MASTER OF SCIENCE IN

FINANCE

MASTER´S FINAL WORK

DISSERTATION

MODELLING VOLATILITY IN CARBON FUTURES MARKETS: A GARCH-MIDAS APPROACH WITH UNCERTAINTY INDEXES

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ABSTRACT

The European Union Emissions Trading System is a platform that allows investors to buy or sell carbon emission allowances. Its goal is to help achieve decarbonization through the establishment of annual emissions caps with which companies must comply.

This dissertation investigates the impact that various uncertainties indexes, namely the global economic policy uncertainty, the climate policy uncertainty and the geopolitical risk, have on the volatility of the carbon futures returns in the EU ETS.

To assess that impact, the statistical model GARCH-MIDAS was employed. This specific model allows to associate high frequency variables, such as financial returns, with low frequency variables, such as macroeconomic variables.

The results show that both global economic policy uncertainty and geopolitical risk have a positive correlation with the long-term volatility of the European carbon futures returns whereas climate policy uncertainty displays a negative correlation.

This study can shed some light on the dynamics of carbon markets, helping policy makers and investors take better decisions regarding this peculiar market.

KEYWORDS: Volatility; EU ETS; Economic Policy Uncertainty; Climate Policy Uncertainty; Geopolitical Risk; GARCH-MIDAS

ACKNOWLEDGEMENTS

First and foremost, I want to thank Professor Tiago Gonçalves for his priceless encouragement and guidance throughout this academic journey and for believing in my capabilities since day one.

I would also like to thank all my friends and family, you make life so fun and I am forever grateful to have you by my side.

Last but not least, I want to express my deepest gratitude to my parents for investing in my education and for being my biggest supporters.

GLOSSARY

AIC – Akaike Information Criterion

CPU – Climate Policy Uncertainty

CO_2 – Carbon Dioxide

ETS – Emissions Trading System

EU – European Union

EUA – European Union Allowance

GARCH - Generalized Autoregressive Conditional Heteroskedasticity

GDP – Gross Domestic Product

GEPU – Global Economic Policy Uncertainty

GHG – Greenhouse Gas

GPR – Geopolitical Risk

ICE – Intercontinental Exchange

MFW – Master’s Final Work

MIDAS – Mixed Data Sampling

VIF – Variance Inflation Factor

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1. INTRODUCTION

Carbon markets have been gaining increasing attention over the last couple of decades as global warming progresses. As a collective effort to combat climate change, numerous international agreements have been defined. The first of its kind was the Kyoto Protocol, set in 1997. Since then, the European Union took the lead and established the European Union emissions trading system in 2005 (European Commission, N.D.). The creation of the EU ETS was a revolutionary achievement, not only allowing governments to set annual emissions caps on greenhouse gases but also giving companies the option to trade emission allowances according to their needs.

Understanding the behaviour of these unique financial instruments became therefore critical, especially for policymakers and investors. As such, it is worth exploring how macroeconomic variables impact the volatility on carbon markets. Forecasting volatility reliably has always been essential for the success of portfolio managers and hedging strategies. Thus, the central research question of this master's final work is: *To what extent do different macroeconomic uncertainty indexes, specifically the global economic policy uncertainty, the climate policy uncertainty and the geopolitical risk, impact the volatility of carbon futures markets?*

While previous studies have examined the volatility dynamics of carbon markets, few have explored the relationship between long-term macroeconomic uncertainty/risk and short-term price movements in carbon futures. To tackle this type of research, the statistical GARCH-MIDAS model is usually implemented.

This model, proposed by Engle et al. (2013), captures the combined effect of long-term low-frequency macroeconomic data on short-term high-frequency financial data. The GARCH part of the model tries to explain short-term variations on carbon futures prices due to temporary changes on the demand/supply forces whereas the MIDAS element explores the long-term impact of macroeconomic uncertainty on carbon futures volatility.

This research will attempt to contribute to the existing literature by applying a GARCH-MIDAS model to the carbon futures returns while using three different explanatory macroeconomic variables. This is unique for two reasons: firstly, the data used for the carbon returns are generally the carbon spot returns; secondly, two of the three explanatory variables used (CPU and GPR) have rarely been employed in studies due to how recent they are.

Dai et al. (2022) have explored the relationship between economic policy uncertainty (both European economic policy uncertainty and global economic policy uncertainty) and the volatility of European carbon spot returns. The results of that study show that the volatility of European carbon spot returns can be better forecasted by global economic policy uncertainty and that there is a positive correlation between GEPU and the volatility of European carbon spot returns.

This MFW strives to build upon that study by not only including two extra explanatory variables (CPU and GPR) in the GARCH-MIDAS model, but also using European carbon futures returns for the short-term high-frequency financial data instead.

The remainder of this MFW is organized as follows. Chapter 2 summarizes a detailed review of all the existing literature that is relevant for this study. Chapter 3 describes the data and methodology used. Chapter 4 presents the empirical results and analyses the implications of the GARCH-MIDAS model estimations. Finally, Chapter 5 concludes the MFW.

2. Literature Review

2.1. Carbon markets and the EU ETS

In an attempt to contain climate change and even reverse its effects, governments all around the world decided to cooperate and come up with measures that would reduce GHGs emissions (particularly carbon dioxide). After numerous agreements over the years, carbon markets were created as a mechanism to help put in practice those reductions (Raphael Calel, 2013).

Companies that are required to reduce GHGs emissions can buy or sell carbon credits or allowances in this type of financial markets, according to their own needs. One carbon credit unit (or allowance) represents a grant to emit a metric ton of CO_2 or an equivalent GHG (Kenton, 2024).

By allowing demand and supply forces to set a price on carbon emissions, companies are encouraged to reduce their carbon footprint. Way et al. (2022) argue that companies should take the initiative to research and implement more environmentally friendly practices and thus make the transition from fossil fuels to renewable energies. As a result, they will save a lot of money in the future, since they do not have to buy carbon credits anymore.

There are two main types of carbon markets: compliance markets and voluntary markets.

Compliance carbon markets are regulated at a national or international level. The most outstanding example is the EU ETS, which was established in 2005, and still is to this day the world's largest carbon market. The EU ETS operates on a cap-and-trade principle, where governments will every year decide on the limit of emissions allowed (European Commission, N.D.).

Companies that are obliged to participate in the EU ETS (for instance, companies in energy-intensive industry sectors, aviation and maritime transportation) receive or buy carbon allowances. If those companies emit less than their total annual allowance, they can sell the excess credits. If, on the other hand, they exceed their cap, they must purchase additional allowances, which creates a financial incentive to reduce emissions (European Commission, N.D.).

The EU ETS has evolved through four distinct phases and major reforms were introduced at the end of each stage in order to improve its effectiveness. Phase I, spanning from 2005 to 2008, served as a first trial. In this phase there was an over-allocation of allowances that resulted in a major drop of carbon prices (European Commission, N.D.).

In phase II (2008–2012) there was better alignment with the goals that were defined in the Kyoto Protocol, resulting in an introduction of a tighter cap and also allowing companies to use international carbon credits for compliance. However, the global financial crisis of 2008 led to an oversupply of allowances, causing prices to collapse once again (European Commission, N.D.).

In phase III (2013–2020), major structural reforms were put in place, such as the implementation of a single EU-wide cap and the introduction of auctions as the primary method for distributing allowances. Moreover, the Market Stability Reserve was created in order to address oversupply (European Commission, N.D.).

Finally, phase IV, which is still underway, started in 2021 and is expected to last until 2030. This current phase matches the EU ambitious climate goals under the European Green Deal (which targets climate neutrality by 2050). This phase includes further cap reductions and a proposed Carbon Border Adjustment Mechanism to prevent carbon leakage from non-EU countries (carbon leakage is the concept where organizations would transfer their production operations to other countries with less severe emission constraints).

The price of carbon allowances in compliance markets are influenced by numerous variables: regulatory changes, technological innovations, GDP and external shocks (such as energy price fluctuations).

Ellerman et al. (2010) have studied these variables in the context of trying to understand the effectiveness of the EU ETS in reducing GHGs emissions. They confirmed that the EU ETS had a significant impact in reducing GHGs emissions, especially since the beginning of Phase II. They argued that the major reason for this success was the gradual tightening of the cap on emissions allowed.

Over time, the EU ETS has become a model for other regions and many of its characteristics were taken into account during the implementation of similar markets in California, China and New Zealand (Hintermann et al., 2016).

To assure the stability of the EU ETS and swift decarbonization, maintenance of low volatility levels would be ideal. The topic of volatility in the EU ETS has been investigated across multiple studies in order to fully grasp the dynamics that drive this peculiar market.

In one of these studies, Guo et al. (2020) proved the existence of high volatility clustering in the EU ETS, meaning that large changes in prices tend to be followed by large changes, and small changes in prices are followed by small changes.

Also, Feng et al. (2011) argue that current carbon prices do not totally reflect past carbon price information, meaning that carbon markets are not a weak-form efficient market (weak form efficiency states that prices reflect all current information).

In addition to compliance markets, voluntary carbon markets allow companies to purchase carbon offsets to neutralize their emissions (Dawes et al., 2023). Carbon offsets are typically generated by projects that reduce or capture GHGs emissions (such as reforestation or renewable energy initiatives).

In contrast to compliance markets, participation in voluntary markets is not mandatory. However, with the recent boom of ESG practices, participation in these voluntary markets has increased in popularity (Kossoy et al., 2015). Wang et al. (2019) interestingly argued that compliance transactions affect long-term carbon price trends whereas non-compliance transactions (the ones that occur in voluntary carbon markets) mainly lead to short-term carbon price fluctuations.

2.2. Global Economic Policy Uncertainty

Although the preceding literature studies the carbon price dynamics from a micro perspective, to fully understand what drives the volatility of the European carbon market it is important to also look at the macro component. Economic uncertainty significantly influences the performance and stability of financial markets, including the European carbon market.

Bredin and Muckley (2011) have analysed the volatility on the EU ETS and found out that economic recessions lead to increased volatility in carbon prices. Economic downturns reduce industrial activity and consequently GHG emissions are also reduced. This has an impact on the demand for emission allowances, increasing the volatility of carbon markets.

The economic policy uncertainty index, designed by Baker et al. (2016), works as a good proxy to understand the state of the economy in terms of GDP and unemployment expectations. It is derived from a collection of newspapers and it is regularly updated on their website (http://www.policyuncertainty.com/).

Their findings suggest that periods of high economic policy uncertainty correspond to increased volatility in the European carbon market since companies and investors have difficulty in forecasting future regulatory and economic conditions.

As it was mentioned above, Dai et al. (2022) investigated the correlation between economic policy uncertainty (both European and global economic policy uncertainty) and the volatility of the European carbon market, by making use of the economic policy uncertainty index. The results of this study concluded that both European and global economic policy uncertainty have a positive correlation with the long-term volatility of European carbon spot return, with the global uncertainty having a bigger impact.

2.3. Climate Policy Uncertainty

To further expand on this last study and since carbon markets were developed to fight climate change, it would be relevant to also include a climate policy uncertainty index. Climate policy uncertainty perfectly captures the ambiguity around future regulatory changes or governmental policies regarding climate goals.

Su et al. (2024) study how companies tend to adjust their investment behaviours in response to uncertainties regarding climate regulation. They argue that companies tend to delay major investment decisions when there is a lack of clarity on future environmental policies, which in turn affects market sentiment and volatility.

In their perspective, governments should strive to reduce climate policy uncertainty and appropriately manage market expectations to minimise the impact of CPU on carbon prices. Like the economic policy uncertainty index, a climate policy uncertainty index was developed by Gavriilidis, K. (2021).

2.4. Geopolitical Risk

The geopolitical risk index is also included, to account for the external shocks that drive carbon prices.

Zheng et al. (2023) examined how geopolitical risk affected different types of financial markets: stock markets, foreign exchange markets, bond markets and even commodity markets. However, little research has been conducted regarding the direct relationship between geopolitical risk and carbon markets.

Ferrari et al. (2024) investigated the connection between oil markets and geopolitical risk. They state that a rise in geopolitical risk can result in economic slowdown, due to trade wars or conflicts. That contraction often leads to lower demand for energy, including oil. Moreover, conflicts in regions such as the Middle East, which exports large quantities of oil to other countries, can disrupt oil production and create supply constraints. This effect leads to an increase in oil prices.

The effects described on the above paragraph are relevant when connecting with the study performed by Tan et al. (2020). They found an indirect relationship on how geopolitical risk impacting the oil market can transfer to the carbon markets. In that study, they argue that carbon markets are deeply connected with other energy markets, particularly with the crude oil market, resulting in volatility spillovers between markets. In practical terms, sudden sharp changes in oil prices will have a substantial impact on carbon prices.

Similarly to GEPU and CPU indexes, Caldara and Iacoviello (2018) constructed the geopolitical risk index based on newspaper articles covering geopolitical tensions all over the globe.

This paper has the intention of fulfilling the present gap identified on the literature in order to address the research question: "*To what extent do different macroeconomic uncertainty indexes, specifically the GEPU, the CPU and the GPR, impact the volatility of carbon futures markets?*

3. Sample and Methodology

3.1. Sample Construction

This study utilizes daily data on carbon futures prices and monthly data for the macroeconomic uncertainty indices (GEPU, CPU and GPR), spanning a 10-year period from the 1st of January 2013 to 31st of December 2022. According to Stock et al. (1999), a 10-year period allows to draw significant conclusions, and it is especially relevant when conducting economic studies, as it allows for different business cycles to occur.

This study covers both phase III (2013-2020) and the beginning of phase IV (2021-2030) of the EU ETS development. Important to mention that phase III was a highly relevant period, as significant reforms were made. It is also often seen as the portion of historical data that better represents the current state of carbon markets, so it is the best in terms of quality of data. Additionally, during this time frame, at least three important events happened with implications at an economic, climatic and geopolitical standpoints: firstly, the 2015 Paris agreement; secondly, the COVID-19 Pandemic that began in 2020 and finally the Russian invasion of Ukraine in 2022 that is still ongoing.

The carbon futures data was retrieved from the (https://www.investing.com/) website. Regarding the futures contract specifications, the name of the product is EUA futures, with a contract size of 1 lot of 1000 emissions allowances (each emission allowance grants the right to emit one tonne of carbon dioxide or the same amount of other GHG). This product is traded in the ICE exchange and the currency is in euros. To prepare this data, in order to get it ready to implement it in the statistical model, the last step was to calculate the daily logarithmic returns, through the formula:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

where P_t represents the price of the carbon futures on day t.

The data for all the macroeconomic uncertainty indices (GEPU, CPU and GPR) was retrieved from the policy uncertainty website (https://www.policyuncertainty.com/).

3.2. Methodology

To appropriately model and predict carbon market volatility using GEPU, CPU and GPR as our explanatory variables, the GARCH-MIDAS model is employed. This statistical model is relatively modern and only over the last few years has been used to explore volatility dynamics. Due to that, the body of literature exploring its applications and possible refinements is not that vast. Nonetheless, this model, first proposed by Engle et al. (2013), allows to combine the short-term volatility dynamics captured by GARCH models with the impact caused by macroeconomic variables on the long-term volatility component.

GARCH models, introduced by Tim Bollerslev (1986), built on the ARCH models (Engle, 1982) and helped to more accurately predict the volatility of returns on financial assets. However, the GARCH models require the use of the same type of high-frequency data (usually daily), that is typical of stock returns, when using a variable to study the volatility. Thus, it does not allow the usage of low-frequency (monthly data), such as macroeconomic uncertainty indexes, to study the volatility of high-frequency price returns.

To overcome this issue, Ghysels et al. (2004) proposed mixed data sampling regression models. MIDAS regression models involve time series data with varying frequencies, eliminating the previous restriction of same frequency data.

Finally, Engle et al. (2013) manage to connect the two models, after laying the foundation on a previous paper (Engle and Rangel, 2008). In their findings, GARCH-MIDAS model performs better than any other of the previous models in predicting long-term volatility of the stock market.

In this MFW, the GARCH-MIDAS model was employed to study the impact of GEPU, CPU and GPR on the volatility of the European carbon futures market. Three GARCH-MIDAS models were constructed to assess the individual impact of each of the three uncertainties plus a combined model with all the variables.

The carbon futures return on day *i* in month *t* obeys the following process:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\, \varepsilon_{i,t}, \quad \forall i = 1, \ldots, \mathbb{N}_t \tag{2}$$

$$\varepsilon_{i,t} \mid \phi_{i-1,t} \sim \mathbb{N}(0,1) \tag{3}$$

where μ is the expected carbon futures return on day i in month t. Following Dai et al. (2022) and Wei et al. (2017), μ is set as a constant, since the average daily return of the carbon futures is fairly small. Also, N_{t} is the number of trading in month t and $\phi_{i-1,t}$ is the information set up to day $i-1$ of month t.

Any GARCH-MIDAS model is divided into two main parts: a short-term volatility component (GARCH) and a long-term volatility portion (MIDAS).

For every model, the short-term volatility component follows a standard GARCH (1,1) process:

$$g_{i,t} = (1-\alpha-\beta) + \alpha \frac{\left(r_{i-1,t} - \mu\right)^2}{\tau_t} + \beta g_{i-1,t} \tag{4}$$

where α (alpha) captures how much past squared errors influence current volatility and β represents the persistence of volatility over time (volatility clustering). Also, $\omega = (1-\alpha-\beta)$ (appearing in the tables as omega), represents the short-term intercept or baseline volatility level.

On the other hand, the long-term volatility component τ_t, obtained via MIDAS regression, is different for each model, depending on which uncertainty or combination of uncertainties we are analysing.

In this section, there was a departure from standard GARCH-MIDAS model, which typically incorporates a lag segment. For the GEPU model, the standard long-term volatility term would be expressed as:

$$\tau_t = m + \theta \sum_{k=1}^{k} \phi_k \, GEPU_{t-k} \tag{5}$$

where k is the number of lagged periods that contribute to the long-term volatility component. However, in this study, it was opted to remove the lags, allowing to understand the immediate impact of the macroeconomic uncertainties on the volatility of European carbon futures returns.

Therefore, we get the following equations for the individual models:

$$\tau_t = m + \theta\, GEPU_t \tag{6}$$

$$\tau_t = m + \theta\, CPU_t \tag{7}$$

$$\tau_t = m + \theta\, GPR_t \tag{8}$$

where m (constant) is the long-term intercept and θ (theta) is the slope, which represents the effect that each of the uncertainty's indices (GEPU, CPU and GPR) has on the long-term volatility of carbon futures returns. Intuitively, the corresponding long-term volatility component for the combined model is expressed as follows:

$$\tau_t = m + \theta_1\, GEPU_t + \theta_2\, CPU_t + \theta_3\, GPR_t \tag{9}$$

Finally, the total conditional variance is defined as:

$$\sigma^2_{i,t} = \tau_t\, g_{i,t} \tag{10}$$

It is important to point out that prior to the GARCH estimation, the logarithmic returns of the carbon futures were rescaled by multiplying them by 10, in order to enhance model convergence. Even though this procedure changes the magnitude of the coefficients estimated, it does not alter the volatility dynamics that the model is trying to study. That is, the relative relationships captured by the model (such as volatility clustering or the impact of each uncertainty) remain consistent, only their absolute magnitude changes.

Also, the decision to not incorporate a lagged structure on the GARCH-MIDAS model, which is the standard methodology, has to do with the fact that nowadays the spread of information is almost instantaneous.

Even though typical macroeconomic variables, such as GDP, inflation, interest rates and unemployment, have this lagged effect or delayed impact on financial markets (Gibson, 1970), the uncertainty indexes are just a collection of newspapers that contain certain terms alluding to risk.

Noticeably, the moment the newspaper or article comes out, that information is instantaneous and available to everyone that reads it. That can cause rapid and abrupt changes on market sentiment, with such fast and sophisticated algorithms making trading decisions nowadays.

Therefore, as the goal is to link these uncertainty indexes with volatility in the carbon futures market to study its relationship, the decision to not include the lags is logical. It also allows for future studies comparison with GARCH-MIDAS models that include the lagged structure.

4. Empirical Results

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics of the variables employed within the GARCH-MIDAS models. As it is possible to observe, the average of the logarithmic returns of the carbon futures is quite small. For that reason, the scaling by a factor of 10 was indeed required.

Also, important to point out that all macroeconomic indices (GEPU, CPU and GPR) display significant variability, expressed by the large standard deviation and range values. This suggests that they might significantly impact the long-term volatility of carbon future returns.

A portrayal of the sample data regarding these four variables is depicted in Figures 1-4.

TABLE 1 – DESCRIPTIVE STATISTICS

	Log Returns	**GEPU**	**CPU**	**GPR**
Mean	0,0010	197,6697	153,5957	100,2531
Median	0,0014	180,0516	138,3029	92,5960
Standard Deviation	0,0325	76,7634	74,6028	32,3364
Kurtosis	16,8249	-0,5081	0,2370	17,8747
Skewness	-1,0506	0,5719	0,7603	3,3134
Minimum	-0,4347	86,6765	38,0921	58,4208
Maximum	0,2405	431,6134	411,2888	318,9549
Count	2581	2581	2581	2581

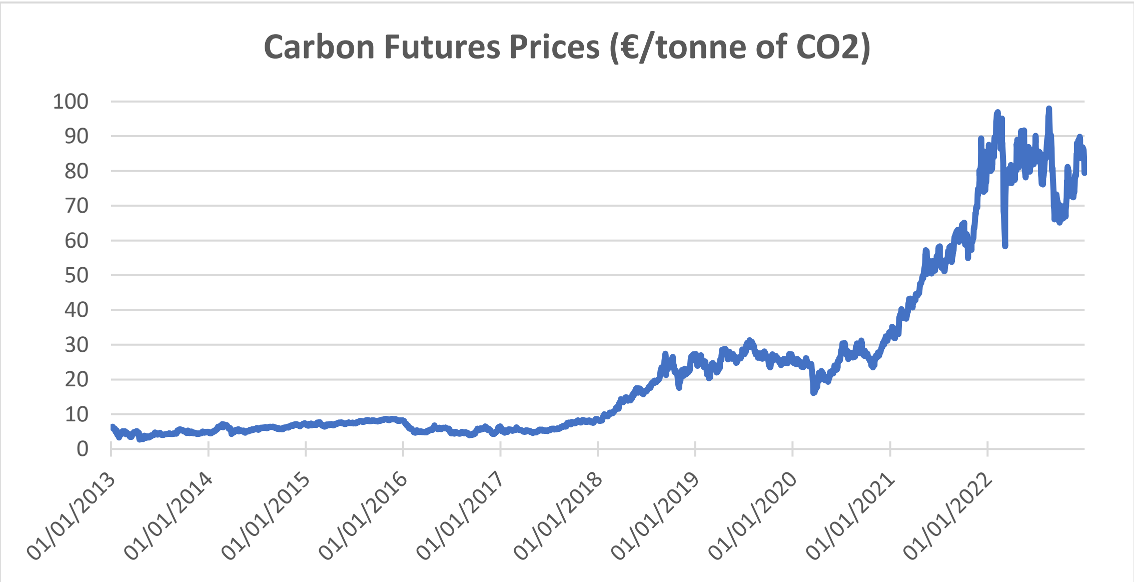

Figure 1 – Carbon futures prices in EU ETS. Source: ICE

4.2. Results from GARCH-MIDAS-GEPU model

The GARCH-MIDAS-GEPU model captures the effect of global economic policy uncertainty on the volatility of European carbon futures returns. As it is possible to observe in Table 2, all the coefficients are significant at least at 5% level (except omega, which is significant at 10% level), proving the model is valid.

Examining the alpha (0.1155), the value implies that about 11.55% of the current volatility is caused by the immediate effect of past squared shocks from the previous period. In essence, a significant market movement in any direction causes an increase in volatility for the following period.

For the beta (0.8759), the high value indicates a substantial level of volatility clustering, coherent with the results from the study performed by Guo et al. (2020). These clusters of volatility are illustrated in Figure 1. Noticeably, in the first couple of years there is low volatility, followed by moderate levels and then in the beginning of 2020 the volatility rises considerably, forming another large cluster in the last few years. As a side note, neither alpha nor beta estimations are affected by the scaling of the logarithmic returns.

Analysing the θ of this model, which in this case is GEPU, the value is positive, implying a positive effect on the long-term volatility of the carbon futures market in the EU. This is consistent with the findings of Dai et al. (2022).

For the following models, only the MIDAS regression component is discussed, since the coefficients estimated by the GARCH component remain the same in all models.

TABLE 2 – ESTIMATED RESULTS OF GARCH-MIDAS-GEPU MODEL

	Value	Std.	t stat.	P>|t|
μ	0.0154***	0.0050	3.1026	0.0019
alpha	0.1155***	0.0273	4.2351	0.0000
beta	0.8759***	0.0288	30.3631	0.0000
omega	0.0016*	0.0009	1.8826	0.0598
constant	0.2879***	0.0077	37.3331	0.0000
GEPU	0.0001**	0.0000	2.2093	0.0272
AIC	-2756			

Note: ***, **, * indicate significance level at 1%, 5% and 10%, respectively.

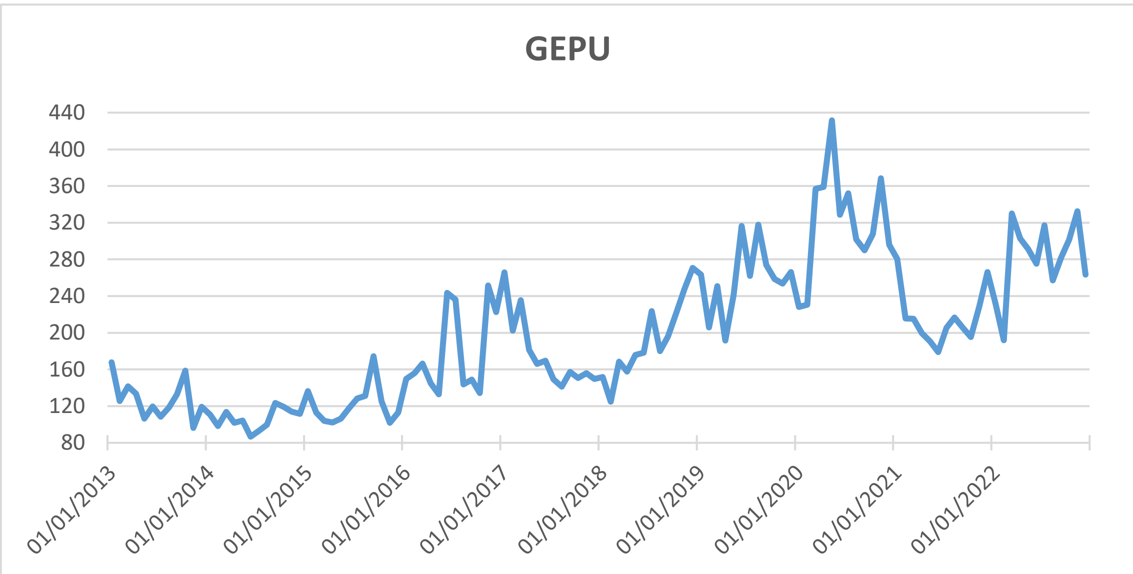

Figure 2 – Global economic policy uncertainty index

4.3. Results from GARCH-MIDAS-CPU model

The GARCH-MIDAS-CPU model connects the long-term volatility of the European carbon futures returns with the climate policy uncertainty index. Observing the values from Table 3, all the estimated coefficients are significant at 1% level (except omega).

The coefficient of the CPU variable is a negative number, indicating that a high degree of climate policy uncertainty results in a negative impact in the long-term volatility of the carbon futures returns. In essence, an increase in CPU will result in less volatility in the carbon futures returns. There are a few possible reasons for this to happen.

First, high CPU could mean that the government has not disclosed its next steps regarding EU ETS regulations and reforms. Because of that, traders and speculators have less information on the direction that the price of futures contracts will take in the following months and therefore decide to reduce trading activity.

Second, the opposite could also be true. During periods of high stability (low CPU), the market becomes more speculative and risk-seeking behaviour takes place. Traders believe that they have all the information needed to determine in which direction the market will go next because the authorities have been transparent about the next measures they will take. This is consistent with the findings of Su et al. (2024).

Comparing the AIC (a metric used to assess model goodness of fit, with lower AIC indicating better model fit) of the GARCH-MIDAS-GEPU model (-2756) with this GARCH-MIDAS-CPU (-2760), it is observed that the GARCH-MIDAS-CPU model holds the stronger explanatory ability in describing the long-term volatility of the European carbon futures market.

TABLE 3 – ESTIMATED RESULTS OF GARCH-MIDAS-CPU MODEL

	Value	Std.	t stat.	P>|t|
μ	0.0154***	0.0050	3.1026	0.0019
alpha	0.1155***	0.0273	4.2351	0.0000
beta	0.8759***	0.0288	30.3631	0.0000
omega	0.0016*	0.0009	1.8826	0.0598
constant	0.3212***	0.0064	50.2951	0.0000
CPU	-0.0001***	0.0000	-3.0160	0.0026
AIC	-2760			

Note: ***, **, * indicate significance level at 1%, 5% and 10%, respectively.

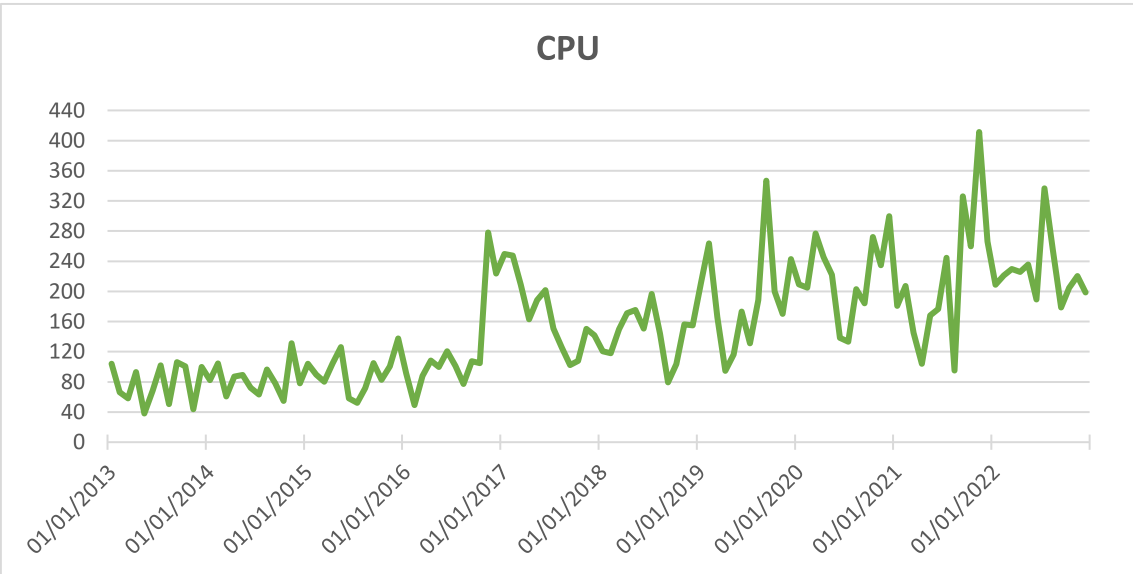

Figure 3 – Climate policy uncertainty index

4.4. Results from GARCH-MIDAS-GPR model

The GARCH-MIDAS-GPR model tries to assess if geopolitical risk impacts the long-term volatility of European carbon futures returns. Once again, looking at the values from Table 4, all the estimated coefficients besides omega are significant at least at 5% level.

The estimation of the theta in this model (GPR) is positive, indicating that an increase in geopolitical risk results in an increase in volatility of the carbon futures market in the EU ETS. This result is in line with the findings of Ferrari et al. (2024) and Tan et al. (2020).

When looking at comparative metrics, the GARCH-MIDAS-GPR model has a slightly higher AIC (-2755) than the previous two models (-2760 and -2756), meaning a slightly lower explanatory ability.

TABLE 4 – ESTIMATED RESULTS OF GARCH-MIDAS-GPR MODEL

	Value	**Std.**	**t stat.**	**P>|t|**
μ	0.0154***	0.0050	3.1026	0.0019
alpha	0.1155***	0.0273	4.2351	0.0000
beta	0.8759***	0.0288	30.3631	0.0000
omega	0.0016*	0.0009	1.8826	0.0598
constant	0.2862***	0.0091	31.4575	0.0000
GPR	0.0002**	0.0001	2.0398	0.0415
AIC	-2755			

Note: ***, **, * indicate significance level at 1%, 5% and 10%, respectively.

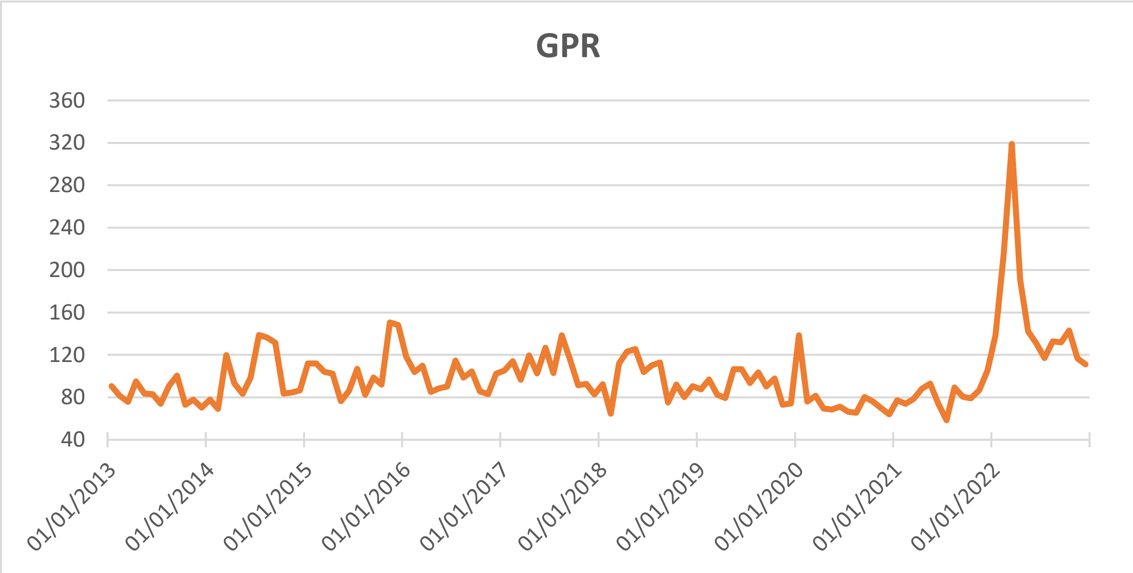

Figure 4 – Geopolitical risk index

4.5. Results from GARCH-MIDAS-Combined model

Finally, the GARCH-MIDAS-Combined model was employed to analyse the collective impact of the three macroeconomic variables on the long-term volatility of the carbon futures in the EU ETS. Its goal was to assess if by combining all three uncertainties in one specific model it would be possible to reach a better fit compared to the models with individual explanatory variables.

Looking at Table 5, all estimated coefficients are statistically significant at least at 5% level (excluding omega).

Also, all the estimated coefficients of the three explanatory variables (GEPU, CPU and GPR) kept the same sign they had in each of the individual models, respectively. This represents robustness and reinforces the model's validity.

The increase in the estimated coefficients of the variables GEPU and CPU in the combined model when compared to the individual models (0.0003 vs 0.0001 for GEPU) and (-0.0003 vs -0.0001 for CPU) could be due to the influence of multicollinearity. To assess this, the VIF of each of the explanatory variables was computed (1.92 for GEPU, 1.93 for CPU, 1.01 for GPR), revealing VIFs well below 5 and disregarding multicollinearity as an issue.

Regarding the explanatory power of the model, the AIC value of -2798, which is substantially lower than any of the other three models (-2755, -2760, -2756), indicates that the GARCH-MIDAS-Combined model is the one that performs better in explaining the volatility of the European carbon futures market.

TABLE 5 – ESTIMATED RESULTS OF GARCH-MIDAS-COMBINED MODEL

	Value	**Std.**	**t stat.**	**P>|t|**
μ	0.0154***	0.0050	3.1026	0.0019
alpha	0.1155***	0.0273	4.2351	0.0000
beta	0.8759***	0.0288	30.3631	0.0000
omega	0.0016*	0.0009	1.8826	0.0598
constant	0.2747***	0.0112	24.5110	0.0000
GEPU	0.0003***	0.0000	6.0307	0.0000
CPU	-0.0003***	0.0001	-6.5211	0.0000
GPR	0.0002**	0.0001	2.4579	0.0140
AIC	-2798			

Note: ***, **, * indicate significance level at 1%, 5% and 10%, respectively.

4.6. Discussion of the Results

The results from the GARCH-MIDAS models show that the estimated short-term volatility of the European carbon futures market has high volatility clustering, which is consistent with Guo et al. (2020) findings.

Furthermore, all three macroeconomic uncertainty indexes are statistically significant and correlate with the long-term volatility of the carbon futures returns on the EU ETS.

GEPU and GPR appear to cause a positive impact on the long-term volatility whereas the CPU displays a negative correlation.

Therefore, the results of this study can provide valuable insights to policymakers, investors and companies obliged to participate in the EU ETS compliance market. For instance, these companies can predict market volatility in the EU ETS by looking at the uncertainty indexes and can hedge their position by purchasing futures contracts of EUAs.

The persistence of high uncertainty is especially undesirable in carbon markets. Su et al. (2024) and Adediran et al. (2023) claim that global uncertainty postpones investment decisions, thus delaying decarbonization and the transition to clean and renewable energy alternatives.

Accordingly, governments and international entities should strive to be transparent and mitigate uncertainty in order to reach carbon neutrality goals.

5. CONCLUSION

This study examines the impact of uncertainty indexes on the volatility of the carbon futures returns in the EU ETS. By including GEPU, CPU and GPR to study the volatility dynamics, the GARCH-MIDAS methodology helps in assessing both short-term and long-term volatility impacts and their source.

The results from the GARCH-MIDAS models provided several insights. First, all three uncertainty indexes significantly affect long-term volatility of European carbon futures returns.

An increase in GEPU results in a rise in the long-term volatility (positive coefficient in both individual and combined GARCH-MIDAS model), which is coherent with Dai et al. (2022).

A rise in CPU negatively impacts the long-term volatility (negative coefficient in both individual and combined GARCH-MIDAS model), proving Su et al. (2024) assumptions to be accurate.

A surge in GPR leads to an increase in the long-term volatility of the carbon futures returns (positive coefficient in both individual and combined GARCH-MIDAS model), which is aligned with Ferrari et al. (2024) and Tan et al. (2020) findings.

Second, the premise by Guo et al. (2020) that the EU ETS has high levels of volatility clustering also proved to be valid, as it is possible to infer by the high beta value.

Lastly, the GARCH-MIDAS-Combined model proved to have the greatest explanatory power for the long-term volatility of carbon futures returns.

Nonetheless, there are certain limitations regarding this study. First and foremost, the lack of additional analysis and robustness tests. Such analysis could include an in-sample vs out-of-sample testing or even loss functions (such as the root mean squared error). Secondly, this study was limited to only three uncertainty indexes. The inclusion of additional variables or another mixing sample would prove to be relevant.

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APPENDICES

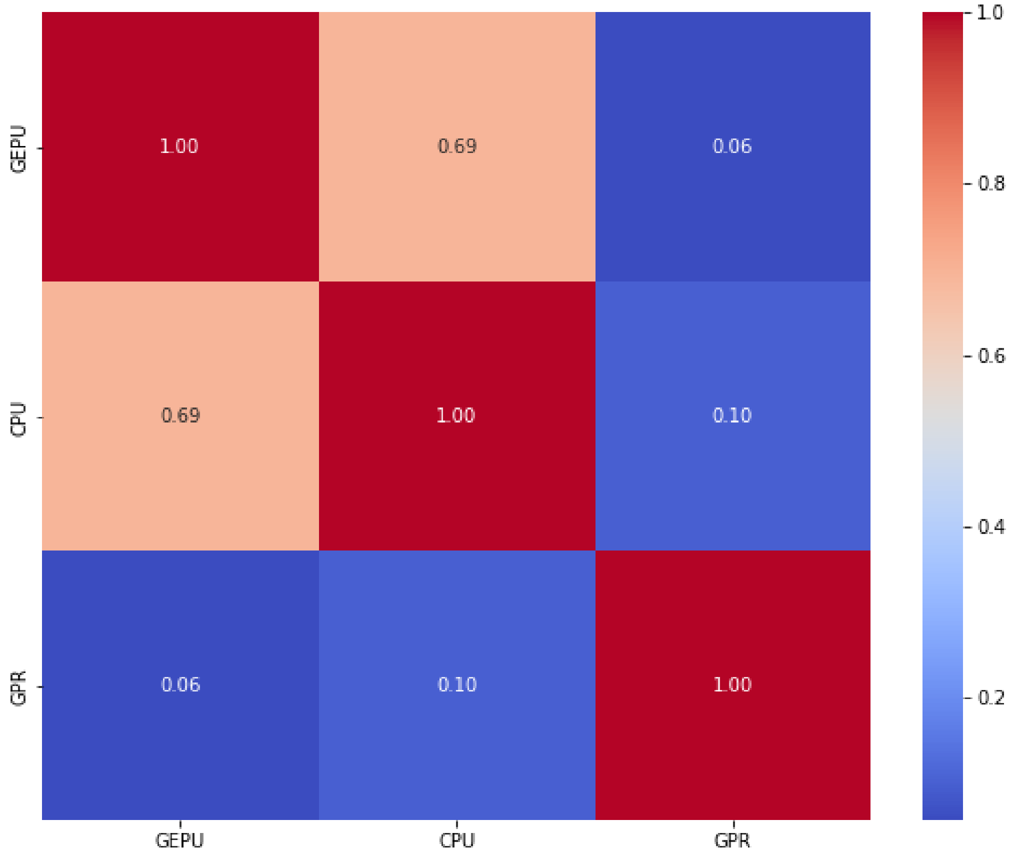

Figure A.5 – Correlation Matrix

TABLE A.6 – VARIANCE INFLATION FACTOR (VIF)

Variable	VIF
GEPU	1.92
CPU	1.93
GPR	1.01

AI DISCLAIMER

This project was developed with strict adherence to the academic integrity policies and guidelines set forth by ISEG, Universidade de Lisboa. The work presented herein is the result of my own research, analysis, and writing, unless otherwise cited. In the interest of transparency, I provide the following disclosure regarding the use of artificial intelligence (AI) tools in the creation of this project:

I disclose that AI tools were employed during the development of this thesis as follows:

- AI-based research tools were used to assist in literature review and data collection.
- AI-powered software was utilized for data analysis and visualization.
- Generative AI tools were consulted for brainstorming and outlining purposes. However, all final writing, synthesis, and critical analysis are my own work. Instances where AI contributions were significant are clearly cited and acknowledged.

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I understand the importance of maintaining academic integrity and take full responsibility for the content and originality of this work.

15th October 2024,

Ricardo Barreiros