Real Effects of Carbon Financialization*

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Abstract

The recent influx of financial traders into carbon allowance markets has raised concerns about its distortive effects on carbon allowance prices and its repercussions for firms that rely on these price signals to make emissions decisions. This paper studies how financial carbon trading affects the allocative efficiency of carbon allowance markets and highlights the importance of facilitating financial arbitrages rather than imposing restrictions. Exploiting allowance transaction data in the European carbon market and using carbon policy shocks as supply shifters, I identify a price-inelastic carbon demand by large financial traders. The lack of elastic arbitrage capital is associated with a decline in the carbon price informativeness and contributes to the carbon market crash during the Russia-Ukraine war. The decreased informativeness has real effects: I find that firms with inferior private information reduce their emissions less efficiently when the carbon price is less informative, and the cross-sectional dispersion of carbon intensity increases with the informational inefficiency. I develop a macro-finance model with managerial learning from carbon prices that rationalizes these novel empirical findings.

JEL Classification: G14, O11, Q54

Keywords: Cap-and-trade, carbon financialization, limits to arbitrage, price informativeness, managerial learning, carbon misallocation

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1 Introduction

The looming climate crisis has placed carbon pricing regulations at the forefront of the global policy agenda, with cap-and-trade systems emerging as the leading carbon pricing instrument, covering roughly 18% of global CO2 emissions (World Bank, 2023). The carbon allowance markets, established for firms within cap-and-trade systems to trade emissions allowances, have experienced a notable influx of financial traders in recent years. This increasing financialization of carbon allowance markets has sparked widespread debates about whether financial traders have compromised the allocative efficiency of these systems and whether restrictions on their access to these markets are warranted (ESMA, 2021, 2022). Despite its policy significance, there is scant empirical evidence on the impact of carbon financialization. Has financial trading influenced the informativeness of carbon allowance prices, thereby affecting the emissions decisions of firms that depend on these price signals? What is the aggregate impact on the allocation of carbon allowances and associated green transition?

This paper answers these questions empirically, guided by a model built on Sockin and Xiong (2015) and Goldstein and Yang (2022). The model predicts that the informativeness of carbon prices is determined by the relative intensity of two distinct trading motives among financial traders—speculation and hedging. Financial speculators gather information on the fundamental shifts in carbon demand and supply and engage with carbon markets to capitalize on arbitrage opportunities. Their trading helps improve the price informativeness. On the other hand, some financial investors enter the market to diversify and hedge their other investments. These investors may be hit by liquidity shocks and may introduce these shocks (noise) to carbon prices through their flows. In the model, firms covered by the cap-and-trade system use carbon prices as public signals of the aggregate shocks to make their emissions decisions. Hence, financial carbon trading has real affects by affecting the informativeness of the carbon price signals. Drawing insights from Gondhi (2023), the model further predicts that noise in the price signal might crowd out managerial learning of the idiosyncratic shock, resulting in the misallocation of carbon allowances.

To test the model's predictions on carbon price informativeness, I propose a novel approach to identify the relative intensity of hedging and speculation motives, exploiting institutional features of the European carbon market and comprehensive transaction data of EU allowances (EUAs). The

European Union Emissions Trading System (EU ETS) is the largest carbon market in the world, covering around 40% of the EU's emissions and offering rich policy shocks regarding the supply of allowances (Känzig, 2023). I start by identifying a comprehensive set of traders from the European Union Transaction Log (EUTL) through manual scrutiny of names linked to accounts and their owners. This meticulous approach brings to light the key players in the European carbon market, some of whom remain hidden from public scrutiny. The uncovered traders include investment banks such as Morgan Stanley and Macquarie, leading independent commodity trading firms like Vitol and Mercuria, investment firms specializing in carbon trading (henceforth, carbon specialists) such as Belektron and Vertis, and carbon offsetters who participate in both compliance and voluntary carbon markets[1], such as RedShaw Advisors and nserve . Using data on their EUA transactions and leveraging carbon policy shocks (Känzig, 2023) as instruments, I then estimate the price elasticities of these financial traders in response to changes in EUA basis—the difference between EUA futures price and EUA spot price. My hypothesis is that financial speculators who engage in basis arbitrage within the carbon markets are likely to be price-elastic. I find that only carbon specialists are elastic, with 1% increase in EUA basis inducing 4% increase in their demands for EUA spot. Investment banks have a moderate elasticity of 0.8, while the elasticities of independent commodity trading firms and carbon offsetters are insignificant.

I provide multiple supporting evidence to map the trader-level price elasticities to the market-level price informativeness. First, despite the absence of comprehensive accounting data for financial traders, suggestive evidence indicates that elastic carbon specialists[2] are more likely to face capital constraints than those inelastic traders, such as leading commodity trading firms[3] and investment banks, who tend to have abundant capital. In other words, the limited capital of elastic traders indicates the presence of limits to arbitrage in the carbon allowance market (Duffie, 2010). Second, I use the carbon market crash precipitated by the Russia-Ukraine war as an event study to illustrate how limits to arbitrage may intensify the impact of liquidity shocks transmitted via financial traders. Third, I present indicative evidence that the emergence of carbon index investing and sustainability-

[1] See Pedersen (2023) for a discussion of the compliance and voluntary carbon markets.

[2] For example, Belektron is a Slovenia-based trading company that is not affiliated with any large banking or energy group.

[3] For instance, Vitol, recognized as the world's largest independent energy trader, reported revenues of $505 billion in 2022 that would position it as the second-largest company globally—surpassing the revenues of steller firms such as Amazon and Apple.

linked products could be driving the increase in financial carbon investing, predominantly motivated by hedging and diversification purposes. I document volatile fund flows into carbon ETFs, which potentially stem from impact investing and may act as a source of behavioral disturbance, as outlined by Gabaix and Koijen (2022), that can introduce noise into an inelastic market. Fourth, I construct price delay and absolute variance ratios as two price informativeness measures and show that carbon financialization is associated with a decline in carbon price informativeness.

I test the model's predictions on firm-level emissions with a comprehensive sample of firms under the EU ETS, exploiting variations in firm's internal carbon pricing mechanisms. According to CDP, the global disclosure system on environment-related information, over 400 companies covered by the EU ETS had disclosed the use of an internal carbon pricing mechanism to manage their environmental impacts (CDP, 2021)[4]. Additionally, I document substantial reallocations of allowances within conglomerate divisions from the EUA transaction data. Based on these institutional features, I make the identifying assumption that firms with well-established internal carbon pricing mechanisms likely have superior private information about the carbon market dynamics and therefore may depend less on the public information embedded in the carbon price when making their emissions decisions. To this end, I construct two proxies for private information from internal carbon pricing. The first is the ratio of the firm's internal carbon trading to its total emissions, while the second is a dummy variable indicating whether the firm has disclosed an internal carbon pricing mechanism. I show that firms with inferior private information are more reactive to changes in EUA prices and reduce their emissions less efficiently. Notably, the differences in responsiveness and efficiency are more pronounced when the EUA price is less informative.

Lastly, I present macro-level evidence of the impact of financialization on the allocative efficiency of the carbon allowance market. I calculate the cross-sectional dispersions in carbon intensity (emissions scaled by sales) to proxy for the degree of carbon misallocation. The intuition is that the marginal revenue product of carbon allowances should be equalized across firms, otherwise reallocating allowances to firms who can use them more efficiently could increase the aggregate output. I show that carbon misallocation is positively correlated with the inflows of financial traders. Overall, my results suggest that the financialization of carbon allowance market is characterized by limits of arbitrage and a surge in financial hedging motives. These features contribute to the

[4]Financial Times, September 22, 2023, Companies Find Carbon Costing Aids Strategic Planning.

decrease in carbon price informativeness, which in turn prompts firms to reduce emissions less efficiently, leading to the misallocation of carbon allowances.

My findings highlight that the prevalent concerns about excessive speculation in the EUA market are unfounded. Instead, the evidence points toward insufficient speculation. The policy takeaway is clear: rather than 'throwing sand in the wheels' (Tobin, 1978), we should welcome more financial speculation to enhance market efficiency.

Related Literature. This paper is broadly related to three strands of literature. The first is the growing literature studying the role of financial institutions in the carbon allowance market, which is largely descriptive. Cludius and Betz (2020) provide both empirical and survey evidence on the decline in banks' proprietary carbon trading after the introduction of MiFID. Cludius et al. (2022) investigate the impact of buy-and-hold strategies on the EUA market and find no evidence of "squeezing" or "cornering" from financial investors. Quemin and Pahle (2023) use the Working T-index to examine the presence of excess speculation in the EUA market and advocate for improved monitoring and integrated regulation. While these existing works offer important insights, they do not examine the impact of financial traders on the informativeness of carbon allowance price, which is key to the functioning of a cap-and-trade system. Using a comprehensive set of transaction-level data, I present evidence on how the information content in the carbon allowance price is shaped by financial traders with different trading motives[5].

A large literature on commodity financialization has studied the impacts of financial traders on commodity markets (Mou, 2010; Tang and Xiong, 2012; Cheng and Xiong, 2014; Singleton, 2014; Cheng et al., 2015; Sockin and Xiong, 2015; Henderson et al., 2015; Basak and Pavlova, 2016; Bhardwaj et al., 2016; Ready and Ready, 2022; Goldstein and Yang, 2022; Da et al., 2023). My paper contributes to this literature by providing the following insights: First, the transaction-level data enable me to examine the trading behaviors of commodity trading firms, which are not well studied despite their significant role in commodity markets, largely due to their private status

[5] In environmental economics, there is extensive literature on the trading behaviors of firms covered by the cap-and-trade systems (Zaklan, 2013; Jaraitė-Kažukauskė and Kažukauskas, 2015; Betz and Schmidt, 2016; Cludius, 2018; Naegele, 2018; Borghesi and Flori, 2018; Karpf et al., 2018; Zaklan, 2020; Guo et al., 2020; Baudry et al., 2021; N'Gatta et al., 2022; Abrell et al., 2022; Hintermann and Ludwig, 2023). My paper focuses on the trading behaviors of financial investors, especially those commodity trading firms and carbon specialists who potentially act as the marginal investors in the carbon allowance market.

and secrecy culture. Second, the comprehensive firm-level emissions data allow me to uncover the distributive effects of financialization. These effects have been largely overlooked in the existing literature, primarily because of limitations in data availability. Additionally, the focus on allocative efficiency addresses the debates on the ideal welfare criterion in studying the real effects of commodity financialization (Goldstein and Yang, 2022) and connects to the large literature on misallocation (Hsieh and Klenow, 2009; Moll, 2014; David et al., 2016; Whited and Zhao, 2021; David et al., 2022) and reallocation (Eisfeldt and Shi, 2018).

The second strand of related literature is the expanding body of research that investigates the implications of carbon pricing at the firm level. Martinsson et al. (2022) find a negative relationship between emissions and marginal carbon pricing based on Swedish data. Bolton et al. (2023) document a negative relationship between daily carbon price and contemporaneous stock prices for public firms covered by the EU ETS with a shortfall of carbon allowances. In the context of California's cap-and-trade system, Bartram et al. (2022) find that financially constrained firms shift emissions and output to non-regulated states in response to local carbon pricing regulation. Bustamante and Zucchi (2022) show that carbon pricing could potentially lead to short-termism in firms' behavior. Unlike these existing works that examine the effects of carbon pricing *level*, this paper focuses on the impact of carbon price *informativeness*. To the best of my knowledge, this paper is among the first to provide evidence that firm emissions decisions and efficiency are influenced by the informational efficiency of carbon allowance prices. From this perspective, the paper also contributes to the large literature on the real effects of financial markets as surveyed by Bond et al. (2012) and Goldstein (2023), and particularly on the real effects of commodity markets (Brogaard et al., 2019).

Finally, this paper contributes to the recent literature on the design of climate policy instruments (Pedersen, 2023; Allen et al., 2023; Oehmke and Opp, 2022; Heider and Inderst, 2022; Biais and Landier, 2022; Dávila and Walther, 2022; Döttling and Rola-Janicka, 2023; Huang and Kopytov, 2023). Notably, Pedersen (2023) shows that green finance may raise welfare when the carbon price is lower than the social optimal. My paper highlights that, even with a low carbon price, some forms of green finance (for example, carbon index investing and sustainability-linked products) may have adverse effects if they dampen the informativeness of carbon prices. Similarly, Allen et al. (2023) demonstrate that carbon-contingent securities, as specific green finance instruments, may reduce welfare if they crowd out carbon pricing regulations. My paper points out that investment flows into and out of these emission-linked structured products might introduce noise into carbon prices through the hedging activities of issuers, thereby further impairing the efficacy of carbon pricing regulations. By highlighting potential negative interactions between financial market frictions and cap-and-trade systems, the paper also adds to the long-lasting debate since Weitzman (1974) on whether quantity-based regulation (cap-and-trade system) or price-based regulation (carbon tax) is the better carbon pricing policy instrument.

The outline of the paper is as follows. Section 2 provides institutional background. Section 3 illustrates data and motivating stylized facts. Section 4 develops a model to demonstrate the economic mechanisms. Section 5 and 6 provide empirical evidence to support the model's predictions. Section 7 concludes.

2 Institutional Background

This section provides institutional background about the European carbon market and its financialization. Carbon pricing and financialization of other cap-and-trade systems are discussed in the Appendix A.1.

2.1 The European carbon market

Initiated in 2005, the EU Emissions Trading System (EU ETS) now operates in all thirty EEA states (EU countries plus Iceland, Liechtenstein and Norway), covers all manufacturing and energy firms, and accounts for around 40% of the EU's greenhouse gas emissions. Figure 1 shows the evolution of European Union Allowance (EUA) price. It is clear that the cost of emitting greenhouse gases in Europe has surged in recent years, with the price reaching around €100 per tonne in 2022.

The development of the EU ETS consists of four phases. Phase 1 (2005-2007) and Phase 2 (2008-2012) largely reflect institutional experimentation. During Phase 3 (2013-2020) and the ongoing Phase 4 (2021-2030), substantial improvements in the policy environment and trading infrastructure have been made. As of now, the European carbon market consists of auctions, spot, and futures markets. In 2022, the total value of the market exceeded €750 billion, with a trading volume of approximately 1,000 million tonnes of CO2 (Refinitiv, 2023). This large and active carbon market is crucial for the effective functioning of a cap-and-trade system, ensuring that emissions are reduced where it is most cost-effective. I briefly describe the structure of this market below, some of the institutional details are key to my analysis.

2.1.1 Primary spot market

The primary spot market is where the EU distributes emission allowances to firms covered in the EU ETS. The three main distribution methods are the free allocations, the auctioning, and the use of international credits.

Free allocation. During Phases 1 and 2 (2005-2012), auctioning was the main method for distributing EUAs. At the beginning of Phase 3, the manufacturing industry received 80% of its allowances for free. However, this proportion was set to decrease gradually each year, reaching 30% in 2020. Power plants have not received any free allowances since 2013, but some EU Member States still provide free allocation to facilitate the modernization of their respective energy sectors. In Phase 4 (2021-2030), sectors with a low risk of carbon leakage (i.e., leaving the EU for countries with lenient carbon regulations) are projected to see a phase-out of free allocations. It's noteworthy that, with the rise in carbon price, firms granted substantial free allowance allocations experience stock price appreciation (Bolton et al., 2023) and financial windfalls[6]. It is crucial to account for these windfalls in the firm-level analyses.

Auctions. During Phase 3 (2013-2020), the auction became the default method for allocating EUAs, accounting for approximately 57% of the total amount of allowances. The annual auctioning volume is determined as stipulated by the ETS Directive and is subject to pre-defined adjustment rules under the Market Stability Reserve. The European Energy Exchange (EEX) in Leipzig currently serves as the common auction platform for EEA countries, with the exception of Germany and Poland. It conducts EUA auctions on Mondays, Tuesdays, and Thursdays each week, and the total EUAs auctioned in 2022 amounted to approximately 500 million tonnes, valued at around €40 billion (Refinitiv, 2023).

The use of international credits. International credits are financial instruments representing the removal or reduction of CO2 from the atmosphere, achieved through an emissions reduction project.

[6] The Wall Street Journal, March 27, 2023, Europe's Big Polluters Win Carbon-Credit Windfall.

At present, two such instruments are the credits—Certified Emission Reductions (CERs) and the Emission Reduction Units (ERUs), which are generated through the Clean Development Mechanism (CDM) and Joint Implementation (JI), respectively and established, as eligible mechanisms, under the Kyoto Protocol. Until 2020, participants in the EU ETS had been permitted to use CERs or ERUs to fulfill a portion of their obligations, subject to both qualitative (i.e., specific requirements for the projects) and quantitative (i.e., maximum limits) restrictions. The EU has set a domestic emissions reduction target and, as it currently stands, does not plan to continue allowing the use of international credits for compliance with the EU ETS post-2020[7].

2.1.2 Secondary spot and futures market

The EUAs can be traded either on exchanges, including Bluenext in Paris, Nord Pool in Oslo, and EEX in Leipzig, or via OTC. As with commodities like oil and gas, EUA futures market is more liquid than the spot market. Two European futures exchanges, ICE in London (it moved to Amsterdam in 2021) and EEX in Leipzig, offer EUA futures contracts, with the former dominating the price discovery process (Stefan and Wellenreuther, 2020). In 2022, a total of 8,450 million tonnes of EUAs (both spot and futures) was traded on the exchanges, with a value of €685 billion, while only 335 million tonnes were traded via OTC markets, accounting for €27 billion (Refinitiv, 2023). Several EUA futures contracts are traded on the market, among which the front-December contract is the most liquid, accounting for more than 80% of the total open interest.

2.1.3 Internal carbon market

According to CDP, a global disclosure system for environment-related information, over 2000 companies around the world have disclosed their current or projected use of internal carbon pricing, 425 of which are regulated by the EU ETS (CDP, 2021). The disclosed implementation ranges from shadow pricing to internal trading, including implicit pricing, and internal fees. Internal trading is similar to government-run cap-and-trade systems whereby companies can allocate carbon allowances to different business units. Although the exact internal trading price is unobservable, extensive transactions of EUAs among firms within the same conglomerate have been documented,

[7]There is also heated debate regarding the quality and efficiency of carbon offset projects. See Calel et al. (2021) and the discussion in Pedersen (2023).

as detailed in the following section.

2.2 Financialization of the EUA market

Emission allowances and related derivatives are classified as financial instruments under EU financial regulation (MiFID II). Recently, the European carbon market has seen a significant influx of financial traders. The right axis in Figure 2 shows the evolution of the number of investment funds that reported positions in the EUA futures market. The number has increased from 150 in 2020 to above 400 in 2023. Concurrently, the EUA price has shown increased fluctuations. The left axis in Figure 2 illustrates the two-year rolling AR(1) coefficient of EUA futures returns (left axis)[8]. The decreasing and negative AR(1) coefficient suggests that the EUA prices tend to overshoot before reversing.

This situation has raised concerns about whether financial traders have caused excess speculation in the carbon market and distorted its well functioning. In response, EU member states have called upon the European Commission to conduct a thorough investigation into the level of speculation in the EUA market. Some member states have even proposed enacting measures to restrict financial traders' participation in the market to curb such speculation (Refinitiv, 2023). The remainder of this paper addresses these concerns and offers policy recommendations based on both theoretical and empirical analyses.

3 Data and Motivating Facts

In this section, I provide a overview of the data used in the paper, highlighting key stylized facts that are instrumental in shaping the model and guiding the empirical analysis.

3.1 Data

I have sourced data from multiple outlets, including account-level EUA allocation, transaction, and surrender data from the European Union Transaction Log (EUTL), firm-level accounting and ownership data from the Bureau van Dijk (BvD) Orbis, firm-level voluntary disclosure data from

[8]As described in Section 3, I roll EUA front-December contracts annually at the start of November to construct the EUA futures price series and calculate corresponding log returns.

CDP, and market data of EUA spot and futures from Bloomberg and Refinitiv. I use a sample spanning 2013 to 2022 which covers the entire Phase 3 and the first two years of Phase 4.

3.1.1 Firm-level transaction, emission, and accounting data

The European Union Transaction Log (EUTL) is the registry platform for the EU ETS. It allows the European Commission to disclose information publicly regarding the compliance of regulated entities, the participants in the program, and the transactions between these participants. Specifically, it records all activities at the account level, covering verification, surrender, retirement, and transfer of EUAs. The EUTL data are publicly available on the European Commission website. I have retrieved the structured version (EUETS.INFO) provided by Abrell (2023).

The EUETS.INFO data have three main building blocks. The account block provides the id, name, and bvdID (the BvD Orbis identifier) for all accounts and the corresponding account holders. The match to BvD Orbis is based on Letout (2021) and is refined by Abrell (2023) using the location information from Google Maps API. The compliance block consists of the annual and cumulative amount of EUAs allocated to and surrendered by each regulated account. These regulated accounts are at the installation level. The transaction block records the date and amount of all EUA transfers between accounts, together with a transaction type code that classifies transactions into various categories including issuance, cancellation, internal, and external.

I divide accounts into two categories: compliance-account if in the compliance block and non-compliance-account if otherwise. For compliance accounts , I consolidate both allocated and surrendered EUAs to the firm level. Subsequently, I merge this consolidated firm-level data with BvD Orbis to retrieve accounting variables and ownership information including immediate shareholders, domestic ultimate owners, and global ultimate owners. Although the ownership linkages in Orbis are static and do not keep track of historical changes in ownership (Bolton et al., 2023), I follow Jaraitė et al. (2016) that iteratively retrieve the historical largest shareholder of regulated firm's bvdID each year to find its historical parent firm. The historical ownership can be verified using the transaction type code contained in the transaction block. If the two parties of an internal transaction (external transaction) belong to two different owners (to the same owner), the changes in ownership are manually checked and recorded. Given the historical ownership structure, the number and amount of EUA transactions taking place between firms owned by the same conglomerate (*within-conglomerate between-firm transactions*) are recorded accordingly. Such transactions are designated here as *internal transactions*. Note that transactions between accounts owned by the firm (*within-firm transactions*) have been excluded[9].

For non-compliance accounts, I parse and clean the names of their holders with standard textual analysis procedures. I manually identify the account holders and classify them into various investor groups. Specifically, I first identify account holders that have trading accounts listed on the UK Emissions Trading Registry. Although the EUTL does not offer such a list, the UK list serves as a valuable approximation of the investor cohort given that the UK ETS is only separated from the EU ETS since 2021. Next, I sort account holders that are not on the UK list by their trading amounts and manually search for their names. In particular, I have conducted a comprehensive search for financial institutions featured in the Environmental Finance magazine. The detailed data cleaning procedure is documented in the Appendix B. The identified account holders include independent commodity trading firms such as Vitol, Mercuria, and Cargill; investment banks such as Morgan Stanley, Macquarie, and Citi; and companies that engage in providing either technology-based (e.g., renewable energy) or nature-based (e.g., carbon offset project) climate solutions, such as Statkraft, C-Quest Capital, and RedShaw Advisors. Importantly, I have identified a group of investment firms that specialize in carbon trading, including ACT, Belektron, and Vertis. They are not belong to any financial or energy group but turn out to play important roles in the carbon allowance market. Finally, I remove transactions between accounts owned by the same account holder (*within-investor transactions*), and aggregate the remaining transactions into the account holder level.

After the data cleaning procedure, I end up with two blocks of information: the non-compliance block that contains information of all transactions involving consolidated non-compliance entities, and the compliance block that records all internal transactions, as well as emissions and accounting information of compliance firms. I restrict my sample to the period between 2013 and 2022 to avoid the two experimental phases, Phase 1 (2005-2007) and Phase 2 (2008-2012). In the regulation block, I also exclude UK firms as they left the EU ETS during my sample period. Note that EUTL transaction data are disclosed with a three-year delay. Consequently, the last observation of the transaction information is the end of April, 2020. In the regulation blocks, there are 9984 stationary

[9]The *within-firm transactions* include transfers between compliance-related accounts (Operator Holding Accounts) and trading-only accounts (Personal Holding Accounts which were transferred to Trading Accounts) owned by the same firm.

installations that belong to 5061 Orbis firms. Using the ownership information, these firms can be consolidated to 3794 consolidated firms, of which 247 are public companies[10]. I further require firms to have non-missing values for total asset, sales, and firm-level control variables. Table 1 shows number of installations, firms, consolidated firms, and public firms by country. Table B.1 lists the top 30 conglomerates by the number of regulated firms. Table B.2 shows the top 60 conglomerates by the number of internal transactions.

3.1.2 Market-level EUA spot and futures data

I collect EUA spot and futures data on Refinitiv. Daily EUA spot price, volume, and auction data are from the European Energy Exchange (EEX). Daily EUA futures price and volume data, and weekly Commitments of Traders (COT) reports data on EUA futures positions are from the Intercontinental Exchange Inc (ICE).

Following Pedersen (2023), I roll EUA front-December contract annually at the start of November to construct the EUA futures price series. In addition to futures price levels, excess returns are computed as the ratio of prices of the same contract. In the robustness check, I also construct the futures price series by rolling front-month contracts at the seventh calendar day of each month following Kang et al. (2020) or directly using the S&P GSCI Carbon Emission Allowances Index. The results are similar.

3.1.3 Other market data

I retrieve the daily price levels of S&P GSCI Commodity Index, S&P GSCI Energy Index, S&P GSCI Carbon Emission Allowances Index, STOXX Euro 600 Index, ICE Euro Corp Bond Index, and prices and positions of Dutch TTF Natural Gas Futures are from Refinitiv.

3.2 Motivating facts

As emphasized by Goldstein and Yang (2022), financial investors are not all made alike. Two distinct trading motives—speculation and hedging—characterize different financial investors to different degrees. While the line between speculation and hedging is blurred in practice (Cheng

[10] Note that if UK firms are included, my sample covers more installations and firms than that of Bolton et al. (2023).

and Xiong, 2014), I present stylized facts of main players in the EU carbon market. Figure 3 shows the top 10 EUA traders. I classify these traders into groups and discuss their trading motives briefly. An in-depth analysis of the participants in the carbon market can be found in the Appendix C.1.

Commodity trading firms. The largest trader in the EUA market is Vitol, the world's largest independent energy trader, and with a revenue of $505 billion, it would rank as the second-largest company worldwide by revenue in 2022[11]. Pirrong (2014) emphasizes the crucial role of independent commodity trading firms, such as Vitol, Mercuria, and Glencore, in the efficient functioning of commodity markets. These firms are extensively involved in every aspect of the value chain. My analysis reveals that Vitol has established itself as the largest trader of EUAs, engaging in the trading of approximately 140 million EUAs during the sample period. The panel A of Table 2 reports the EUA trading behavior of leading commodity trading firms. A concern arises from the possibility that these commodity trading firms may own energy producers regulated by the EU ETS, implying that their trading activities are primarily driven by compliance requirements. To address this concern, I investigate their activities in the compliance block, and only find that Bunge has significant amount of emissions under the regulation. In the robustness analysis, I exclude Bunge from the group of commodity trading firms.

Carbon specialists. I manage to identify a group of investment firms specializing in carbon trading, including Belektron, and Vertis, and EcoWay. These investors are the specialists in the theory of Grossman and Miller (1988) who offer immediacy to buyers and sellers whose orders arrive asynchronously. As highlighted in Duffie (2010), the limited capital or intermediary capacity of these specialist can lead to price surges and return reversals as documented in Figure 2. While these specialists are typically privately owned, I have conducted an online search for their details and examined their registration under MiFID II. The panel B of Table 2 reports the trading behaviors of top carbon specialists. In the Appendix C.1, I present suggestive evidence showing that these investors generally possess significantly less capital compared to major commodity trading firms and investment banks. This is noteworthy given their extensive and dynamic trading activities in the carbon allowance market.

Carbon offsetters. In voluntary carbon markets, investors may have the option to purchase and then cancel carbon allowances from compliance markets like the EUA market. This approach serves

[11] Vitol's 2022 volumes and review can be found here.

as an alternative to buying voluntary offsets. By doing so, these investors effectively reduce the number of available allowances in a cap-and-trade system (Pedersen, 2023). In Table 3, I list the top 30 carbon offsetters. These carbon offsetters, including some climate consulting and advisory firms, tend to provide a comprehensive set of services ranging from energy efficiency improvement, carbon offset project development, carbon risk management, to carbon trading execution. Given this range of services, there is a potential overlap with the roles and functions of carbon specialists. This overlap suggests that these carbon offsetters, while primarily focused on carbon offsetting, may also engage in arbitrage and speculation in the compliance market.

Banks and securities companies. Investment banks and securities firms, including Deutsche Bank and Mitsui Bussan Commodities, have been key players in the carbon allowance market. Table 4 reports the trading behaviors of top 30 investment banks and securities companies. As Cludius and Betz (2020) emphasize, a significant number of these institutions have decommissioned their proprietary carbon trading desks in response to the enactment of MiFID. This regulatory change has curtailed their speculative activities and have impacted their ability to provide liquidity in the market.

Building upon these stylized facts, the following section introduces a model that incorporates financial intermediaries. These intermediaries play a pivotal role in the carbon allowance market by engaging in speculative activities. Their speculation not only provides liquidity to manufacturing firms but also helps to absorb demand shocks that stem from the hedging and diversification motives of financial investors.

4 The Model

I present a two-period model with managerial learning from carbon prices to illustrate the economic mechanisms and derive testable predictions. The model draws heavily on Sockin and Xiong (2015), but features the insights of Goldstein and Yang (2022) that the price informativeness is determined by the arbitrage behavior of financial speculators and the demand shocks introduced by financial investors with hedging or diversification motives.

4.1 Model setup

There is a continuum of islands of total mass one. Each island owns a manufacturing firm that uses energy as input to produce a single good, which can be consumed at "home" or traded for another good produced "away" by another island. A key feature of the model is that energy usage generates CO2 emissions, which are regulated by a cap-and-trade system. That is, carbon allowance is the perfect complement of energy. Firms can trade carbon allowances on the carbon market. Similar to Sockin and Xiong (2015), the carbon market is also platform to aggregate private information about the strength of the global economy, which ultimately determines the global demand for carbon.

There are four types of agents: households on the islands, manufacturing firms on the islands, a representative financial intermediary, and a group of financial hedgers. The manufacturing firms trade carbon allowances with the financial intermediary at $t = 1$ and use carbon allowances to cover their emissions at $t = 2$. Their produced goods are distributed to the households on their respective islands at $t = 2$. The households then trade their goods with each other and consume.

4.1.1 Island households

Each island has a representative household. I assume a particular structure for goods trading between households on different islands. Each island is randomly paired with another island at $t = 2$. The households on the two islands trade their goods with each other and consume both goods produced by the islands. For a pair of matched islands, we assume that the preference of the households on these islands over the consumption bundle (C_i, C_i^*), where C_i represents consumption of the "home" good while C_i^* consumption of the "away" good, is determined by a utility function $U(C_i, C_i^*)$. The utility function increases in both C_i and C_i^*. The households on the two islands thus trade their goods to maximize the utility of each. I assume that the utility function of the island households takes the Cobb-Douglas form

$$U(C_i, C_i^*) = \left(\frac{C_i}{1-\eta}\right)^{1-\eta} \left(\frac{C_i^*}{\eta}\right)^{\eta} \tag{1}$$

where $\eta \in [0, 1]$ measures the utility weight of the "away" good, which determines the degree of complementarity in the islands' goods production.

4.1.2 Manufacturing firms

Each island has a locally owned representative manufacturing firm to organize its goods production. Production requires use of energy as an input and the usage of energy generates proportional CO2 emissions. That is,

$$K_i = fE_i$$

where E_i is the energy input, K_i is the carbon emissions, and f is the scope-1 fossil intensity (emissions per energy use). This production technology is consistent with Pedersen (2023). Manufacturing firms are subject to a cap-and-trade regulation. They need to submit enough allowances to cover their emissions at $t = 1$. This cap-and-trade regulation implies that energy and carbon allowance are perfect complement in the production. Specifically, each island has the following decreasing-returns-to-scale production function

$$\begin{aligned} Y_i &= AX_i^{\phi} \\ X_i &= \min(fE_i, K_i) \end{aligned} \tag{2}$$

where Y_i is the output produced by island i, and X_i is the energy-carbon composite. Parameter $\phi \in (0, 1]$ measures the degree to which the production function exhibits decreasing returns to scale. For simplicity, I assume that each island's productivity does not have an idiosyncratic component. Since the island structure implies that production across islands are complementary from the household's perspective, A represents the strength of the global economy. I assume that A is a random variable that becomes observable only when the firms complete their production at $t = 2$. I further assume that A has a log-normal distribution,

$$\log A \sim \mathcal{N}(\bar{a}, \tau_A^{-1}),$$

where $\bar{a}$ is the mean of $\log A$ and τ_A^{-1} is its variance. At $t = 1$, the firm on each island observes a private signal about $\log A$,

$$s_i = \log A + \varepsilon_i,$$

where $\varepsilon_i \sim \mathcal{N}(0, \tau_s^{-1})$ is random noise independent of $\log A$ and independent of noise in other firm's signals, and τ_s is the precision of the signal. The signal allows the firm to form its expectation of the strength of the global economy and determine its production decision and demand for energy and carbon. The energy and carbon market serve to aggregate the private signals dispersed among the producers. As each firm's private signal is noisy, the publicly observed energy and carbon price also serve as a useful price signal to form its expectation. For simplicity, in the baseline model I assume that firms can always import energy at a fixed price p^E. Without any loss of generality, I further assume that $p^E = 0$. These assumptions can be relaxed to capture the correlation between energy prices and carbon prices.

At $t = 1$, the firm on island i maximizes its expected profit by choosing its composite input X_i,

$$\max_{X_i} \mathbf{E}[P_i Y_i | \mathcal{I}_i] - P_X X_i \tag{3}$$

where P_i is the price of the good produced by the island and P_X is the price of energy-carbon composite. By assuming a zero energy price, P_X is essentially the carbon allowance price P_K. The firm's information set $\mathcal{I}_i = \{s_i, P_K\}$ includes its private signal s_i and the carbon price P_K. The goods price P_i is determined at $t = 2$ based on the matched trade with another island.

4.1.3 Financial intermediary

I assume there is a representative financial intermediary who receives carbon allowances distributed by the government at $t = 1$ and then acts as the allowance supplier in this economy. Note that this modelling setup is consistent with the market structure of the European carbon market. I assume that the financial intermediary faces a convex cost

$$\frac{\xi}{\xi + 1} K_S^{\frac{1+\xi}{\xi}}$$

in supplying the carbon allowances, where K_S is the quantity supplied, and $\xi \in (0, 1)$ is a constant parameter. This convex cost can be micro-founded as the aversion to basis risk, as the financial intermediary tends to hedge its position in the spot market by taking an opposite position in the futures market (Acharya et al., 2013). In this sense, parameter ξ measures the financial intermediary's ability to take the basis risk which captures the degree of limits to arbitrage (Duffie, 2010). Based on the above, given a carbon allowance price P_K, the financial intermediary faces the following optimization problem:

$$\max_{K_S} P_K K_S - \frac{\xi}{\xi+1} K_S^{\frac{1+\xi}{\xi}}. \tag{4}$$

The first order condition of 4 implies that the financial intermediary's optimal supply curve is

$$K_S = P_K^{\xi} \tag{5}$$

where ξ is the price elasticity.

4.1.4 Demand shocks from hedging and diversification

Following Goldstein and Yang (2022), I assume that there is a group of financial investors who enter the carbon market to hedge their other investments. In the baseline model (without a carbon futures market), I assume that financial investors directly trade on the spot market and their aggregate trading is proportional to the aggregate demand from manufacturing firms

$$K_H = (e^{\theta} - 1) \int_{-\infty}^{\infty} K_i(s_i, P_K) d\Phi(\varepsilon_i) \tag{6}$$

where the component $\theta \sim \mathcal{N}(\bar{\theta}, \tau_\theta^{-1})$, a random Gaussian variable with mean $\bar{\theta}$ and variance τ_θ^{-1}, captures trading induced by hedging and diversification motives and is not related to the fundamentals and unobservable to other market participants.

4.2 Equilibrium

The model features the joint equilibrium of the goods markets between each pair of matched islands and the market for the carbon allowance. Equilibrium requires clearing of each of these markets:

- At $t = 2$, for each pair of randomly matched islands $\{i, j\}$, the households of these islands trade their produced goods and clear the market for each good,

$$C_i + C_j^* = AX_i^\phi,$$
$$C_i^* + C_j = AX_j^\phi.$$

- At $t = 1$, in the carbon allowance market, the aggregate demand from firms and financial hedgers collectively equals the supply,

$$\int_{-\infty}^{\infty} K_i(s_i, P_K)d\Phi(\varepsilon_i) + K_H(\theta, P_K) = K_S(P_K) \tag{7}$$

  where each firm's carbon allowance demand $K_i(s_i, P_K)$ depends on its private signal s_i and the carbon allowance price P_K, and demand shock $K_H(\theta, P_K)$ is proportional to firms' aggregate demand with a multiplier that depends on the hedging motives θ. The demand from firms is integrated over the noise ε_i in their private signals.

I leave the derivation of the equilibrium in the Appendix E. The following proposition summarizes the carbon allowance price and each firm's carbon allowance demand in this equilibrium.

Proposition 1. *At time $t = 1$, the carbon allowance market has a unique log-linear equilibrium:*

1. *The carbon allowance price is a log-linear function of $\log A$ and θ,*

$$\log P_K = h_A \log A + h_\theta \theta + h_0. \tag{8}$$

   with the coefficients h_A, h_θ, and h_0 given in the Appendix E, respectively.

2. *The carbon allowance purchased by manufacturing firm i is a log-linear function of its private signal s_i and $\log P_K$,*

$$\log K_i = l_s s_i + l_p \log P_K + l_0 \tag{9}$$

   with the coefficients l_s and l_p given in the Appendix E.

4.3 Model predictions

I derive two predictions based on the Proposition 1. These two predictions are tested in Section 5 and 6, respectively.

4.3.1 Carbon price informativeness

In the presence of informational frictions, the equilibrium carbon allowance price serves as a public signal of the global fundamental $\log A$. This price signal is contaminated by the noise θ introduced by financial hedgers. The noise's price impact depends on the price elasticity ξ of financial intermediary, which capture s the degree of limits to arbitrage in the carbon allowance market. The informativeness of the price signal is determined by the ratio of the contributions to the price variance of $\log A$ and θ:

$$\pi = \frac{\tau_\theta}{\tau_A} \frac{h_A^2}{h_\theta^2}$$

The following prediction characterizes how the price informativeness measure π depends on the key parameter τ_θ and ξ.

Prediction 1. *The carbon price informativeness π is monotonically decreasing in the noise introduced by financial hedgers τ_θ^{-1}, and increasing in the price elasticity ξ of the financial intermediary.*

The intuition is as follows. As τ_θ^{-1} decrease, there is more noise from the financial hedgers interfering with the carbon allowance price reflecting $\log A$. Thus, the carbon allowance price tends to become noisier. The impact of this noise on the price informativeness depends on its price impact. In an inelastic market (Gabaix and Koijen, 2022)——where financial intermediaries have a limited capacity to bear risk——even a small amount of noise can induce significant changes in the carbon allowance price.

4.4 Feedback effects on carbon allowance demand

In the presence of informational frictions, the noise introduced by the hedging and diversification motives of financial investors, by distorting the price signal, can affect firm-level demand for carbon allowances. The carbon allowance demand of firm i is

$$\log K_i = l_s s_i + l_P h_A \log A + l_p h_\theta \theta + l_p h_0 + l_0.$$

Prediction 2. *The carbon allowance demand of firm i is a function of the noise θ, with the sensitive depending on τ_θ and ξ.*

The intuition is as follows. As θ drops, the commodity price falls. Since firms cannot differentiate a price decrease caused by θ from one caused by a weaker global economy, they partially attribute the reduced price to a weaker economy. This motivates them to cut their demand for energy and carbon allowances.

5 Inelastic Carbon Market and Carbon Price Informativeness

This section test the model's prediction 1. I first estimate financial trader's price-elasticity ξ. I then provide evidence on the growing financial hedging motives that map to the parameter τ_θ. I conclude with empirical measures of price informativeness π.

5.1 Estimation of price-elasticity

Financial intermediaries have been investing a lot to acquire information on the fundamental developments of demand and supply to guide their speculative trading. Consequently, it's reasonable to expect that their demands would be sensitive to exogenous price changes. To gauge the extent of an investor's speculative motive, I estimate demand elasticities at the investor level.

5.1.1 Identification

A causal identification of demand elasticities requires exogenous variation in prices that is orthogonal to the investor's own demand shocks. In other words, one needs to find exogenous shifts in the supply curve to identify demand elasticity. The literature has proposed a variety of potential instruments in the context of equity markets, including index inclusions, mutual fund flows or dividend reinvestments. However, constructing such instruments in carbon markets (generally, commodities markets) is challenging, given the intrinsic connection between the demand and supply for spot and futures.

In this paper, I exploit institutional features of the EU carbon markets and use carbon policy shocks as instruments to identify demand elasticities. These carbon policy shocks, constructed by Känzig (2023), are identified from an event study approach which exploits high-frequency EUA futures price changes around regulatory events when the EU updated its policies on the future supply of emission allowances[12]. These regulatory events can take the form of a decision by the

[12] These shocks have been used in other recent papers. For instance, see Hengge et al. (2023); Berthold et al. (2023).

European Commission, a vote in the European Parliament, or a judgment from a European court. The news about allowance supply covers regulatory changes in the overall cap of the EU ETS, the free allocation of allowances, the auctioning of allowances, as well as the use of international credits[13]. During my sample period, decisions on the timing and quantities of emission allowances to be auctioned are the most important regulatory news. Appendix A.2 provides the details of these regulatory events and Figure A.2 plots the monthly carbon policy shock series from January 2013 to December 2019.

The logic of this instrument can be understood as follows: When the EU announces a cut in future allowance supply, firms under the EU ETS are likely to increase their hedging demands for EUA futures, triggering a shift in the demand curve in the EUA futures market. Consequently, this increased demand for futures can widen the difference, or basis, between futures and spot prices, making the spot cheaper *relative* to the futures. This decrease in the *relative* price of spot induces demands in the spot market. Financial speculators who actively engage in basis arbitrage typically react by supplying futures to meet firms' hedging demands while simultaneously demanding spot. Note that the supply elasticity of investors in the futures market is mirrored by their demand elasticity in the spot market. Given this relationship, the sensitivity of an investor's demand for spot to the exogenous variation in the *relative* price of spot clearly identifies her willingness to accommodate shifts in market conditions. Specifically, define the EUA basis in month t, Basis_t, as

$$\text{Basis}_t = \log F_t - \log S_t,$$

where F_t is the price of EUA front-December contract in month t and S_t is EUA spot price in month t. Change in EUA basis, ΔBasis_t, can be decomposed as

$$\begin{aligned}\Delta\text{Basis}_t &= (\log F_t - \log S_t) - (\log F_{t-1} - \log S_{t-1}) \\ &= (\log F_t - \log F_{t-1}) - (\log S_t - \log S_{t-1}) \\ &= \Delta \log F_t - \Delta \log S_t\end{aligned} \tag{10}$$

The carbon policy shocks, ε_t^{CP}, as identified in Känzig (2023), isolate the component in $\Delta \log F_t$ that is attributable to firms' policy-driven hedging demands. Exploiting these carbon policy shocks

[13] The allowance distribution methods are discussed in detail in Section 2.

as instruments, the elasticities can be obtained in a simple two-stage least squares procedure. Let ΔQ_{it}^{g} denotes the signed amount of EUA traded by investor i from group g in month t[14], and $\Delta \hat{\text{Basis}}_t$ denote the fitted value from regressing changes in EUA basis, ΔBasis_t, onto carbon policy shocks, ε_t^{CP}. The second stage regression of investor-specific trades ΔQ_{it}^{g} onto the instrumented changes in basis $\Delta \hat{\text{Basis}}_t$ allows identifying their demand elasticities ξ^g. Formally, for every investor group g the two stages are given by:

$$\begin{aligned} \text{1st Stage:} \quad & \Delta\text{Basis}_t = \theta \varepsilon_t^{CP} + \Gamma X_t + \epsilon_t \\ \text{2nd Stage:} \quad & \Delta Q_{it}^{g} = \xi^g \Delta \hat{\text{Basis}}_t + \Gamma X_t + \epsilon_{it} \end{aligned} \tag{11}$$

where the matrix of control variables X_t includes Amihud ratios of the EUA spot and futures market[15], EUA auction cover ratios, and the volatility index of Euro stock market, VSTOXX. I also add investor fixed effects, year fixed effects and month fixed effects. Barnichon and Mesters (2020) demonstrate that using structural shocks as instruments to estimate structural equations is robust to weak instruments and is valid regardless of the shocks' variance contribution.

Table 5 reports the results from the estimation of demand elasticities. Given the construction of the instrument, the 1st-stage F statistics are large (above 100). Models (1) and (2) present the elasticities of top investment banks and securities companies reported in Table 4. Consistent with Cludius and Betz (2020), these financial institutions exhibit a moderate elasticity, with 1% increase in the EUA basis translating to less than 1% purchasing of EUA spot, potentially due to the change in financial regulations. Models (3) and (4) report insignificant elasticities of leading commodity trading firms in the Panel A of Table 2. These trading houses invest a significant amount in carbon allowances, but their trading are not sensitive to the changes in basis, indicating other trading motives such as hedging for climate exposures of other business lines or for compliance requirements in the future. Models (5) and (6) display the results for carbon specialists in the Panel B of Table 2. The large and significant elasticity estimates, approximately around 4, suggest that these specialists are actively involved in arbitrage within the EUA market, positioning them as the

[14] To simplify the interpretation of the regression coefficient, I normalize the trading volumes by dividing them by the average trading volumes in the EUA spot market for month t, thereby converting the figures into *percentage* terms.

[15] I use Amihud (2002) ratio as the proxy for carbon liquidity, as Marshall et al. (2012) have shown that, in commodities markets, this measure has the largest correlation with liquidity benchmarks and transaction costs.

marginal investors. Although these carbon specialists are private firms and do not publicly disclose information about their assets under management or leverage ratios, indicative evidence suggests that they are relatively small in size and are likely to face capital constraints, possibly at important times like the outbreak of Russia-Ukraine war.

Despite my thorough search and investigation, the classification of carbon specialists requires a degree of discretion. Specifically, climate consulting and advisory firms, such as RedShaw Advisors and nserve, tend to provide a comprehensive set of services ranging from energy efficiency improvement, carbon offset project development, carbon risk management, to carbon trading execution. That is, there may be overlap with the carbon offsetters described in the Appendix C.1 and reported in Table 3. As a robustness check, I run the two-stage regressions for the top 30 carbon offsetters and top 30 carbon end-users. The results are reported in Table D.5. It is clear that the trading of these investors are not sensitive to the changes in EUA basis.

5.2 Carbon market crash

The carbon market crash following the Russia-Ukraine war illustrates how external shocks, even if not directly linked to the carbon market, can be transmitted to it. When the carbon market is inelastic, such shocks can have large price impacts, thereby injecting noise into the carbon price. Russia is one of the world's largest exporters of natural gas, and many countries in Europe rely on Russian gas, which often flows through Ukrainian pipelines, to meet a substantial portion of their energy demands. When the Russia-Ukraine conflict escalated on 24 February 2022, fears of war-induced disruptions to Russian gas supplies sent ripples through the natural gas market. The natural gas price surged by approximately 150%, reaching all-time highs just days after the onset of the war. The black line in the upper panel of Figure 4 traces the progression of front-month Dutch TTF natural gas futures price, the benchmark for natural gas prices in Europe.

There is a strong economic connection between natural gas prices and carbon prices. Carbon prices act as a differential between coal and gas prices, prompting power plants to toggle between coal and natural gas for electricity generation. After the war's outbreak, while coal prices remained relatively unchanged, the surge in gas prices may encourage more power plants to switch from gas to coal. Given coal's higher emission intensity, this would bolster the demand for carbon allowances, consequently exerting upward pressure on the carbon price. See the Appendix C.2 for a discussion of the carbon-gas correlation and its connections with the clean dark and spark spreads (i.e., profit margins for coal and gas plants when accounting for the cost of carbon).

In spite of the upward pressure on the carbon price due to rising gas prices, EUA prices plummeted from €95/t to €55/t in just over a week. The black line in the lower panel of Figure 4 represents the fluctuations in prices for the EUA front-December contracts. This market crash is difficult to attribute solely to long-term factors, such as Europe's expedited green transition or the bleak economic outlook due to elevated energy prices. Anecdotal evidence from the industry suggests that this crash was due to market participants liquidating their EUA positions to cover margin calls in energy commodities like gas (Refinitiv, 2023). The red (grey) bars in the upper and lower panels of Figure 4 shows the weekly long (short) positions of investment funds in the gas and carbon futures markets, respectively. Despite the relatively low frequency, the position data indicate that the rapid liquidation of EUA long positions is associated with the reduction in gas short positions. This association is aligned with the co-movements in gas and carbon prices, consistent with the industry's observations.[16]

It took around a week for the EUA price to rebound to approximately €80/t from the liquidation-induced low point. If more capital were dedicated to the carbon market, making it more elastic, we would expect a lower price impact of the liquidation and a quicker recovery of the carbon price. As Singleton (2014) points out "in any market setting where there are limits to the amount of capital investors are willing to commit to an asset class . . . large increases in desired long or short positions by any class of investors can potentially impact prices."

5.3 Measures of Price Informativeness

To establish formal evidence that carbon price has become noisier in recent years, I construct two price informativeness measures that are widely used in the literature (Brogaard et al., 2019). These measures are also used in the firm-level regressions in the next section. Specifically, my price informativeness measures are the price delay (Hou and Moskowitz, 2005) and the absolute variance ratio (Lo and MacKinlay, 1988).

The first measure, price delay, is a measure of the delay with which fundamental information are reflected in prices. The idea is that in efficient markets fundamental information are fully and

[16] Bloomberg, March 1, 2022, Carbon Tumbles Most in Almost a Decade as War Spooks Investors.

immediately priced in when they become available. The greater the delay, the greater the deviation from the ideal world of market efficiency. Specifically, for both the pre-2020 and post-2020 periods, I calculate R^2 as a measure of price delay from weekly return regression of the form:

$$r_t = \alpha_i + \sum_{j=1}^{4} \Gamma_j r_{t-j} + \varepsilon_{i,t} \tag{12}$$

That is, the measure is the R^2 from a regression of current weekly EUA futures returns on four lags of their own. The underlying assumption here is that EUA's own past futures returns have incorprated all the public information (Brogaard et al., 2019).

My second measure of price inefficiency is the absolute value of the centered variance ratio statistic (Boehmer and Kelley, 2009). Specifically, for each year p, I compute bias-corrected variance ratio statistics over horizons of $q = 2, 4, 6$, and 8 trading days using overlapping observations (Lo and MacKinlay, 1988). I then center these ratios and use their absolute values:

$$AVR_p(q) = |1 - VR_p(q)| \tag{13}$$

If EUA price is informationally efficient then the variance ratio should equal one. Therefore, $AVR = 0$ indicates weak-form efficiency, and the larger the value of AVR, the further the commodity price process is from the random-walk benchmark.

The top panel of Figure 5 shows the evolution of the first measure, while the bottom panel depicts the evolution of the second measure[17]. Both measures indicate that there is a decline in price efficiency in the recent years, potentially associated with the trading of financial investors.

5.4 Discussions

Despite the extensive evidence presented in the earlier sections, one might question why financial speculators aren't entering this market to capitalize on arbitrage opportunities. Indeed, financial speculation is on the rise, but its growth is potentially slower than that of financial hedgers. This section delves into the possible reasons behind this trend.

[17] I have defined the year in my analysis as spanning from May to May. This definition aligns with the requirement for firms covered by the EU ETS to surrender allowances by the end of April to cover their emissions from the previous year.

Constraints on financial speculation. For financial speculators, time is perhaps the primary constraint. Speculation in the carbon market demands a deep understanding of global energy market operations, the development of renewable technology, and familiarity with policy regulations. Amassing experts in these areas and establishing an efficient carbon trading desk entails considerable time, even for well-established hedge funds and investment banks. Another significant factor in play is the scarcity of seasoned carbon experts. Search frictions within the job market can pose challenges, potentially deterring top environmental analysts from transitioning to capital-rich investment firms. This bottleneck in talent mobility can stifle the growth of financial speculation, despite the allure of arbitrage opportunities. It's worth highlighting that potential speculators are actively recruiting carbon experts, gearing up to capitalize on the market[18]. However, the rapid rise of financial hedgers combined with misconceptions held by policymakers could potentially diminish these efforts.

Drivers of financial hedging. The surge in financial hedging within the carbon allowance market can be attributed to two factors. First, the widespread embrace of market-based climate policy instruments, both in academia and industry, inherently boosts the use of carbon futures for hedging purposes[19]. Investment banks, when issuing green bonds (Flammer, 2021), sustainability-linked bonds (Berrada et al., 2022), or emissions-linked notes (Allen et al., 2023) have to effectively manage their associated risks. It's likely that they will view carbon allowance futures as effective hedging tools. Consequently, the emergence of green structured products naturally spurs hedging demand among these financial investors. The inflow and outflow of investments in these products may be passed to and withdrawn from the carbon allowance futures market via issuers' trades to hedge their liability to these products. Similar mechanism has been documented in the commodity-linked notes (CLNs) market (Henderson et al., 2015).

Second, carbon allowances are broadly marketed as a means of diversification in the asset manangement industry (Swinkels and Yang, 2022). Recent innovations in index investing and ETFs

[18] Financial Times, June 9, 2021, Andurand Hires Top Environmental Analyst in Green Fund Push.

[19] For instance, the Tramontana Asset Management issues EUA-based structured debt by repackaging EUAs into a standardised note that can help firms manage their exposures to carbon pricing risks. This structured product wins the Sustainable Investment Awards 2023 held by the Environmental Finance magazine, as the best ESG investment initiative (fixed income) of the year.

have paved the way for easier entry into the carbon market. Figure 6 plots the evolution of fund flows of four major index-tracking carbon ETFs, i.e., GRN (iPath Series B Carbon ETN), KRBN (KraneShares Global Carbon Strategy ETF), KARB (Carbon Strategy ETF), KEUA (KraneShares European Carbon Allowance Strategy ETF), from January 2021 to April 2022. It's worth pointing out that these inflows and outflows might come from impact investors who perceive investing in carbon as a meaningful way to affect climate change. Given that there's no foundational premise suggesting carbon investing yields impact, the flows from these investors could serve as an illustration of the behavioral disturbances discussed in Gabaix and Koijen (2022). Given the inelastic carbon market that has been documented, it's plausible to argue that these behavioral disturbances may have price impacts, introducing noise into the carbon price.

6 Do Firms Respond to Noise in Carbon Allowance Price?

In this section, I present empirical evidence on the model's prediction 2 at both micro and macro levels. At the micro-level, I document that firms with better internal information environment––proxied by either the intensity of internal carbon trading or whether the firm has voluntarily disclosed an internal carbon pricing mechanism to CDP—are significantly less responsive to changes in EUA price, and this difference in responsiveness is particularly pronounced during periods of high EUA price inefficiency. At the macro-level, I find a positive correlation between the cross-sectional dispersion in carbon intensity, which serves as a measure of carbon misallocation, and the level of EUA price inefficiency.

6.1 The heterogeneous responses to noises in carbon price

The large literature on the feedback effects (Goldstein, 2023) argue that the information content in market prices can impact firm real decisions, such as investment, abatement, and production. Given the evidence in Section 5 that financialization has introduced noises into EUA price, the feedback channel predicts that firms would make less efficient real decisions. Even when firms manage to partially detect these noises, the overall decline in signal quality would likely make them allocate more information capacity in processing signal contained in EUA price, crowding out their learning of idiosyncratic uncertainty and resulting in less informed real decisions. To test these predictions, this subsection provides micro-level evidence that compliance firms indeed respond to noises in EUA price, while subsection 6.2 links the informational efficiency of EUA price with macro-level allocative efficiency.

6.1.1 Identification

An empirical challenge to examining how firms respond to noises in carbon price is identifying heterogeneity across firms (Nakamura and Steinsson, 2018) that aligns with the proposed feedback mechanism. The key question here is: Are firms that more rely on the information content in the carbon price exhibit greater responsiveness to the increased noises in that price? I address this challenge by exploiting the rich heterogeneity in internal information environment across firms.

My identification strategy relies on the assumption that firms with better internal *private* information will rely less on the *public* information contained in the EUA price to make their real decisions. I use two measures of a firm's internal carbon pricing mechanism to proxy for its internal information environment and thus its reliance on EUA price as information source. First, I measure the intensity of internal carbon trading $ITI_{j,t}$ as the firm's total amount of *internal transaction* (i.e., *within-conglomerate between-firm transactions*) of EUAs scaled by its total amount of emissions. Second, I construct a dummy variable, $\mathbf{1}_{j,t}^{ICP}$, which takes on the value of one if the firm has disclosed the presence of an internal carbon pricing mechanism to CDP and zero otherwise.

The idea is that an active and well-established internal carbon pricing mechanism can generate better internal *private* information that substitutes *public* information in EUA price. The cross-sectional variations in these two measures facilitate a within-year comparison of real decisions for firms with varying reliance on the *public* information. Both of these measures vary at the firm-by-year level, so the key identifying assumption is that these variations are independent of other firm-by-year shocks.

6.1.2 Baseline results

In this section I test whether firms respond to the noise component in carbon price. The main dependent variable of interest is the change in firms' carbon emissions intensity, $\Delta \log y_{j,t+1}$, where $y_{j,t+1}$ are the verified emissions (equivalently, the surrendered allowances) of the firm j in year $t+1$.

Specifically, I estimate the regression model:

$$\Delta \log y_{j,t+1} = \alpha_j + \alpha_{st} + \beta_1 H_{j,t-1} \times Ret_t^{EUA} + \beta_2 H_{j,t-1} \times Ret_t^{EUA} \times \text{INEFF}_t^{EUA} + \Gamma' Z_{j,t-1} + e_{j,t} \quad (14)$$

where α_j is a firm j fixed effect, α_{st} is a sector s by year t fixed effect, Ret_t^{EUA} is the log return of EUA futures price during year t, $H_{j,t-1}$ is the proxy of the inefficiency of the internal information environment of firm j in year $t-1$ (either $1 - ITI_{j,t-1}$ or $1 - \mathbf{1}_{j,t-1}^{ICP}$)[20], INEFF_t^{EUA} is the EUA price inefficiency at year t, $Z_{j,t-1}$ is a vector of firm-level controls, and $e_{j,t}$ is a residual.

The first coefficient of interest is β_1, which measures how the semielasticity of the change in carbon intensity $\Delta \log y_{j,t+1}$ with respect to the change in EUA futures price depends on the variations in firms' internal information environment. Note that the interpretation of β_1 is similar to the semielasticity of investments to monetary policy shocks in Ottonello and Winberry (2020). Following Martinsson et al. (2022), I use log differences specification to alleviate problems of unit roots in variables and cluster standard errors at the firm level[21].

The second coefficient of interest is β_2, which measures how the heterogeneity in the responsiveness to change in EUA price depends on the information inefficiency. I use the average of bias-corrected variance ratio statistics over horizons of $q = 2, 4, 6$, and 8 trading days from Section 5 to represent the information inefficiency INEFF_t^{EUA} and use its interaction with EUA log return to proxy for the noise component in changes in EUA price. Ideally, I could construct instruments for the noise component from carbon ETF arbitrage or other non-fundamental trade of financial investors. However, the limited sample length does not allow me to do so. Nonetheless, the use of information inefficiency measures in the interaction term aligns with the specifications in Chen, Goldstein, and Jiang (2007).

I control for a number of factors that may simultaneously affect the change in carbon intensity and firms' reliance on the information content in EUA price but which are outside the econometric model. The firm fixed effects α_j capture permanent differences in change in carbon intensity across firms and the sector-by-quarter fixed effects α_{st} capture differences in how broad sectors are exposed

[20]I use inefficiency rather than efficiency of internal information environment to keep consistent with that of public information. This treatment also facilitate the interpretation as higher carbon price results in lower emissions in general.

[21]The results are robust to double clustering at the firm and year levels. I choose to only report standard errors clustered at the firm level since the short sample period might pose a threat to the asymptotically consistency of year clustered standard errors. This specification is consistent with Brogaard et al. (2019).

to the changes in EUA price. I define the sector at the 4-digit NACE level to ensure granularity. The vector $Z_{j,t-1}$ includes total asset and the windfalls generated from free-allocated allowances which might contribute to the change in abatement and other firm behaviors (Bolton et al., 2023). Specifically, I define the windfalls as $Windfalls_t = \frac{FreeAllowance_{j,t-1} \times Return_t^{EUA}}{sales_{j,t-1}}$. All the variable definations can be found in the Appendix. The estimation sample includes all firms over the period 2013 to 2022.

Table 6 displays the coefficients estimates with t-statistics, calculated using standard errors clustered by firm. Model (1) and (4) confirm that the average negative responses of carbon intensity to increases in EUA price. Consistent with the theoretical predictions, the estimated β_1 coefficients are significantly negative for all firms (model 2) and manufacturing firms (model 5). The negative β_1 estimates imply that firms with worse private information are reduce their emissions more when EUA price increases. The coefficient magnitudes are economically large. For example, in models (2) and (5), carbon intensity decrease by approximately 6% for firms with worse price information (relative to the firms with better private information). Importantly, these differences in responsiveness are much more pronounced when the EUA price is less informative. In model (3) and (6), carbon intensity decline by over 10% and 20% respectively for firms with worse private information relatively when the EUA price inefficiency increases. Overall, the results show that firms with worse private information reduce emissions more relative to firms with better private information, especially when there is more noise in the EUA price that serves as a public signal.

6.1.3 Does noise in carbon price affect firm emission efficiency?

The above results indicate that firm emissions become less responsive to carbon prices whenever carbon prices become less informative. Yet, the results do not capture the full scope of how financialization influences firm emissions decisions. For instance, should firms be able to accurately discern and disregard the noise causing the decrease in carbon price informativeness, their emissions decision-making quality would remain unchanged. On the other hand, if firms struggle to isolate this noise, it could lead to adverse effects on emissions.

To address these concerns, I test whether the quality of emissions decisions are affected by the noise in carbon price by re-estimating the model with proxies for the inefficiency of firm emissions as the outcome variable. Intuitively, if financialization negatively affected firms, then one would expect a decline in emissions efficiency as a result of poorer decision-making by these firms. Following Brogaard et al. (2019) and drawing opon the literature on investment inefficiency (Biddle et al., 2009; Stoughton et al., 2017), my proxy for emissions inefficiency is the absolute residual from a regression of firm emissions on lagged realizations of emissions cost scaled by sales (Martinsson et al., 2022). The emissions cost is calculated by multiplying the volume of emissions with the EUA price. This residual aims to quantify the deviation from a firm's ex-ante optimal level of emissions, including both over and under reaction.

I denote the measure of emissions inefficiency by $|\varepsilon_{j,t}|$. I then test whether noise associated with financialization increases emissions inefficiency via the following regression:

$$|\varepsilon_{j,t}| = \alpha_j + \alpha_{st} + \beta_1 H_{j,t-1} \times Ret_t^{EUA} + \beta_2 H_{j,t-1} \times Ret_t^{EUA} \times \text{INEFF}_t^{EUA} + \Gamma' Z_{j,t-1} + e_{j,t} \quad (15)$$

Coefficient estimates from Equation (15) are shown in Table 7. I find a positive and statistically significant effect of financialization on emissions inefficiency. The β_1 coefficient estimate of 0.02 in model (1) and (2) and (0.01 in model (4) and (5)) represents a 2% (1%) increase from the unconditional mean level of inefficiency. This indicates that firms with worse private information are less efficient in making their emissions decisions. The β_2 coefficient estimates are around 0.2 in both model (3) and (4), implying that the differences in emissions efficiency are much larger when EUA price is less informative. Overall, the results indicate that the increased noise in EUA price has led to a less efficient emission reduction, particularly for firms with inferior private information.

6.1.4 Robustness

A concern of the above analysis is that the observed decline in carbon price informativeness and associated carbon financialization may stem from the categorization of EUA as financial instrument under MiFID II, a designation that was implemented only as of 2018. To address this concern, I re-estimate Equation (14) and (15) using the sample over the period 2018 to 2022. The results are presented in Table D.6 and D.7 in the Appendix D. These results are consistent with the full-sample estimation.

6.2 The misallocation of carbon

The fact that firms' carbon intensity respond to the decline in carbon price informativeness does not necessarily imply that the overall allocative efficiency is negatively affected by carbon financialization. In fact, firms may actually benefit from carbon financialization due to the well-known Hirshleifer (1971) effect — less information may improve risk sharing and better allow firms to achieve trading gains in the carbon futures markets - i.e., only firms which do not participate in carbon futures markets are harmed by financialization (Goldstein and Yang, 2022). To better understand the aggregate real effects, I provide macro-level evidence that links carbon price (in)efficiency with the (mis)allocation of carbon allowances.

As underscored by Hsieh and Klenow (2009), and subsequently supported by a large literature on misallocation, the cross-sectional dispersion of the marginal revenue product of a certain input is a measure of misallocation of that input. One can draw an analogy here that the misallocation of carbon allowances can be represented by the cross-sectional dispersions of carbon intensity (emissions scaled by sales). The economic intuition behind this is that the marginal revenue productivity of one unit of carbon allowance should be equalized across firms. Otherwise, reallocating carbon allowances to firms that can utilize them more effectively could lead to an increase in the aggregate Total Factor Productivity (TFP) and because the total emissions are fixed by the cap, a reduction in the aggregate carbon intensity. To this end, Figure 7 plots the evolution of cross-sectional dispersions in carbon intensity from 2013 to 2022. A higher level of dispersion indicates a more severe misallocation. The observed trend of misallocation aligns with the carbon price informativeness measures depicted in Figure 5. This correlation implies that information frictions may be a potential underlying factor driving the misallocation. The identification strategies described in David and Venkateswaran (2019) can be employed once sufficient data is available.

7 Conclusion

In recent years, there has been a significant rise in financial trading within carbon allowance markets. My research examines whether this influx of investment capital influences the allocative efficiency of these markets and the efficacy of cap-and-trade regulation.

Exploiting a comprehensive set of allowance transaction and surrender data, I find that financialization of the European carbon market is characterized by limits to arbitrage—price-elastic carbon specialists are more likely to face capital constaints than inelastic large financial institutions. Consequently, demand shocks driven by financial investors' hedging and diversification motives can have price impacts, resulting in a decline in carbon price informativess. This decrease in informativeness has real effects on firms' emissions decisions: I find that firms with inferior private information, proxied by the internal carbon pricing mechanism, reduce their emissions less efficiently when the carbon price is less informative.

Overall, this paper provides novel evidence that carbon financialization, characterized by limits to arbitrage, is not just a side-show: it can affect firm emission decisions and generate negative externalities in the real economy. A clear policy implication arises from these findings: to improve the allocative efficiency of carbon markets, there is a need to encourage financial speculation.

Table 1 Sample description of the compliance block

The table presents descriptive statistics for the compliance block of the sample. The “#Installation” column indicates the number of installations regulated by the EU ETS within each country. The “#Firm” column displays the count of unique firms, each identified by a distinct Orbis BvD ID. The ”Consolidated” column lists the number of unique consolidated firms, identified by either a unique domestic ultimate owner (DUO) or global ultimate owner (GUO) BvD ID. The “#Public” column specifies the number of unique public consolidated firms. This sample covers the period from 2013 to 2022. Notably, firms in the UK are not included in the sample due to the UK’s departure from the EU ETS during this period.

Country	#Installation	#Firm	#Consolidated	#Public
Austria	217	102	73	6
Belgium	273	140	104	11
Bulgaria	140	104	80	6
Croatia	62	42	30	5
Cyprus	6	5	1	1
Czech Republic	325	206	160	2
Denmark	213	94	76	5
Estonia	46	27	18	1
Finland	671	169	132	9
France	1051	615	380	26
Germany	1475	563	423	38
Greece	63	50	46	1
Hungary	238	139	111	3
Iceland	7	7	5	0
Ireland	5	1	6	6
Italy	1153	669	543	13
Latvia	48	34	32	0
Lithuania	98	62	56	4
Luxembourg	17	11	13	4
Malta	3	2	2	0
Netherlands	254	122	102	16
Norway	154	78	66	11
Poland	911	467	349	20
Portugal	237	165	121	3
Romania	200	133	101	11
Slovakia	146	92	62	2
Slovenia	49	45	38	5
Spain	997	661	470	22
Sweden	925	256	194	16
Total	9984	5061	3794	247

Table 2 Commodity trading firms and carbon specialists in the EUA market

This table reports the EUA trading behaviors of leading commodity trading firms (Panel A) and carbon specialists (Panel B) by net amounts of external EUA transactions. Leading commodity trading firms are those included in the Appendix of Pirrong (2014). Carbon specialists are those investment firms specializing in carbon trading. These carbon specialists are identified from the Environmental Finance magazine and additional manual research. The columns "#Trade" indicate the number of EUA transactions. The columns "Amount" detail the volume of EUAs traded by each trader, with the figures expressed in millions of tonnes of CO2. The columns "%Futures" indicate the fraction of transactions that occured during the EUA futures delivery period. This data is sourced from the European Union Transaction Log (EUTL) and covers the period from April 30, 2013, to April 30, 2020.

Panel A. Leading Commodity Trading Firms							
	Net Buy	Buy			Sell		
Name	Amount	#Trade	Amount	%Futures	#Trade	Amount	%Futures
Mercuria	6.15	145	12.44	20.15%	79	6.30	0.10%
Cargill	2.99	45	3.01	0.00%	3	0.02	0.00%
Gunvor	1.74	61	2.22	99.62%	10	0.48	0.00%
Mercuria-EcoSecurities	0.64	45	3.47	2.90%	41	2.83	7.20%
Bunge	0.12	4	0.46	16.30%	2	0.33	0.00%
Bunge-Climate Change Capital	0.00	20	7.90	12.44%	20	7.90	0.00%
Vitol	-51.40	104	41.52	54.75%	110	92.92	0.48%
Noble	-2.63	3	1.04	0.00%	35	3.67	33.58%
Cargill-Green Hercules Trading	-0.12	10	1.45	0	13	1.57	0
Panel B. Carbon specialists							
	Net Buy	Buy			Sell		
Name	Amount	#Trade	Amount	%Futures	#Trade	Amount	%Futures
Belektron	40.94	314	57.13	9.90%	203	16.19	5.97%
Amsterdam Capital Trading	21.59	634	72.86	10.63%	669	51.27	7.10%
DASCO Commodities	19.82	113	33.12	4.64%	48	13.30	4.59%
Vertis Environmental Finance	11.49	155	12.93	23.83%	38	1.44	23.03%
STX Commodities	1.03	86	3.80	0.13%	47	2.76	12.55%
Ohana LLP	-47.34	58	3.94	2.05%	247	51.28	11.74%

Table 3 Top 30 carbon offsetters by net external EUA transactions

This table reports the EUA trading behaviors of top 30 carbon offsetters by net amounts of external EUA transactions. Carbon cancelers are entities that engage in either nature-based climate solutions (e.g., development of carbon offset projects) or technology-based climate solutions (e.g., renewable energy). The columns "#Trade" indicate the number of EUA transactions. The columns "Amount" detail the volume of EUAs traded by each trader, with the figures expressed in millions of tonnes of CO2. The columns "%Futures" indicate the fraction of transactions that occured during the EUA futures delivery period. This data is sourced from the European Union Transaction Log (EUTL) and covers the period from April 30, 2013, to April 30, 2020.

	Net Buy	Buy			Sell		
Name	Amount	#Trade	Amount	%Futures	#Trade	Amount	%Futures
Statkraft	27.37	529	54.94	32.71%	412	27.57	35.33%
China Carbon	6.02	134	28.44	14.56%	268	22.42	16.00%
NE Climate	3.38	1	3.38	0.00%	0	0.00	0.00%
Bujagali Energy	3.25	5	5.42	0.00%	4	2.16	0.00%
Kinect	3.18	16	8.53	0.00%	5	5.35	0.00%
Zukunftswerk eG	2.52	105	2.60	10.23%	2	0.08	0.00%
atmosfair	2.37	74	2.89	16.00%	67	0.52	13.12%
Global Factor	2.20	98	3.05	5.72%	5	0.85	58.94%
Atmoz	1.89	20	1.77	3.20%	7	0.15	0.01%
ALLCOT	1.62	39	1.82	29.40%	8	0.25	0.00%
Redshaw Advisor	1.57	74	2.29	16.68%	15	0.81	24.32%
Natural Capital Partners	1.48	103	10.58	22.96%	88	9.45	8.19%
Sindicatum Renewable Energy	1.12	27	2.70	6.22%	31	1.59	9.49%
C-Quest Capital	1.12	32	1.10	5.03%	0	0.00	0.00%
ECOACT	1.10	45	2.33	29.32%	14	1.43	51.39%
GET2C	0.90	61	1.53	7.42%	49	0.74	16.41%
Eneco	0.79	45	3.47	2.90%	41	2.83	7.20%
N.serve	0.64	292	14.15	11.21%	282	13.70	2.59%
First Climate	0.45	52	2.32	8.44%	56	1.92	11.96%
Numerco	0.40	12	4.33	28.90%	8	4.03	33.82%
CARBON	0.30	101	4.31	0.30	35	2.41	0.02
FairClimateFund	0.26	14	0.37	13.51%	23	0.11	4.38%
Agrinergy	0.23	39	4.33	23.65%	48	4.10	18.82%
Climate Bridge	0.22	38	3.87	15.48%	35	3.65	10.48%
South Pole	0.13	16	0.13	0.00%	0	0.00	0.00%
Carbon Road	0.07	17	3.58	37.65%	15	3.51	33.39%
Carbon Rooster	0.00	22	7.95	32.36%	21	7.95	26.15%
Aither	0.00	1	0.80	0.00%	3	0.80	6.25%
Wind to Market	-1.02	18	0.57	0.00%	55	0.58	6.46%
Arreon Carbon	-0.72	23	4.79	0.00%	53	5.51	18.78%

Table 4 Top 30 banks and securities companies by net external EUA transactions

This table reports the EUA trading behaviors of banks and securities companies by net amounts of external EUA transactions. The columns "#Trade" indicate the number of EUA transactions. The columns "Amount" detail the volume of EUAs traded by each trader, with the figures expressed in millions of tonnes of CO2. The columns "%Futures" indicate the fraction of transactions that occured during the EUA futures delivery period. This data is sourced from the European Union Transaction Log (EUTL) and covers the period from April 30, 2013, to April 30, 2020.

	Net Buy	Buy			Sell		
Name	Amount	#Trade	Amount	%Futures	#Trade	Amount	%Futures
VTB Capital	9.45	30	11.73	0.00%	20	2.28	91.23%
Royal Bank of Scotland	9.16	13	9.16	0.00%	0	0.00	0.00%
Societe Generale	8.74	100	8.74	9.53%	0	0.00	0.00%
Citigroup	8.59	157	10.66	12.94%	60	2.07	26.60%
Macquarie Bank	3.07	45	5.19	9.94%	50	2.12	15.46%
Mitsui Bussan Commodities	2.98	432	19.64	27.92%	151	16.66	13.16%
Merrill Lynch	2.72	54	3.61	63.37%	16	0.89	51.84%
Morgan Stanley	2.07	150	2.08	20.88%	2	0.00	0.00%
UniCredit	1.44	67	1.44	15.63%	0	0.00	0.00%
J.P. Morgan Securities	1.16	22	1.28	93.18%	1	0.11	0.00%
Commerzbank	0.89	42	1.47	40.16%	9	0.57	5.83%
ICBC Standard Bank	0.48	19	1.21	2.81%	20	0.73	0.00%
Credit Suisse	0.40	12	0.40	23.57%	0	0.00	0.00%
Westpac	0.24	12	0.42	2.38%	6	0.18	0.00%
Nomura International	0.18	3	0.19	0.00%	1	0.01	0.00%
Rabobank	0.07	1	0.07	100.00%	1	0.00	0.00%
Goldman Sachs	0.06	9	0.24	23.66%	1	0.18	0.00%
Mizuho Securities	0.06	4	0.06	0.00%	2	0.01	0.00%
AMRO	0.00	12	0.09	82.73%	1	0.08	0.00%
ING Bank	0.00	2	0.83	0.00%	4	0.83	0.00%
Standard Chartered Bank	0.00	1	0.38	0.00%	1	0.38	0.00%
Deutsche Bank	-9.87	871	13.60	0.60%	293	23.48	32.26%
Barclays	-3.40	203	4.53	2.25%	173	7.93	23.92%
ANZ	-2.86	4	0.26	9.61%	34	3.12	8.02%
UBS Bank	-2.09	29	1.00	0.00%	94	3.09	90.53%
BNP Paribas	-1.92	9	0.46	55.94%	56	2.37	39.46%
Hana Bank	-1.58	0	0.00	0.00%	29	1.58	0.00%
Bayerische Landesbank	-0.88	4	0.18	0.00%	13	1.06	99.34%
DB Energy Commodities	-0.60	14	1.81	1.45%	7	2.40	2.08%
J.P. Morgan Ventures Energy	-0.52	6	2.23	0.00%	9	2.75	54.57%

Table 5 The estimation of price elasticity

This table reports the results from the estimation of price elasticity for different investor groups with the following two-stage least squares regressions:

$$\text{1st Stage:} \quad \Delta\text{Basis}_t = \theta\varepsilon_t^{CP} + \Gamma X_t + \epsilon_t \qquad \text{2nd Stage:} \quad \Delta Q_{it}^g = \xi^g \Delta\hat{\text{Basis}}_t + \Gamma X_t + \epsilon_{it}$$

where $\text{Basis}_t = \log F_t - \log S_t$, F_t is the price of EUA front-December contract in month t and S_t is EUA spot price in month t; ε_t^{CP} are carbon policy shocks sourced from Känzig (2023); X_t includes Amihud ratios of the EUA spot and futures market, EUA auction cover ratios, and the volatility index of Euro stock market, VSTOXX; ΔQ_{it}^g is the signed amount of EUA traded by investor i from group g in month t; $\Delta\hat{\text{Basis}}_t$ is the fitted value from regressing changes in EUA basis, ΔBasis_t, onto carbon policy shocks, ε_t^{CP}. Models (1) and (2) report the results for top 30 investment banks and securities companies in Table 4; Models (3), (4) and (5), (6) report the results for leading commodity trading firms (CTF) and carbon specialists (Carbon) in Table 2, respectively. The sample is monthly from January 2013 to December 2019. The 1st-stage F statistics are above 100.

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\hat{Basis}$	0.79**	0.80***	3.03	4.78	4.32***	4.45***
	(0.32)	(0.23)	(3.13)	(3.59)	(1.22)	(0.95)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	No	Yes	No	Yes
Group	Banks	Banks	CTF	CTF	Carbon	Carbon
N	2059	2059	426	426	710	710

Table 6 Heterogeneous responses of carbon intensity to change in carbon price informativeness

This table reports the results from the test of whether firms respond to the noise component in carbon price. The dependent variable is the change in firms' carbon emissions intensity, $\Delta \log y_{j,t+1}$, where $y_{j,t+1}$ are the verified emissions (equivalently, the surrendered allowances) of the firm j in year $t+1$. The table reports the results from the regression:

$$\Delta \log y_{j,t+1} = \alpha_j + \alpha_{st} + \beta_1 H_{j,t-1} \times Ret_t^{EUA} + \beta_2 H_{j,t-1} \times Ret_t^{EUA} \times \text{INEFF}_t^{EUA} + \Gamma' Z_{j,t-1} + e_{j,t}$$

where α_j is a firm j fixed effect, α_{st} is a sector s by year t fixed effect, Ret_t^{EUA} is the log return of EUA futures price during year t. $H_{j,t-1}$ is the proxy of the inefficiency of the private information of firm j in year $t-1$, constructed as one minus the ratio of the firm's total amount of internal transaction of EUAs to its total amount of emissions; INEFF_t^{EUA} is the EUA price inefficiency at year t, proxied by the average of bias-corrected variance ratio statistics over horizons of $q = 2, 4, 6$, and 8 trading days from Section 5; $Z_{j,t-1}$ is a vector of firm-level controls, including total asset and windfalls from free allocation; $e_{j,t}$ is a residual. Models (1), (2), and (3) are for all firms, while models (4), (5), (6) are for manufacturing firms. The sample spans from 2013 to 2022. Standard errors are clustered at the firm level, and t statistics are reported in the brackets.

	(1)	(2)	(3)	(4)	(5)	(6)
Return	-0.06***			-0.06***		
	(-7.57)			(-8.10)		
H × Ret		-0.06***	0.00		-0.07***	0.05***
		(-7.49)	(0.12)		(-7.87)	(2.62)
H × Ret × INEFF			-0.13***			-0.24***
			(-3.08)			(-5.90)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-NACE4 FE	No	Yes	Yes	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector	All	All	All	Manu	Manu	Manu
N	22252	16270	16270	11295	8374	8374
R^2	0.13	0.14	0.14	0.15	0.16	0.17

Table 7 Does noise in carbon price increase firm emissions inefficiency?

This table reports the results from the test of test whether the quality of emissions decisions are affected by the noise in carbon price. The dependent variable is the proxy for the inefficiency of firm emissions, $|\varepsilon_{j,t}|$, the absolute residual from a regression of firm emissions on lagged realizations of emissions cost scaled by sales (Martinsson et al., 2022). The table reports the results from the regression:

$$|\varepsilon_{j,t}| = \alpha_j + \alpha_{st} + \beta_1 H_{j,t-1} \times Ret_t^{EUA} + \beta_2 H_{j,t-1} \times Ret_t^{EUA} \times \text{INEFF}_t^{EUA} + \Gamma' Z_{j,t-1} + e_{j,t}$$

where α_j is a firm j fixed effect, α_{st} is a sector s by year t fixed effect, Ret_t^{EUA} is the log return of EUA futures price during year t. $H_{j,t-1}$ is the proxy of the inefficiency of the private information of firm j in year $t-1$, constructed as one minus the ratio of the firm's total amount of internal transaction of EUAs to its total amount of emissions; INEFF_t^{EUA} is the EUA price inefficiency at year t, proxied by the average of bias-corrected variance ratio statistics over horizons of $q = 2, 4, 6$, and 8 trading days from Section 5; $Z_{j,t-1}$ is a vector of firm-level controls, including total asset and windfalls from free allocation; $e_{j,t}$ is a residual. Models (1), (2), and (3) are for all firms, while models (4), (5), (6) are for manufacturing firms. The sample spans from 2013 to 2022. Standard errors are clustered at the firm level, and t statistics are reported in the brackets.

	(1)	(2)	(3)	(4)	(5)	(6)
H × Ret	0.02***	0.02**	-0.10***	0.01**	0.01*	-0.08***
	(3.09)	(2.52)	(-7.44)	(2.22)	(1.91)	(-5.62)
H × Ret × INEFF			0.23***			0.19***
			(8.38)			(6.41)
Firm Controls	No	Yes	Yes	No	Yes	Yes
Year-NACE4 FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector	All	All	All	Manu	Manu	Manu
N	19617	16270	16270	10009	8374	8374
R^2	0.47	0.47	0.47	0.45	0.46	0.46

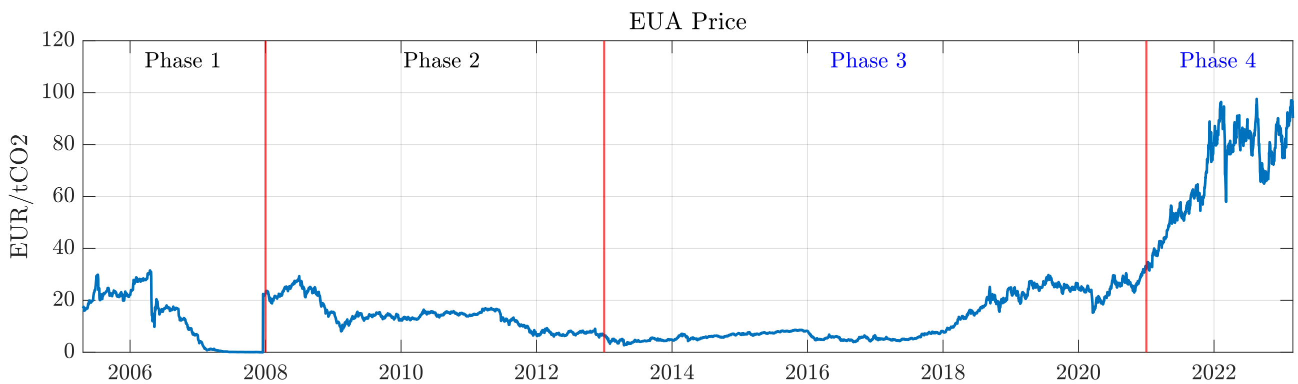

Figure 1. The evolution of the price of European Union Allowance (EUA). This figure illustrates the evolution of European Union Allowance (EUA) price from 2005 to April 2023. The development of EU Emissions Trading System (EU ETS) consists of four phases. Phase 1 (2005-2007) and Phase 2 (2008-2012) largely reflect institutional experimentation. During Phase 3 (2013-2020) and the ongoing Phase 4 (2021-2030), substantial improvements in the policy environment and trading infrastructure have been made. I use a sample spanning 2013 to 2022 which covers the entire Phase 3 and the first two years of Phase 4.

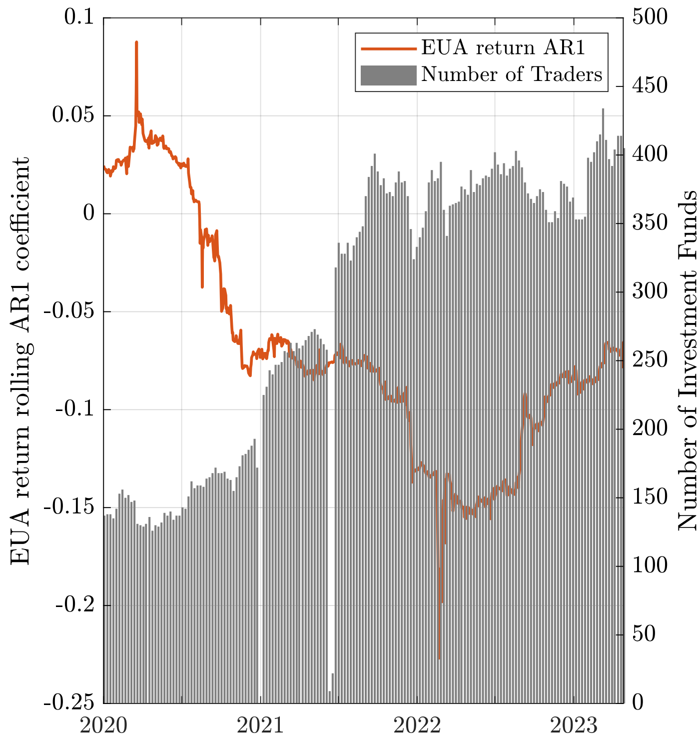

Figure 2. The finanicalization of the European carbon market. The right axis shows the evolution of the number of investment funds that reported positions in the European Union Allowance (EUA) futures market. The data is retrieved from the Commitments of Traders (COT) reports provided by ICE. The left axis illustrates the two-year backward rolling AR(1) coefficient of EUA futures returns. I annually roll over the front-December EUA contracts traded at ICE at the start of November, following Pedersen (2023). I then use the resulting EUA futures price series to calculate log returns as the returns on EUA futures. The decreasing and negative AR(1) coefficient suggests that the EUA prices tend to exhibit overshoots and reversals. This is a sign of increasing noise driven by illiquidity (Hu et al., 2013).

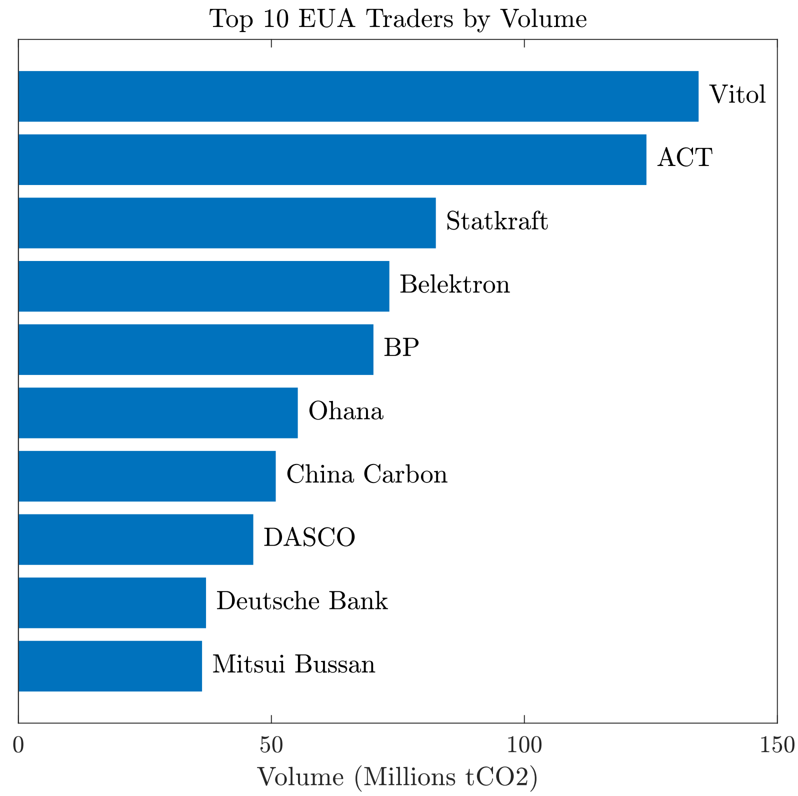

Figure 3. Top 10 EUA traders from 2013 to 2020. This figure shows the Top 10 EUA traders by trading volumes (Millions of tCO2). The trading volumes are retrieved from European Union Transaction Log (EUTL) and have been consolidated to the account holder level. These trades can be broadly classified into groups: commodity trading firms, carbon-specializing investment firms, investment banks and securities companies, carbon end-users, and carbon offsetters. An in-depth analysis of these traders with summarized trading behaviors can be found in the Appendix C.1.

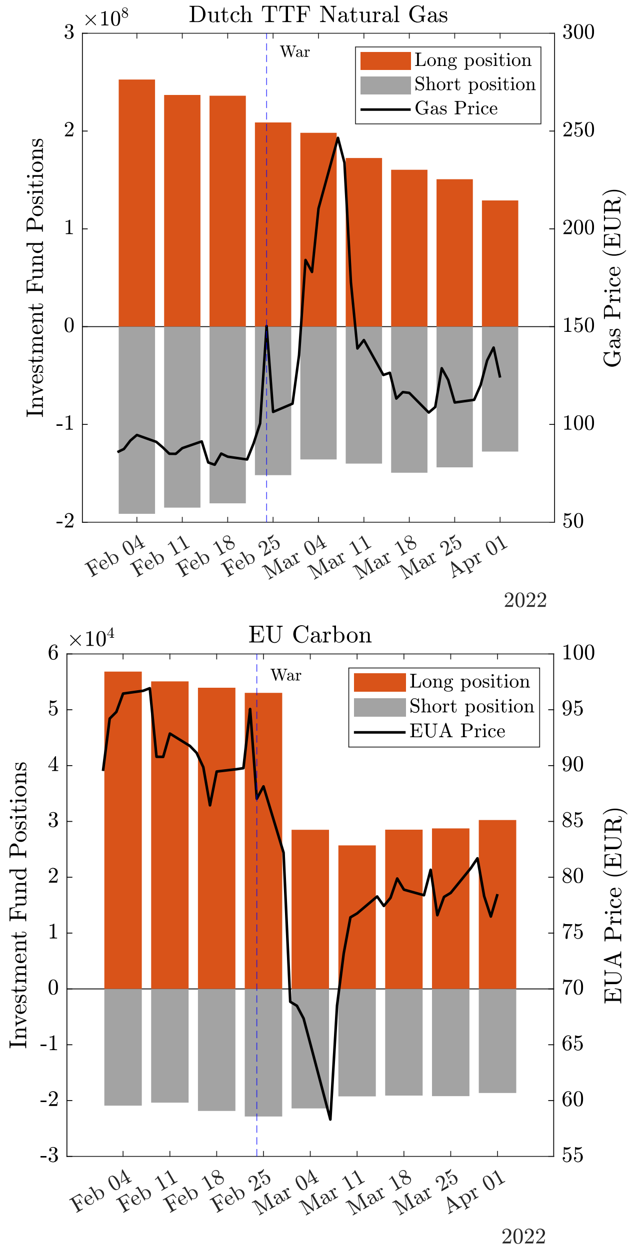

Figure 4. Gas and carbon allowance prices at the onset of Russia-Ukraine War. In the upper panel, the black line illustrates the daily evolution of front-month Dutch TTF natural gas futures prices, the European benchmark, from February 4th, 2022 to April 1st, 2022. The lower panel's black line shows the daily price fluctuations of the EUA front-December contracts over the same period. The red (grey) bars in both panels represent the weekly long (short) positions of investment funds in the Dutch TTF natural gas and EUA futures markets, respectively. Despite the weekly frequency of position data, it indicates a association between the rapid liquidation of EUA long positions and a decrease in Dutch TTF natural gas short positions.

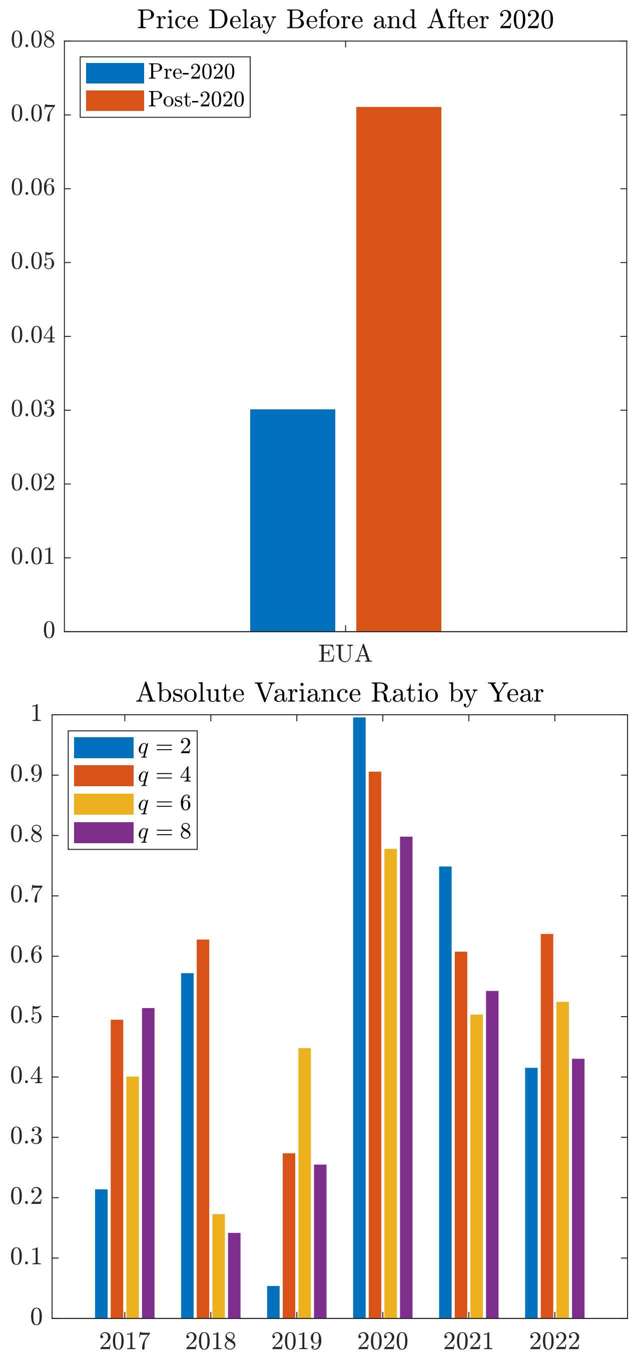

Figure 5. Carbon price informativeness measures. The top panel shows the price delay measures (Hou and Moskowitz, 2005) before and after 2020. The price delay measure is the R^2 from the weekly return regression of the form $r_t = \alpha_i + \sum_{j=1}^{4} \Gamma_j r_{t-j} + \varepsilon_{i,t}$. The bottom panel shows the absolute value of the centered variance ratio statistics (Boehmer and Kelley, 2009) each year from 2017 to 2022. Specifically, for each year p, I compute bias-corrected variance ratio statistics over horizons of $q = 2, 4, 6$, and 8 trading days using overlapping observations (Lo and MacKinlay, 1988). I then center these ratios and use their absolute values: $AVR_p(q) = |1 - VR_p(q)|$. The returns r_t and price levels are constructed as follows. I annually roll over the front-December EUA contracts traded at ICE at the start of November, following Pedersen (2023). I then use the resulting EUA futures price series to compute bias-corrected variance ratio statistics and to construct log weekly returns for the price delay measures.

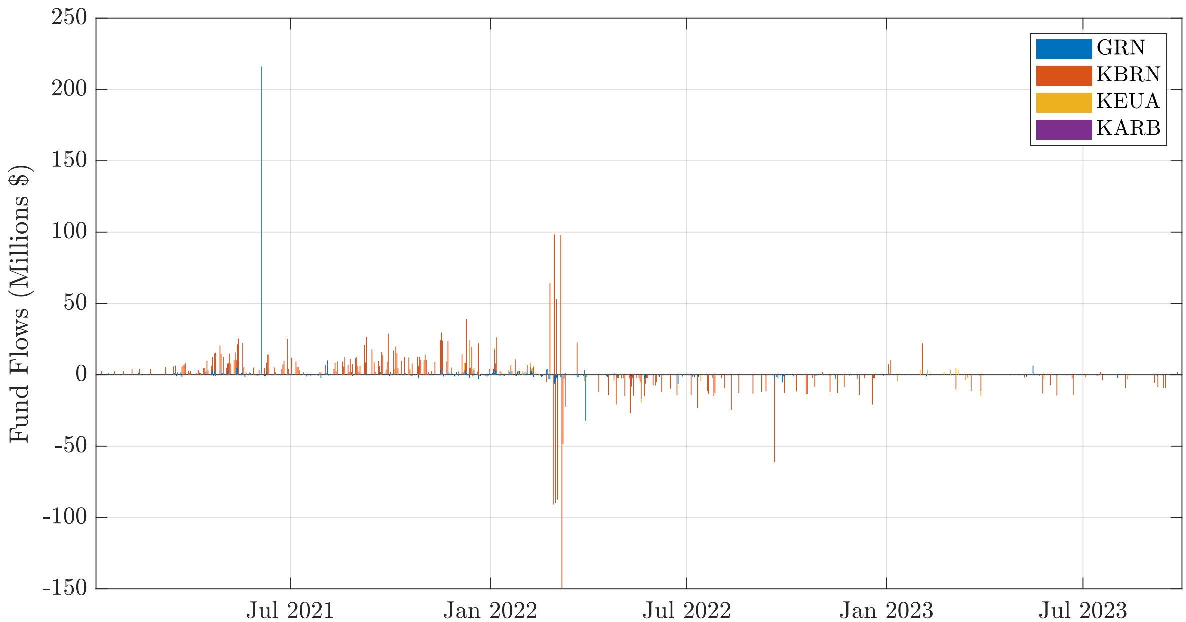

Figure 6. Fund flows of major carbon ETFs. This figure shows the evolution of fund flows of four major index-tracking carbon ETFs, i.e., GRN (iPath Series B Carbon ETN), KRBN (KraneShares Global Carbon Strategy ETF), KARB (Carbon Strategy ETF), KEUA (KraneShares European Carbon Allowance Strategy ETF), from January 2021 to April 2022. The data are sourced from ETF Global.

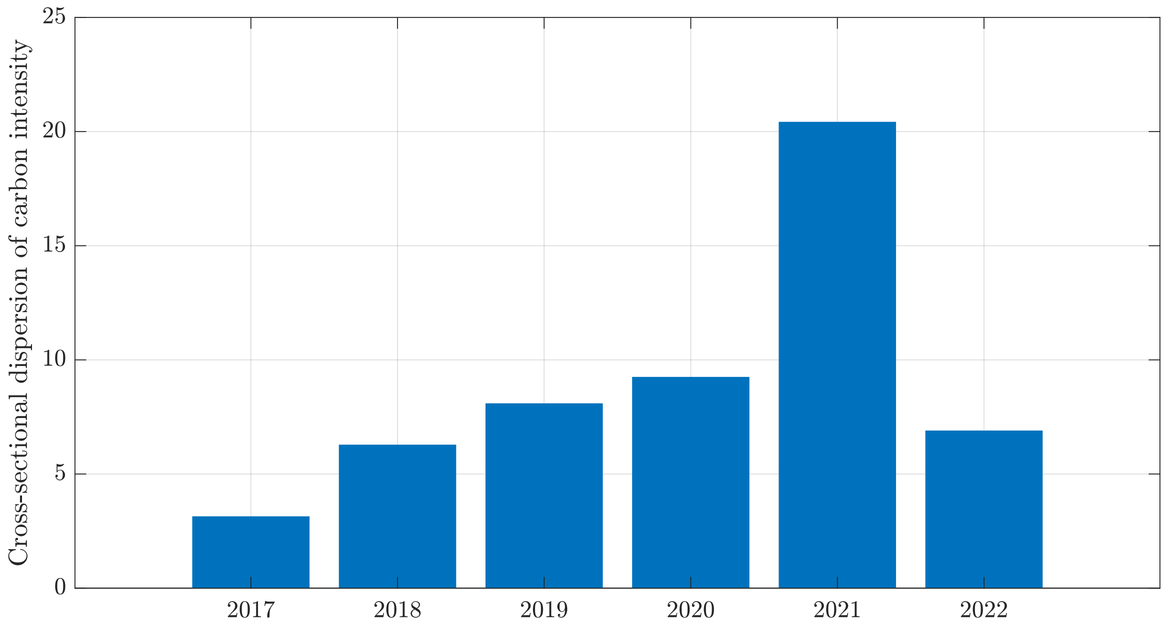

Figure 7. The misallocation of carbon allowances. This figure shows the evolution of the cross-sectional dispersion of carbon intensity from 2017 to 2022. Carbon intensity is defined as emissions scaled by sales, at the consolidated firm level. The cross-sectional dispersion of carbon intensity is a measure of carbon allowance misallocation.

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Appendix

Real Effects of Carbon Financialization

Zhimin Chen[†]

SFI and UNIL

January 22, 2024

Contents

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A Additional Institutional Backgrounds

A.1 Carbon pricing and carbon financialization

This section provides additional backgrounds on carbon pricing and the financialization of carbon markets around the world. In response to mounting scientific evidence that carbon emissions contribute significantly to global climate change, policy makers around the world are devoting substantial attention to policy instruments to reduce carbon emissions. Despite the heterogeneity in policy implementations, there is broad consensus across countries that carbon pricing — which includes carbon taxes and cap-and-trade programs— is a necessary component of any effective policy that can achieve cost-effective carbon reductions (Stavins, 2022).

The cap-and-trade program is a system of tradable emissions allowances. Unlike a carbon tax, in such a program, the authorities set the maximum amount of certain greenhouse gases that can be emitted by compliance installations in the system. Below this cap, compliance firms buy or receive emissions allowances, which can be traded. These firms must surrender sufficient allowances each year to cover their emissions. Hence, a firm with surplus allowances may sell them to other firms with an allowance deficit. The purpose of such trade is to allocate carbon allowances via the price signal so that "emissions are cut where it costs least to do so".

Despite a long ongoing debate as to whether a carbon tax or a cap-and-trade program is better (Weitzman, 1974), the latter has gained in popularity in recent years as a carbon pricing instrument. As of April 2023, there had been 73 active carbon pricing regulations in the world, covering approximately 23% of the global CO2 emissions, of which cap-and-trade programs represent 18%. Among these cap-and-trade programs, the European Union Emissions Trading Scheme (EU ETS) has the longest implementation history and the largest market share. Initiated in 2005, it now operates in all thirty EEA states (EU countries plus Iceland, Liechtenstein and Norway) and accounts for around 40% of the EU's greenhouse gas emissions alone. Although there are no national cap-and-trade programs in the North America, several subnational programs such as the Regional Greenhouse Gas Initiative (RGGI) and the Western Climate Initiative (WCI) have been established there. On other continents, countries such as China, Japan, South Korea, and New Zealand, are experiencing similar developments (World Bank, 2023).

One prominent feature of the major cap-and-trade programs is their accessibility to financial investors. Emission allowances and related derivatives are financial instruments subject to EU and UK financial regulations[1]. The RGGI and the WCI are also open to financial investors[2]. Recent developments in carbon trading infrastructures and increasing concerns over climate change have attracted investment capital to these carbon allowance markets. Large commodity trading firms, such as Vitol, Mercuria, Glencore, and Trafigura have been expanding their carbon trading teams and are playing an important role in carbon allowance markets. Hedge fund managers have been giving increased attention to these markets and may have added fuel to the carbon allowance price rally[3]. Investment banks, insurance companies, and pension funds have also shown increased interest, seeking to profit from in-house speculation or to hedge against climate-related exposures of their portfolios[4].

Not only are institutional investors on Wall Street expressing enthusiasm, but retail investors are flocking to carbon allowance markets through various vehicles including exchange-traded products (ETPs)[5] and even cryptocurrency. As of April 2023, there had been six ETPs investing in carbon allowance markets. A prevailing theme in the prospectuses of these products focuses on expediting global decarbonization and facilitating the transition to a net-zero economy. Despite their infamous association with adverse environmental implications, crypto investors are also pursuing opportunities to have a positive impact through carbon investing. To this end, a climate tech company called Carbon Credit Technology has issued the first EUA-backed crypocurrency, the Carbon Credit Token (CC Token).

Figure A.1 below shows the evolution of the number, long positions, and short postions of commercials and compliances, investment firms, and investment funds. It is clear that both investment funds and investment firms have increased their participation in recent years. Note that the missing data in 2021 is because that the EU carbon secondary market on ICE migrated in full from the UK trading venue ICE Futures Europe to the Dutch entity ICE Endex in June.

[1] See the revised Markets in Financial Instruments Directive and associated Regulation (MiFID II) for the EU financial regulation and the Financial Services and Markets Act 2000 (Regulated Activities) Order 2001 for the UK financial regulation.

[2] The list of active accounts in the Regional Greenhouse Gas Initiative and Western Climate Initiative can be found in the RGGI CO2 Allowance Tracking System and CITSS Registrants Report, respectively.

[3] Bloomberg, November 17, 2021, Hedge Funds Seek Riches in California's Carbon Market.

[4] Financial Times, August 23, 2020, Carbon Trading: the 'One-Way' Bet for Hedge Funds.

[5] Financial Times, June 16, 2023, Carbon Trading: a Slow Burn for Investors.

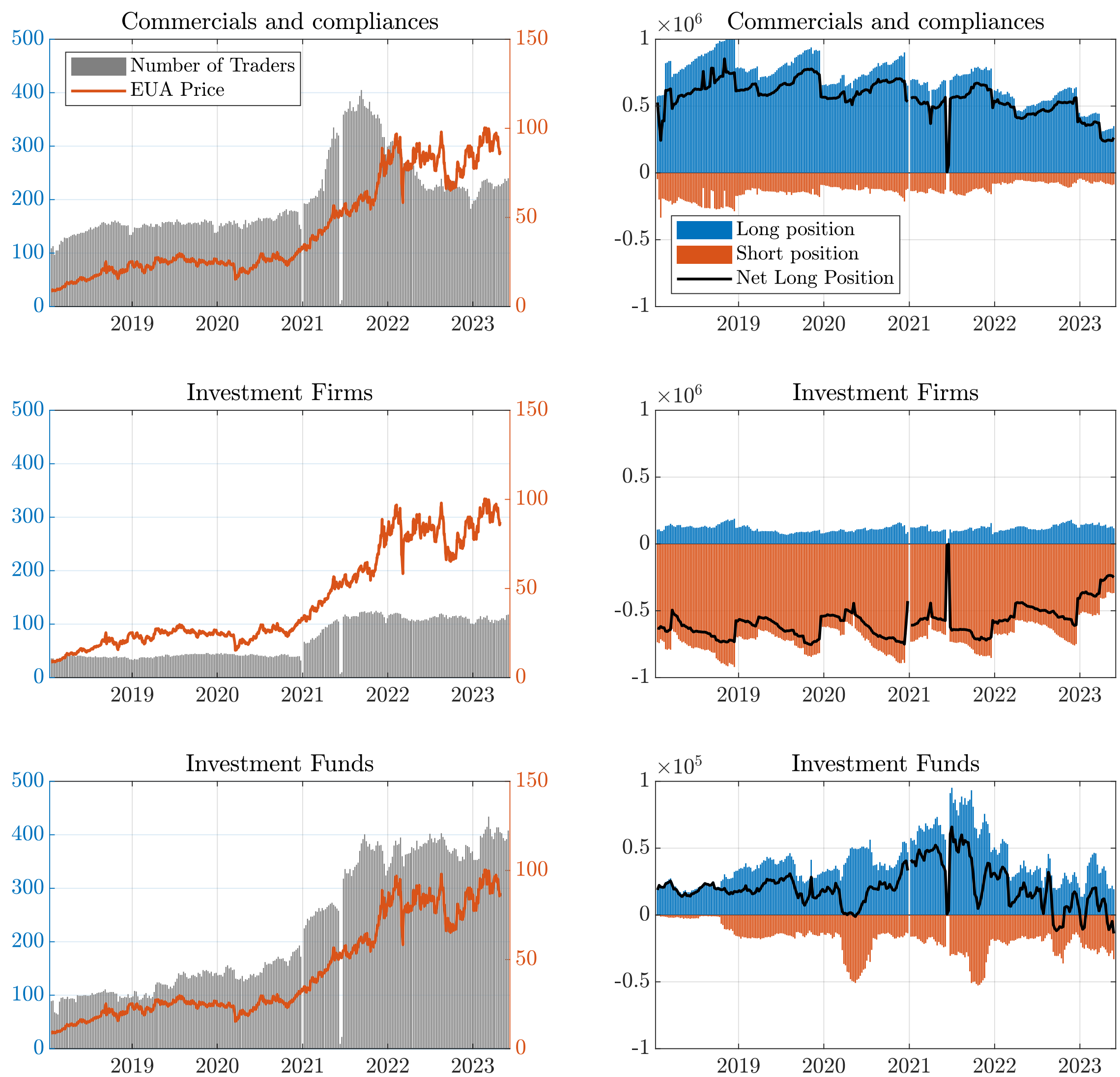

Figure A.1. Financialization of the EUA futures market. The left axis in the three left panels illustrate the evolution of the number of commercials and compliances, investment firms, and investment funds, respectively, from January 2018 to April 2023. For comparison, the right axis plots in these letf panels plots the evolution of EUA front-December futures prices, rolled annually at the beginning of each November. The three right panel plot the long positions (blue bars), short positions (red bars), and net long positions (black lines) for commercials and compliances, investment firms, and investment funds, respectively.

A.2 Carbon policy shocks

Building on the event study literature, Känzig (2023) identify 126 events regarding the supply of emission allowances during the period from 2005 to 2019. These events are identified through a number of different sources, including the European Commission Climate Action news archive, the official journal of the European Union, and decisions on the national allocation plans (NAP) retrieved from Mansanet-Bataller and Pardo (2009).

Only a few events pertain to setting the overall cap within the system. During the initial two phases, pivotal events revolved around decisions concerning the National Allocation Plans (NAP) of individual member states. This included the Commission's approval or rejection of allocation plans, as well as court decisions in legal disputes over the free allocation of allowances. With the shift to auctioning as the primary method of allocating allowances, the key regulatory developments in phase three focused on decisions regarding the timing and volume of emission allowances for auctioning. Additionally, from phase two onwards, several significant events emerged concerning the entitlement and utilization of international credits.

Figure A.2 plots the evolution of carbon policy shocks from 2013 to 2019. The shock series are retrieved from the website of Diego Känzig. In the baseline analysis, I use the carbon policy shocks in percentage as the instrument ε^{CP} rather than the carbon policy surprises. This specification is consistent with the discussions in Barnichon and Mesters (2020).

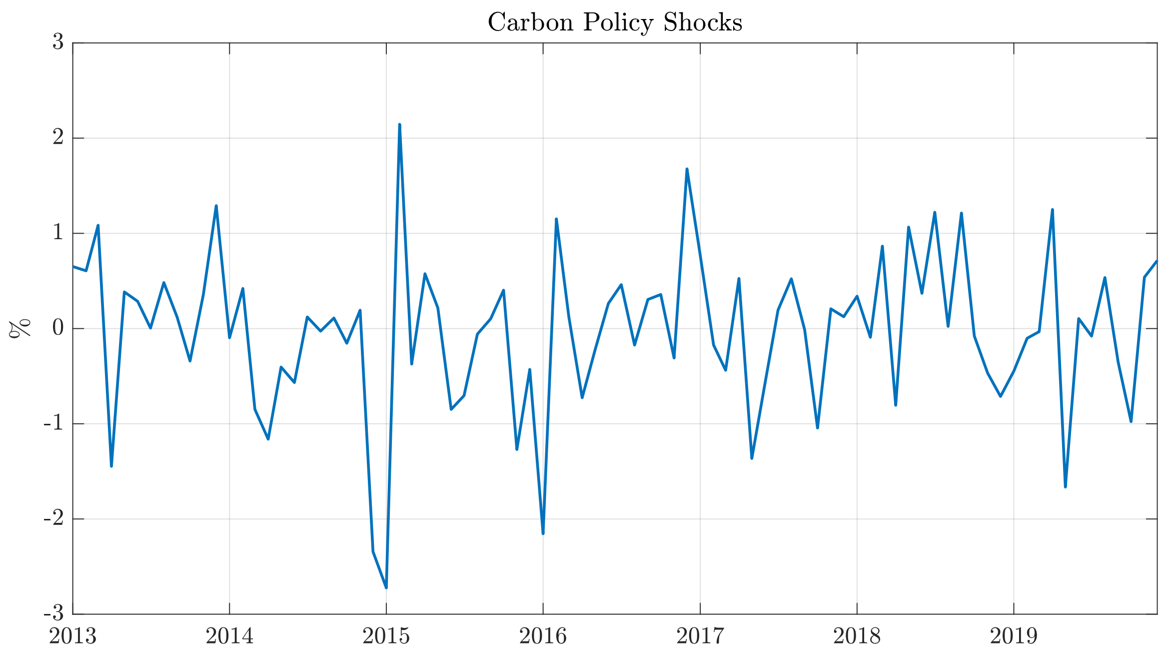

Figure A.2. Carbon policy shocks from 2013 to 2019. This figure plots the evolution of carbon policy shocks in percentage retrieved from the website of Diego Känzig and construced in Känzig (2023).

B Details on Sample Construction

I provide details on sample construction in the transaction block and the compliance block, respectively.

B.1 Transaction block

I manually identify the names of accounts and corresponding account holders and aggregate the trading amounts to the account holder level. Note that in the European Union Transaction Log (EUTL), especially during the early sample periods, the account holders are CEO or the head of the trading desk of the corresponding entities. for example, Michael Curran was the head of carbon trading desk at Vitol, and Barna Barath was the CEO of Vertis Environment. I carefully record and exclude the internal transactions between Person Holding Account and Trading Account of the same entity. See Abrell (2023) for more details[6].

I first identify account holders that have trading accounts listed on the UK Emissions Trading Registry, including Goldman Sachs, Jane Street, J.P. Morgan, STX Commodities. Next, I conducted a comprehensive search for financial institutions featured in the Environmental Finance magazine, including Aither, Redshaw Advisor, and Vertis Environment Service. Finally, I sort account holders that are not on the UK list by their trading amounts and manually search for their names. I have managed to identify a group of financial traders that are absent in the literature, including Traditional Investment Fund, ORBEO, Clearblue Markets, Element Markets, FXX Capital, Fern Capital Trading, Andurand Capital, Freepoint, Castleton Commodities International, Neptune, EcoWay, Holcim Environment Services.

As a double check, I search keywords and finanical institutions that have been identified in the literature. For commodity trading firms, the keywords include *commodity, commodities, trading, trade, limited, partner* and the 12 stand-alone entities in Pirrong (2014): ADM Group, Bunge, Cargill, Louis Dreyfus, Glencore, Gunvor, Mercuria, Trafigura, Vitol, Olam, Noble Resources, and Wilmar; For banks and securities, the keywords include *bank, security, securities, capital, broker, dealer* and the 20 names identified in Cludius and Betz (2020): Barclays, Deutsche Bank, Société Générale, Macquarie Bank, UBS, Merril Lynch, Citigroup, Nordea, Unicredit, Credit Suisse, BNP

[6] I thank Jan Abrell for the patience and insightful discussions.

Paribus, Morgan Stanley, Commerzbank, ABN AMRO, SAS Rue La Biétie, Sal. Oppenheim, Royal Bank of Scotland, Ageas, KfW, and European Investment Bank. During this procedure, I have identified traders that are subsidiaries or affiliates of other financial institutions.

The trading behaviors of identified financial traders are illustrated in the Appendix C.1. Note that commodity trading firms have largely escaped regulatory scrutiny in the EU under both MiFID I and II, despite their potentially significant role in derivatives markets (Furtuna et al., 2022).

B.2 Compliance block

The data cleaning procedure for the compliance block closely follows Abrell (2023). It is important that I retrieve the historical ownership information following Jaraitė et al. (2016) and Kalemli-Ozcan et al. (2015). Table B.1 displays the top 30 conglomerates participating in the EU ETS, ranked by the number of firms. Additionally, the table provides information on the number of installations, as well as the count of countries and industries in which each firm operates. To illustrate the functioning of internal carbon markets, Table B.2 lists top 60 conglomerates by the number of internal EUA transactions.

Table B.1 Top 30 Conglomerates by Number of Firms Covered by the EU ETS

The table details the top 30 conglomerates based on the number of their division firms included in the EU ETS. The "#Installation" column displays the count of installations owned by each firm and covered by the EU ETS. The "#Firm" column indicates the number of unique divisions (each with a distinct Orbis BvD ID) within the conglomerate. The "#Country" column represents the number of countries under the EU ETS where the conglomerate operates. Finally, the "#Industry" column shows the number of NACE-4 industries in which the conglomerate is involved.

Name	#Firm	#Installation	#Country	#Industry
Engie	78	190	9	12
Veolia Environnement	45	168	13	12
Compagnie De Saint-Gobain	45	79	18	19
E.ON SE	29	115	8	7
Wienerberger AG	28	200	20	4
Totalenergies SE	23	45	9	12
Arcelormittal SA	21	71	8	7
Heidelberg Materials AG	19	65	14	6
Holcim Ltd.	18	54	13	5
Rethmann Se & Co. KG	18	28	6	10
Smurfit Kappa Group PLC	18	33	10	5
Essity Aktiebolag	17	35	10	4
BASF SE	16	87	7	10
Heineken Family	16	34	15	2
Polski Koncern Naftowy Orlen SA.	16	56	2	6
DS Smith PLC	15	23	7	3
OMV Aktiengesellschaft	14	52	8	8
Metsaliitto Osuuskunta	14	35	5	9
Atlantica Sustainable Infrastructure PLC	14	14	1	1
Eni S.P.A.	14	53	4	9
Stora Enso Oyj	13	21	5	4
CRH PLC	13	49	9	5
Stellantis N.V.	13	21	5	4
Rockwool A/S	12	17	11	3
L'air Liquide	12	27	7	5
Etex N.V.	11	26	7	5
Bunge	11	18	9	4
Nestle S.A.	11	24	8	7
RWE Aktiengesellschaft	11	49	5	6
Bouygues	11	18	3	5

Table B.2 Top 60 Conglomerates by the Number of Internal EUA Transactions

The table enumerates the leading conglomerates based on the number of internal EUA transactions. The "#Trade" column indicates the number of trades conducted, while the "Amount" column details the volume of EUAs traded by each conglomerate, with the figures expressed in millions of tonnes of CO2.

Name	#Trade	Amount	Name	#Trade	Amount
Engie	973	286.12	Tauron Polska Energia SA	91	88.21
Enel Spa	900	463.21	MOL	89	14.87
Shell PLC	634	59.80	Deutsche Lufthansa AG	89	8.86
OMV Aktiengesellschaft	506	53.67	Mondi PLC	76	4.69
E.ON SE	484	10.84	Moravia Steel A.S.	71	5.58
Eni S.P.A.	481	91.26	Fincorporativa Sl	70	1.20
Holcim Ltd.	335	122.50	Mercedes-Benz Group AG	65	5.28
L'air Liquide	296	10.14	TUI AG	62	1.79
Arcelormittal Sa	262	116.20	Heidelberg Materials AG	61	12.93
Compagnie De Saint-Gobain	252	4.39	Hargreaves Services PLC	58	1.55
Lyondellbasell Industries N.V.	243	11.41	Mitsubishi Corporation	57	9.27
Totalenergies SE	237	28.89	Bouygues	57	0.08
A2A S.P.A.	218	25.04	Sappi Limited	54	2.94
Repsol S.A	212	40.52	Harbour Energy PLC	54	1.85
Iberdrola SA	210	37.96	Rockwool A/S	45	0.81
RWE Aktiengesellschaft	201	266.45	Vidrala SA	44	1.76
Smurfit Kappa Group PLC	194	6.21	KLM Royal Dutch Airlines NV	42	2.69
Polski Koncern Naftowy Orlen SA.	166	34.27	BG Holding S.R.L.	42	0.45
BP PLC	164	60.18	Enbw	40	16.11
Voestalpine AG	157	18.56	Outokumpu Oyj	40	2.24
BASF SE	151	2.97	Exxon Mobil	38	3.10
EDP - Energias De Portugal S.A.	149	108.02	Billerud	37	3.39
Metsaliitto Osuuskunta	149	5.32	Renault	37	0.61
SSE PLC	144	61.18	EPV Energia Oy	35	1.98
Atlantik Advisors Gmbh & Co. KG	140	26.85	Lanxess Ag	35	0.55
CRH PLC	131	10.32	Sodim, Sgps, S.A.	33	1.37
Veolia Environnement	126	2.79	Nordzucker Holding AG	33	0.78
Stora Enso Oyj	120	5.02	SSAB AB	32	13.23
Wienerberger AG	120	1.00	Yara International	31	3.16
Centrica PLC	94	34.58	Nippon Sheet Glass Company	31	1.08

C Additional Empirical Evidence

C.1 Classification of EUA Traders

This subsection provides an in-depth analysis of EUA traders. I broadly classify these traders into five groups and summarize the trading behavior of top trades in each group. Specifically, I report the number and amount (in Millions tCO2) of transactions, and the fraction of transactions that occur during the EUA futures delivery period[7].

Carbon allowance end-users. Regulated firms in the EU ETS are by definition carbon end-users. They trade in the EUA market to meet regulatory requirements or exploit the benefits of reducing carbon emissions. Large energy and industrial conglomerates tend to have specialized trading operations (Pirrong, 2014), for example, Shell Trading and RWE Supply & Trading. These trading operations serve as the bridge between the conglomerate's internal carbon market and investors outside the boundaries of the corporations (Bryant, 2019). In the EUTL data, a large fraction of internal transactions takes place between the trading operation and industrial divisions of the conglomerate (for example, transactions between Shell Trading and Shell Spain). Table C.3 lists the top 30 carbon end-users according to their net trading volume with large energy companies such as BP, EDF, and Vattenfall occupying the top spots. It should be noted that these specialized trading operations often engage in the trading of a variety of other commodities, such as oil, gas, power, weather, and renewable energy certificates. Consequently, their trading strategies may involve multiple assets and may not be dedicated to timing the carbon market.

Commodity trading firms. Commodity trading firms play a crucial role in commodity market (Pirrong, 2014), however, our understanding of them is limited due to their private nature and a cultural emphasis on privacy. The granular data in the EUTL allow me to take a close look at their role in the EUA market. Two facts merit emphasis. Firstly, large independent commodity trading firms, which are pivotal in the commodity market, emerge as the dominant players in the carbon market. Panel A of Table 2 displays the transactions undertaken by these firms. Significantly, Vitol

[7] EUA Delivery Period means the period beginning at 09.00 hours (LLT) on the Business Day following the last day of trading of a Contract and ending at 15.00 hours (LLT) on the third Business Day following that last day of trading. Where an EUA Delivery Delay becomes applicable to a Contract, the period shall end at such later time as the Clearing House may direct, which in any event shall not be a time beyond 15.00 hours (LLT) on the fourth Business Day after the last day of trading. I assume that all transactions are between accounts on the trusted account list and are within business hours so that transfers are executed immediately.

has engaged in the trading of approximately 140 million EUAs during the sample period, establishing itself as the largest net seller of EUAs. Secondly, pinpointed here is a group of commodity trading firms specializing in carbon trading which, according to Duffie (2010), potentially act as the marginal investors in the carbon market. The amount of capital these firms can deploy significantly influences the presence of "limits to arbitrage" in this market. Panel B in Table 2 summarizes the activities of these specialized carbon trading firms.

Banks and securities companies. The carbon trading behaviors of banks and securities companies are extensively studied in the earlier literature (Cludius and Betz, 2020; Quemin and Pahle, 2023; Mansanet-Bataller and Pardo, 2023). Table 4 lists the top 30 banks and securities by the net amount of trading amount. It is noteworthy that these institutions not only offer intermediary services but also engage in hedging or speculation through their own trading desks.

Other financial investors. While many investors may not be directly involved in the spot market but rather only invest in the futures market to pursue hedging and diversification benefits (Goldstein and Yang, 2022), I have identified a few financial investors including investment funds, development banks and funds, and PE/VC that actively trade in the EUA spot market. Their trading activity is summarized in Panel A, B, and C of Table C.4, respectively. Note that there might be investors whose trading is motivated by climate concerns rather than hedging or speculation. Such traders include warm-glow non-consequentialist investors, who have a desire for investing in carbon allowances rather than a concern about the investment's ultimate impact (Inderst and Opp, 2022) , and deontological investors (Hart et al., 2022), who care about doing the right thing irrespective of consequences[8].

[8] See the empirical evidence in Riedl and Smeets (2017); Humphrey et al. (2021); Bonnefon et al. (2022).

Table C.3 Top 30 carbon end-users by net external EUA transactions

This table reports the EUA trading behaviors of top 30 carbon end-users by net amounts of external EUA transactions. Carbon users are compliance entities in the EU ETS that are required to surrender allowances to cover their yearly emissions. The columns "#Trade" indicate the number of EUA transactions. The columns "Amount" detail the volume of EUAs traded by each trader, with the figures expressed in millions of tonnes of CO2. The columns "%Futures" indicate the fraction of transactions that occured during the EUA futures delivery period. This data is sourced from the European Union Transaction Log (EUTL) and covers the period from April 30, 2013, to April 30, 2020.

	Net Buy	Buy			Sell		
Name	Amount	#Trade	Amount	%Futures	#Trade	Amount	%Futures
BP	22.08	307	46.12	22.87%	157	24.04	14.35%
Gazprom	10.25	291	18.07	15.81%	212	7.82	39.86%
EDF	9.69	122	10.65	30.57%	34	0.96	19.96%
Vattenfall	9.45	196	18.16	6.24%	199	8.71	7.67%
SSE	4.66	73	5.03	49.77%	11	0.37	41.08%
RWE	4.41	159	6.30	26.09%	39	1.89	3.39%
ENEL	4.22	196	8.68	17.92%	22	4.46	16.84%
British Steel	3.19	14	3.19	28.26%	0	0.00	0.00%
Shell	2.65	142	10.11	11.95%	130	7.45	20.13%
ENGIE	2.23	195	6.65	17.85%	84	4.42	9.43%
British Gas	2.02	6	2.02	0.00%	0	0.00	0.00%
A2A	1.47	15	1.47	0.00%	1	0.00	100.00%
TotalEnergies	1.31	120	1.67	29.19%	11	0.36	1.65%
UPM	1.13	91	3.62	8.32%	46	2.49	11.26%
Eni	1.00	1	1.00	0.00%	0	0.00	0.00%
Uniper	1.02	25	1.02	6.15%	0	0.00	0.00%
ČEZ	0.72	56	1.12	0.00%	22	0.40	0.00%
Equinor	0.46	127	0.47	22.41%	1	0.00	0.00%
Ørsted	0.31	84	0.63	14.27%	4	0.32	100.00%
E.ON	0.20	31	1.14	4.31%	36	0.94	15.21%
LITASCO	0.05	2	0.37	0.00%	1	0.32	0.00%
ConocoPhillips	0.03	6	0.26	0.00%	3	0.23	0.00%
Solvay	-1.65	41	2.88	17.84%	36	4.53	34.38%
Fortum	-1.18	60	0.74	24.81%	48	1.93	0.00%
LG	-0.58	7	1.30	0.00%	3	1.88	100.00%
MOL	-0.51	1	0.01	0.00%	10	0.52	1.74%
EDP	-0.47	94	0.15	7.26%	33	0.62	35.30%
Chevron	-0.42	7	0.69	99.92%	7	1.11	17.97%
EnBW	-0.11	34	0.15	0.00%	10	0.26	0.00%
BKW Energie	-0.03	113	0.91	41.16%	117	0.94	0.00%

Table C.4 Other financial traders in the EUA market

This table reports the EUA trading behaviors of investment funds (Panel A), development banks and funds (Panel B), and PE/VC (Panel C) by net amounts of external EUA transactions. The columns "#Trade" indicate the number of EUA transactions. The columns "Amount" detail the volume of EUAs traded by each trader, with the figures expressed in millions of tonnes of CO2. The columns "%Futures" indicate the fraction of transactions that occured during the EUA futures delivery period. This data is sourced from the European Union Transaction Log (EUTL) and covers the period from April 30, 2013, to April 30, 2020.

Panel A. Investment Funds

	Net Buy	Buy			Sell		
Name	Amount	#Trade	Amount	%Futures	#Trade	Amount	%Futures
CFP Energy Limited	9.00	303	21.27	7.24%	250	12.27	7.97%
Trading Emissions PLC	-1.30	15	3.01	1.12%	18	4.31	68.63%
Luso Carbon Fund	-1.26	33	4.29	3.75%	56	5.55	2.13%

Panel B. Development Banks and Funds

	Net Buy	Buy			Sell		
Name	Amount	#Trade	Amount	%Futures	#Trade	Amount	%Futures
Nordic Environment Finance	18.81	138	10.05	12.59%	435	8.73	53.48%
Asian Development Bank	1.32	163	21.69	9.88%	210	2.89	10.06%

Panel C. PE/VC

	Net Buy	Buy			Sell		
Name	Amount	#Trade	Amount	%Futures	#Trade	Amount	%Futures
Opus Capital Limited	0.49	36	0.49	0.00%	0	0.00	0.00%

C.2 The cross-correlations between EUA and other assets

The tight economic linkage between carbon and natural gas creates a source of long-term correlations between their futures returns (Casassus et al., 2013). Despite the economic links with other commodities, Swinkels and Yang (2022) argue that carbon alloawances are good tools fro diversification in general. During an interview, Cormac Nevin, a fund manager at You Asset Management, claims that the low correlation between carbon allowances and other asset classes is one key reason why he includes carbon allowance in the fund across various multi-asset portfolios[9]. The theory in Basak and Pavlova (2016) predicts that the hedging and diversification motives can result in an increase in the cross-correlation between the financializing commodities (here, carbon allowance) and other assets. To this end, I plot the 252-day rolling cross-correlations between carbon allowance and other assets in Figure C.3 from January 2017 to April 2023. These assets include commodities (GSCI), energy commodities (GSEN), natural gas (Dutch TTF), stock (STOXX Euro 600), and bond (ICE Euro Corp Bond). It is clear the cross-correlations have increased in recent years before the market crash at the onset of the Russia-Ukraine war.

To eliminate the possibility that other commodities experienced a similar financialization during the sample period, I present a 2-year rolling AR(1) coefficients plot for carbon, energy, and other commodities in Figure C.4. I find no evidence of illiquidity in commodities (GSCI) and energy commodities (GSEN).

[9]Financial Times, October 4, 2021, Carbon Trading: a Slow Burn for Investors.

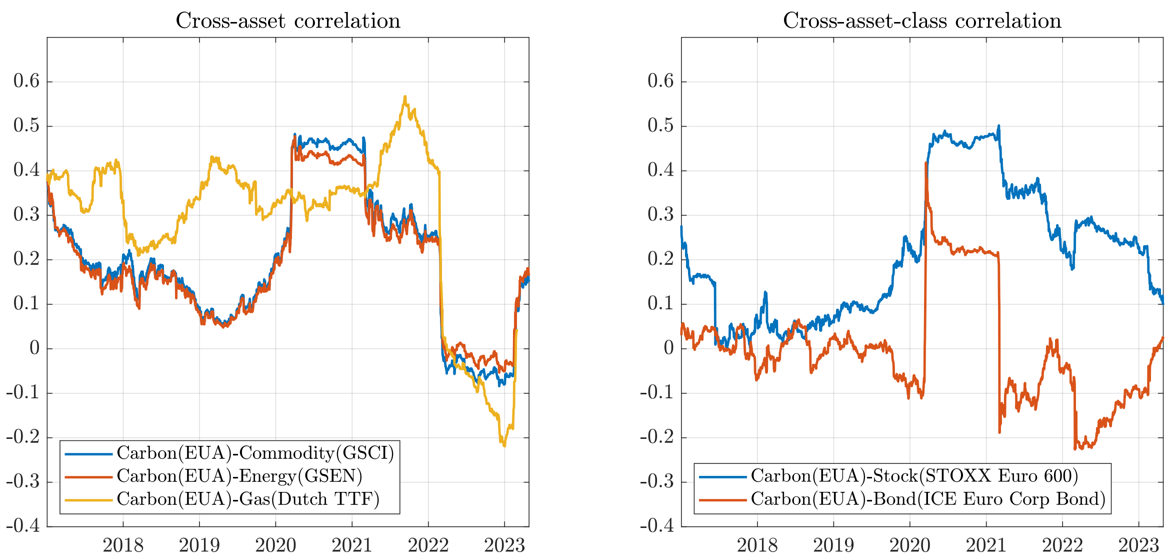

Figure C.3. The 252-day rolling cross-correlations between carbon allowance and other assets. The left panel shows the backward rolling 252-day return correlations between EUA and GSCI total return index (blue line), correlations between EUA and GSEN total return index (red line), and correlations between EUA and Dutch TTF natural gas front-month contracts (yellow line), from January 2017 to April 2023. The right panel shows the backward rolling 252-day return correlations between EUA and STOXX Euro 600 index and correlations between EUA and ICE Euro Corp Bond index for the same period.

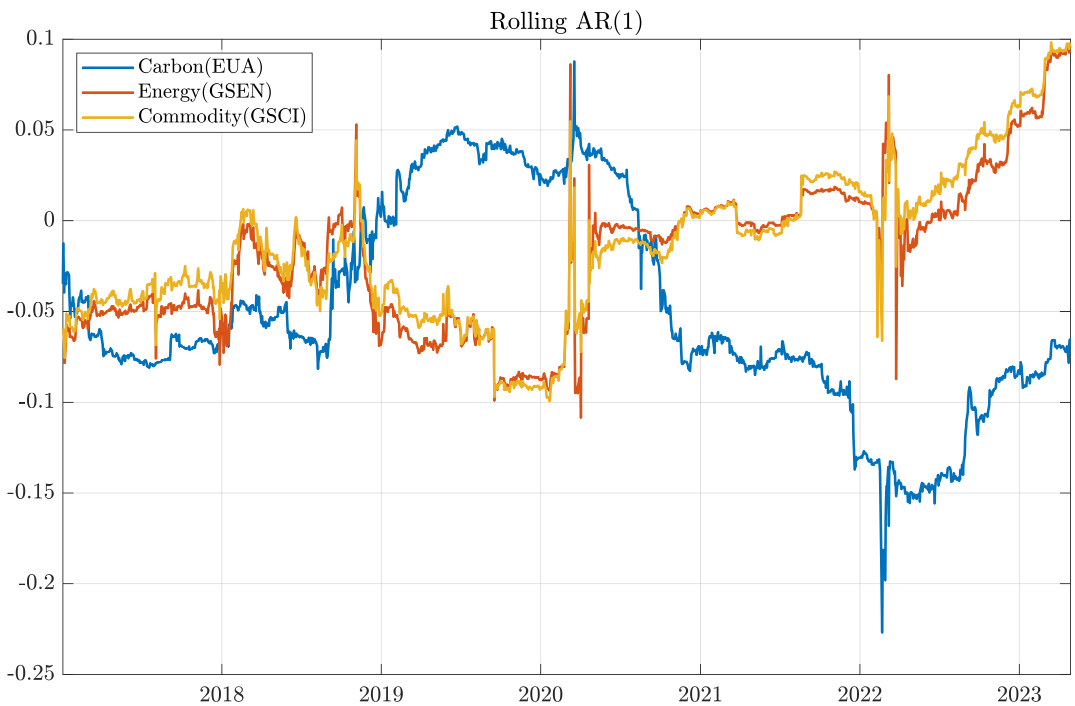

Figure C.4. The 2-year rolling AR(1) coeffiencts on carbon, energy, and commodity. This figure shows the two-year backward rolling AR(1) coefficient of EUA futures returns (blue line), GSEN total returns (red line), and GSCI total returns (yellow line) from January 2017 to April 2023.

D Robustness

Table D.5 The estimation of price elasticity for carbon offsetters and end-users

This table reports the results from the estimation of price elasticity for different investor groups with the following two-stage least squares regressions:

$$\text{1st Stage:} \quad \Delta\text{Basis}_t = \theta\varepsilon_t^{CP} + \Gamma X_t + \epsilon_t \qquad \text{2nd Stage:} \quad \Delta Q_{it}^g = \xi^g \Delta\hat{\text{Basis}}_t + \Gamma X_t + \epsilon_{it}$$

where $\text{Basis}_t = \log F_t - \log S_t$, F_t is the price of EUA front-December contract in month t and S_t is EUA spot price in month t; ε_t^{CP} are carbon policy shocks sourced from Känzig (2023); X_t includes Amihud ratios of the EUA spot and futures market, EUA auction cover ratios, and the volatility index of Euro stock market, VSTOXX; ΔQ_{it}^g is the signed amount of EUA traded by investor i from group g in month t; $\Delta\hat{\text{Basis}}_t$ is the fitted value from regressing changes in EUA basis, ΔBasis_t, onto carbon policy shocks, ε_t^{CP}. Models (1) and (2) report the results for top carbon offsetters in Table 3; Models (3) and (4) report the results for carbon end-users in Table C.3, respectively. The sample is monthly from January 2013 to December 2019. The 1st-stage F statistics are above 100.

	(1)	(2)	(3)	(4)
$\Delta\hat{Basis}$	0.02	0.25	1.17	1.22
	(0.32)	(0.23)	(1.13)	(1.51)
Controls	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	No	Yes	No	Yes
Group	Offsetters	Offsetters	End-users	End-users
N	2130	2130	2130	2130

Table D.6 Heterogeneous responses of carbon intensity to change in carbon price since 2018

This table reports the results from the test of whether firms respond to the noise component in carbon price. The dependent variable is the change in firms' carbon emissions intensity, $\Delta \log y_{j,t+1}$, where $y_{j,t+1}$ are the verified emissions (equivalently, the surrendered allowances) of the firm j in year $t+1$. The table reports the results from the regression:

$$\Delta \log y_{j,t+1} = \alpha_j + \alpha_{st} + \beta_1 H_{j,t-1} \times Ret_t^{EUA} + \beta_2 H_{j,t-1} \times Ret_t^{EUA} \times \text{INEFF}_t^{EUA} + \Gamma' Z_{j,t-1} + e_{j,t}$$

where α_j is a firm j fixed effect, α_{st} is a sector s by year t fixed effect, Ret_t^{EUA} is the log return of EUA futures price during year t. $H_{j,t-1}$ is the proxy of the inefficiency of the private information of firm j in year $t-1$, constructed as one minus the ratio of the firm's total amount of internal transaction of EUAs to its total amount of emissions; INEFF_t^{EUA} is the EUA price inefficiency at year t, proxied by the average of bias-corrected variance ratio statistics over horizons of $q = 2, 4, 6,$ and 8 trading days from Section 5; $Z_{j,t-1}$ is a vector of firm-level controls, including total asset and windfalls from free allocation; $e_{j,t}$ is a residual. Models (1), (2), and (3) are for all firms, while models (4), (5), (6) are for manufacturing firms. The sample spans from 2018 to 2022. Standard errors are clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
Ret	-0.03***			-0.03***		
	(-2.21)			(-2.74)		
H × Ret		-0.01***	0.06***		-0.03***	0.08***
		(-2.34)	(2.86)		(-2.66)	(4.53)
H × Ret × INEFF			-0.14***			-0.24***
			(-3.17)			(-5.69)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-NACE4 FE	No	Yes	Yes	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector	All	All	All	Manu	Manu	Manu
N	10842	10842	10842	5529	5529	5529
R^2	0.15	0.15	0.15	0.16	0.16	0.17

Table D.7 Carbon price informativeness and firm emissions inefficiency since 2018

This table reports the results from the test of test whether the quality of emissions decisions are affected by the noise in carbon price. The dependent variable is the proxy for the inefficiency of firm emissions, $|\varepsilon_{j,t}|$, the absolute residual from a regression of firm emissions on lagged realizations of emissions cost scaled by sales (Martinsson et al., 2022). The table reports the results from the regression:

$$|\varepsilon_{j,t}|= \alpha_j + \alpha_{st} + \beta_1 H_{j,t-1} \times Ret_t^{EUA} + \beta_2 H_{j,t-1} \times Ret_t^{EUA} \times \text{INEFF}_t^{EUA} + \Gamma' Z_{j,t-1} + e_{j,t}$$

where α_j is a firm j fixed effect, α_{st} is a sector s by year t fixed effect, Ret_t^{EUA} is the log return of EUA futures price during year t. $H_{j,t-1}$ is the proxy of the inefficiency of the private information of firm j in year $t-1$, constructed as one minus the ratio of the firm's total amount of internal transaction of EUAs to its total amount of emissions; INEFF_t^{EUA} is the EUA price inefficiency at year t, proxied by the average of bias-corrected variance ratio statistics over horizons of $q = 2, 4, 6$, and 8 trading days from Section 5; $Z_{j,t-1}$ is a vector of firm-level controls, including total asset and windfalls from free allocation; $e_{j,t}$ is a residual. Models (1), (2), and (3) are for all firms, while models (4), (5), (6) are for manufacturing firms. The sample spans from 2018 to 2022. Standard errors are clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
H × Ret	0.02***	0.03***	-0.12***	0.03***	0.03***	-0.10***
	(3.06)	(4.03)	(-8.78)	(4.96)	(5.32)	(-6.86)
H × Ret × INEFF			0.20***			0.16***
			(7.38)			(5.31)
Firm Controls	No	Yes	Yes	No	Yes	Yes
Year-NACE4 FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector	All	All	All	Manu	Manu	Manu
N	11424	10842	10842	5756	5529	5529
R^2	0.57	0.57	0.57	0.54	0.54	0.55

E Model Derivations

Proof of Proposition 1: The good market equilibrium is standard as in Angeletos and La'O (2013) and its proof can be resorted to the Appendix in Sockin and Xiong (2015). I start from the carbon allowance market equilibrium.

I conjecture that the carbon allowance price and each firm's carbon allowance demand take the log-linear forms:

$$\log P_K = h_0 + h_A \log A + h_\theta \theta \tag{E.1}$$

$$\log K_i = l_0 + l_s s_i + l_p \log P_K \tag{E.2}$$

where the coefficients h_0, h_A, h_θ, l_0, l_s, and l_p will be determined by equilibrium conditions.

Define the carbon allowance price signal z as

$$z = \frac{\log P_K - h_0 - h_\theta \bar{\theta}}{h_A} = \log A + \frac{h_\theta}{h_A}(\theta - \bar{\theta})$$

Then, conditional on observing its private signal s_i and the carbon allowance price P_K, firm i's expectation of $\log A$ is

$$\mathbf{E}[\log A | s_i, \log P_K] = \mathbb{E}[\log A | s_i, z] = \frac{1}{\tau_A + \tau_s + \frac{h_A^2}{h_\theta^2}\tau_\theta}\left(\tau_A \bar{a} + \tau_s s_i + \frac{h_A^2}{h_\theta^2}\tau_\theta z\right)$$

and its conditional variance of $\log A$ is

$$var[\log A | s_i, \log P_K] = \left(\tau_A + \tau_s + \frac{h_A^2}{h_\theta^2}\tau_\theta\right)^{-1}$$

The first order condition of firm i implies that

$$K_i = \left(\frac{\phi \mathbf{E}[A K_j^{\phi\eta} | s_i, P_K]}{P_K}\right)^{\frac{1}{1-\phi(1-\eta)}} \tag{E.3}$$

Thus,

$$\log K_i = \frac{1}{1-\phi(1-\eta)}\left(\log \phi + \log(\mathbf{E}[A K_j^{\phi\eta} | s_i, \log P_K]) - \log P_K\right) \tag{E.4}$$

By using equation (E.2) and recognizing that $cov[\varepsilon_j \log A | s_i, \log P_K] = 0$ and substituting the expressions of $\mathbf{E}[\log A|s_i, \log P_K]$, $var[\log A|s_i, \log P_K]$, and $var[\varepsilon_j|s_i, \log P_K]$, one can obtain

$$\begin{aligned}
\log K_i = & \frac{1}{1-\phi(1-\eta)}\log\phi + \frac{\phi\eta}{1-\phi(1-\eta)} + \frac{1}{1-\phi(1-\eta)}(\phi\eta l_p - 1)\log P_K \\
& + \frac{1+\phi\eta l_s}{1-\phi(1-\eta)}\left(\tau_A + \tau_s + \frac{h_A^2}{h_\theta^2}\tau_\theta\right)^{-1}\left(\tau_A\bar{a} + \tau_s s_i + \frac{h_A^2}{h_\theta^2}\tau_\theta\frac{\log P_K - h_0 - h_\theta\bar{\theta}}{h_A}\right) \\
& + \frac{(1+\phi\eta l_s)^2}{2(1-\phi(1-\eta))}\left(\tau_A + \tau_s + \frac{h_A^2}{h_\theta^2}\tau_\theta\right)^{-1} + \frac{\phi^2\eta^2 l_s^2}{2(1-\phi(1-\eta))}\tau_s^{-1}
\end{aligned}$$

Matching the above equation with the conjectured equilibrium equation of $\log K_i$ yields:

$$\begin{aligned}
l_0 = & \left(\frac{1+\phi l_s}{1-\phi(1-\eta)}\right)\left(\tau_A + \tau_s + \frac{h_A^2}{h_\theta^2\tau_\theta}\right)^{-1}\left(\tau_A\bar{a} - \frac{h_A}{h_\theta^2}\tau_\theta(h_0 + h_\theta\bar{\theta})\right) \\
& + \frac{(1+\phi\eta l_s)^2}{2(1-\phi(1-\eta))}\left(\tau_A + \tau_s + \frac{h_A^2}{h_\theta^2\tau_\theta}\right)^{-1}\frac{\phi\eta}{1-\phi(1-\eta)}l_0 \\
& + \frac{\phi^2\eta^2 l_s^2}{2(1-\phi(1-\eta))}\tau_s^{-1} + \frac{1}{1-\phi(1-\eta)}\log\phi
\end{aligned} \tag{E.5}$$

$$l_s = \frac{1+\phi\eta l_s}{1-\phi(1-\eta)}\left(\tau_A + \tau_s + \frac{h_A^2}{h_\theta^2\tau_\theta}\right)^{-1}\tau_s \tag{E.6}$$

$$l_P = \frac{\phi\eta}{1-\phi(1-\eta)}l_P + \frac{1+\phi\eta l_s}{1-\phi(1-\eta)}\left(\tau_A + \tau_s + \frac{h_A^2}{h_\theta^2}\tau_\theta\right)^{-1}\frac{h_A}{h_\theta^2}\tau_\theta - \frac{1}{1-\phi(1-\eta)} \tag{E.7}$$

Imposing the fixed point system yields

$$l_s = \frac{1+(1-\phi)l_P}{1-\phi(1-\eta)}\frac{h_\theta^2}{h_A}\tau_s\tau_\theta^{-1} \tag{E.8}$$

$$l_s = \left(\tau_A + \frac{1-\phi}{1-\phi(1-\eta)}\tau_s + \frac{h_A^2}{h_\theta^2}\tau_\theta\right)^{-1}\frac{\tau_s}{1-\phi(1-\eta)} \tag{E.9}$$

Carbon allowance supply equation (5) implies that

$$\log K_S = \xi \log P_K$$

We now use the market-clearing condition for the carbon allowance market to determine three other equations for the coefficients in the conjectured log-linear carbon allowance price and demand:

$$\begin{aligned}\log\left[\int_{-\infty}^{\infty} K(s_i, P_K) d\Phi(\varepsilon_i)\right] &= \log\left[\int_{-\infty}^{\infty} e^{l_0 + l_s s_i + l_P \log P_K} d\Phi(\varepsilon_i)\right] \\ &= \log\left[\int_{-\infty}^{\infty} e^{l_0 + l_s(\log A + \varepsilon_i) + l_P(h_0 + h_A \log A + h_\theta \theta)} d\Phi(\varepsilon_i)\right] \\ &= (l_s + l_P h_A)\log A + l_P h_\theta \theta + l_0 + l_P h_0 + \frac{1}{2} l_s^2 \tau_s^{-1}\end{aligned} \tag{E.10}$$

The market clearing condition (7)

$$\log\left[(e^\theta - 1 + 1)\int_{-\infty}^{\infty} K(s_i, P_K) d\Phi(\varepsilon_i)\right] = \log P_K = \xi \log P_K$$

requires that the coefficients on $\log A$ and θ and the constant term be identical on both sides:

$$l_s + l_P h_A = \xi h_A \tag{E.11}$$

$$l_P h_\theta + 1 = \xi h_\theta \tag{E.12}$$

$$l_0 + l_P h_0 + \frac{1}{2} l_s^2 \tau_s^{-1} = \xi h_0 \tag{E.13}$$

The fixed point system implies that

$$l_P = \xi - h{-1}^\theta \tag{E.14}$$

$$l_s = h_\theta^{-1} h_A \tag{E.15}$$

and

$$l_s^3 + \left(\tau_A + \frac{1-\phi}{1-\phi(1-\eta)}\tau_s\right) l_s - \frac{\tau_s}{\tau_\theta[1-\phi(1-\eta)]} = 0 \tag{E.16}$$

Solving the cubic polynomial yields a unique equilibrium as in Sockin and Xiong (2015).

References Appendix

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