 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'L3:L181')./100 ;       % Monthly Series
(X4)
xMonth12 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'M3:M181')./100 ;       % Monthly Series
(X5)
xMonth13 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'N3:N181')./100 ;       % Monthly Series
(X6)
xMonth14 = xlsread ('PhD_Data_Full.xlsx', 'Monthly', 'O3:O181')./100 ;       % Monthly Series
(X7)

% Repeat the monthly value throughout the days in that month
nobs = size(Carbonp,1);
[~,yDate] = xlsread ('PhD_Data_Full.xlsx', 'Daily', 'A2 : A3904');
[~,yDay] = datevec (yDate);
xDay = NaN (nobs,1);

xDay1 = NaN (nobs,1);
xDay2 = NaN (nobs,1);
xDay3 = NaN (nobs,1);
xDay4 = NaN (nobs,1);
xDay5 = NaN (nobs,1);
xDay6 = NaN (nobs,1);
xDay7 = NaN (nobs,1);
xDay8 = NaN (nobs,1);
xDay9 = NaN (nobs,1);
xDay10 = NaN (nobs,1);
xDay11 = NaN (nobs,1);
xDay12 = NaN (nobs,1);
xDay13 = NaN (nobs,1);
xDay14 = NaN (nobs,1);

count = 1;
```

```
for t = 1:nobs
    if t > 1 && yDay(t) ~= yDay(t-1)
        count = count + 1;
        if count > length(xMonth1)
            break
        end

 xDay1(t) = xMonth1(count);
    xDay2(t) = xMonth2(count);
    xDay3(t) = xMonth3(count);
    xDay4(t) = xMonth4(count);
    xDay5(t) = xMonth5(count);
    xDay6(t) = xMonth6(count);
    xDay7(t) = xMonth7(count);
    xDay8(t) = xMonth8(count);
    xDay9(t) = xMonth9(count);
    xDay10(t) = xMonth10(count);
    xDay11(t) = xMonth11(count);
    xDay12(t) = xMonth12(count);
    xDay13(t) = xMonth13(count);
    xDay14(t) = xMonth14(count);
end

% Estimate the GARCH-MIDAS model with the exogenous regressor [X]
[estParams, EstParamCov, Variance, LongRunVar] = GarchMidas
(Carbonp, 'Period', period,' NumLags', numLags, 'X', xDay14,  'RollWindow',1,'ThetaM',1);
% x denotes the exogenous factor

%
********************************************************************************
**************************************
```

APPENDIX B

PROGRAMME CODES FOR THE SECOND ESSAY

Appendix B1: Pre –estimation programme codes

Series Transformation

```
series reua=100*log (eua/eua(-1))
series geco=100*log (eco/eco(-1))
series leco=log (eco)
series gcpu=100*log (cpu/cpu(-1))
series lcpu=log (cpu)
```

Descriptive Statistics

```
'Group all series
group stat_series reua geco tmp fs spec gcpu

'Descriptive Stat
Freeze (descriptive_stat) stat_series.stats
```

Serial Correlation test

```
'Carbon prices
equation serial_eq_reua.ls reua c
freeze (qstat11_reua) serial_eq_reua.correl(4)
freeze (qstat21_reua) serial_eq_reua.correlsq(4)
freeze (qstat12_reua) serial_eq_reua.correl(8)
freeze (qstat22_reua) serial_eq_reua.correlsq(8)
freeze (qstat13_reua) serial_eq_reua.correl(12)
freeze (qstat23_reua) serial_eq_reua.correlsq(12)

'Economic activity
equation serial_eq_geco.ls geco c
freeze (qstat11_geco) serial_eq_geco.correl(4)
freeze (qstat21_geco) serial_eq_geco.correlsq(4)
freeze (qstat12_geco) serial_eq_geco.correl(8)
freeze (qstat22_geco) serial_eq_geco.correlsq(8)
freeze (qstat13_geco) serial_eq_geco.correl(12)
freeze (qstat23_geco) serial_eq_geco.correlsq(12)
```

```
'Weather condition
equation serial_eq_tmp.ls tmp c
freeze (qstat11_tmp) serial_eq_tmp.correl(4)
freeze (qstat21_tmp) serial_eq_tmp.correlsq(4)
freeze (qstat12_tmp) serial_eq_tmp.correl(8)
freeze (qstat22_tmp) serial_eq_tmp.correlsq(8)
freeze (qstat13_tmp) serial_eq_tmp.correl(12)
freeze (qstat23_tmp) serial_eq_tmp.correlsq(12)

'Fuel_Switch
equation serial_eq_fs.ls fs c
freeze (qstat11_fs) serial_eq_fs.correl(4)
freeze (qstat21_fs) serial_eq_fs.correlsq(4)
freeze (qstat12_fs) serial_eq_fs.correl(8)
freeze (qstat22_fs) serial_eq_fs.correlsq(8)
freeze (qstat13_fs) serial_eq_fs.correl(12)
freeze (qstat23_fs) serial_eq_fs.correlsq(12)

'Speculation
equation serial_eq_spec.ls spec c
freeze (qstat11_spec) serial_eq_spec.correl(4)
freeze (qstat21_spec) serial_eq_spec.correlsq(4)
freeze (qstat12_spec) serial_eq_spec.correl(8)
freeze (qstat22_spec) serial_eq_spec.correlsq(8)
freeze (qstat13_spec) serial_eq_spec.correl(12)
freeze (qstat23_spec) serial_eq_spec.correlsq(12)

'CPU
equation serial_eq_gcpu.ls gcpu c
freeze (qstat11_gcpu) serial_eq_gcpu.correl(4)
freeze (qstat21_gcpu) serial_eq_gcpu.correlsq(4)
freeze (qstat12_gcpu) serial_eq_gcpu.correl(8)
freeze (qstat22_gcpu) serial_eq_gcpu.correlsq(8)
freeze (qstat13_gcpu) serial_eq_gcpu.correl(12)
freeze (qstat23_gcpu) serial_eq_gcpu.correlsq(12)
```

Conditional Heteroscedasticity test

```
'Carbon prices
freeze (arch_reua_4) serial_eq_reua.archtest(4)
freeze (arch_reua_8) serial_eq_reua.archtest(8)
freeze (arch_reua_12) serial_eq_reua.archtest(12)

'Economic activity
freeze (arch_geco_4) serial_eq_geco.archtest(4)
```

```
freeze (arch_geco_8) serial_eq_geco.archtest(8)
freeze (arch_geco_12) serial_eq_geco.archtest(12)

'Weather condition
freeze (arch_tmp_4) serial_eq_tmp.archtest(4)
freeze (arch_tmp_8) serial_eq_tmp.archtest(8)
freeze (arch_tmp_12) serial_eq_tmp.archtest(12)

'Fuel Switch
freeze (arch_fs_4) serial_eq_fs.archtest(4)
freeze (arch_fs_8) serial_eq_fs.archtest(8)
freeze (arch_fs_12) serial_eq_fs.archtest(12)

'Speculation
freeze (arch_spec_4) serial_eq_spec.archtest(4)
freeze (arch_spec_8) serial_eq_spec.archtest(8)
freeze (arch_spec_12) serial_eq_spec.archtest(12)

'CPU
freeze (arch_gcpu_4) serial_eq_gcpu.archtest(4)
freeze (arch_gcpu_8) serial_eq_gcpu.archtest(8)
freeze (arch_gcpu_12) serial_eq_gcpu.archtest(12)
```

Persistence test

```
'Economic activity
equation geco_pers.ls geco c geco(-1)
series resid_geco=resid

'Weather condition
equation tmp_pers.ls tmp c tmp(-1)
series resid_tmp=resid

'Fuel Switch
equation fs_pers.ls fs c fs(-1)
series resid_fs=resid

'Speculation
equation spec_pers.ls spec c spec(-1)
series resid_spec=resid

'CPU
equation gcpu_pers.ls gcpu c gcpu(-1)
series resid_gcpu=resid
```

Endogeneity test

```
'Endogeneity between carbon prices & eco prices
equation geco_eqn.ls reua c geco(-1)
series resid_reua_geco=resid
equation endo_reua_geco.ls resid_reua_geco resid_geco(-1)

'Endogeneity between carbon prices & tmp prices
equation tmp_eqn.ls reua c tmp(-1)
series resid_reua_tmp=resid
equation endo_reua_tmp.ls resid_reua_tmp resid_tmp(-1)

'Endogeneity between carbon prices & fuel switch
equation fs_eqn.ls reua c fs(-1)
series resid_reua_fs=resid
equation endo_reua_fs.ls resid_reua_fs resid_fs(-1)

'Endogeneity between carbon prices & spec prices
equation spec_eqn.ls reua c spec(-1)
series resid_reua_spec=resid
equation endo_reua_spec.ls resid_reua_spec resid_spec(-1)

'Endogeneity between carbon prices & cpu prices
equation gcpu_eqn.ls reua c gcpu(-1)
series resid_reua_gcpu=resid
equation endo_reua_gcpu.ls resid_reua_gcpu resid_gcpu(-1)
```

Appendix B2: Main estimation programme codes

```
'generate log of series

series reua=log(eua)
series reco=log(eco)
series gcpu=log(cpu)
series spec_cpu=spec*gcpu

series reco_adj = reco-reco(-1)
series tmp_adj = tmp-tmp(-1)
series fs_adj = fs-fs(-1)
series spec_adj = spec-spec(-1)
series spec_cpu_adj = spec_cpu-spec_cpu(-1)

''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
```

```
Pagestruct (none)

smpl 1 180

'rollh8g wh8dow analyses

'set window size
!window = 20

' set step size
!step = 1

' get size of workfile
!length = @obsrange

'calculate number of rolls
!nrolls = @floor((!length-!window)/!step)

'matrix to store coefficient estimates
matrix (3,!nrolls) coefmat ' where 3 is the number of coefficients

'redundant series for catching start and end points
series ser = 1
%start = @otod(@ifirst(ser))
%end = @otod(@ilast(ser))

'variable keeping track of how many rolls we've done
!j=0
'move sample !step obs at a time
for !i = 1  to  !length-!window+1-!step step !step
   !j=!j+1

'set sample for estimation period
%first = @otod(@dtoo(%start)+!i-1)
%last = @otod(@dtoo(%start)+!i+!window-2)
```

'In-Sample Predictability Test

```
smpl 1 180

'OLS
equation model_1_ols.ls reua reco(-1) tmp(-1)
equation model_2_ols.ls reua reco(-1) tmp(-1) fs(-1)
equation model_3_ols.ls reua reco(-1) tmp(-1) fs(-1) spec(-1)
equation model_4_ols.ls reua reco(-1) tmp(-1) fs(-1) spec(-1) spec_cpu(-1)
```

```
'AOLS
equation model_1_aols.ls reua reco(-1) reco_adj tmp(-1) tmp_adj
equation model_2_aols.ls reua reco(-1) reco_adj tmp(-1) tmp_adj fs(-1) fs_adj
equation model_3_aols.ls reua reco(-1) reco_adj tmp(-1) tmp_adj fs(-1) fs_adj spec(-1) spec_adj
equation model_4_aols.ls reua reco(-1) reco_adj tmp(-1) tmp_adj fs(-1) fs_adj spec(-1) spec_adj
spec_cpu(-1) spec_cpu_adj

'FQGLS
equation model_1_fgls.arch reua reco(-1) reco_adj tmp(-1) tmp_adj
equation model_2_fgls.arch reua reco(-1) reco_adj tmp(-1) tmp_adj fs(-1) fs_adj
equation model_3_fgls.arch reua reco(-1) reco_adj tmp(-1) tmp_adj fs(-1) fs_adj spec(-1)
spec_adj @trend
equation model_4_fgls.arch reua reco(-1) reco_adj tmp(-1) tmp_adj fs(-1) fs_adj spec(-1)
spec_adj spec_cpu(-1) spec_cpu_adj @trend
```

Statisical Models

```
equation ha.ls reua c
equation ar_model.ls reua c ar(1)
equation arma_model.ls d(reua) c ar(1) ma(1)
equation arf_model.ls reua c ar(1) ma(1) d
```

'In-sample forecast evaluation

```
smpl 1 162

'OLS
model_1_ols.forecast(e, g) model_1_ols_f
scalar rm_model_1_ols_in =@rmse(reua,model_1_ols_f)
scalar mse_model_1_ols_in =(rm_model_1_ols_in )^2

model_2_ols.forecast(e, g) model_2_ols_f
scalar rm_model_2_ols_in =@rmse(reua,model_2_ols_f)
scalar mse_model_2_ols_in =(rm_model_2_ols_in )^2

model_3_ols.forecast(e, g) model_3_ols_f
scalar rm_model_3_ols_in =@rmse(reua,model_3_ols_f)
scalar mse_model_3_ols_in =(rm_model_3_ols_in )^2

model_4_ols.forecast(e, g) model_4_ols_f
scalar rm_model_4_ols_in =@rmse(reua,model_4_ols_f)
scalar mse_model_4_ols_in =(rm_model_4_ols_in )^2
```

```
'AOLS
model_1_aols.forecast(e, g) model_1_aols_f
scalar rm_model_1_aols_in =@rmse(reua,model_1_aols_f)
scalar mse_model_1_aols_in =(rm_model_1_aols_in )^2

model_2_aols.forecast(e, g) model_2_aols_f
scalar rm_model_2_aols_in =@rmse(reua,model_2_aols_f)
scalar mse_model_2_aols_in =(rm_model_2_aols_in )^2

model_3_aols.forecast(e, g) model_3_aols_f
scalar rm_model_3_aols_in =@rmse(reua,model_3_aols_f)
scalar mse_model_3_aols_in =(rm_model_3_aols_in )^2

model_4_aols.forecast(e, g) model_4_aols_f
scalar rm_model_4_aols_in =@rmse(reua,model_4_aols_f)
scalar mse_model_4_aols_in =(rm_model_4_aols_in )^2


'FQGLS
model_1_fgls.forecast(e, g) model_1_fgls_f
scalar rm_model_1_fgls_in =@rmse(reua,model_1_fgls_f)
scalar mse_model_1_fgls_in =(rm_model_1_fgls_in )^2

model_2_fgls.forecast(e, g) model_2_fgls_f
scalar rm_model_2_fgls_in =@rmse(reua,model_2_fgls_f)
scalar mse_model_2_fgls_in =(rm_model_2_fgls_in )^2

model_3_fgls.forecast(e, g) model_3_fgls_f
scalar rm_model_3_fgls_in =@rmse(reua,model_3_fgls_f)
scalar mse_model_3_fgls_in =(rm_model_3_fgls_in )^2
model_4_fgls.forecast(e, g) model_4_fgls_f
scalar rm_model_4_fgls_in =@rmse(reua,model_4_fgls_f)
scalar mse_model_4_fgls_in =(rm_model_4_fgls_in )^2

ha.forecast(e, g) ha_f
scalar rm_ha_in =@rmse(reua,ha_f)
scalar mse_ha_in =(rm_ha_in)^2

ar_model.forecast(e, g) ar_model_f
scalar rm_ar_model_in =@rmse(reua,ar_model_f)
scalar mse_ar_model_in =(rm_ar_model_in)^2

arma_model.forecast(e, g) arma_model_f
scalar rm_arma_model_in =@rmse(reua,arma_model_f)
scalar mse_arma_model_in =(rm_arma_model_in)^2
```

```
arf_model.forecast(e, g) arf_model_f
scalar rm_arf_model_in =@rmse(reua,arf_model_f)
scalar mse_arf_model_in =(rm_arf_model_in)^2
```

'C-T & C-W tests using the preferred estimator (FQGLS)

```
scalar ct_model_3_1_in=1-(mse_model_3_fgls_in/mse_model_1_fgls_in)
scalar ct_model_3_2_in=1-(mse_model_3_fgls_in/mse_model_2_fgls_in)
scalar ct_model_4_3_in=1-(mse_model_4_fgls_in/mse_model_3_fgls_in)

scalar ct_model_3_ha_in=1-(mse_model_3_fgls_in/mse_ha_in)
scalar ct_model_3_ar_model_in=1-(mse_model_3_fgls_in/mse_ar_model_in)
scalar ct_model_3_arma_model_in=1-(mse_model_3_fgls_in/mse_arma_model_in)
scalar ct_model_3_arf_model_in=1-(mse_model_3_fgls_in/mse_arf_model_in)

series fgls_1_in=(reua-model_1_fgls_f)^2
series fgls_3_in=(reua-model_3_fgls_f)^2-(model_1_fgls_f-model_3_fgls_f)^2
series fgls_model_1_3_in=fgls_1_in-fgls_3_in
equation cw_3_1_in.ls fgls_model_1_3_in c

series fgls_2_in=(reua-model_2_fgls_f)^2
series fgls_3_in=(reua-model_3_fgls_f)^2-(model_2_fgls_f-model_3_fgls_f)^2
series fgls_model_2_3_in=fgls_2_in-fgls_3_in
equation cw_3_2_in.ls fgls_model_2_3_in c

series fgls_3_in=(reua-model_3_fgls_f)^2
series fgls_4_in=(reua-model_4_fgls_f)^2-(model_3_fgls_f-model_4_fgls_f)^2
series fgls_model_3_4_in=fgls_3_in-fgls_4_in
equation cw_4_3_in.ls fgls_model_3_4_in c

series fgls_ha_in=(reua-ha_f)^2
series fgls_3_in=(reua-model_3_fgls_f)^2-(ha_f-model_3_fgls_f)^2
series fgls_model_ha_in=fgls_ha_in-fgls_3_in
equation cw_fgls_ha_in.ls fgls_model_ha_in c

series fgls_ar_model_in=(reua-ar_model_f)^2
series fgls_3_in=(reua-model_3_fgls_f)^2-(ar_model_f-model_3_fgls_f)^2
series fgls_model_ar_model_in=fgls_ar_model_in-fgls_3_in
equation cw_fgls_ar_model_in.ls fgls_model_ar_model_in c

series fgls_arma_model_in=(reua-arma_model_f)^2
series fgls_3_in=(reua-model_3_fgls_f)^2-(arma_model_f-model_3_fgls_f)^2
series fgls_model_arma_model_in=fgls_arma_model_in-fgls_3_in
equation cw_fgls_arma_model_in.ls fgls_model_arma_model_in c
```

```
series fgls_arf_model_in=(reua-arf_model_f)^2
series fgls_3_in=(reua-model_3_fgls_f)^2-(arf_model_f-model_3_fgls_f)^2
series fgls_model_arf_model_in=fgls_arf_model_in-fgls_3_in
equation cw_fgls_arf_model_in.ls fgls_model_arf_model_in c
```

'Out-of-sample forecast evaluation

```
'h=4
smpl 1 166

'OLS
model_1_ols.forecast(e, g) model_1_ols_f
scalar rm_model_1_ols_h4 =@rmse(reua,model_1_ols_f)
scalar mse_model_1_ols_h4 =(rm_model_1_ols_h4 )^2

model_2_ols.forecast(e, g) model_2_ols_f
scalar rm_model_2_ols_h4 =@rmse(reua,model_2_ols_f)
scalar mse_model_2_ols_h4 =(rm_model_2_ols_h4 )^2

model_3_ols.forecast(e, g) model_3_ols_f
scalar rm_model_3_ols_h4 =@rmse(reua,model_3_ols_f)
scalar mse_model_3_ols_h4 =(rm_model_3_ols_h4 )^2

model_4_ols.forecast(e, g) model_4_ols_f
scalar rm_model_4_ols_h4 =@rmse(reua,model_4_ols_f)
scalar mse_model_4_ols_h4 =(rm_model_4_ols_h4 )^2

'AOLS
model_1_aols.forecast(e, g) model_1_aols_f
scalar rm_model_1_aols_h4 =@rmse(reua,model_1_aols_f)
scalar mse_model_1_aols_h4 =(rm_model_1_aols_h4 )^2
model_2_aols.forecast(e, g) model_2_aols_f
scalar rm_model_2_aols_h4 =@rmse(reua,model_2_aols_f)
scalar mse_model_2_aols_h4 =(rm_model_2_aols_h4 )^2

model_3_aols.forecast(e, g) model_3_aols_f
scalar rm_model_3_aols_h4 =@rmse(reua,model_3_aols_f)
scalar mse_model_3_aols_h4 =(rm_model_3_aols_h4 )^2

model_4_aols.forecast(e, g) model_4_aols_f
scalar rm_model_4_aols_h4 =@rmse(reua,model_4_aols_f)
scalar mse_model_4_aols_h4 =(rm_model_4_aols_h4 )^2
```

```
'FQGLS
model_1_fgls.forecast(e, g) model_1_fgls_f
scalar rm_model_1_fgls_h4 =@rmse(reua,model_1_fgls_f)
scalar mse_model_1_fgls_h4 =(rm_model_1_fgls_h4 )^2

model_2_fgls.forecast(e, g) model_2_fgls_f
scalar rm_model_2_fgls_h4 =@rmse(reua,model_2_fgls_f)
scalar mse_model_2_fgls_h4 =(rm_model_2_fgls_h4 )^2

model_3_fgls.forecast(e, g) model_3_fgls_f
scalar rm_model_3_fgls_h4 =@rmse(reua,model_3_fgls_f)
scalar mse_model_3_fgls_h4 =(rm_model_3_fgls_h4 )^2

model_4_fgls.forecast(e, g) model_4_fgls_f
scalar rm_model_4_fgls_h4 =@rmse(reua,model_4_fgls_f)
scalar mse_model_4_fgls_h4 =(rm_model_4_fgls_h4 )^2

ha.forecast(e, g) ha_f
scalar rm_ha_h4 =@rmse(reua,ha_f)
scalar mse_ha_h4 =(rm_ha_h4)^2

ar_model.forecast(e, g) ar_model_f
scalar rm_ar_model_h4 =@rmse(reua,ar_model_f)
scalar mse_ar_model_h4 =(rm_ar_model_h4)^2

arma_model.forecast(e, g) arma_model_f
scalar rm_arma_model_h4 =@rmse(reua,arma_model_f)
scalar mse_arma_model_h4 =(rm_arma_model_h4)^2

arf_model.forecast(e, g) arf_model_f
scalar rm_arf_model_h4 =@rmse(reua,arf_model_f)
scalar mse_arf_model_h4 =(rm_arf_model_h4)^2
```

'C-T & C-W tests using the preferred estimator (FQGLS)

```
scalar ct_model_3_1_h4=1-(mse_model_3_fgls_h4/mse_model_1_fgls_h4)
scalar ct_model_3_2_h4=1-(mse_model_3_fgls_h4/mse_model_2_fgls_h4)
scalar ct_model_4_3_h4=1-(mse_model_4_fgls_h4/mse_model_3_fgls_h4)

scalar ct_model_3_ha_h4=1-(mse_model_3_fgls_h4/mse_ha_h4)
scalar ct_model_3_ar_model_h4=1-(mse_model_3_fgls_h4/mse_ar_model_h4)
scalar ct_model_3_arma_model_h4=1-(mse_model_3_fgls_h4/mse_arma_model_h4)
scalar ct_model_3_arf_model_h4=1-(mse_model_3_fgls_h4/mse_arf_model_h4)
```

```
series fgls_1_h4=(reua-model_1_fgls_f)^2
series fgls_3_h4=(reua-model_3_fgls_f)^2-(model_1_fgls_f-model_3_fgls_f)^2
series fgls_model_1_3_h4=fgls_1_h4-fgls_3_h4
equation cw_3_1_h4.ls fgls_model_1_3_h4 c

series fgls_2_h4=(reua-model_2_fgls_f)^2
series fgls_3_h4=(reua-model_3_fgls_f)^2-(model_2_fgls_f-model_3_fgls_f)^2
series fgls_model_2_3_h4=fgls_2_h4-fgls_3_h4
equation cw_3_2_h4.ls fgls_model_2_3_h4 c

series fgls_3_h4=(reua-model_3_fgls_f)^2
series fgls_4_h4=(reua-model_4_fgls_f)^2-(model_3_fgls_f-model_4_fgls_f)^2
series fgls_model_3_4_h4=fgls_3_h4-fgls_4_h4
equation cw_4_3_h4.ls fgls_model_3_4_h4 c

series fgls_ha_h4=(reua-ha_f)^2
series fgls_3_h4=(reua-model_3_fgls_f)^2-(ha_f-model_3_fgls_f)^2
series fgls_model_ha_h4=fgls_ha_h4-fgls_3_h4
equation cw_fgls_ha_h4.ls fgls_model_ha_h4 c

series fgls_ar_model_h4=(reua-ar_model_f)^2
series fgls_3_h4=(reua-model_3_fgls_f)^2-(ar_model_f-model_3_fgls_f)^2
series fgls_model_ar_model_h4=fgls_ar_model_h4-fgls_3_h4
equation cw_fgls_ar_model_h4.ls fgls_model_ar_model_h4 c

series fgls_arma_model_h4=(reua-arma_model_f)^2
series fgls_3_h4=(reua-model_3_fgls_f)^2-(arma_model_f-model_3_fgls_f)^2
series fgls_model_arma_model_h4=fgls_arma_model_h4-fgls_3_h4
equation cw_fgls_arma_model_h4.ls fgls_model_arma_model_h4 c

series fgls_arf_model_h4=(reua-arf_model_f)^2
series fgls_3_h4=(reua-model_3_fgls_f)^2-(arf_model_f-model_3_fgls_f)^2
series fgls_model_arf_model_h4=fgls_arf_model_h4-fgls_3_h4
equation cw_fgls_arf_model_h4.ls fgls_model_arf_model_h4 c

'h=8
smpl 1 170

'OLS
model_1_ols.forecast(e, g) model_1_ols_f
scalar rm_model_1_ols_h8 =@rmse(reua,model_1_ols_f)
scalar mse_model_1_ols_h8 =(rm_model_1_ols_h8 )^2

model_2_ols.forecast(e, g) model_2_ols_f
scalar rm_model_2_ols_h8 =@rmse(reua,model_2_ols_f)
scalar mse_model_2_ols_h8 =(rm_model_2_ols_h8 )^2
```

```
model_3_ols.forecast(e, g) model_3_ols_f
scalar rm_model_3_ols_h8 =@rmse(reua,model_3_ols_f)
scalar mse_model_3_ols_h8 =(rm_model_3_ols_h8 )^2

model_4_ols.forecast(e, g) model_4_ols_f
scalar rm_model_4_ols_h8 =@rmse(reua,model_4_ols_f)
scalar mse_model_4_ols_h8 =(rm_model_4_ols_h8 )^2

'AOLS
model_1_aols.forecast(e, g) model_1_aols_f
scalar rm_model_1_aols_h8 =@rmse(reua,model_1_aols_f)
scalar mse_model_1_aols_h8 =(rm_model_1_aols_h8 )^2
model_2_aols.forecast(e, g) model_2_aols_f
scalar rm_model_2_aols_h8 =@rmse(reua,model_2_aols_f)
scalar mse_model_2_aols_h8 =(rm_model_2_aols_h8 )^2

model_3_aols.forecast(e, g) model_3_aols_f
scalar rm_model_3_aols_h8 =@rmse(reua,model_3_aols_f)
scalar mse_model_3_aols_h8 =(rm_model_3_aols_h8 )^2

model_4_aols.forecast(e, g) model_4_aols_f
scalar rm_model_4_aols_h8 =@rmse(reua,model_4_aols_f)
scalar mse_model_4_aols_h8 =(rm_model_4_aols_h8 )^2

'FQGLS
model_1_fgls.forecast(e, g) model_1_fgls_f
scalar rm_model_1_fgls_h8 =@rmse(reua,model_1_fgls_f)
scalar mse_model_1_fgls_h8 =(rm_model_1_fgls_h8 )^2

model_2_fgls.forecast(e, g) model_2_fgls_f
scalar rm_model_2_fgls_h8 =@rmse(reua,model_2_fgls_f)
scalar mse_model_2_fgls_h8 =(rm_model_2_fgls_h8 )^2
model_3_fgls.forecast(e, g) model_3_fgls_f
scalar rm_model_3_fgls_h8 =@rmse(reua,model_3_fgls_f)
scalar mse_model_3_fgls_h8 =(rm_model_3_fgls_h8 )^2

model_4_fgls.forecast(e, g) model_4_fgls_f
scalar rm_model_4_fgls_h8 =@rmse(reua,model_4_fgls_f)
scalar mse_model_4_fgls_h8 =(rm_model_4_fgls_h8 )^2

ha.forecast(e, g) ha_f
scalar rm_ha_h8 =@rmse(reua,ha_f)
scalar mse_ha_h8 =(rm_ha_h8)^2
ar_model.forecast(e, g) ar_model_f
scalar rm_ar_model_h8 =@rmse(reua,ar_model_f)
scalar mse_ar_model_h8 =(rm_ar_model_h8)^2
```

```
arma_model.forecast(e, g) arma_model_f
scalar rm_arma_model_h8 =@rmse(reua,arma_model_f)
scalar mse_arma_model_h8 =(rm_arma_model_h8)^2

arf_model.forecast(e, g) arf_model_f
scalar rm_arf_model_h8 =@rmse(reua,arf_model_f)
scalar mse_arf_model_h8 =(rm_arf_model_h8)^2
```

'C-T & C-W tests using the preferred estimator (FQGLS)

```
scalar ct_model_3_1_h8=1-(mse_model_3_fgls_h8/mse_model_1_fgls_h8)
scalar ct_model_3_2_h8=1-(mse_model_3_fgls_h8/mse_model_2_fgls_h8)
scalar ct_model_4_3_h8=1-(mse_model_4_fgls_h8/mse_model_3_fgls_h8)

scalar ct_model_3_ha_h8=1-(mse_model_3_fgls_h8/mse_ha_h8)
scalar ct_model_3_ar_model_h8=1-(mse_model_3_fgls_h8/mse_ar_model_h8)
scalar ct_model_3_arma_model_h8=1-(mse_model_3_fgls_h8/mse_arma_model_h8)
scalar ct_model_3_arf_model_h8=1-(mse_model_3_fgls_h8/mse_arf_model_h8)

series fgls_1_h8=(reua-model_1_fgls_f)^2
series fgls_3_h8=(reua-model_3_fgls_f)^2-(model_1_fgls_f-model_3_fgls_f)^2
series fgls_model_1_3_h8=fgls_1_h8-fgls_3_h8
equation cw_3_1_h8.ls fgls_model_1_3_h8 c

series fgls_2_h8=(reua-model_2_fgls_f)^2
series fgls_3_h8=(reua-model_3_fgls_f)^2-(model_2_fgls_f-model_3_fgls_f)^2
series fgls_model_2_3_h8=fgls_2_h8-fgls_3_h8
equation cw_3_2_h8.ls fgls_model_2_3_h8 c

series fgls_3_h8=(reua-model_3_fgls_f)^2
series fgls_4_h8=(reua-model_4_fgls_f)^2-(model_3_fgls_f-model_4_fgls_f)^2
series fgls_model_3_4_h8=fgls_3_h8-fgls_4_h8
equation cw_4_3_h8.ls fgls_model_3_4_h8 c

series fgls_ha_h8=(reua-ha_f)^2
series fgls_3_h8=(reua-model_3_fgls_f)^2-(ha_f-model_3_fgls_f)^2
series fgls_model_ha_h8=fgls_ha_h8-fgls_3_h8
equation cw_fgls_ha_h8.ls fgls_model_ha_h8 c

series fgls_ar_model_h8=(reua-ar_model_f)^2
series fgls_3_h8=(reua-model_3_fgls_f)^2-(ar_model_f-model_3_fgls_f)^2
series fgls_model_ar_model_h8=fgls_ar_model_h8-fgls_3_h8
equation cw_fgls_ar_model_h8.ls fgls_model_ar_model_h8 c
```

```
series fgls_arma_model_h8=(reua-arma_model_f)^2
series fgls_3_h8=(reua-model_3_fgls_f)^2-(arma_model_f-model_3_fgls_f)^2
series fgls_model_arma_model_h8=fgls_arma_model_h8-fgls_3_h8
equation cw_fgls_arma_model_h8.ls fgls_model_arma_model_h8 c

series fgls_arf_model_h8=(reua-arf_model_f)^2
series fgls_3_h8=(reua-model_3_fgls_f)^2-(arf_model_f-model_3_fgls_f)^2
series fgls_model_arf_model_h8=fgls_arf_model_h8-fgls_3_h8
equation cw_fgls_arf_model_h8.ls fgls_model_arf_model_h8 c

'h=12

smpl 1 174

'OLS
model_1_ols.forecast(e, g) model_1_ols_f
scalar rm_model_1_ols_h12 =@rmse(reua,model_1_ols_f)
scalar mse_model_1_ols_h12 =(rm_model_1_ols_h12 )^2

model_2_ols.forecast(e, g) model_2_ols_f
scalar rm_model_2_ols_h12 =@rmse(reua,model_2_ols_f)
scalar mse_model_2_ols_h12 =(rm_model_2_ols_h12 )^2

model_3_ols.forecast(e, g) model_3_ols_f
scalar rm_model_3_ols_h12 =@rmse(reua,model_3_ols_f)
scalar mse_model_3_ols_h12 =(rm_model_3_ols_h12 )^2

model_4_ols.forecast(e, g) model_4_ols_f
scalar rm_model_4_ols_h12 =@rmse(reua,model_4_ols_f)
scalar mse_model_4_ols_h12 =(rm_model_4_ols_h12 )^2

'AOLS
model_1_aols.forecast(e, g) model_1_aols_f
scalar rm_model_1_aols_h12 =@rmse(reua,model_1_aols_f)
scalar mse_model_1_aols_h12 =(rm_model_1_aols_h12 )^2

model_2_aols.forecast(e, g) model_2_aols_f
scalar rm_model_2_aols_h12 =@rmse(reua,model_2_aols_f)
scalar mse_model_2_aols_h12 =(rm_model_2_aols_h12 )^2

model_3_aols.forecast(e, g) model_3_aols_f
scalar rm_model_3_aols_h12 =@rmse(reua,model_3_aols_f)
scalar mse_model_3_aols_h12 =(rm_model_3_aols_h12 )^2

model_4_aols.forecast(e, g) model_4_aols_f
scalar rm_model_4_aols_h12 =@rmse(reua,model_4_aols_f)
```

```
scalar mse_model_4_aols_h12 =(rm_model_4_aols_h12 )^2

'FQGLS
model_1_fgls.forecast(e, g) model_1_fgls_f
scalar rm_model_1_fgls_h12 =@rmse(reua,model_1_fgls_f)
scalar mse_model_1_fgls_h12 =(rm_model_1_fgls_h12 )^2

model_2_fgls.forecast(e, g) model_2_fgls_f
scalar rm_model_2_fgls_h12 =@rmse(reua,model_2_fgls_f)
scalar mse_model_2_fgls_h12 =(rm_model_2_fgls_h12 )^2
model_3_fgls.forecast(e, g) model_3_fgls_f
scalar rm_model_3_fgls_h12 =@rmse(reua,model_3_fgls_f)
scalar mse_model_3_fgls_h12 =(rm_model_3_fgls_h12 )^2

model_4_fgls.forecast(e, g) model_4_fgls_f
scalar rm_model_4_fgls_h12 =@rmse(reua,model_4_fgls_f)
scalar mse_model_4_fgls_h12 =(rm_model_4_fgls_h12 )^2

ha.forecast(e, g) ha_f
scalar rm_ha_h12 =@rmse(reua,ha_f)
scalar mse_ha_h12 =(rm_ha_h12)^2

ar_model.forecast(e, g) ar_model_f
scalar rm_ar_model_h12 =@rmse(reua,ar_model_f)
scalar mse_ar_model_h12 =(rm_ar_model_h8)^2

arma_model.forecast(e, g) arma_model_f
scalar rm_arma_model_h12 =@rmse(reua,arma_model_f)
scalar mse_arma_model_h12 =(rm_arma_model_h12)^2

arf_model.forecast(e, g) arf_model_f
scalar rm_arf_model_h12 =@rmse(reua,arf_model_f)
scalar mse_arf_model_h12 =(rm_arf_model_h12)^2
```

'C-T & C-W tests using the preferred estimator (FQGLS)

```
scalar ct_model_3_1_h12=1-(mse_model_3_fgls_h12/mse_model_1_fgls_h12)
scalar ct_model_3_2_h12=1-(mse_model_3_fgls_h12/mse_model_2_fgls_h12)
scalar ct_model_4_3_h12=1-(mse_model_4_fgls_h12/mse_model_3_fgls_h12)

scalar ct_model_3_ha_h12=1-(mse_model_3_fgls_h12/mse_ha_h12)
scalar ct_model_3_ar_model_h12=1-(mse_model_3_fgls_h12/mse_ar_model_h12)
scalar ct_model_3_arma_model_h12=1-(mse_model_3_fgls_h12/mse_arma_model_h12)
scalar ct_model_3_arf_model_h12=1-(mse_model_3_fgls_h12/mse_arf_model_h12)
```

```
series fgls_1_h12=(reua-model_1_fgls_f)^2
series fgls_3_h12=(reua-model_3_fgls_f)^2-(model_1_fgls_f-model_3_fgls_f)^2
series fgls_model_1_3_h12=fgls_1_h12-fgls_3_h12
equation cw_3_1_h12.ls fgls_model_1_3_h12 c

series fgls_2_h12=(reua-model_2_fgls_f)^2
series fgls_3_h12=(reua-model_3_fgls_f)^2-(model_2_fgls_f-model_3_fgls_f)^2
series fgls_model_2_3_h12=fgls_2_h12-fgls_3_h12
equation cw_3_2_h12.ls fgls_model_2_3_h12 c

series fgls_3_h12=(reua-model_3_fgls_f)^2
series fgls_4_h12=(reua-model_4_fgls_f)^2-(model_3_fgls_f-model_4_fgls_f)^2
series fgls_model_3_4_h12=fgls_3_h12-fgls_4_h12
equation cw_4_3_h12.ls fgls_model_3_4_h12 c

series fgls_ha_h12=(reua-ha_f)^2
series fgls_3_h12=(reua-model_3_fgls_f)^2-(ha_f-model_3_fgls_f)^2
series fgls_model_ha_h12=fgls_ha_h12-fgls_3_h12
equation cw_fgls_ha_h12.ls fgls_model_ha_h12 c

series fgls_ar_model_h12=(reua-ar_model_f)^2
series fgls_3_h12=(reua-model_3_fgls_f)^2-(ar_model_f-model_3_fgls_f)^2
series fgls_model_ar_model_h12=fgls_ar_model_h12-fgls_3_h12
equation cw_fgls_ar_model_h12.ls fgls_model_ar_model_h12 c

series fgls_arma_model_h12=(reua-arma_model_f)^2
series fgls_3_h12=(reua-model_3_fgls_f)^2-(arma_model_f-model_3_fgls_f)^2
series fgls_model_arma_model_h12=fgls_arma_model_h12-fgls_3_h12
equation cw_fgls_arma_model_h12.ls fgls_model_arma_model_h12 c

series fgls_arf_model_h12=(reua-arf_model_f)^2
series fgls_3_h12=(reua-model_3_fgls_f)^2-(arf_model_f-model_3_fgls_f)^2
series fgls_model_arf_model_h12=fgls_arf_model_h12-fgls_3_h12
equation cw_fgls_arf_model_h12.ls fgls_model_arf_model_h12 c

next
```

APPENDIX C

PROGRAMME CODES FOR THE THIRD ESSAY

Appendix C1: Pre –estimation programme codes

Descriptive Statistics

```
'Group all series
group stat_series tmp eua spec
```

'Descriptive Stat

```
Freeze (descriptive_stat) stat_series.stats
```

Serial Correlation test

```
'Weather condition
equation serial_eq_tmp.ls tmp c
freeze (qstat11_tmp) serial_eq_tmp.correl(4)
freeze (qstat21_tmp) serial_eq_tmp.correlsq(4)
freeze (qstat12_tmp) serial_eq_tmp.correl(8)
freeze (qstat22_tmp) serial_eq_tmp.correlsq(8)
freeze (qstat13_tmp) serial_eq_tmp.correl(12)
freeze (qstat23_tmp) serial_eq_tmp.correlsq(12)

'Carbon prices
equation serial_eq_eua.ls eua c
freeze (qstat11_eua) serial_eq_eua.correl(4)
freeze (qstat21_eua) serial_eq_eua.correlsq(4)
freeze (qstat12_eua) serial_eq_eua.correl(8)
freeze (qstat22_eua) serial_eq_eua.correlsq(8)
freeze (qstat13_eua) serial_eq_eua.correl(12)
freeze (qstat23_eua) serial_eq_eua.correlsq(12)

'Speculation
equation serial_eq_spec.ls spec c
freeze (qstat11_spec) serial_eq_spec.correl(4)
freeze (qstat21_spec) serial_eq_spec.correlsq(4)
freeze (qstat12_spec) serial_eq_spec.correl(8)
freeze (qstat22_spec) serial_eq_spec.correlsq(8)
freeze (qstat13_spec) serial_eq_spec.correl(12)
freeze (qstat23_spec) serial_eq_spec.correlsq(12)
```

'Conditional Heteroscedasticity test

'Climate change
Freeze (arch_tmp_4) serial_eq_tmp.archtest(4)
Freeze (arch_tmp_8) serial_eq_tmp.archtest(8)
Freeze (arch_tmp_12) serial_eq_tmp.archtest(12)

'Carbon prices
Freeze (arch_eua_4) serial_eq_eua.archtest(4)
Freeze (arch_eua_8) serial_eq_eua.archtest(8)
Freeze (arch_eua_12) serial_eq_eua.archtest(12)

'Speculation
Freeze (arch_spec_4) serial_eq_spec.archtest(4)
Freeze (arch_spec_8) serial_eq_spec.archtest(8)
Freeze (arch_spec_12) serial_eq_spec.archtest(12)

Persistence test

'Carbon prices
equation eua_pers.ls eua c eua(-1)
series resid_eua=resid

'Speculation
equation spec_pers.ls spec c spec(-1)
series resid_spec=resid

Endogeneity test

'Endogeneity between climate change and carbon prices

equation eua_eqn.ls tmp c eua(-1)
series resid_tmp_eua=resid
equation endo_tmp_eua.ls resid_tmp_eua resid_eua(-1)

'Endogeneity between climate change and speculation

equation spec_eqn.ls tmp c spec(-1)
series resid_tmp_spec=resid
equation endo_tmp_spec.ls resid_tmp_spec resid_spec(-1)

''

Appendix C2: Main estimation programme codes

```
''''
'generate log of series
series tmp=log(co2)
series cp=log(eua)
series cp_spec=cp*spec

series cp_adj = cp-cp(-1)
series spec_adj = spec-spec(-1)
series cp_spec_adj = cp_spec-cp_spec(-1)

''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''

pagestruct(none)

smpl 1 180

'rollh8g wh8dow analyses

'set window size
!window = 20

' set step size
!step = 1

' get size of workfile
!length = @obsrange

'calculate number of rolls
!nrolls = @floor((!length-!window)/!step)

'matrix to store coefficient estimates
matrix(3,!nrolls) coefmat ' where 3 is the number of coefficients

'redundant series for catching start and end points
series ser = 1
%start = @otod(@ifirst(ser))
%end = @otod(@ilast(ser))

'variable keeping track of how many rolls we've done
!j=0

'move sample !step obs at a time
for !i = 1  to  !length-!window+1-!step step !step
   !j=!j+1
```

'set sample for estimation period
%first = @otod(@dtoo(%start)+!i-1)
%last = @otod(@dtoo(%start)+!i+!window-2)

'In-Sample Predictability Test

smpl 1 180

'FQGLS
equation model_1_fgls.arch tmp cp(-1) cp_adj
equation model_2_fgls.arch tmp cp(-1) cp_adj spec(-1) spec_adj
equation model_3_fgls.arch tmp cp(-1) cp_adj spec(-1) spec_adj cp_spec(-1) cp_spec_adj

'In-sample forecast evaluation

smpl 1 162

model_1_fgls.forecast(e, g) model_1_fgls_f
scalar rm_model_1_fgls_in =@rmse(tmp,model_1_fgls_f)
scalar mse_model_1_fgls_in =(rm_model_1_fgls_in)^2

model_2_fgls.forecast(e, g) model_2_fgls_f
scalar rm_model_2_fgls_in =@rmse(tmp,model_2_fgls_f)
scalar mse_model_2_fgls_in =(rm_model_2_fgls_in)^2

model_3_fgls.forecast(e, g) model_3_fgls_f
scalar rm_model_3_fgls_in =@rmse(tmp,model_3_fgls_f)
scalar mse_model_3_fgls_in =(rm_model_3_fgls_in)^2

'C-T & C-W tests using the preferred estimator (FQGLS)

scalar ct_model_3_1_in=1-(mse_model_3_fgls_in/mse_model_1_fgls_in)
scalar ct_model_3_2_in=1-(mse_model_3_fgls_in/mse_model_2_fgls_in)

series fgls_1_in=(tmp-model_1_fgls_f)^2
series fgls_3_in=(tmp-model_3_fgls_f)^2-(model_1_fgls_f-model_3_fgls_f)^2
series fgls_model_1_3_in=fgls_1_in-fgls_3_in
equation cw_3_1_in.ls fgls_model_1_3_in c

series fgls_2_in=(tmp-model_2_fgls_f)^2
series fgls_3_in=(tmp-model_3_fgls_f)^2-(model_2_fgls_f-model_3_fgls_f)^2
series fgls_model_2_3_in=fgls_2_in-fgls_3_in
equation cw_3_2_in.ls fgls_model_2_3_in c

```
'Out-of-sample forecast evaluation
'h=4

smpl 1 166

'FQGLS
model_1_fgls.forecast(e, g) model_1_fgls_f
scalar rm_model_1_fgls_h4 =@rmse(tmp,model_1_fgls_f)
scalar mse_model_1_fgls_h4 =(rm_model_1_fgls_h4 )^2

model_2_fgls.forecast(e, g) model_2_fgls_f
scalar rm_model_2_fgls_h4 =@rmse(tmp,model_2_fgls_f)
scalar mse_model_2_fgls_h4 =(rm_model_2_fgls_h4 )^2

model_3_fgls.forecast(e, g) model_3_fgls_f
scalar rm_model_3_fgls_h4 =@rmse(tmp,model_3_fgls_f)
scalar mse_model_3_fgls_h4 =(rm_model_3_fgls_h4 )^2

scalar ct_model_3_1_h4=1-(mse_model_3_fgls_h4/mse_model_1_fgls_h4)
scalar ct_model_3_2_h4=1-(mse_model_3_fgls_h4/mse_model_2_fgls_h4)

series fgls_1_h4=(tmp-model_1_fgls_f)^2
series fgls_3_h4=(tmp-model_3_fgls_f)^2-(model_1_fgls_f-model_3_fgls_f)^2
series fgls_model_1_3_h4=fgls_1_h4-fgls_3_h4
equation cw_3_1_h4.ls fgls_model_1_3_h4 c

series fgls_2_h4=(tmp-model_2_fgls_f)^2
series fgls_3_h4=(tmp-model_3_fgls_f)^2-(model_2_fgls_f-model_3_fgls_f)^2
series fgls_model_2_3_h4=fgls_2_h4-fgls_3_h4
equation cw_3_2_h4.ls fgls_model_2_3_h4 c

'h=8

smpl 1 170

'FQGLS
model_1_fgls.forecast(e, g) model_1_fgls_f
scalar rm_model_1_fgls_h8 =@rmse(tmp,model_1_fgls_f)
scalar mse_model_1_fgls_h8 =(rm_model_1_fgls_h8 )^2

model_2_fgls.forecast(e, g) model_2_fgls_f
scalar rm_model_2_fgls_h8 =@rmse(tmp,model_2_fgls_f)
scalar mse_model_2_fgls_h8 =(rm_model_2_fgls_h8 )^2

model_3_fgls.forecast(e, g) model_3_fgls_f
scalar rm_model_3_fgls_h8 =@rmse(tmp,model_3_fgls_f)
```

```
scalar mse_model_3_fgls_h8 =(rm_model_3_fgls_h8 )^2

scalar ct_model_3_1_h8=1-(mse_model_3_fgls_h8/mse_model_1_fgls_h8)
scalar ct_model_3_2_h8=1-(mse_model_3_fgls_h8/mse_model_2_fgls_h8)

series fgls_1_h8=(tmp-model_1_fgls_f)^2
series fgls_3_h8=(tmp-model_3_fgls_f)^2-(model_1_fgls_f-model_3_fgls_f)^2
series fgls_model_1_3_h8=fgls_1_h8-fgls_3_h8
equation cw_3_1_h8.ls fgls_model_1_3_h8 c

series fgls_2_h8=(tmp-model_2_fgls_f)^2
series fgls_3_h8=(tmp-model_3_fgls_f)^2-(model_2_fgls_f-model_3_fgls_f)^2
series fgls_model_2_3_h8=fgls_2_h8-fgls_3_h8
equation cw_3_2_h8.ls fgls_model_2_3_h8 c


'h=12

smpl 1 174

model_1_fgls.forecast(e, g) model_1_fgls_f
scalar rm_model_1_fgls_h12 =@rmse(tmp,model_1_fgls_f)
scalar mse_model_1_fgls_h12 =(rm_model_1_fgls_h12 )^2

model_2_fgls.forecast(e, g) model_2_fgls_f
scalar rm_model_2_fgls_h12 =@rmse(tmp,model_2_fgls_f)
scalar mse_model_2_fgls_h12 =(rm_model_2_fgls_h12 )^2

model_3_fgls.forecast(e, g) model_3_fgls_f
scalar rm_model_3_fgls_h12 =@rmse(tmp,model_3_fgls_f)
scalar mse_model_3_fgls_h12 =(rm_model_3_fgls_h12 )^2

scalar ct_model_3_1_h12=1-(mse_model_3_fgls_h12/mse_model_1_fgls_h12)
scalar ct_model_3_2_h12=1-(mse_model_3_fgls_h12/mse_model_2_fgls_h12)

series fgls_1_h12=(tmp-model_1_fgls_f)^2
series fgls_3_h12=(tmp-model_3_fgls_f)^2-(model_1_fgls_f-model_3_fgls_f)^2
series fgls_model_1_3_h12=fgls_1_h12-fgls_3_h12
equation cw_3_1_h12.ls fgls_model_1_3_h12 c

series fgls_2_h12=(tmp-model_2_fgls_f)^2
series fgls_3_h12=(tmp-model_3_fgls_f)^2-(model_2_fgls_f-model_3_fgls_f)^2
series fgls_model_2_3_h12=fgls_2_h12-fgls_3_h12
equation cw_3_2_h12.ls fgls_model_2_3_h12 c
```

09-10-2023
Mr Kazeem Ovanero Isah (220080899)
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Westville

Dear Mr Kazeem Ovanero Isah,

Original application number: 00017830
Project title: Analysis of the dynamics of carbon pricing: The role of speculation in the emissions trading system (ETS)

Exemption from Ethics Review

In response to your application received on 08 October 2023 , your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:
Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

[redacted]

Prof Josue Mbonigaba
Academic Leader Research
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