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February 2025

Working paper No. 2025 – 02

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This version 17 January 2025

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Abstract: This study examines the positions of carbon traders in the European Carbon Futures Market and their predictive power, revealing distinct roles among participants. *Investment Firms and Credit Institutions* predominantly take short positions, serving as liquidity providers for *Compliance Entities and Other Non-financial* participants, who mainly hold long positions. Correlation analysis shows that as the number of entities grows, carbon volatility decreases or remains stable, but never increases. In the short term, trader positions have no impact on carbon returns or the bid-ask spread. However, shifts in the net positions of *Investment Firms and Credit Institutions* and *Compliance Entities and Other Non-financial* traders increase carbon market volatility over the following two weeks. Finally, while the net positions of *Investment Funds* and *Other Financial Institutions* significantly forecast long-term carbon returns, *Compliance Entities* and *Other Non-financial* participants offer no predictive insight, despite their considerable compliance-driven market activity.

Keywords: Commitments of Traders reports, EUA, EU ETS, price, volatility

Acknowledgements: The authors also acknowledge the editorial assistance provided by Neil Larsen. Sole responsibility for the content of this work lies with the authors.

Funding: This research has been supported by the Spanish Ministry of Science and Innovation and the European Regional Development Fund (Grant PID2023-153128NB-I00 funded by MCIU/AEI/10.13039/501100011033/FEDER, UE).

Highlights

- Investment Firms hold short positions, while Compliance Entities mostly hold longs.
- More entities reduce or stabilize carbon market volatility, but never increase it.
- Trader positions have no impact on carbon returns or the bid-ask spread.
- Volatility rises with Investment Firm shorts and Compliance Entity longs.
- Only Inv. Funds & Other Fin. Inst. reliably predict long-term carbon price changes.

1. Introduction

A common focus in the literature on derivatives markets is the influence of the trading activity of financial players on price dynamics, volatility, and market liquidity. In particular, when non-commercial traders account for a significant portion of futures and options trading, concerns about the proper functioning of derivatives markets and their impact on spot markets are often raised in the media, regulatory reports, and academic studies. The European Carbon Futures Market (ECFM) has faced similar scrutiny. The sharp rise in carbon prices since 2021, coupled with the growing participation of financial institutions in the carbon market, has reignited debate about their role in the European Union Emissions Trading Scheme (EU ETS) and the impact of their trading activities on carbon prices, volatility, and market liquidity.

Quemin and Pahle (2023) argue that while financial agents perform several essential market functions, excessive speculation in the ECFM can undermine market stability by increasing price volatility, creating price bubbles, or enabling manipulation. They further emphasize that these concerns are particularly acute in politically created markets, such as the carbon allowance market. Indeed, the European Securities and Markets Authority (ESMA) highlighted in its preliminary report on emission allowances and their derivatives (ESMA, 2021) that the number of position holders in European Union Allowances (EUA) futures grew more rapidly in the category of investment firms compared to compliance entities and other non-financial participants between 2018 and 2021.

In response, the European Commission requested ESMA to assess whether certain trading behaviors warranted additional regulatory measures. In its final report on emission allowances and their derivatives, ESMA (2022a) concluded that data analysis did not reveal any significant abnormalities or fundamental issues with the functioning of the EU carbon market from a financial supervisory perspective. In addition, ESMA (2024) found that position holders in the derivatives markets align with the annual ETS compliance cycle, with non-financial firms holding long positions and financial entities holding short positions.

Since January 2018, ESMA has published weekly Commitments of Traders (COT) reports in accordance with Article 58(1)(a) of Directive 2014/65/EU (Markets in Financial Instruments Directive II). These reports provide detailed information for each participant category, including the number of traders and the long and short positions they hold. These data present new opportunities to better understand the impact of trader positions on the ECFM.

Our contribution to the literature is twofold. First, to the best of our knowledge, no prior research has investigated the potential to predict carbon prices based on trader positions. Second, no previous studies have examined the impact of trading positions on EU carbon prices, volatility, and bid-ask spreads using Commitments of Traders (COT) data. Consequently, the results presented here offer the first empirical evidence in the context of the ECFM.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature. Section 3 describes the main features of the EU ETS and details the carbon data used in this study. Section 4 provides a preliminary analysis of the positions held by carbon market participants. Section 5 examines the price predictability of these positions in both the short and long term. The final section presents the main conclusions of the paper.

2. Review of Literature

COT report data has been widely used to investigate various aspects of derivatives markets, including the ability of futures traders across different markets to consistently generate profits. On the one hand, several studies suggest that trader positions have negligible or low predictive power for forecasting prices. For example, Hartzmark et al. (1991) analyze nine U.S. agricultural and financial futures markets and conclude that traders' success is primarily due to luck rather than predictive skill. While some traders appear to possess superior forecasting abilities, the study finds that fewer traders exhibit significant skill than would be expected by chance, while more traders underperform than would be expected by random trading. Moreover, forecasting ability tends to be inconsistent over time; traders who initially perform well often regress to average performance in later periods. Thus, trader performance is largely attributable to chance.

Similarly, Merkoulova (2020) uses a nonparametric methodology to investigate the forecasting ability of speculators in energy futures markets. Her findings reveal that, while speculators can achieve profitable positions, the magnitude of this effect is smaller than that observed in agricultural markets. Furthermore, the returns of energy speculators are explained by the presence of risk premiums rather than their forecasting ability.

On the other hand, several studies provide empirical evidence of significant forecasting ability in predicting futures prices. Leuthold et al. (1994) analyze data from large traders in the U.S. frozen pork bellies futures market and find that their returns are not random. A subset of elite traders exhibits substantial forecasting ability, consistently anticipating price movements and correctly positioning themselves during significant price changes. This suggests that some traders accumulate experience and knowledge that enable them to generate considerable profits. Similarly, Buchanan et al. (2001) apply a method to predict the direction of spot price movements in the U.S. natural gas market for the following month, based on the positions of market participants in the futures market. Their findings reveal that the positions held by large speculators provide valuable insights for predicting both the direction and magnitude of future price changes.

Furthermore, Wang (2001) examines the forecasting ability of a trader position-based sentiment index in predicting future prices across six major U.S. agricultural futures markets. By constructing an investor sentiment index based on current aggregate positions and historical data, the study finds that the sentiment of large speculators is effective in forecasting price continuations, while the sentiment of large hedgers successfully predicts price reversals. In contrast, small trader sentiment has little predictive power, and large speculators do not demonstrate superior forecasting ability. This highlights the distinct predictive capabilities of different types of traders in futures markets. Finally, Dunbar and Owusu-Amoako (2023) assess how the trading behavior decisions of futures market participants can serve as predictors of cryptocurrency returns. Their findings suggest that cryptocurrency returns are influenced by the trading behavior of speculative retail traders. Specifically, net-short trading behavior (calculated as the total number of short positions minus the number of long positions held by these traders) emerges as a strong and statistically significant predictor of cryptocurrency returns.

COT report data is also commonly used to ascertain whether changes in trader positions significantly affect short-term returns and volatility, and vice versa. In this regard, some studies have found a significant impact of trader activity on various market variables. Bu (2011), for instance, examines the relationship between speculative trader positions and returns in crude oil futures markets, finding that changes in speculative positions significantly affect crude oil prices. Granger causality tests reveal that returns precede speculative positions, suggesting that non-commercial, or managed money, traders, behave as trend followers. Mayer et al. (2017) investigate the lead-lag relationship between the futures trading activity of commercial and non-commercial participants and the cash prices and volatility of major metal commodities. Contrary to prevailing assumptions, they observe that commercial traders and long positions exert a more substantial influence on price levels and volatility than non-commercial traders. Furthermore, their findings indicate that there is also strong evidence that commodity prices and volatility significantly drive changes in trader positions. Building on these findings, Kang et al. (2020) demonstrate that position changes are significantly correlated with both contemporaneous and lagged returns of commodity futures. However, the direction of the observed correlations differs between the two groups: non-commercial traders, who act as momentum traders, exhibit correlations with returns that are opposite in sign to those observed for commercial traders, who tend to behave as contrarians.

However, other studies have found no substantial impact of trader positions on price levels and volatility. For example, Sanders et al. (2004) and Sanders et al. (2009) analyze COT data for crude oil, unleaded gasoline, heating oil, and natural gas futures contracts, as well as for ten agricultural futures markets, respectively. Both studies conclude that traders' net positions are not generally effective in predicting market returns. Mutafoglu et al. (2012) employ Granger causality tests to assess the relationship between trader positions and market prices in precious metal markets. Their findings indicate that while market returns significantly influence trader positions across all trader types, traders' net positions do not typically predict market returns.

In the context of the carbon futures market, the extant literature reveals a lack of research in this area. To our knowledge, the only study that addresses this issue is by Shi and Zhai (2024), which focuses on the California carbon allowance futures market. Utilizing a mixed-frequency vector autoregressive model, the authors find that changes in the trading positions of commercial and non-commercial participants influence carbon futures returns. The study reveals that commercial participants, who are typically hedgers, tend to increase their net short positions in the current week after observing a positive futures return in the previous week. Conversely, non-commercials, or speculators, tend to increase their net long positions. This behavior is analogous to that observed in other commodity futures markets, where commercials act as contrarians, while non-commercials exhibit momentum trading behavior.

3. Market structure and data

3.1. EU ETS specificities

The EU ETS is characterized by its status as a politically forged market that emerged in 2005. In this market, supply is predetermined by the regulator (the European Commission), thereby rendering it completely inelastic. Therefore, the system's efficacy hinges on political decisions, leading to significant regulatory uncertainty. This, in turn, has affected EUA prices, as evidenced by the works of Mansanet-Bataller and Pardo (2009), Koch et al. (2016), Fan et al. (2017), Kalantzis et al. (2024), among others. The objective of each regulatory change introduced by the European Commission has been to strengthen the European Union's main policy against climate change by providing the EU ETS with the requisite instruments to achieve its objectives, which can be encapsulated as follows: (i) reducing CO_2 emissions, (ii) promoting clean technologies, and (iii) fostering energy efficiency, by setting an appropriately high price on European carbon emissions.

Specifically, according to Bua et al. (2021), the main regulatory changes during the four phases of its operation are related to the following issues: (i) the scope and sectors of application; (ii) the method of allowance distribution (auction or free allocation); (iii) the supply of allowances (cap) in the emissions system; and (iv) the creation of the Market Stability Reserve (MSR).

In this way, the EU ETS regulates greenhouse gas emissions from approximately 10,000 installations within the energy and manufacturing sectors, in addition to aircraft operators within the EU and on flights to Switzerland and the UK. As of January 2024, the scope of the program has expanded to encompass emissions from maritime transport. Regarding the distribution of allowances, while EUAs were initially allocated at no cost, auctioning has been the prevailing method in the EU ETS since 2013. It is estimated that up to 57% of general allowances will be auctioned during the 2021-2030 period. Concerning the emissions cap, it has been progressively tightened since the scheme's inception. In Phase III (2013-2020), a reduction trajectory for annual European emissions was set at a rate of 1.74%, which was increased to 2.2% in Phase IV (2021-2030). Finally, it is worth noting that until 2018, prices were considered too low to effectively address climate change. This led to the introduction of the MSR at the conclusion of Phase III, a mechanism designed to regulate the imbalance between the supply and demand of emission allowances.[1]

3.2. Carbon markets

The EU ETS is divided into primary and secondary markets for EU Allowances (EUAs), with trading organized as follows: (i) Member States auction their EUAs, often collectively and primarily through the European Energy Exchange (EEX), which is regulated by Germany; (ii) each contract represents one allowance, with a minimum lot size of 500 EUAs; and (iii) allowances are subsequently traded in various secondary markets, the most significant of which is the Intercontinental Exchange (ICE). Following the UK's departure from the European Union in June 2021 (Brexit), ICE operations migrated to the Dutch-based ICE Endex. Additional

[1] For more details on the EU ETS see https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets_en (last accessed in November 2024).

trading platforms include the EEX and Nasdaq Oslo. Since Brexit, UK ETS allowances have been traded on ICE Futures Europe.

Various contract types are traded in the secondary European carbon market, including: (i) spot contracts with daily expiry, also known as “daily futures”; (ii) futures contracts with varying maturities; and (iii) options on EUA futures. Derivatives contracts are set at 1,000 allowances (equivalent to 1,000 tonnes of CO_2). Additionally, as of April 22, 2024, ICE listed a mini futures contract with a lot size of 100 allowances. Notably, ICE December futures contracts are central to most ECFM transactions and are widely considered the benchmark for European carbon prices due to their influence on market pricing.

In Figure 1, we present the evolution of ICE’s EUA futures prices and trading volumes from January 19, 2018, to December 15, 2023. It is evident that EUA prices have increased significantly, rising from €8 per tonne at the start of 2018 to approximately €100 per tonne by February 2023.

(Please, insert Figure 1)

This period is characterized by the following: (i) a price drop in March 2020 due to COVID-19 lockdowns; (ii) a price rally in 2021, during which approximately forty price records were set, driven by the EU’s “Fit for 55” greenhouse gas emissions reduction target; (iii) an all-time high of nearly €100, the price at which the December 2023 futures contract settled in February 2023; and (iv) a price decline after the February 2023 peak, caused by two main factors: an economic slowdown leading to reduced energy consumption, and an increase in EUA volumes auctioned as a mechanism to accelerate renewable energy programs.

Bua et al. (2021) attribute the 2020-2021 price increase to three key factors: increased energy demand in Europe due to adverse weather conditions, the reopening of the global economy following COVID-19 restrictions, and market speculation anticipating further price rises. In contrast, Refinitiv’s Carbon Market Report (2023) suggests that 2022 prices were primarily driven by EU ETS policy developments closely tied to energy market fundamentals. Finally, ESMA (2024), attributes 2023 price movements to economic factors such as weak industrial activity, declining natural gas prices, and political decisions to auction additional allowances to fund renewable energy programs.

3.3. Carbon data

The Markets in Financial Instruments Directive (MiFID) II specifies in point (11) of Section C in Annex I of Directive 2014/65/EU that emission allowances are classified as a distinct category of financial instruments. In addition, point (4) of the same section and annex includes derivatives based on emission allowances.[2,3] This means that emission allowance derivatives are not required to maintain position limits, but are subject to weekly position reporting of commitments of EUA traders to ESMA.[4]

Accordingly, since January 2018, ESMA has published weekly COT reports in accordance with Article 58(1)(a) of Directive 2014/65/EU (MiFID II). This provision stipulates that Member States are responsible for ensuring that the commitments of traders participating in emissions allowances are published on a weekly basis. This applies to all market participants that operate a trading venue within this market. Specifically, Article 58(4) requires that the classification of participants holding positions in an emission allowance must be based on the nature of their main business. The following possibilities are delineated: (a) *Investment Firms or Credit Institutions*; (b) *Investment Funds*; (c) *Other Financial Institutions*, including insurance undertakings and reinsurance undertakings; (d) *Commercial Undertakings*, and (e) *Operators with Compliance Obligations under Directive 2003/87/EC*.[5] Note that the first three categories (a, b and c) are financial institutions.

[2] For the consolidated version, see https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32014L0065 (last accessed in November 2024). For the EU ETS legal perspective, see https://www.emissions-euets.com/ (last accessed in November 2024).

[3] Note that the classification of the EUA as a financial asset on the spot market may initially appear contradictory, given its tendency to behave like a commodity, i.e. an input in the production process of other goods or services. In fact, some of the key characteristics of EUAs contribute to their categorization as a special asset class (Medina and Pardo, 2023). In contrast to physical commodities, the storage cost of allowances is minimal, and there are no apparent advantages to holding them. Moreover, unlike other financial assets, the real underpinning of the scheme, namely the needs of compliance obligations entities, can be estimated (see Berta et al., 2017).

[4] A position limit is defined as the maximum position in futures contracts that a trader can hold on one side of the market.

[5] According to ESMA (2022b, question 22), members and participants of trading venues are expected to apply their knowledge and judgment effectively to categorize both their own activities and those of their clients accurately when providing information to support the preparation of weekly reports by the venues.

In addition, for each category of participant, this report provides not only the number of individuals, but also (i) the aggregate positions, (ii) the number of long and short positions, and (iii) the percentage of the total open interest. While it is important to emphasize that COT reports aggregate open interest across all contracts and maturities with a sufficient number of position holders for both futures and options, it is noteworthy that ESMA (2024, p.10) states that futures transactions accounted for 99% of total transactions and 81% of trading volumes in 2023.

To examine the role of carbon market participants, we have used weekly position data reported to ESMA by both ICE Endex and EEX, as well as data obtained from Refinitiv. The weekly data is collected from Friday to Friday, as reports are published each Friday. It is important to note that, as described in ESMA (2022a) and Quemin and Pahle (2023), ex-post amendments to previously released weekly reports occur regularly due to classification and reporting issues. To conduct our analysis, price and COT report data were collected from Refinitiv on June 2, 2024. Weekly position reports for EUA futures were available on ICE Futures Europe from January 19, 2018, until early June 2021. Since June 2021, these reports have been available on ICE Endex. Notably, the reports for June 11 and 18, 2021, are absent from the ESMA database. For EEX, the database begins on January 5, 2018, and both databases end on December 15, 2023. While ICE Endex remains the largest marketplace for EUAs and their derivatives, EEX now accounts for approximately one-quarter of the market in terms of open futures positions.

4. Preliminary analysis

4.1. Descriptive Statistics

However, the following provision is included in the guidance: "*Investment firms or credit institutions includes banks and other firms regulated under MiFID II. Investment funds are those entities holding investments directly in the commodity derivatives market as a form of collective investment scheme, including hedge, pension and exchange-traded funds. Other financial institutions are those financial firms not falling within any of the other categories including pension funds. Commercial undertakings are non-financial entities using commodity derivatives (for example firms using those markets to hedge the risk they directly incur from dealing in physical commodities such as producers, end users, processors, manufacturers, shippers and merchants). Operators with compliance obligations under the EU ETS Directive include commercial airlines, entities in power and heat generation, energy-intensive industry sectors including oil refineries, steel works, production of iron, aluminium, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids and bulk organic chemicals.*"

COT reports provide valuable insights into trading behaviors and shifts in participant activity, making them an essential tool for analyzing dynamics within the ECFM. Figure 2 illustrates the percentage of long and short positions held by different categories of carbon market participants on both ICE Endex and EEX. The categories include *Investment Firms and Credit Institutions* (IFCI), *Investment Funds* (IF), *Other Financial Institutions* (OFI), *Commercial Undertakings* (CU), and *Operators with Compliance Obligations*. (OC). The data indicate that the majority of long positions are held by *Commercial Undertakings* (CU) and *Operators with Compliance Obligations* (OC), accounting for 80.7% of the total open interest. In contrast, the majority of short positions are held by *Investment Firms and Credit Institutions* (IFCI), *Investment Funds* (IF), and *Other Financial Institutions* (OFI), which collectively represent 83.2% of the total. This distribution suggests that, in contrast to the findings of Brunetti and Reiffen (2014) on futures markets for physical commodities and Shi and Zhai (2024) on the California carbon allowance futures market, long positions held by compliance entities and other non-financial operators in the ECFM (i.e., *Commercial Undertakings* and *Operators with Compliance Obligations*) are offset by short positions taken by financial players. As noted by ESMA (2024), this aligns with the compliance cycle of the EU ETS.

(Please, insert Figure 2)

Table 1 presents the descriptive statistics of carbon returns, volatility, net positions, and the number of entities for each group of participants in both the ICE Endex and EEX markets. We calculate weekly returns as $R_t = \log(P_t/P_{t-1})$, where P_t is the price level at week *t*. The weekly volatility (σ_t) has been calculated using the measure proposed by Parkinson (1980):

$$\sigma_t = \sqrt{\frac{1}{4\log 2}\left(\log P_{H,t} - \log P_{L,t}\right)^2}$$

where $P_{H,t}$ and $P_{L,t}$ are the highest and lowest futures prices observed during week *t*. Finally, the net positions have been calculated as the difference between long positions and short positions, expressed as a percentage.

(Please, insert Table 1)

As shown in Table 1, the net positions of *Investment Firms and Credit Institutions*, reflected by the mean, median, maximum, and minimum values, are negative. This indicates that, despite rising prices, these entities predominantly hold short positions in the European carbon market on a weekly basis. This behavior suggests that these financial players engage in short positions to execute carry trades in the carbon futures markets, seeking to profit from price differences between the auction and futures markets. Note that ESMA (2024, p. 9) indicates that 80% of auctioned EUAs were purchased by entities not directly subject to compliance obligations under the EU ETS, such as *Investment Firms and Credit Institutions*. Consequently, it is not unexpected that participants in both primary and secondary markets include not only compliance entities but also financial traders.

The remaining categories of financial participants, *Investment Funds* and *Other Financial Institutions*, exhibit a maximum net positive position, while their minimum positions are negative. This pattern indicates that they hold both long and short positions in the ECFM, suggesting that their strategies align with using EUAs as a portfolio diversifier, a hedge, or a safe-haven asset (see Palao and Pardo, 2022).

In contrast, *Commercial Undertakings* and *Operators with Compliance Obligations under Directive 2003/87/EC* display positive values for mean, median, maximum, and minimum, reflecting their predominant long positions in the carbon futures market. Notably, secondary carbon markets play a crucial role for compliance entities, allowing them to purchase allowances without participating in the primary auction. This approach facilitates their adherence to the Directive's requirements.

In general, the above results stand in sharp contrast to those of Shi and Zhai (2024) for the California carbon allowance futures market. They observe that, although both commercial and non-commercial traders take weekly long and short positions, the average net long position is negative for commercial traders and positive for non-commercials.

The preceding results are based on data from ICE Endex, but similar findings are observed for EEX. However, it is noteworthy that *Investment Funds* and *Other Financial Institutions* are largely absent from EEX, with no long or short positions on 99% and 96% of the days, respectively. In addition, *Investment Firms and Credit Institutions* exhibit only minimal participation. For these reasons, the remainder of the paper will focus on ICE Endex data.

Furthermore, both *Commercial Undertakings* and *Operators with Compliance Obligations* in the ICE market show a structural break on January 8, 2021. To address this, we constructed the "*Compliance Entities and Other Non-financials*" (CO) series, which combines both *Commercial Undertakings* and *Operators with Compliance Obligations under Directive 2003/87/EC*.[6] Note that in the ESMA (2022a) report, *Commercial Undertakings* and *Operators with Compliance Obligations under Directive 2003/87/EC* are also considered in the same category.

4.2. Correlation analysis

In order to better understand the role of financial and non-financial participants in the ECFM, we have performed two Pearson cross-correlation analyses; the first is focused on the positions of carbon traders and the second on the number of entities. Panel A of Table 2 presents the cross-correlation analysis that takes into account the net positions. The correlation coefficient for the *Compliance Entities and Other Non-financials* series is negative and significant at the 1% level with both *Investment Firms and Credit Institutions* (-83.61%) and *Other Financial Institutions* (-41.05%), while it is positive with the *Investment Funds* series (32.38%). Given that *Investment Firms and Credit Institutions* primarily hold net short positions and *Compliance Entities and Other Non-financials* hold net long positions, a negative and significant correlation suggests that when *Compliance Entities and Other Non-financials* increase their net long positions, *Investment Firms and Credit Institutions* increase their net short positions. This implies that *Investment Firms and Credit Institutions* may be acting as liquidity providers for

[6] The Augmented Dickey-Fuller test statistic is -7.6444 for the net positions of *Commercial Undertakings* and -13.3519 for the net positions of operators subject to compliance obligations under Directive 2003/87/EC. Note that the asymptotic one-sided p-values are -4.9491, -4.4436 and -4.1936 for the 1%, 5% and 10% levels, respectively.

Compliance Entities and Other Non-financials in the ECFM. This aligns with ESMA (2024, p.16), which indicates that most EU ETS operators prefer to obtain allowances through financial intermediaries. In this way, *Compliance Entities and Other Non-financials* operators hedge their future carbon exposure by adopting a buy-and-hold strategy, maintaining long positions in the nearest December futures contract.

(Please, insert Table 2)

A positive and significant correlation at the 5% level is observed between carbon returns and net long positions for *Investment Funds*, suggesting that *Investment Funds* increase their long (short) positions when prices increase (decrease). In addition, the positive and statistically significant correlation at the 1% level observed between carbon volatility and net positions for *Compliance Entities and Other Non-financials*, indicates that as long positions by *Compliance Entities and Other Non-financials* increase, carbon volatility also rises. Conversely, a negative and statistically significant correlation at the 1% level is observed between carbon volatility and net positions for *Investment Firms and Credit Institutions*. This negative correlation suggests that when *Investment Firms and Credit Institutions* increase their short positions, carbon volatility likewise rises.[7] Thus, the simultaneous increase in long positions by *Compliance Entities and Other Non-financials,* along with short positions by *Investment Firms and Credit Institutions,* appears to be associated with increases in carbon volatility. Note that volatility remained particularly low during the second half of 2023, as shown in Figure 3. Finally, there is no significant correlation between the net positions of either *Investment Funds* or *Other Financial Institutions* and carbon volatility.

(Please, insert Figure 3)

Panel A of Table 3 presents the Pearson cross-correlation coefficients, controlling for the number of entities in each category. Contrary to Quemin and Pahle (2023), no correlation is observed between carbon returns and the number of entities in any trader category. Furthermore, the results indicate a positive and statistically

[7] This is because net positions are defined as long positions minus short positions, and *Investment Firms and Credit Institutions* mainly hold short positions.

significant correlation at the 1% level among *Investment Firms and Credit Institutions*, *Investment Funds*, and *Compliance Entities and Other Non-financials* (80.42% and 80.81%, respectively). In contrast, these three categories exhibit a negative and statistically significant correlation, also at the 1% level, with *Other Financial Institutions*. These findings suggest that the market is expanding with increased participation from *Investment Firms and Credit Institutions*, *Investment Funds*, and *Compliance Entities and Other Non-financials*, while the presence of *Other Financial Institutions* in the market is declining.

Regarding the correlation between the number of entities and carbon volatility, we observe that it is negative and statistically significant at the 10% level for *Investment Firms and Credit Institutions*, as well as for *Investment Funds*, while it is null for *Other Financial Institutions* and *Compliance Entities and Other Non-financials*.

(Please, insert Table 3)

This trend is also illustrated in Figure 3, which depicts the evolution of carbon volatility and the number of firms trading on the ICE Endex market. The figure shows that since January 2021, the number of *Investment Firms and Credit Institutions*, *Investment Funds*, and *Compliance Entities and Other Non-financials* has increased. In contrast, the number of *Other Financial Institutions* has declined sharply, dropping dramatically to approximately 100 within four months, plummeting to 22 by early July 2021, and stabilizing at around 10 since March 2023. We also observe a decline in carbon volatility toward the end of the sample period, despite the increasing number of entities in the market, including both financial entities and *Compliance Entities and Other Non-financials*. These findings, together with those obtained from Table 3, suggest that as the number of entities increases, carbon volatility either declines or remains unchanged, but does not increase.

Panels B of Tables 2 and 3 present the Spearman cross-correlation analysis, which yields results that are both qualitatively and quantitatively similar to those obtained from the Pearson analysis. From these two analyses, we conclude that the roles of the three types of financial players in the carbon market are not homogeneous. First, while the net positions of *Investment Funds* and *Other Financial Institutions* do not impact carbon volatility, an increase in the short positions of *Investment Firms and Credit Institutions* is correlated with a rise in carbon volatility. This coincides with an increase in the long positions held by *Compliance Entities and Other Non-financials*. Second, the market is expanding with the participation of *Investment Firms and Credit Institutions*, *Investment Funds*, and *Compliance Entities and Other Non-financials*, while the number of *Other Financial Institutions* participating in the market is declining. Finally, we observe a drop in carbon volatility towards the end of the sample period, despite an increase in the number of entities in the market, including both financial entities and *Compliance Entities and Other Non-financials*. [8]

5. The forecasting ability of carbon market positions

5.1. Predictive capacity over the short term

To further the analysis, we investigate the short-term forecasting ability of carbon traders using the Granger causality test (Granger, 1969, 1980) with weekly data. In addition to examining the short-term relationship between trader positions and carbon returns, we also explore their relationship with volatility and the bid-ask spread to better understand market dynamics. Specifically, analyzing how trader positions influence carbon market volatility helps determine whether trading behaviors amplify or mitigate EUA price fluctuations, providing insight into market stability. Furthermore, studying the relationship between trader positions and the bid-ask spread sheds light on the impact of trading activity on market liquidity and transaction costs.

As shown in Table 1, the weekly returns of carbon futures, along with the net long positions of financial and non-financial entities, are reasonably stationary according to the Kwiatkowski-Phillips-Schmidt-Shin (KPSS, 1992) test statistic,

[8] Another approach to examining whether COT reports provide valuable insight into the carbon futures market is to develop a sentiment index for each type of trader based on their actual positions (see Wang, 2001). These indexes are typically calculated using the maximum and minimum positions held by traders over the previous three to five years, applying a moving window to track changes. However, as ESMA only began publishing carbon COT reports in early 2018, implementing these sentiment indexes would substantially limit the available sample size.

with significance at the 10% level. These stationary series are used to construct the model outlined in equations (1) and (2):

$$MV_t = \alpha + \sum_{j=1}^{m} \gamma_j MV_{t-j} + \sum_{k=1}^{n} \beta_k NP_{i,t-k} + \mu_{i,t} \quad \textit{Eq. (1)}$$

$$NP_{i,t} = \varphi + \sum_{j=1}^{m} \lambda_j NP_{i,t-j} + \sum_{k=1}^{n} \theta_k MV_{t-k} + \epsilon_{i,t} \quad \textit{Eq. (2)}$$

where $NP_{i,t}$ is the net open interest position of trader *i* at time *t* and MV_t is the market variable at time *t*. The market variables considered are the weekly return of carbon prices (R_t), the Parkinson (1980) volatility measure of the price data series (σ_t), and the bid-ask spread of the last day of the week (S_t), which coincides with the COT publication day. The lag structure (*m, n*) for each OLS regression is selected using the Akaike Information Criterion. To ensure the correct specification of the equation, we apply the VAR residual serial correlation Lagrange Multiplier (LM) test to examine residual serial correlation.

If the β_k coefficients in Eq. (1) are significant, it indicates that the net positions of carbon traders play a role in explaining the dynamics of the carbon market. Furthermore, it is important to emphasize that when analyzing Eq. (2) with carbon returns as the market variable, the significance of the θ_k coefficients can lead to three possible scenarios. First, if returns lead net long positions (i.e., the difference between long and short positions of traders) with a uniformly positive impact, this suggests that traders are trend followers or positive feedback traders, as they increase (decrease) long (short) positions when prices rise. On the other hand, if returns lead net long positions with a negative impact, traders are identified as negative feedback traders, as they increase (decrease) long (short) positions when prices fall. Finally, if the θ_k coefficients are not significantly different from zero, price changes have no impact on traders' positions.

Table 4 presents the results concerning the short-term relationship between carbon returns and traders' positions. The β_k coefficients are not significant across any trader category, suggesting that none of the trader positions have a measurable impact on carbon returns. The same is true for the θ_k coefficients for financial players (*Investment Firms and Credit Institutions*, *Investment Funds*, and *Other Financial Institutions*), indicating that weekly returns do not influence their trading positions. However, weekly returns do lead to changes in net long positions for *Compliance Entities and Other Non-financials* traders. Specifically, there is a statistically significant positive impact at the 10% level, suggesting that *Compliance Entities and Other Non-financial* traders tend to behave as trend followers, that is to say, they increase their long positions when prices rise. This result differs from that of Shi and Zhai (2024), who provide empirical evidence that commercial entities in the California carbon futures market act as contrarian traders.

(Please, insert Table 4)

Table 4 also presents the results on the relationship between net positions and volatility. The analysis reveals that the net positions of both *Investment Firms and Credit Institutions*, as well as *Compliance Entities and Other Non-financial* traders, affect volatility. In the case of *Investment Firms and Credit Institutions*, the impact is negative and statistically significant at the 10% level, suggesting that a higher number of short positions held in recent weeks is associated with higher current volatility. For *Compliance Entities and Other Non-financial* traders, the impact is positive and statistically significant at the 5% level, indicating that a higher number of long positions held in past weeks is related to greater current volatility. These findings align with the results reported in Table 2.

Finally, the last two columns of Table 4 present the results examining the relationship between net positions and the bid-ask spread. The lagged coefficients are not statistically significant in either regression. Therefore, the results suggest that net positions do not have a significant impact on the bid-ask spread for either financial or non-financial participants. These results imply that the bid-ask spread is independent of changes in trader positions, suggesting that there are no liquidity problems arising from trader positions in the ICE Endex carbon futures market.[9]

[9] Note that as explained in Section 4 (Data description), throughout the paper we only present the results for ICE Endex. However, we have also used EEX data in order to perform the same analysis. The results are heterogeneous and the justification for not presenting them is consistent with the fact that there are few open positions. This choice is further supported by the results presented in Table 4 for the EEX, which demonstrate that the bid-ask spread increases with the rise in short positions held by *Investment Firms and Credit Institutions*, as well as with the rise in

In summary, the positions of traders do not affect carbon returns or the bid-ask spread. However, changes in the net positions of both *Investment Firms and Credit Institutions* and *Compliance Entities and Other Non-financial* traders do contribute significantly to increasing carbon market volatility in the two following weeks.

5.2. Predictive capacity over the long term

To further the analysis, we address the research question of whether carbon prices can be predicted using trader positions. For this purpose, we employ the methodology proposed by Buchanan et al. (2001). In their paper, the authors propose estimating the forecast conviction for the percentage change in the closing price of a futures contract through the following approach:

$$\Delta\tilde{R}_{(t-T)} = \alpha + \beta_{NP} NP_{i,t} + \epsilon_{i,t} \qquad \textit{Eq. (3)}$$

where $\Delta\tilde{R}_{(t-T)}$ is obtained as the mean percentage change in the closing price between time *t* and *T*, so:

$$\Delta\tilde{R}_{(t-T)} = \frac{1}{n}\sum_{n=t}^{T} \ln\left(\tilde{F}_T/\tilde{F}_t\right) \qquad \textit{Eq. (4)}$$

where $\tilde{F}_t$ is the futures price at week *t* and $\tilde{F}_T$ is the futures price in the last trading week of the annual futures contract. $NP_{i,t}$ is the net open interest position (the difference between long positions and short positions) of trader *i* at time *t* and $\epsilon_{i,t}$ is a random error term that has an unknown source of heteroskedasticity.[10]

Table 5 presents the estimates of the forecast conviction for the percentage change in the closing price of carbon futures contracts with annual expirations. If β_{NP} is significant and greater than zero, it would indicate that the carbon trader has forecasting ability. As we can see, the beta coefficient is only statistically significant at the 5% level for *Investment Firms and Credit Institutions* and for

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long positions held by *Compliance Entities and Other Non-financials*. This suggests a lack of liquidity in the EEX.

[10] Note that since the COT reports are published every Friday, we have calculated for each week of the sample the mean percentage change in the closing price as the sum of all weekly returns from the week the position was opened until the last Friday before the maturity of the December futures contract.

Investment Funds. This suggests, first, that neither *Other Financial Institutions* nor *Compliance and Commercial* participants are effective forecasters, as their coefficients are not significantly different from zero. Second, the positions of *Investment Funds* are effective forecasters, as the coefficient is positive (0.21%), indicating that they take long (short) positions when the carbon price increases (decreases). Third, the positions of *Investment Firms and Credit Institutions* have an inverse effect on carbon returns, suggesting that they are ineffective forecasters, as their market positions tend to be larger in the opposite direction of price changes as these changes intensify.

(Please, insert Table 5)

However, the adjusted R^2 values are low or even negative in all cases presented in Table 5, indicating that the model performs worse than a model without predictors. This fact suggests that the selection of variables or the structure of all the models needs to be improved. Following Buchanan et al. (2001), we have included in Eq. (3) six yearly dummy variables equal to 1 in the corresponding year and 0 otherwise. We propose to estimate the following model:

$$\Delta\tilde{R}_{(t-T)} = \alpha + \sum_{y=2018}^{2023} \beta_y NP_{i,t} D_y + \epsilon_{i,t} \quad \textit{Eq. (5)}$$

where D_y is a yearly dummy variable equal to 1 in the corresponding year (from 2018 to 2023) and 0 otherwise. Note that, as mentioned above, the most traded EUA futures contract each year is the one with maturity in December, and thus this dummy is consistent with the specificities of the EU ETS. The results of this model are presented in Table 6. It is worth noting that the introduction of the yearly dummy variables significantly increases the adjusted R^2 values compared to those of the previous models.

(Please, insert Table 6)

Table 6 shows that neither *Investment Firms and Credit Institutions* nor *Compliance Entities and Other Non-financials* are able to predict changes in carbon prices. On the other hand, both *Investment Funds* and *Other Financial Institutions* demonstrate anticipatory adjustments to European carbon futures prices in four and three of the six years of the sample period, respectively, taking long positions before carbon futures prices increase. This aligns with the ESMA (2024) report, which indicates that *Investment Funds* tend to track EUA price developments more closely.

In summary, in the financial investors group, *Investment Funds* and *Other Financial Institutions* demonstrate statistically significant forecast conviction, which could lead those investors who are aware of this information to implement trading strategies that go long (short) when the net position of these two investor groups increases (decreases) in order to make an economic profit. However, this is not the case for the *Investment Firms and Credit Institutions*, which are ineffective forecasters. The same happens with the position of *Compliance Entities and Other Non-financials*. Therefore, the two categories with the highest number of open positions, both long and short, in the ECFM do not provide valuable information for predicting the direction of subsequent carbon price changes in the long term.

6. Conclusion

Amid growing concerns over climate change, rising energy prices, and elevated carbon prices, there is significant controversy surrounding the role of financial institutions in the European Carbon Futures Market (ECFM) and the impact of their activities on EUA prices, volatility, and market liquidity. This controversy is heightened by the notable increase in the number of financial entities participating in the ECFM, which accounted for over 64% of all participants by late 2023. This paper analyzes carbon traders' positions in the ECFM and their predictive power.

Our results indicate that *Investment Firms and Credit Institutions* primarily take short positions in the ECFM, while *Compliance Entities and Other Non-financial* participants predominantly go long. These findings suggest that *Investment Firms and Credit Institutions* engage in short positions in the ECFM to execute carry trades in the carbon futures markets in order to profit from price differences between auction and futures markets. Consequently, they act as liquidity providers for *Compliance Entities and Other Non-financial* participants in the ECFM. These systematic patterns observed over the last six years appear to contradict the notion that financial players are driving up carbon futures prices and thereby hindering compliance by entities under Directive 2003/87/EC. This would only be the case if financial players were predominantly taking long positions, which would drive up EUA futures prices. However, our results indicate that the main contributors to the upward pressure on EUA prices are *Compliance Entities and Other Non-financial* participants taking long positions to cover their actual emissions in an increasingly restrictive system. In contrast, other financial participants, such as *Investment Funds* and *Other Financial Institutions*, hold a mix of long and short positions, suggesting that they utilize EUAs as a portfolio diversifier, hedge, or safe-haven asset (see Palao and Pardo, 2022).

Correlation analysis reveals that as the number of entities increases, carbon volatility either decreases or remains unchanged across all trader categories. Furthermore, it shows that the number of entities is not a significant variable in explaining carbon prices. Therefore, the rise in the number of financial institutions participating in the ECFM is not responsible for the increase in EUA futures prices, unlike what has been observed in other markets (see Natoli, 2021).

Regarding the impact on volatility, both the correlation and the short-term impact analysis of net positions suggest that volatility increases with the rise of (i) short positions taken by *Investment Firms and Credit Institutions*, (ii) long positions held by *Operators with compliance obligations under Directive 2003/87/EC and Other Non-financials*, or (iii) the lagged net positions of these types of traders. Notably, net positions held by *Investment Funds* and *Other Financial Institutions* have no significant impact on carbon volatility. The analysis of the short-term impact of net positions also reveals that trader positions do not affect carbon returns or the bid-ask spread. This indicates that changes in the positions of the most active traders in the ICE Endex carbon futures market do not cause liquidity issues.

With respect to the impact of net positions on carbon returns in the long term, neither *Investment Firms and Credit Institutions* nor *Compliance Entities and Other Non-financial* participants offer much predictive value for future carbon price changes. However, a significant relationship emerges with the net positions of *Investment Funds* and *Other Financial Institutions*, which prove to be effective forecasters capable of successfully timing the carbon market, despite accounting for only 6.7% of long and short positions.

Despite the unique features of the European carbon market, the net positions of *Compliance Entities and Other Non-financial* participants provide little predictive insight into future price movements, even though they engage in the market to fulfill compliance obligations. Overall, these findings highlight that the influence of different carbon market participants is far from uniform.

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Table 1. Descriptive statistics

	Price		IFCI		IF		OFI		CU		OC		CO	
Panel A: ICE	Returns	Volatility	Positions	Entities	Positions	Entities	Positions	Entities	Positions	Entities	Positions	Entities	Positions	Entities
Mean	0.0069	0.0559	-62.6887	69.5752	2.0622	252.5719	-1.6207	72.4314	26.9648	157.0425	35.2824	45.3922	62.2472	202.4346
Median	0.0110	0.0499	-63.3572	46.0000	2.0470	190.5000	-0.0338	103.5000	9.0588	113.0000	46.8303	43.5000	63.5763	179.5000
Maximum	0.1670	0.2685	-36.8943	114.0000	8.8701	455.0000	5.4678	172.0000	59.4378	342.0000	67.0707	69.0000	72.6836	375.0000
Minimum	-0.3089	0.0122	-76.3740	32.0000	-5.3289	64.0000	-9.3203	0.0000	2.5572	56.0000	8.2299	10.0000	40.8379	97.0000
Std. Dev.	0.0650	0.0291	7.4402	30.4219	2.2757	136.4096	3.0576	54.4118	21.2480	76.3517	22.9437	17.5689	6.7392	62.7852
Skewness	-0.5987	2.9247	0.9697	0.1233	-0.2153	0.1423	-0.6197	-0.1771	0.1372	0.6775	0.0225	-0.2080	-0.8717	0.9331
Kurtosis	5.6877	17.6755	3.7978	1.1468	4.3102	1.2246	2.6489	1.2338	1.1557	2.3188	1.0774	1.6870	3.1224	3.0484
KPSS	0.3693*	0.2355	0.3670*	1.9043***	0.4029*	1.9777***	0.7913***	1.7010***	1.6261***	1.2530***	1.6901***	1.2859***	0.4484*	1.1367***
Jarque-Bera	110.3847***	3182.2410***	56.0730***	44.5641***	24.2520***	41.2195***	21.1594***	41.3735***	44.3286***	29.3269***	47.1529***	24.1857***	38.9410***	44.4296***
Panel B. EEX	Returns	Volatility	Positions	Entities	Positions	Entities	Positions	Entities	Positions	Entities	Positions	Entities	Positions	Entities
Mean	0.0070	0.0536	-74.7582	18.4800	0.0012	0.0500	-1.5126	0.2033	61.4388	50.5367	12.4182	5.4333	73.8570	55.9700
Median	0.0083	0.0475	-76.0382	18.0000	0.0000	0.0000	0.0000	0.0000	70.9519	49.0000	1.1349	0.0000	76.5237	60.0000
Maximum	0.1670	0.2698	-28.9971	39.0000	0.0303	5.0000	0.3083	6.0000	100.0000	78.0000	65.5590	20.0000	100.0000	83.0000
Minimum	-0.3093	0.0065	-100.0000	0.0000	-0.0104	0.0000	-24.6805	0.0000	2.2366	0.0000	-4.4008	0.0000	15.7198	0.0000
Std. Dev.	0.0662	0.0289	20.2175	6.2171	0.0044	0.4983	3.1389	0.9993	33.0790	12.1326	22.8740	6.9102	24.7890	13.6694
Skewness	-0.5305	2.9283	0.4114	0.2805	3.5539	9.8498	-3.1332	4.7209	-0.3731	-0.1809	1.6001	0.9735	-0.7322	-0.6490
Kurtosis	5.5260	17.9274	2.1115	3.5266	22.7295	98.0101	15.8551	23.3937	1.6918	3.7465	3.7203	2.4112	2.5006	3.4412
KPSS	0.3562*	0.2773	0.4683**	1.2795***	0.2220	0.1024	0.6611**	0.2654	1.5441***	0.6835**	1.1657***	1.5356***	0.6196**	1.4555***
Jarque-Bera	93.8313***	3214.0730***	18.3297***	7.4018**	5497.1760***	117687.0000***	2556.5220***	6313.1020***	28.3535***	8.6001**	134.5000***	51.7179***	29.9222***	23.4908***

These panels show the main descriptive statistics of the carbon COT data series. Returns and Volatility are the logarithmic return and the Parkinson (1980) volatility measure of the price data series, EUA December Futures nearby contract. Positions and Entities represents the aggregate net position and the number of entities for each category of participant: *Investments Firms and Credit Institutions* (IFCI), *Investment Funds* (IF), *Other Financial Institutions* (OFI), *Commercial Undertakers* (CU), *Operators with Compliance Obligations* (OC) and *Compliance Entities and Other Non-financials* (CO). Panel A shows the results for ICE Endex and Panel B for EEX. The sample period consists of weekly data from January 19, 2018, to December 15, 2023, for ICE Endex, and from January 5, 2018, to May 31, 2024, for EEX, comprising 306 and 300 weekly observations, respectively. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) statistic tests for the null hypothesis that the series have a unit root and the Jarque-Bera statistic tests for the null hypothesis of normality for the distribution of the series. The ***, ** and * indicate rejection of the null hypothesis at the 1%, 5% and 10% levels, respectively.

Table 2. Correlation analysis with net positions

Panel A. Pearson	Returns	Volatility	IFCI	IF	OFI
Volatility	-0.1036*				
IFCI	-0.0528	-0.1927***			
IF	0.1452**	0.0188	-0.6700***		
OFI	0.0773	-0.0839	-0.0918	0.1723***	
CO	-0.0259	0.2444***	-0.8361***	0.3238***	-0.4105***

Panel B. Spearman	Returns	Volatility	IFCI	IF	OFI
Volatility	0.0931				
IFCI	-0.0681	-0.1758***			
IF	0.1504***	-0.0011	-0.5428***		
OFI	0.1036*	-0.0225	-0.4067***	0.3878***	
CO	-0.0302	0.2195***	-0.7289***	0.1250**	-0.2450***

This table presents the cross-correlation analysis with net positions. *Returns* represent the logarithmic returns of the EUA December Futures nearby contract; *Volatility* refers to the volatility measure of Parkinson (1980) for the EUA December Futures nearby contract; *Investment Firms and Credit Institutions (IFCI)*, *Investment Funds (IF)*, *Other Financial Institutions (OFI)*, and *Compliance Entities and Other Non-financials (CO)* denote the net positions for each category. Panel A (B) shows the results of Pearson's (Spearman's) cross-correlation analysis. The null hypothesis in both panels is that the cross-correlation coefficient equals 0. ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively. The sample period covers weekly data from January 19, 2018, to December 15, 2023.

Table 3. Correlation analysis with number of entities

Panel A. Pearson	Returns	Volatility	IFCI	IF	OFI
Volatility	-0.1036*				
IFCI	-0.0551	-0.1116*			
IF	-0.0597	-0.0999*	0.9670***		
OFI	0.0525	0.0165	-0.9036***	-0.9308***	
CO	-0.0169	-0.0615	0.8042***	0.8081***	-0.6874***

Panel B. Spearman	Returns	Volatility	IFCI	IF	OFI
Volatility	0.0932				
IFCI	-0.0868	-0.1764***			
IF	-0.0557	-0.1510***	0.8818***		
OFI	0.0309	-0.0098	-0.6883***	-0.6751***	
CO	-0.0416	-0.0903	0.8033***	0.8780***	-0.5859***

This table presents the cross-correlation analysis with the number of entities. *Returns* represent the logarithmic returns of the EUA December Futures nearby contract; *Volatility* refers to the volatility measure of Parkinson (1980) for the EUA December Futures nearby contract; *Investment Firms and Credit Institutions (IFCI)*, *Investment Funds (IF)*, *Other Financial Institutions (OFI)*, and *Compliance Entities and Other Non-financials (CO)* denote the net positions for each category. Panel A (B) shows the results of Pearson's (Spearman's) cross-correlation analysis. The null hypothesis in both panels is that the cross-correlation coefficient equals 0. ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively. The sample period covers weekly data from January 19, 2018, to December 15, 2023.

Table 4. Granger causality tests

		$NP \rightarrow R$	$R \rightarrow NP$	$NP \rightarrow \sigma$	$\sigma \rightarrow NP$	$NP \rightarrow S$	$S \rightarrow NP$
	(m,n)	3,3		2,2		5,5	
IFCI	p-value	0.7615	0.2426	0.05	0.3574	0.7954	0.8067
	Impact	Zero	Zero	(-)	Zero	Zero	Zero
	(m,n)	3,3		3,3		4,4	
IF	p-value	0.6411	0.5296	0.1748	0.6767	0.4661	0.8113
	Impact	Zero	Zero	Zero	Zero	Zero	Zero
	(m,n)	2,2		2,2		2,2	
OFI	p-value	0.1979	0.7346	0.3969	0.8392	0.2001	0.7111
	Impact	Zero	Zero	Zero	Zero	Zero	Zero
	(m,n)	6,6		2,2		2,2	
CO	p-value	0.9526	0.0823	0.0172	0.4752	0.5144	0.9766
	Impact	Zero	(+)	(+)	Zero	Zero	Zero

The table presents the estimates from the Granger causality tests between the net position of the different categories of participants (*Investments Firms and Credit Institutions* (IFCI), *Investment Funds* (IF), *Other Financial Institutions* (OFI) and *Compliance Entities and Other Non-financials* (CO)) and the weekly logarithmic returns (R_t,), the volatility (σ_t) and the bid-ask spread (S_t). The sample period consists of weekly data from January 19, 2018, to December 15, 2023. (m,n) denotes the lag structure for each OLS regression. The p-value from the Wald chi-squared test evaluates the null hypothesis that the first variable does not Granger-cause the second variable. Impact represents the cumulative impact of the lagged values in each case: positive (+), negative (-) or zero.

Table 5. Forecast conviction using OLS

Carbon trader	α	β_{NETPOS}	F-STAT	Adjusted - R^2
IFCI	-0.0376*	-0.0007**	21.4624	0.0641
IF	0.0006	0.0021**	20.0435	0.0599
OFI	0.0055**	0.0003	0.6470	-0.0012
CO	-0.0269	0.0005	9.7597	0.0285

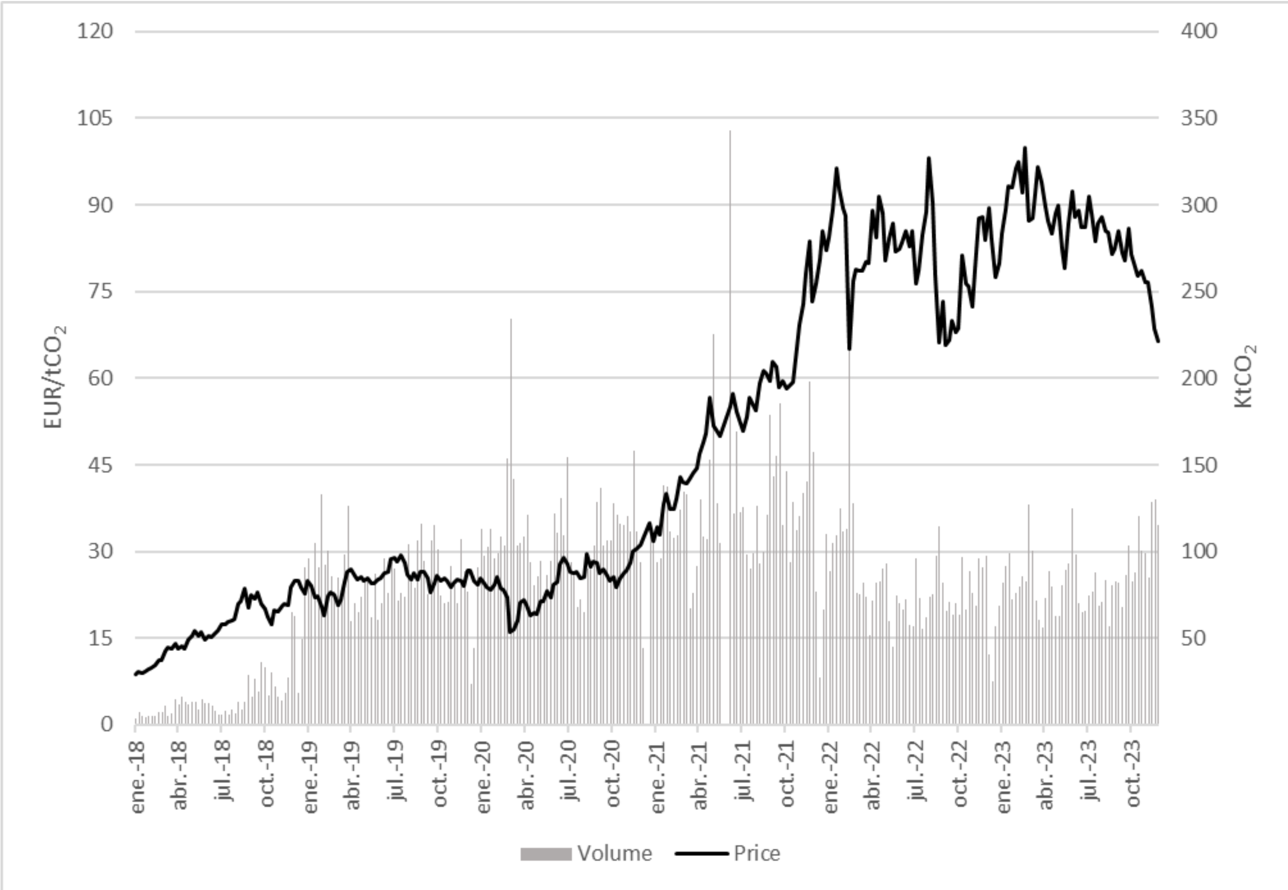
The table presents the estimates of the forecast conviction for the percentage change in the closing prices of carbon futures contracts with annual expirations. These estimates are conditioned on the net open interest positions of the different carbon market participants. *Investment Firms and Credit Institutions* (IFCI), *Investment Funds* (IF), *Other Financial Institutions* (OFI), and *Compliance Entities and Other Non-financials* (CO). The sample period covers weekly data from January 19, 2018, to December 15, 2023. β_{NETPOS} represents the forecast ability of participants based on their positions in the carbon market. The ***, ** and * indicate rejection of the null hypothesis at the 1%, 5% and 10% levels, respectively.

Table 6. Forecast conviction by year using OLS

Carbon trader	α	β_{2018}	β_{2019}	β_{2020}	β_{2021}	β_{2022}	β_{2023}	F-STAT	Adjusted - R^2
IFCI	-0.0076	-0.0005	-0.0001	-0.0003	-0.0003	-0.0001	0.0001	28.3116	0.3540
IF	-0.0004	0.0105***	-0.0013	0.0058**	0.0021***	-0.0004	0.0039*	19.9425	0.2424
OFI	0.0056	-0.0095***	0.0013**	-0.0005	0.0025***	-0.0377	0.3605***	20.1370	0.2775
CO	-0.0055	0.0005	0.0000	0.0003	0.0003	0.0001	-0.0002	29.2477	0.3618

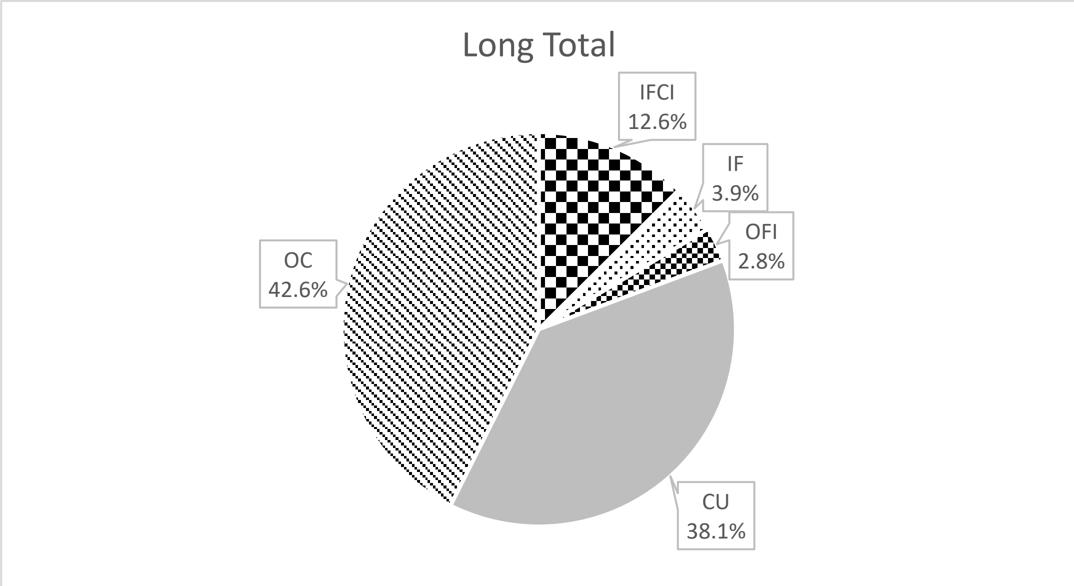
The table presents the estimates of forecast conviction for the percentage change in the closing price of each carbon futures contract with annual expirations, conditioned on the net open interest positions of various participant categories. *Investment Firms and Credit Institutions* (IFCI), *Investment Funds* (IF), *Other Financial Institutions* (OFI), and *Compliance Entities and Other Non-financials* (CO). The sample period comprises weekly data from January 19, 2018, to December 15, 2023. β_y represents the forecast ability for each year y, where y ranges from 2018 to 2023. The dummy variables take the value of 1 for the respective years 2018, 2019, 2020, 2021, 2022, and 2023, and 0 otherwise. The symbols ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

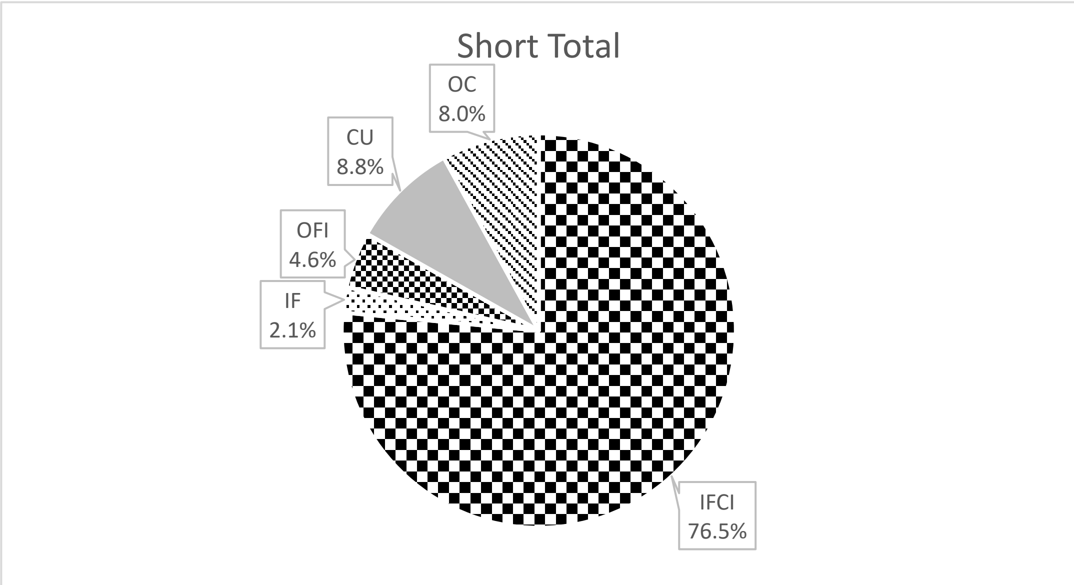
Figure 1. EUA price and volume evolution



The figure shows the evolution of the settlement price of the COT report publication day quoted in EUR/tCO_2 and the weekly cumulative volume (KtCO_2) of the EUA December Futures nearby contract. The sample period consists of weekly data from January 19, 2018, to December 15, 2023.

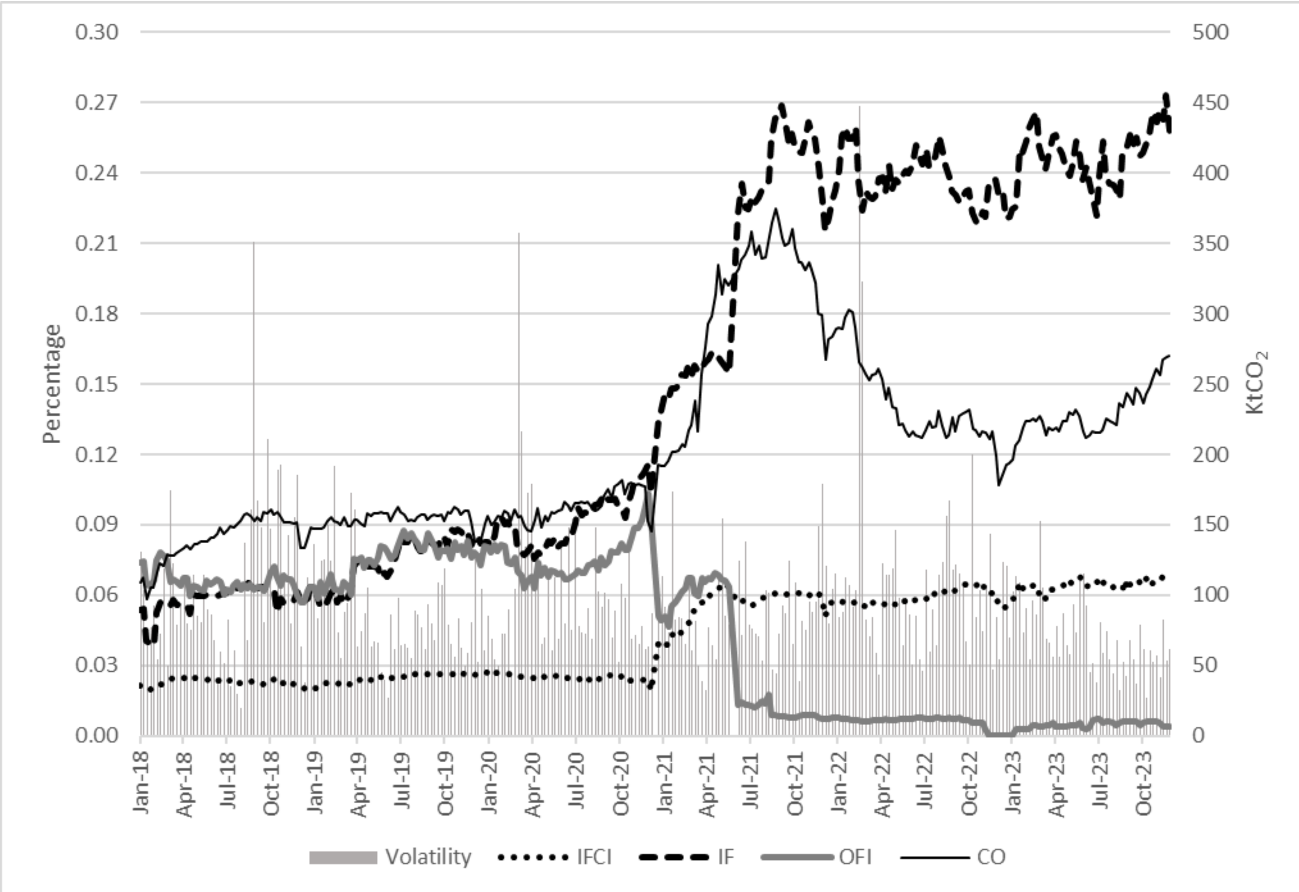
Figure 2. Long and short positions by category





These figures illustrate the percentage of long and short positions held by different categories of carbon market participants on ICE Endex and EEX. Participants are divided into the following categories: *Investments Firms and Credit Institutions* (IFCI), *Investment Funds* (IF), *Other Financial Institutions* (OFI), *Commercial Undertakers* (CU) and *Operators with Compliance Obligations* (OC). The analysis is based on weekly data for the period from January 19, 2018, to December 15, 2023.

Figure 3. Evolution of volatility and the number of firms



The figure shows the evolution of the weekly volatility measure of Parkinson (1980) and the number of firms of the different participant categories on the ICE market: *Investments Firms and Credit Institutions* (IFCI), *Investment Funds* (IF), *Other Financial Institutions* (OFI) and *Compliance Entities and Other Non-financials* (CO) ($KtCO_2$) of the EUA December Futures nearby contract. The sample period consists of weekly data from January 19, 2018, to December 15, 2023.