# The Carbon Policy Paradox: Divergent Impacts of Short-term vs. Long-term Policies

I-Hsuan Ethan Chiang[1] Shih-Kuei Lin[2] Zong-Wei Yeh[3]

December 16, 2024

**Abstract**

We investigate the impact of the EU Emission Trading Scheme (EU ETS) policies on oil market in this paper. Using a novel term structure model of oil and carbon futures, we filter out factors specific to carbon markets and establish links to short-term and long-term carbon policies. A horizon analysis of the carbon policies' impacts on oil supply and demand dynamics uncovers a "carbon policy paradox": while short-term carbon policies intend to curb fossil fuel use through temporary carbon market intervention, they inadvertently lead to unintended consequences, including increased oil supply and consumption. In contrast, long-term carbon policies that demonstrate the EU ETS's commitment to decarbonization are able to effectively reduce oil dependence. Our findings highlight the divergent impacts of carbon policies on emission reduction targets, underscoring the importance of policy horizon in achieving sustainable outcomes.

*Keywords:* emission trading scheme; EUA futures; oil futures; carbon policy; affine term structure model

[1]Department of Finance, University of North Carolina at Charlotte; `ethan.chiang@charlotte.edu`.
[2]Department of Money and Banking, National Chengchi University; `square@nccu.edu.tw`.
[3]Department of Money and Banking, National Chengchi University; `111352502@nccu.edu.tw`.

# 1 Introduction

The looming threat of climate change presents the global community with unprecedented challenges. As a result, climate-related risks, including physical risks and transition risks,[1] have become a central topic among academics and practitioners (Stroebel and Wurgler, 2021). In an effort to achieve the goal of net zero carbon emissions by 2050,[2] global policy-makers have begun to implement emissions policies, such as cap-and-trade or carbon tax, to reduce greenhouse gas (GHG) emissions.

In this context, the energy markets, the oil market in particular, are at the forefront of transition risks. With the long-term objective of decarbonization, there are growing concerns about whether fossil fuel resources may become stranded assets as carbon policies continue to evolve (Van der Ploeg, 2016; Van der Ploeg and Rezai, 2020). In response to these policies, oil market participants may adjust production, shift investments, or modify consumption patterns to mitigate future risks and costs associated with carbon pricing, arguably leading to an unintended consequence called the "green paradox": fossil fuel resource owners may accelerate oil extraction, and increase oil production, which ultimately worsens global warming. This context motivates our research question: How does carbon policy influence the behavior of market participants in the oil market? By examining these interactions, we aim to shed light on the broader implications of carbon policies for the dynamics of energy markets.

In this paper, we focus primarily on the EU Emission Trading Scheme (EU ETS), which is widely considered to be the pioneer of global carbon markets (Känzig, 2023). As the world's largest carbon market, covering approximately 40% of EU emissions, and with a long history of development since 2005, the EU ETS provides a benchmark for carbon policies. The price

[1] Transition risks refer to the uncertainty associated with the process of decarbonization and the transition to a low-carbon economy, while physical risks describe the increased exposure to climate hazards caused by climate change. For a further discussion of climate-related risks, see Venturini (2022).

[2] The 21st Session of the Conference of the Parties (COP21) to the United Nations Framework Convention on Climate Change adopted the Paris Agreement in 2015. The Agreement mandates the containment of the global average temperature increase to well below $2°C$ above preindustrial levels. To reach this goal, numerous countries have committed to achieving net zero carbon emissions by 2050.

of EU allowances (EUAs) is therefore a meaningful indicator of carbon policy exposure. In addition to spot auction trading, futures contracts are also offered for EUAs, which means that the term structure may also contain information about market expectations and policy-related risks over different time horizons. Much like the Federal Reserve uses various instruments of monetary policy, such as adjustments to federal funds rates and open market operations, to influence the yield curve and achieve policy objectives, the EU ETS employs both short-term and long-term policy instruments to stabilize the carbon market and promote emissions reductions (Känzig, 2023; Koch et al., 2016). Short-term carbon policies focus on temporary supply interventions in EUAs to stabilize or support carbon prices, while long-term carbon policies set ambitious long-term emissions reduction targets, signaling a stronger commitment to decarbonization.

To extract policy-relevant information from the term structure of carbon futures, we begin with a novel model based on commodity futures pricing. Specifically, we use a five-factor affine term structure model (ATSM) that jointly captures the dynamics of both carbon and oil futures. This five-factor model has one common factor, two oil market-specific factors, and two carbon market-specific factors. This model incorporates several stylized facts. First, we introduce a common factor for the carbon and oil markets to account for price co-movements between the two markets. The economic rationale is that when global economic expansion stimulates real activity, pushing up both carbon and oil prices. Consequently, this common factor serves as a proxy for global demand. Similarly to the approach of Kilian (2009), by isolating this global demand effect, we can more accurately identify the risk of carbon policy within the fluctuations in carbon prices. Second, inspired by Chiang et al. (2015), we incorporate cross-market information transmission, allowing correlations between market-specific factors within factor dynamics. This setting corresponds to the unspanned factors highlighted in the recent literature. To ensure parsimony of the model and maintain the identifiability of the factors (Delle Chiaie et al., 2022), we assume that the common factor represents an exogenous shock driven by changes in global demand, conceptualized as a factor orthogonal to the factors specific to each market. Furthermore, we assume that the influence of the common factor induces a parallel shift across the entire term structure, implying a persistent effect.

The estimated results show that carbon policy factors can predict the dynamics of the oil market, implying that market participants have priced carbon policy risks into oil prices. In addition, our proposed model fits very well in both carbon and oil futures markets. Comparing the model's fit to a reduced-form specification—one that omits cross-market correlations—highlights the critical role of the unspanned factor framework in capturing the distinct effects of short-term and long-term carbon policies. Therefore, this framework allows us to isolate more precise measures of the impact of carbon policy, in particular by distinguishing between the effects of short-term and long-term carbon policies.

We perform an event study analysis and establish strong ties between carbon factors and carbon policies of various horizons. We confirm that short-term and long-term carbon factors serve as effective indicators of EU ETS policies of different horizons. We collect 47 policy announcements from 2013 to 2023 and classify them according to their attributes as long-term vs. short-term contractionary vs. expansionary policies. In terms of short-term carbon policies, contractionary policies lead to an abnormal increase of the short-term carbon factor by 1.4 standard deviations over a one-week event window, while expansionary policies lead to a stronger market reaction of an abnormal decrease of 1.95 standard deviations in short-term carbon factor. Our results are consistent with Koch et al. (2016), revealing asymmetric market responses to short-term contractionary versus expansionary policies. Weak market confidence in the EU ETS stabilization mechanisms appears to drive this asymmetry. Expansionary policies elicit strong market reactions, whereas contractionary price-support policies receive limited response. On the other hand, long-term carbon policies that signal decarbonization ambitions lead to an increase in long-term carbon factors, making them reliable indicators of market responses to such policies.

As our key empirical evidence, which we term the "carbon policy paradox," we document strikingly divergent impacts of short-term and long-term carbon policies on oil markets. Using a structural vector autoregressive (SVAR) model, we examine how these policies influence oil quantities (oil production and net imports) and oil consumption in Europe, highlighting their role in shaping both supply and demand sides of the oil market. A tightening of short-term carbon policy (a positive shock of 1 standard deviation) leads to a 0.5% increase in oil quantities and consumption within the first few months of the shock, with both returning to equilibrium after about six months. This counterintuitive result echoes the green paradox described by Sinn (2008, 2009), who highlights the accelerated exploitation of resources in response to regulatory constraints. While Sinn's original framework primarily addresses oil producer behavior on the supply side, our findings complement this paradox by providing demand-side evidence. The market price of carbon remaining below the social cost of carbon partly explains this phenomenon.[3] As a result, while short-term carbon policies can increase the cost of emissions, they still fall short of fully internalizing environmental externalities, inadvertently incentivizing increased immediate oil use, as firms seek to maximize profits and hedge against potential stranded assets. This aligns with Lucas's critique of policy effectiveness, which emphasizes that policies often fail when they neglect the adaptive expectations of market participants.

In contrast, a tightening long-term carbon policy (a positive shock of 1 standard deviation) demonstrates a delayed but substantial impact, with oil quantities and consumption declining by nearly 1% eight months after the policy takes effect. We find that long-term carbon policies create stronger outcomes and can effectively curb oil market behavior after a period of adjustment. Setting long-term emission reduction targets, the EU ETS provides market participants with a credible expectation of sustained regulatory pressure on carbon emissions. In sum, these results underscore the critical role of EU ETS policy instruments:

[3] The social cost of carbon quantifies the economic damage caused by an additional tonne of carbon dioxide emissions, including effects such as health problems, loss of agricultural productivity and property damage due to climate change. Recently, an influential study by Rennert et al. (2022) shows that this figure can be as high as $185 per tonne , which is much higher than the carbon emission fee charged by the EU ETS.

while short-term carbon policies may unintentionally undermine efforts to reduce emissions, long-term carbon policies provide credible signals that gradually reduce dependence on fossil fuels.

Our study contributes to the growing literature that examines the impact of climate policies, particularly carbon pricing. Several recent studies have examined the impact of EU ETS policy announcements on macroeconomy or market dynamics.[4] However, most of these analyses rely only on spot prices as a proxy to measure the impact of policy events. Although Känzig (2023) incorporates EUA futures to calculate carbon policy surprises, the discussion remains focused on the price "level," overlooking the rich information embedded in the shape of the term structure. We advance this perspective by modeling the term structure of EUA futures to differentiate market implication to short- and long-term carbon policies.

More substantially, our research also contributes to the empirical literature on the green paradox. Some theoretical studies describe the possibility of a green paradox.[5] Empirically, much of the literature focuses on the impact of climate policy at the firm level.[6] In contrast, we examine the fundamentals of the oil market, which, as emphasized by Ready (2018), provide key insights into the value of oil companies. Some studies have analyzed the impact of climate policy on oil prices (e.g., Bjørnland et al., 2023; Känzig, 2023), but as Kilian (2009) highlights, distinguishing between oil supply and demand effects provides a more complete understanding of the role of carbon policy in the oil market. The most relevant study for our work is Barnett (2023), but unlike their focus, we uncover the carbon policy paradox within the EU ETS framework, capturing both oil supply and demand responses for a more comprehensive view. In addition, by distinguishing between short-term and long-term carbon policies, we reveal both unintended consequences and intended outcomes.

Finally, our research extends the literature on commodity futures pricing. Building on

[4] see Bjørnland et al. (2023); Fan et al. (2017); Hengge et al. (2023); Känzig (2023); Känzig and Konradt (2023); Koch et al. (2016).

[5] see Caldecott et al. (2021); McGlade and Ekins (2015); Semieniuk et al. (2022); Van der Ploeg and Rezai (2020).

[6] see Atanasova and Schwartz, 2019; Bogmans et al., 2024; Donadelli et al., 2021.

extensive research using affine models for commodity derivatives,[7] we propose a novel dual-market framework for carbon and oil that incorporates the importance of cross-market information highlighted in recent literature. For example, Heath (2019) applies unspanned macroeconomic factors to oil futures, Jacobs et al. (2022) extend this approach to electricity markets, and Chiang et al. (2015) also highlight cross-market interactions between oil and equity markets. By integrating these insights, our framework provides a unified perspective on how policy signals propagate between the carbon and oil markets.

# 2 Background of EU ETS

## 2.1 EU ETS Operational Mechanism

The EU ETS is a pioneering cap-and-trade market, established in 2005 under the Kyoto Protocol. It is the cornerstone of the EU's policy architecture for combating climate change, designed to reduce GHG emissions in a cost-effective manner. To date, the EU ETS is recognized as the largest carbon market in the world, covering 27 EU countries as well as Iceland, Liechtenstein, and Norway, for a total of 30 countries.[8] It regulates around 10,000 installations in the energy sector, the manufacturing sector, and parts of the aviation industry based in Europe. This coverage represents about 40% of EU GHG emissions.

The EU ETS operates on a cap-and-trade principle, which involves setting a limit on the total amount of certain GHGs that can be emitted by installations covered by the scheme. To facilitate this, these installations are allocated EUAs, each of which is equivalent to one tonne of $CO_2$. This cap is systematically reduced over time, in line with the EU's ambitious climate change targets, to ensure a gradual and consistent reduction in overall emissions.

EUAs are allocated to installations, with some given away for free based on histori-

[7] see Casassus and Collin-Dufresne, 2005; Chiang et al., 2015; Heath, 2019; Jacobs et al., 2022; Schwartz, 1997; Trolle and Schwartz, 2009.

[8] Following Brexit, the UK formally exited the EU ETS on 1 January 2021. Coinciding with its withdrawal, the UK launched its own carbon emissions trading scheme (UK ETS).

cal emissions and performance benchmarks, and the rest auctioned. The total number of allowances is deliberately limited to create scarcity in the market, thereby incentivizing installations to reduce their emissions efficiently. Installations are required to surrender allowances equal to their emissions at the end of each compliance period. Those that manage to reduce their emissions below their allowance can sell their surplus allowances, promoting a market-based mechanism to incentivize emission reductions.

## 2.2 EU ETS Development History

The EU ETS is a market mechanism built on a foundation of regulatory oversight. As a result, market participants naturally respond to the prevailing policy landscape. This responsiveness underlines the dynamic interaction between policy developments and market behavior, where adjustments in carbon policy can significantly influence market outcomes, including the pricing and allocation of allowances. The evolution of the EU ETS has taken place in several distinct phases, each characterized by targeted regulatory changes, market responses, and environmental objectives. Figure 1 shows the evolution of carbon prices through these operational phases.

[Insert Figure 1 here]

The Phase 1, from 2005 to 2007, served as a fundamental learning period and set the stage for future improvements. This phase was limited to $CO_2$ emissions from power generation and energy-intensive industries, and allowances were distributed free of charge. Despite the establishment of a market price for carbon and the start of trading activities, the initial lack of accurate emissions data led to an oversupply of allowances and a collapse in carbon prices.

During the Phase 2 (2008-2012), which coincided with the Kyoto Protocol's first commitment period, the EU ETS was given concrete emission reduction targets. Drawing on the lessons of the first phase, the cap was reduced by 6.5% from the 2005 levels, with a 10% reduction in free allocation of allowances and the introduction of allowance auctions in some countries. Penalties for non-compliance were increased to €100 per tonne. This phase also extended the scheme to nitrous oxide ($N_2O$) emissions and included the aviation industry from January 2012. Despite these adjustments, the 2008 financial crisis significantly reduced carbon emissions, leading to a continued oversupply of allowances.[9]

The Phase 3 (2013-2020) saw significant reforms to the carbon trading framework. It expanded the range of regulated industries and gases, significantly reduced free allocations and moved towards a predominance of auctioned allowances, with free allocations to the manufacturing sector falling to 30% by 2020. The power sector was required to purchase allowances, underlining the EU's determination to refine the carbon market for emissions reduction.

Currently in its Phase 4 (2021-2030), the EU ETS is aligned with the ambitious goals of the European Green Deal, which aims to achieve carbon neutrality by 2050. This phase sets a target of at least a 55% reduction in net carbon emissions by 2030 and requires covered sectors to reduce emissions by 43% from 2005 levels by the end of the decade. To address the issue of surplus allowances from previous phases, the EU has introduced the Market Stability Reserve (MSR) mechanism for enhanced control and strengthened enforcement measures.

# 3 Model Specification

This section presents the five-factor ATSM with a common factor and market-specific factors for the carbon and oil markets. We then derive the closed form of the commodity futures price and discuss the role that the factors play in the futures price. Finally, we introduce the procedure for Kalman filter to obtain the state variable and unknown parameters.

[9] Bjørnland et al. (2023) also documented that the decline in EUA prices during the second phase was influenced by the global financial crisis and the European sovereign debt crisis, which led to a reduction in economic activity. This in turn led to the hoarding of EUAs, which increased from almost zero at the end of 2008 to around two billion in 2013. In addition, the phenomenon can be partly attributed to companies opting to purchase a limited number of Certified Emission Reductions (CERs) to replace EUAs to offset their emissions.

## 3.1 Affine Term Structure Model

To identify the common factor and market-specific factors in the respective markets, we build an ATSM the five-factor affine model is given by the following risk-neutral Itô diffusion:

$$dX_t = \left(A^{\mathbb{Q}} + B^{\mathbb{Q}} X_t\right) \, dt + \Sigma \, dW_t^{\mathbb{Q}}, \tag{1}$$

where $X_t = \left(X_t^{Com}, X_{s,t}^C, X_{l,t}^C, X_{s,t}^O, X_{l,t}^O\right)^\top$ is a state variables vector and corresponds to the common factor, short-term and long-term market-specific factors in the carbon market, and short-term and long-term market-specific factors in the oil market, respectively. $A^{\mathbb{Q}}$ is $5 \times 1$ vector, $B^{\mathbb{Q}}$ is a $5 \times 5$ matrix, $\Sigma$ is a $5 \times 5$ lower triangular matrix ($\Sigma^\top \Sigma$ is variance-covariance matrix for five factor), and $dW_t^{\mathbb{Q}} \in \mathbb{R}^5$ are independent Brownian motions under risk-neutral measure $\mathbb{Q}$. The log spot price in market $i$ can be express as an affine function of state variables as followings:

$$s_t^i = \delta^{i\top} X_t, \tag{2}$$

where $i \in \{C, O\}$ denote carbon and oil markets. $\delta^C = (\delta_X^C, 1, 0, 0, 0)^\top$ and $\delta^O = (\delta_X^O, 0, 0, 1, 0)^\top$ are the coefficient vectors in both markets. Specifically, in the case of market $i$, the spot price can be expressed as the sum of a common factor and a short-term factor, that is $s_t^i = \delta_X^i X_t^{Com} + X_{s,t}^i$.

Then, we follow the conventional setting of literature on term structure modeling for interest rates and commodities, we opt the market price of risk, $\Lambda_t$ are set as essentially affine type (see Duffee, 2002):

$$\Lambda_t = \lambda_0 + \lambda_1 X_t, \tag{3}$$

where $\lambda_0 \in \mathbb{R}^5$ and $\lambda_1 \in \mathbb{R}^5 \times \mathbb{R}^5$. It means that the dynamic process of state variables under physical measure $\mathbb{P}$ are also affine:

$$dX_t = \left(A^{\mathbb{P}} + B^{\mathbb{P}} X_t\right) \, dt + \Sigma \, dW_t^{\mathbb{P}}, \tag{4}$$

where $A^{\mathbb{P}}$ is $5 \times 1$ vector, $B^{\mathbb{P}}$ is a $5 \times 5$ matrix, and $dW_t^{\mathbb{P}} \in \mathbb{R}^5$ are independent Brownian motion under the physical measure. By the Girsanov theorem, the $\mathbb{P}$- and $\mathbb{Q}$-parameters are therefore related as follows:

$$A^{\mathbb{P}} = A^{\mathbb{Q}} + \Sigma\lambda_0, \tag{5}$$

$$B^{\mathbb{P}} = B^{\mathbb{Q}} + \Sigma\lambda_1. \tag{6}$$

In terms of the characteristics of the state variables within our model, the common factor is perceived as an exogenous shock arising from a change in carbon policy. This distinction causes the common factor to be orthogonal to other market-specific factors in the system. This independence is represented mathematically by the structure of the variance-covariance matrix $\Sigma^\top\Sigma$, denoted as:

$$\Sigma^\top\Sigma = \begin{bmatrix} \sigma_{11} & 0 & 0 & 0 & 0 \\ 0 & \sigma_{22} & \sigma_{23} & \sigma_{24} & \sigma_{25} \\ 0 & \sigma_{23} & \sigma_{33} & \sigma_{34} & \sigma_{35} \\ 0 & \sigma_{24} & \sigma_{34} & \sigma_{44} & \sigma_{45} \\ 0 & \sigma_{25} & \sigma_{35} & \sigma_{45} & \sigma_{55} \end{bmatrix}, \tag{7}$$

As highlighted by Bai and Wang (2014), while the orthogonality assumption between the common factor and market-specific factors can be relaxed by applying alternative restrictions to examine the interaction among these factors, our analysis focuses primarily on separating the market-specific factors from the common factor. Moreover, Doz et al. (2012) shows that the robustness of the estimates can be improved by imposing restrictions on the correlation between the common factor and the other factors. Such setting maintains the parsimony and clarity of the model while ensuring its identifiability (Delle Chiaie et al., 2022).

## 3.2 Futures Pricing

Given the dynamic process of state variables in Equation (1), the time-$t$ commodity futures price with maturity date of $T$ in market $i$ is martingale under the risk-neutral measure given the time-$t$ information set $\mathcal{F}_t$:

$$F^i(t,T) = \mathbb{E}^{\mathbb{Q}}\left[\exp\left(s_T^i\right)\middle|\mathcal{F}_t\right]. \tag{8}$$

The log futures price is also an affine function of state variables; see Appendix A for the derivation. Specifically, the log futures price is given by:

$$\log F^i(t,T) = \mathcal{A}^i(t,T,\Theta^{\mathbb{Q}}) + \mathcal{B}^i(t,T,\Theta^{\mathbb{Q}})X_t, \tag{9}$$

where $\mathcal{A}^i$ and $\mathcal{B}^i$ are functions that satisfy the initial conditions $\mathcal{A}^i(t,t,\Theta^{\mathbb{Q}}) = 0$ and $\mathcal{B}^i(t,t,\Theta^{\mathbb{Q}}) = \delta^{i\top}$, and are expressed as follow:

$$\mathcal{A}^i(t,T,\Theta^{\mathbb{Q},i}) = \int_t^T \delta^{i\top} e^{B^{\mathbb{Q}}(T-s)} A^{\mathbb{Q}} ds + \frac{1}{2}\int_t^T \delta^{i\top} e^{B^{\mathbb{Q}(T-s)}} \Sigma^\top \Sigma (e^{B^{\mathbb{Q}}(T-s)})^\top \delta^i ds, \tag{10}$$

$$\mathcal{B}^i(t,T,\Theta^{\mathbb{Q},i}) = \delta^{i\top} e^{B^{\mathbb{Q}}(T-t)}. \tag{11}$$

To identify the interpretation of state variables, we refer to Chiang et al. (2015) to restrict the parameters under $\mathbb{Q}$ measure. A similar approach is applied in Christensen et al. (2011), who obtain the term structure of interest rates using the framework of Nelson and Siegel (1987) by restricting the mean reversion matrix. This has the advantage of reasonably dissecting the role of each state variable in the term structure. In line with this approach, we apply a specific constraint on the $B^{\mathbb{Q}}$ as follows:

$$B^{\mathbb{Q}} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & -b_C^{\mathbb{Q}} & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -b_O^{\mathbb{Q}} & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}. \tag{12}$$

Consequently, the log futures price in market $i$ is articulated as:

$$\log F^i(t,T) = \mathcal{A}^i(t,T,\Theta^{\mathbb{Q}}) + \delta_X^i\, X_t^{Com} + e^{-b_i^{\mathbb{Q}}(T-t)}\, X_{s,t}^i + \frac{1 - e^{-b_i^{\mathbb{Q}}(T-t)}}{b_i^{\mathbb{Q}}}\, X_{l,t}^i. \tag{13}$$

This equation delineates the log futures price as a function of the model's state variables, incorporating the common factor $X_t^{Com}$ and both the short-term $X_{s,t}^i$ and long-term $X_{l,t}^i$ market-specific factors for the respective markets, modulated by the mean reversion rates $b_i^{\mathbb{Q}}$. Notably, the factor loading attributed to the common factor is characterized by its constancy across different maturities, underscoring its designation as a permanent influence within the model. This implies that the effect exerted by the common factor is consistent, resulting in a parallel shift across the entire term structure. Such a feature highlights the common factor's pivotal role in reflecting systemic changes or shocks that impact the markets uniformly. Conversely, the behavior of the factor loadings for the first and second market-specific factors across maturities reveals distinct temporal characteristics. Specifically, the loading for the first market-specific factor diminishes with increasing maturity, identifying it as a short-term factor. While the loading for the second market-specific factor escalates with maturity, classifying it as a long-term factor.

## 3.3 Estimated Procedure

Given that both the common factor and market-specific factors are unobservable latent variables within our model, coupled with the affine nature of the transition and measurement equations and the assumption that errors follow a Gaussian distribution, the utilization of the Kalman filter emerges as an intuitive approach for extracting these state variables.

Firstly, we display the state-space representations of the ATSM in our model specification. To obtain the transition density of the state variables, a first-order Euler discretization method is used to transform the Equation (4) into this form:

$$\begin{aligned} X_{t+\Delta t} &= A^{\mathbb{P}}\Delta t + \left(I + B^{\mathbb{P}}\Delta t\right) X_t + \sqrt{\Delta t}\Sigma\varepsilon_{t+\Delta t} \\ &= \Phi_0 + \Phi_1 X_t + u_{t+\Delta t}, \end{aligned} \tag{14}$$

where $u_{t+\Delta t} \sim N(0, Q)$, $Q = \Sigma^\top\Sigma\Delta t$. The measurement equation of the ATSM, corresponding to Equation (9), is thus articulated as:

$$\begin{pmatrix} \log F^C \\ \log F^O \end{pmatrix} = \begin{pmatrix} \mathcal{A}^C \\ \mathcal{A}^O \end{pmatrix} + \begin{pmatrix} \mathcal{B}^C \\ \mathcal{B}^O \end{pmatrix}^\top X_t + \nu_t, \tag{15}$$

where $\nu_t \sim N(0, R)$, $R = \sigma_r^2 \cdot I_{N_C+N_O}$. $I_n$ represents the $n \times n$ identity matrix, and $N_C$ and $N_O$ denote the total number of available maturities for each market in the sample. It is important to note that the noise components of both the transition and measurement equations are assumed to be independent. Subsequently, the standard Kalman filter procedure with maximum likelihood estimation is used to extract the filtered state variables along with the unknown parameters.

# 4 Data and ATSM Estimation Results

In this section we detail the data, the ATSM parameter estimation, and the estimation results. Our primary objective is to extract insights from commodity futures prices and to quantitatively assess the impact of carbon policies on the oil market. To ensure the adequacy of the model, we examine its ability to capture the stylized facts observed in the data, thereby confirming the reliability of our empirical results. We present both in-sample and out-of-sample fits of our model and compare its effectiveness with the reduced-form model.

## 4.1 Data

We utilize daily price data for EUA futures and Brent crude oil futures from the Intercontinental Exchange (ICE) in our empirical study.[10] As highlighted in the background of the EU ETS provided earlier, significant changes have been introduced since Phase 3 that have fundamentally altered the regulatory nature of the scheme. With the expansion to a wider range of regulated industries and gases during Phase 3, the free allocation of allowances to regulated entities was significantly reduced. These adjustments effectively mitigated the supply/demand imbalance that precipitated the price collapses observed after Phases 1 and 2. Consequently, our empirical investigation will focus on data from Phase 3 and the ongoing Phase 4, covering the periods from January 2013 to December 2020 and January 2021 to December 2023, respectively.

To take liquidity into account, we follow the contract selection approach prevalent in the commodity derivatives literature. As noted in Trolle and Schwartz (2009), liquidity in oil futures is predominantly concentrated in short-term contracts within a six-month horizon. Consequently, we opt for the six closest monthly futures contracts (M1-M6). In addition, for longer-term futures contracts, trading volume is observed primarily in quarterly contracts and those expiring in December. Therefore, we also select two quarterly contracts (M9 and M12). A similar pattern is observed for the EUA futures, so we select the carbon futures contracts M1, M2, M3, M6, M9 and M12 for our study. Given the sharp decline in open interest due to the early settlement of most contracts in the last two weeks before expiration, we filter out contracts with less than 14 days to maturity.

[10] In addition to the ICE in London, the European Energy Exchange (EEX) in Leipzig also offers EUA futures contracts with nearly identical contract specifications. However, Stefan and Wellenreuther (2020) note that the primary discovery of carbon futures prices occurs predominantly on ICE. This finding underscores the importance of focusing on ICE data, given its leading position in price discovery within the carbon market.

[Insert Figure 2 here]

Figure 2 shows the futures price series for EUA and Brent oil for both two-month and twelve-month futures contracts, with EUA prices converted into USD using the daily EUR/USD. These prices represent short-term and long-term perspectives within the futures term structure. EUA futures are observed to exhibit contango characteristics, where short-term prices are lower than long-term futures prices. This phenomenon is documented in the literature as an inconvenience yield (see Palao and Pardo, 2021) associated with the contract specifications of EUAs, in particular, the absence of storage costs and the fact that EUA do not expire. The interaction between short-term and long-term futures prices for Brent oil is comparatively more complex than for EUA futures. During most economic expansions, demand for spot crude oil typically leads to a backwardation pattern in the term structure, where long-term prices are lower than short-term prices. However, during certain periods, such as 2014 to 2016 or during the COVID-19 pandemic in 2020, the oversupply in the market leads to contango. To mitigate the market uncertainties, oil traders often increase above-ground oil inventories as a precaution against potential shortages. This strategy is documented as a precautionary (storage) demand (Alquist and Kilian, 2010; Kilian and Park, 2009).

## 4.2 Parameter Estimates

Table 1 presents the results of the estimate of the maximum likelihood parameter for the futures of EUA and Brent oil throughout the period, including Phase 3 and the ongoing Phase 4 of the EU ETS. Standard errors are calculated using the outer product of the gradient. Furthermore, Equation (2) includes estimates of the loadings of the common factor on the futures prices of both markets, denoted $\delta_X^C$ and $\delta_X^O$, with estimated values of 1.11 and 1.21 respectively. This common factor influences both markets to move in the same direction, as indicated by the identical signs of these factor loadings. This supports our expectation that the common factor reflects signals related to global real activities. During periods of global economic expansion, increased producer activity pushes up both carbon and oil prices. We will provide more evidence to support this argument in section 5.

[Insert Table 1 here]

All diagonal elements of the diffusion matrix under the $\mathbb{P}$ measure, denoted as $B^{\mathbb{P}}$, are statistically significant, indicating strong within-factor dynamics. Although the off-diagonal elements are generally not statistically significant, they exhibit limited but noteworthy interactions between factors. Specifically, the entries at positions $(4, 3)$ and $(5, 2)$ of $B^{\mathbb{P}}$, with values of 8.598 and $-2.579$ respectively, suggest potential predictive relations between carbon and oil factors. These values imply that the long-term carbon factor positively forecasts the short-term oil factor, while the short-term carbon factor has a negative predictive relation with the long-term oil factor. Furthermore, the covariance matrix $\Sigma\Sigma^{\top}$ reveals a negative correlation between the short-term carbon factor and the oil factor, as well as a positive correlation between the long-term carbon factor and the oil factor. Together, these findings suggest that carbon factors are integrated into oil market's pricing mechanisms, indicating that market participants anticipate and incorporate carbon risks within oil price dynamics.

As discussed in Section 3, the market-specific factor loadings of commodity futures prices on the carbon and oil markets are governed by the diffusion matrix under the $\mathbb{Q}$ measure $B^{\mathbb{Q}}$. Based on the estimation results in Table 1, Figure 3 provides a visual illustration of the factor loadings across different maturities in both markets.

[Insert Figure 3 here]

In the carbon market, the short-term factor loadings remain relatively stable across maturities, reflecting greater persistence over time. By contrast, the loadings on the long-term factor start from zero at zero maturity, and increase with contract maturity, indicating that this factor primarily captures the impact of longer-dated contracts. Thus, the short- and long-term factors in the carbon market are conceptually similar to the level and slope factors described by Nelson and Siegel (1987). In the oil market, the effect of the short-term factor diminishes significantly with longer maturities, with contracts maturing in one year exhibiting an explanatory power of approximately 0.2. Conversely, the loading on the long-term factor increases as maturity extends. This decomposition in the oil market aligns with previous findings by Chiang et al. (2015), providing a meaningful description of the dynamics of short- and long-term oil prices.

## 4.3 Goodness of Fit

To assess pricing accuracy, we use the filtered state variables and estimated parameters to calculate the fitted futures prices. Following the approach of Trolle and Schwartz (2009), we measure accuracy by calculating the daily root mean squared errors (RMSEs), defined as the difference between the fitted and market prices, normalized by the market price. The table reports the average RMSE for the time series.

To further evaluate our model, we compare it to a reduced-form model specification. In this specification, we assume no correlation between the factors in the carbon and oil markets, effectively isolating the impact of the specific market factors while ignoring potential cross-market influences. That is, we consider one common factor and two specific factors in each of the futures markets.[11] Recent studies (Heath, 2019; Jacobs et al., 2022) highlight the importance of unspanned factors in commodity pricing. The reduced model is equivalent to excluding the effect of the unspanned factors.

Panel A of Table 2 presents the in-sample performance of our model in capturing the dynamics of EUA and Brent futures contracts. The estimated futures prices from both the full and reduced models closely match actual market data, particularly for EUA futures. This alignment can be attributed to the consistency in the carbon term structure, which predominantly remains in contango. The relative simplicity in interactions between short- and long-term carbon factors contrasts with the more complex dynamics observed in the

[11] The two-factor structure is also recommended by Gibson and Schwartz (1990), who specifically consider the dynamics of the underlying asset and stochastic convenience yield.

oil market. Nevertheless, our model achieves strong fits across markets. For context, Trolle and Schwartz (2009); Chiang et al. (2015) report RMSE values of approximately 0.39% and 0.28%, respectively, while the full model produces an RMSE of 0.32% in the oil market, demonstrating similar precision in both the whole and the sub-sample periods.[12]

[Insert Table 2 here]

To assess robustness, panel B of Table 2 presents the results of the test outside the sample. We alternately conduct an in-sample estimation in one phase and bring its parameters to another phase for out-of-sample testing. These results indicate that our model is robust and has no signs of overfitting. In general, the proposed model outperforms the reduced specification. More importantly, the results also reveal the importance of the unspanned factor. As emphasized by the parameter estimation results, the oil market has priced the carbon risks. However, it is important to note that the primary objective of this study is not just to develop a more general model with minimized pricing errors. Instead, the results demonstrate that our model adequately captures the essential information conveyed by the market, validating its application in subsequent empirical analysis.

# 5 Carbon Policies and Their Impacts on the Oil Market

In this section, we explore the economic implications of the affine model. First, we establish strong links between carbon policies and our carbon factors through an event study analysis. Then, we address the central question of this paper: What are the impacts of carbon policies on the oil market? To this end, we construct an SVAR model to analyze how the impacts of carbon policy are transmitted to oil supply and demand.

[12] Chiang et al. (2015) used a four-factor affine model with unspanned random volatility to capture the dynamics of the oil market. However, this study also performs joint estimations of the carbon market and the oil market. Therefore, the fitting results are still convincing.

## 5.1 Event Study Analysis

The EU ETS is widely recognized as a barometer for carbon policy, with allowance prices reflecting the market's response to regulatory changes and emissions reduction commitments.[13] A key question is whether the carbon factors extracted by our model also capture the sensitivity of the market to policy changes. To this end, we conduct an event study analysis and aim to link carbon policy announcements to short- and long-term carbon factors derived from the term structure of EUA futures.

The EU ETS, like the Federal Reserve, uses various policy tools to influence the term structure. In the case of the Fed, adjustments to the federal funds rate or open market operations affect the yield curve at different horizons. Similarly, the EU ETS uses short-term and long-term policy mechanisms to stabilize the carbon market and encourage emission reductions. Short-term policies, such as temporary adjustments to the supply of allowances, are designed to stabilize or support carbon prices by addressing immediate market conditions (Känzig, 2023). Long-term policies focus on signaling a stronger commitment to ambitious emission reduction targets (Koch et al., 2016). Examples include the adoption of the Market Stability Reserve (MSR) mechanism in 2015 or the EU's commitment to Fit for 55 targets. While such long-term policy announcements may not have an immediate direct impact on spot market supply and demand, they tend to have a greater impact on futures prices due to increasing hedging pressure (De Roon et al., 2000).

The sample events are primarily sourced from the European Commission Climate Action news archive. We manually compile a list of EU ETS policy announcements.[14] For event selection, we concentrate specifically on policy announcements that introduced new measures or adjustments, as well as updates on medium- and long-term emission reduction targets issued by the European Commission. Any secondary information was excluded, in-

[13] Fan et al. (2017); Känzig (2023); Koch et al. (2016) have analyzed the impact of European carbon policy and regulatory events on EUA prices, emphasizing the critical role of policy and regulatory shifts in shaping allowance prices.

[14] `https://climate.ec.europa.eu/news-your-voice/news_en`.

cluding announcements from individual EU member states and routine updates on market conditions to maintain the focus on impactful policy changes. Our final sample consists of 47 policy announcements spanning the period for 2013 to 2023.[15] Each announcement was classified following economic principles as having either a positive (contractionary) or negative (expansionary) expected impact on carbon market prices. It is noteworthy that all long-term policies are classified as contractionary carbon policies, as they primarily emphasize carbon reduction targets. Consequently, these policies are classified exclusively in the positive impact category.

In our event study methodology, we employ a mean-adjusted model. Given that the EU ETS is a relatively young market with frequent policy announcements, relying solely on raw data could introduce bias in estimating normal mean returns, particularly due to the overlapping of regulatory event dates. To address this, we trim the data by excluding the top and bottom 5% of factor returns within the estimation window, thereby reducing the impact of extreme values and obtaining a more stable mean return. Furthermore, since the carbon market lacks a recognized reduced market model in the literature, we adopted this simple mean-adjusted model as a pragmatic choice. Despite its simplicity, this approach still effectively captures the impact of events and performs comparably to more complex models (Brown and Warner, 1985).

Specifically, let the date of the policy event be defined as $t = 0$. For each event day (day 0), we estimate the following regression over the 60 trading days (around quarter a year) leading up to the event date:

$$\Delta X_t = \alpha + \varepsilon_t, \quad t = -60, \cdots, -2, \tag{16}$$

where $\alpha$ is estimated by the mean after removing the upper and lower 5% quantiles of returns. We then calculate the cumulative abnormal factor (CAF) over the event window between

[15] A detailed description of these policy announcements is provided in Appendix B.

date-$t_1$ and date-$t_2$:

$$CAF_T = \sum_{t=-t_1}^{t_2} \varepsilon_t. \quad (17)$$

Table 3 presents the results of our event study analysis, examining the short-term and long-term carbon factor responses to EU ETS policy announcements. We calculate the CAF for each event as specified in Equation (17), averaging the results by event category. The table summarizes the average CAFs for two event windows: [-1,0], i.e., $t_1$ is set to $-1$ and $t_2$ is set to 0, covering the day before to the day of the announcement, and $[-2{,}2]$ (i.e., $t_1$ is set to $-2$ and $t_2$ is set to 2), capturing the week (5-day) effect surrounding the announcement date. To facilitate comparison, we standardize the original factors.

[Insert Table 3 here]

In Panel A of Table 3, the short-term carbon factor exhibits significant responses to both contractionary and expansionary announcements, aligning with expectations. Contractionary policy announcements generate a relatively moderate response of approximately 0.27 standard deviations on the announcement day, culminating in a cumulative increase of nearly 1.4 standard deviations over the entire event window. In contrast, expansionary policy announcements trigger a more immediate and pronounced market reaction, with a decline of 1.55 standard deviations on the announcement day and a total drop of 1.95 standard deviations over the week. In particular, on 16 April 2013, the European Parliament's rejection of the back-loading proposal led to a roughly 40% decline in EUA prices.[16] Overall, these results corroborate findings from Koch et al. (2016), highlighting fragile market confidence in EU ETS stabilization policies. Expansionary policies elicit stronger reactions, while contractionary policies show limited success in sustaining prices.

On the other hand, Koch et al. (2016) also suggest that long-term policies tend to have limited or even counterintuitive effects on short-term prices. As noted by Hicks (1975);

[16] Following Phase 2 of the EU ETS, a surplus of EUAs accumulated due to the economic downturn, which reduced emissions more than anticipated, resulting in lower-than-expected demand for allowances. The back-loading proposal, introduced by the European Commission, aimed to temporarily reduce oversupply and stabilize EUA prices by postponing the auctioning of a portion of allowances.

Keynes (2024), futures prices often carry a risk premium to account for higher hedging pressures, while long-term policies primarily shape the future carbon policy environment rather than immediate supply-demand conditions. To further explore this, we examine the impact of long-term policies on long-term carbon factors. Panel B of Table 3 shows that following long-term policy announcements, the long-term carbon factor rises by approximately 0.3 standard deviations on the announcement day, with a cumulative increase nearing 0.5 standard deviations over the week. This positive response aligns with the anticipated effects of long-term carbon policy goals, suggesting that markets internalize these announcements as indicative of a more constrained future supply environment. Although the results lack statistical significance, the directional movement of the long-term factor still underscores the signaling power of long-term policies in shaping future carbon market dynamics.[17]

These results underscore the utility of short-term and long-term carbon factors as proxies for the impacts of short-term and long-term carbon policies, respectively, in subsequent empirical analyses. Distinguishing between these policy horizons is critical for interpreting their differential effects on market behavior and understanding how policy measures influence carbon market dynamics across time horizons.

## 5.2 What Are the Impacts of Carbon Policies on the Oil Market?

Through the model estimation, we find that oil market have priced both short-term and long-term carbon factors. As shown in the event study analysis, the short-term carbon factor is sensitive to the policy exposure embedded in the EU ETS through short-term supply interventions. Conversely, the long-term carbon factor responds to the EU ETS's long-term planning, encompassing broader ambitions to gradually reduce emissions.

As emphasized in Hamilton (2003) and Kilian (2009), changes in oil prices are frequently attributed to different sources. The consensus in the literature often categorizes them as

[17] An event study of short-term factors in response to long-term policies found an impact less than half as strong as that on long-term factors, consistent with findings from Koch et al. (2016).

supply-side or demand-side shocks.[18] In general, carbon policies can influence the oil market through various channels. For instance, carbon pricing or emission caps can raise production costs for oil companies, potentially reducing oil supply as firms adjust output to maintain profitability. On the demand side, stricter carbon regulations might lead industries and consumers to substitute oil with cleaner energy sources, thereby decreasing demand. By distinguishing between short-term and long-term effects, we aim to gain a more nuanced understanding of how carbon policies impact the oil market over different time horizons. To shed light on this relation, we utilize SVAR model to analyze the transmission channels through which carbon policy risks affect the oil market. Specifically, consider a standard VAR($p$) model:

$$y_t = b + \sum_{i=1}^{p} B_i y_{t-i} + u_t, \tag{18}$$

where $y_t$ is the vector of endogenous variable; $b$ is the intercept vector; $B_i$ are the coefficient matrices for lagged variables; $u_t$ is a vector of reduce-form error with covariance matrix $\mathrm{Var}(u_t) = \Sigma_u$.

The reduced-form errors can be expressed as a linear combination of structural shocks $\varepsilon_t$ as follows:

$$u_t = S\varepsilon_t, \quad \mathrm{Var}(\varepsilon_t) = \Sigma_\varepsilon. \tag{19}$$

where $S$ is the matrix that maps reduced-form residuals to structural shocks, and $\Sigma_\varepsilon$ is the covariance matrix of the structural shocks. The structural shocks are identified by solving $S$ from the condition $\Sigma_u = S\Sigma_\varepsilon S^\top$. In this study, we use the Cholesky decomposition of the reduced-form residuals' covariance matrix to identify the structural shocks. This is appropriate given the focus on exploring the impact of carbon policy shocks on the oil market.[19]

[18] A comprehensive discussion can be referred to Kilian and Zhou (2023).

[19] Alternative identification schemes, such as sign restrictions or narrative sign restrictions, are discussed in Baumeister and Peersman (2013); Kilian and Murphy (2012); Zhou (2020).

We specify two SVAR models to assess the impact of carbon policies over different time horizons. In both models, we assume that EU ETS policy decisions are primarily driven by internal considerations, such as the supply of EUAs and long-term emission reduction targets, and are unaffected by other variables in the short run. Based on this assumption, the carbon factor is placed first in the vector of endogenous variables $y_t$ within the Cholesky identification scheme, reflecting its exogeneity in the short-run dynamics of the model. For the oil market variables, we include oil quantity and oil consumption in the European region as proxies for oil supply and demand, respectively. Here, oil quantity is defined as the sum of oil production and net imports, while oil consumption is defined as the sum of direct use and refinery intake. It is worth noting that Europe's relatively limited oil production capacity, using oil quantity rather than oil production alone offers a more comprehensive view of the oil supply flow in Europe.

Data on oil production, net imports, direct use, and refinery intake are sourced from the International Energy Forum (IEF), providing a comprehensive overview of the dynamics of the European oil market and allowing the construction of robust oil supply and demand variables.[20] The dataset comprises country-level data on oil-related variables, which we aggregate to represent the combined totals for countries participating in the EU ETS, including the UK. Although the UK exited the European Union in 2020, it remained part of the EU ETS until 2021 and subsequently launched the UK ETS, continuously monitored by carbon policy.[21]

Figure 4 shows the impulse response functions (IRFs) of oil quantity and oil consumption for shocks to short-term and long-term carbon policy factors, based on VAR estimates and a recursive identification structure. Panel A shows the IRFs in response for a shock to the short-term carbon factor, while Panel B shows the IRFs in response for a shock to the long-term carbon factor. The solid lines represent point estimates, and the dark and light shaded

[20] Available via the Joint Organizations Data Initiative (JODI) at `https://www.jodidata.org/oil/database/data-downloads.aspx`.

[21] The UK's inclusion is further justified by its status as Europe's second-largest oil producer.

areas indicate 68 and 90 percent confidence intervals, constructed from 10,000 bootstrap replications. All shocks are normalized to 1 unit standard deviation.

[Insert Figure 4 here]

The results from the cumulative impulse response analysis indicate distinct reactions to short-term and long-term carbon policy shocks. Specifically, a tightening of short-term carbon policies initially leads to a marked increase in oil quantities and oil consumption. Oil quantities peak after about five months and rise by about 0.5%. Oil consumption responds even more strongly. It rises by about 0.5% in the early stages of the shock. In addition, both quickly returned to equilibrium after about half a year. This short-term reaction is counterintuitive, as tightening policies are intended to curb fossil fuel use but instead appear to drive a temporary increase. In contrast, a long-term tightening carbon policy shock shows minimal effect on oil quantities and consumption in the initial period, with significant declines beginning approximately 8 months after the policy takes effect. This delayed response accumulates to nearly a 1% reduction in both oil quantities and consumption, marking a statistically and economically significant impact. Overall, short-term carbon policy shocks seem to drive increases in oil quantities and consumption, while long-term policies lead to opposite effects, with the long-term response being notably stronger.

***Discussion.*** From these observations, we can infer several economic insights. First, the effect of short-term carbon policies appears paradoxical, suggesting a newly uncovered *Carbon Policy Paradox* within the EU ETS framework. This result echoes the Green Paradox proposed by Sinn (2008, 2009), which primarily describes a scenario where anticipated future carbon policies lead to accelerated resource extraction by fossil fuel producers, as they seek to maximize profits before stricter regulations take effect. However, our findings show that this paradox extends beyond the supply side to encompass demand as well: rather than curbing fossil fuel use, short-term tightening policies intended to raise carbon prices are associated empirically with increased oil production by producers and heightened oil consumption by firms in the short run, contrary to policy goals aimed at emission reduction.

This unintended consequence may be due to the current market price of carbon being below the social cost of carbon. As Pedersen (2023) has emphasized, when the carbon price is lower than its true social cost, the efficacy of carbon policies becomes limited. Although short-term policies increase emission costs, it fails to fully internalize the environmental externality, thereby incentivizing increased current oil use rather than reduction to maximize profits and avoid potential stranded assets.

Interestingly, the data also reflect that long-term carbon policies are more effective in aligning oil market behaviors with decarbonization goals. Long-term policies trigger a contraction in both oil quantities and consumption, albeit with a temporal lag. This delayed response underscores the nature of long-term policies, which often influence future market expectations and gradually increase the economic pressure on oil consumption and production through sustained carbon costs. Here, long-term policies implicitly reflect more ambitious emissions reduction targets, which, unlike short-term interventions, succeed in motivating stakeholders to reduce oil reliance over time. Thus, while short-term policy interventions exhibit limited efficacy, the long-term factor demonstrates that the EU ETS can enforce meaningful decarbonization when policies are sustained and future-oriented.

In conclusion, our analysis suggests that short-term carbon policies may not only be ineffective but may also counteract policy objectives by inadvertently encouraging increased oil production and consumption in the near term. This unintended outcome aligns with Lucas's critique of policy effectiveness, which emphasizes that policies often fall short when they fail to account for the adaptive expectations of market participants. This ineffectiveness may stem from the carbon price falling below the social cost of carbon, reducing the policy's deterrent effect on fossil fuel consumption. Additionally, as discussed in the event study analysis, market participants exhibit skepticism regarding the stability and reliability of short-term policies, which may further exacerbate this ineffectiveness that counteract the intended impact of carbon policy.

By contrast, long-term carbon policies exhibit greater alignment with decarbonization objectives. These policies provide a credible, sustained signal that encourages gradual shifts toward reduced fossil fuel dependence, supporting emissions reduction targets. Our study highlights that treating short- and long-term carbon factors as proxies for distinct policy horizons helps clarify the nuanced effects of carbon policies, revealing that long-term commitments are particularly essential in aligning market behaviors with environmental goals.

# 6 Conclusions

This study analyzes the interaction between carbon policies and oil markets, with a focus on how short-term and long-term carbon policies influence oil market dynamics in distinct ways. To this end, we construct an affine term structure model of carbon and oil futures that includes five factors: a common factor influencing both markets, as well as short-term and long-term market-specific factors unique to each market. The model demonstrates robust fitting capabilities within futures markets and captures essential market characteristics, such as the impact of business cycles and cross-market information transmission.

We interpret the short-term and long-term carbon factors as indicators of the EU ETS policy at different time horizons. Our findings reveal that short-term carbon policy shocks often lead to counterproductive effects, increasing oil quantities and consumption rather than curbing them. In contrast, long-term carbon policies demonstrate a more effective alignment with decarbonization goals, as they gradually lead to reductions in both oil quantities and consumption. Although these long-term policies take time to produce measurable effects, they signal a credible and sustained commitment to emissions reduction, encouraging the market to adjust behavior toward reduced fossil fuel dependence. By distinguishing between these policy horizons, our analysis sheds light on the complex impacts of carbon policies on the oil market and underscores the need for stable, long-term policy frameworks to foster meaningful reductions in fossil fuel use.

In summary, this study contributes to the literature on carbon and energy market interdependence by differentiating the impacts of short-term and long-term carbon policies, offering valuable insights for policymakers. Notably, the market's response suggests concerns about oil assets becoming stranded, highlighting an area for further policy consideration. Addressing the transition strategies for oil producers, promoting cleaner energy development, and supporting advancements in green technology are crucial directions for policymakers to explore in guiding the energy transition effectively.

# References


Alquist, R. and L. Kilian (2010). What do we learn from the price of crude oil futures? *Journal of Applied Econometrics 25*(4), 539–573.

Atanasova, C. and E. S. Schwartz (2019). Stranded fossil fuel reserves and firm value. Technical report, National Bureau of Economic Research.

Bai, J. and P. Wang (2014). Identification theory for high dimensional static and dynamic factor models. *Journal of Econometrics 178*(2), 794–804.

Barnett, M. (2023). A run on fossil fuel? climate change and transition risk. *Working Paper*.

Baumeister, C. and G. Peersman (2013). The role of time-varying price elasticities in accounting for volatility changes in the crude oil market. *Journal of Applied Econometrics 28*(7), 1087–1109.

Bjørnland, H. C., J. L. Cross, and F. Kapfhammer (2023). The drivers of emission reductions in the European carbon market.

Bogmans, C., A. Pescatori, and E. Prifti (2024). The impact of climate policy on oil and gas investment: Evidence from firm-level data. *European Economic Review 165*, 104750.

Brown, S. J. and J. B. Warner (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics 14*(1), 3–31.

Caldecott, B., A. Clark, K. Koskelo, E. Mulholland, and C. Hickey (2021). Stranded assets: Environmental drivers, societal challenges, and supervisory responses. *Annual Review of Environment and Resources 46*(1), 417–447.

Casassus, J. and P. Collin-Dufresne (2005). Stochastic convenience yield implied from commodity futures and interest rates. *The Journal of Finance 60*(5), 2283–2331.

Chiang, I.-H. E., W. K. Hughen, and J. S. Sagi (2015). Estimating oil risk factors using information from equity and derivatives markets. *The Journal of Finance 70*(2), 769–804.

Christensen, J. H., F. X. Diebold, and G. D. Rudebusch (2011). The affine arbitrage-free class of Nelson–Siegel term structure models. *Journal of Econometrics 164*(1), 4–20.

De Roon, F. A., T. E. Nijman, and C. Veld (2000). Hedging pressure effects in futures markets. *The Journal of Finance 55*(3), 1437–1456.

Delle Chiaie, S., L. Ferrara, and D. Giannone (2022). Common factors of commodity prices. *Journal of Applied Econometrics 37*(3), 461–476.

Donadelli, M., P. Grüning, and S. Hitzemann (2021). Macro and asset price dynamics during the climate transition: Evidence from the oil sector. *Working Paper*.

Doz, C., D. Giannone, and L. Reichlin (2012). A quasi–maximum likelihood approach for large, approximate dynamic factor models. *Review of Economics and Statistics 94*(4), 1014–1024.

Duffee, G. R. (2002). Term premia and interest rate forecasts in affine models. *The Journal of Finance 57*(1), 405–443.

Fan, Y., J.-J. Jia, X. Wang, and J.-H. Xu (2017). What policy adjustments in the eu ets truly affected the carbon prices? *Energy Policy 103*, 145–164.

Gibson, R. and E. S. Schwartz (1990). Stochastic convenience yield and the pricing of oil contingent claims. *The Journal of Finance 45*(3), 959–976.

Hamilton, J. D. (2003). What is an oil shock? *Journal of Econometrics 113*(2), 363–398.

Heath, D. (2019). Macroeconomic factors in oil futures markets. *Management Science 65*(9), 4407–4421.

Hengge, M., U. Panizza, and R. Varghese (2023). Carbon policy surprises and stock returns: Signals from financial markets. *Available at SSRN 4343984*.

Hicks, J. R. (1975). Value and capital: An inquiry into some fundamental principles of economic theory. *OUP Catalogue*.

Jacobs, K., Y. Li, and C. Pirrong (2022). Supply, demand, and risk premiums in electricity markets. *Journal of Banking & Finance 135*, 106390.

Känzig, D. R. (2023). The unequal economic consequences of carbon pricing. *NBER Working Paper*.

Känzig, D. R. and M. Konradt (2023). Climate policy and the economy: Evidence from europe's carbon pricing initiatives. Technical report, National Bureau of Economic Research.

Keynes, J. M. (2024). *A Treatise on Money: Vol. I.* BoD–Books on Demand.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review 99*(3), 1053–1069.

Kilian, L. and D. P. Murphy (2012). Why agnostic sign restrictions are not enough: understanding the dynamics of oil market var models. *Journal of the European Economic Association 10*(5), 1166–1188.

Kilian, L. and C. Park (2009). The impact of oil price shocks on the us stock market. *International Economic Review 50*(4), 1267–1287.

Kilian, L. and X. Zhou (2023). The econometrics of oil market VAR models. *Advances in Econometrics*, 65–95.

Koch, N., G. Grosjean, S. Fuss, and O. Edenhofer (2016). Politics matters: Regulatory events as catalysts for price formation under cap-and-trade. *Journal of Environmental Economics and Management 78*, 121–139.

McGlade, C. and P. Ekins (2015). The geographical distribution of fossil fuels unused when limiting global warming to 2 c. *Nature 517*(7533), 187–190.

Nelson, C. R. and A. F. Siegel (1987). Parsimonious modeling of yield curves. *Journal of Business*, 473–489.

Palao, F. and Á. Pardo (2021). The inconvenience yield of carbon futures. *Energy Economics 101*, 105461.

Pedersen, L. H. (2023). Carbon pricing versus green finance. *Available at SSRN 4382360*.

Ready, R. C. (2018). Oil prices and the stock market. *Review of Finance 22*(1), 155–176.

Rennert, K., F. Errickson, B. C. Prest, L. Rennels, R. G. Newell, W. Pizer, C. Kingdon, J. Wingenroth, R. Cooke, B. Parthum, et al. (2022). Comprehensive evidence implies a higher social cost of co2. *Nature 610*(7933), 687–692.

Schwartz, E. S. (1997). The stochastic behavior of commodity prices: Implications for valuation and hedging. *The Journal of Finance 52*(3), 923–973.

Semieniuk, G., P. B. Holden, J.-F. Mercure, P. Salas, H. Pollitt, K. Jobson, P. Vercoulen, U. Chewpreecha, N. R. Edwards, and J. E. Viñuales (2022). Stranded fossil-fuel assets translate to major losses for investors in advanced economies. *Nature Climate Change 12*(6), 532–538.

Sinn, H.-W. (2008). Public policies against global warming: a supply side approach. *International Tax and Public Finance 15*, 360–394.

Sinn, H.-W. (2009). The Green Paradox. In *CESifo forum*, Volume 10, pp. 10–13. München: ifo Institut für Wirtschaftsforschung an der Universität München.

Stefan, M. and C. Wellenreuther (2020). London vs. Leipzig: Price discovery of carbon futures during phase III of the ets. *Economics Letters 188*, 108990.

Stroebel, J. and J. Wurgler (2021). What do you think about climate finance? *Journal of Financial Economics 142*(2), 487–498.

Trolle, A. B. and E. S. Schwartz (2009). Unspanned stochastic volatility and the pricing of commodity derivatives. *The Review of Financial Studies 22*(11), 4423–4461.

Van der Ploeg, F. (2016). Fossil fuel producers under threat. *Oxford Review of Economic Policy 32*(2), 206–222.

Van der Ploeg, F. and A. Rezai (2020). Stranded assets in the transition to a carbon-free economy. *Annual Review of Resource Economics 12*(1), 281–298.

Venturini, A. (2022). Climate change, risk factors and stock returns: A review of the literature. *International Review of Financial Analysis 79*, 101934.

Zhou, X. (2020). Refining the workhorse oil market model. *Journal of Applied Econometrics 35*(1), 130–140.

Table 1: The parameter estimates.

This table shows the estimated parameters for the ATSM model, including both common and market-specific factors, using the Kalman filter with maximum likelihood estimation. $X_t^{Com}$ is the common factor, $X_{s,t}^C$ and $X_{l,t}^C$ are the short and long term carbon factors, and $X_{s,t}^O$ and $X_{l,t}^O$ are the short and long term oil factors. Standard deviations are given in parentheses. The sample period is from January 2013 to December 2023. Statistical significance is indicated by ***, ** and * for the 1%, 5% and 10% levels respectively.

| **Panel A. P-Dynamics** | | | | | | |
|---|---|---|---|---|---|---|
| | $A^{\mathbb{P}}$ | | | $B^{\mathbb{P}}$ | | |
| $X_t^{Com}$ | 0.5486<br>(1.3529) | -0.181***<br>(0.041) | 0 | 0 | 0 | 0 |
| $X_{s,t}^C$ | -0.7876<br>(3.8805) | 0 | 1.913***<br>(0.190) | 11.400<br>(9.986) | -6.011<br>(7.478) | 17.097***<br>(2.957) |
| $X_{l,t}^C$ | -0.1594<br>(0.7176) | 0 | -0.703<br>(0.485) | -3.568***<br>(1.051) | 1.967<br>(2.698) | -6.103<br>(4.665) |
| $X_{s,t}^O$ | -2.6567<br>(7.0573) | 0 | 0.875<br>(0.713) | 8.598***<br>(0.466) | -4.198***<br>(2.073) | 8.835<br>(8.222) |
| $X_{l,t}^O$ | -2.6271<br>(2.5278) | 0 | -2.579***<br>(0.429) | -10.502<br>(11.680) | 6.3717<br>(9.249) | -21.663***<br>(8.304) |
| **Panel B. Q-Dynamics** | | | | | | |
| | $A^{\mathbb{Q}}$ | | | $B^{\mathbb{Q}}$ | | |
| $X_t^{Com}$ | 3.094***<br>(0.314) | 0 | 0 | 0 | 0 | 0 |
| $X_{s,t}^C$ | -4.758***<br>(1.454) | 0 | -0.008<br>(0.006) | 1 | 0 | 0 |
| $X_{l,t}^C$ | -0.020<br>(0.031) | 0 | 0 | 0 | 0 | 0 |
| $X_{s,t}^O$ | -2.262***<br>(0.343) | 0 | 0 | 0 | -1.338***<br>(0.034) | 1 |
| $X_{l,t}^O$ | -5.071***<br>(0.236) | 0 | 0 | 0 | 0 | 0 |
| **Panel C. Variance-Covariance Matrix $\Sigma\Sigma^\top$(%)** | | | | | | |
| | $X_t^{Com}$ | $X_{s,t}^C$ | $X_{l,t}^C$ | $X_{s,t}^O$ | $X_{l,t}^O$ | |
| $X_t^{Com}$ | 3.483**<br>(1.506) | | | | | |
| $X_{s,t}^C$ | 0 | 22.357**<br>(10.975) | | | | |
| $X_{l,t}^C$ | 0 | 0.025<br>(0.078) | 0.000<br>(0.001) | | | |
| $X_{s,t}^O$ | 0 | -1.542<br>(6.618) | 0.036<br>(0.047) | 9.857<br>(5.445) | | |
| $X_{l,t}^O$ | 0 | -3.536<br>(2.759) | 0.006<br>(0.020) | 3.899<br>(1.214) | 2.126***<br>(0.445) | |

Table 2: The model fit.

This table presents the model fit for the ATSM, which includes both common and market-specific factors for EUA (Carbon) and Brent oil (Oil) futures. The table is divided into two panels: Panel A presents in-sample performance, while Panel B reports out-of-sample (OOS) performance. In out-of-sample, we estimate the parameters in-sample (IS) and substitute the estimated parameters into the out-of-sample (OOS) data to calculate the average RMSE. Both measured by mean daily RMSEs in basis points (b.p.). $\mathcal{M}_1$ represents the reduced model, whereas $\mathcal{M}_2$ denotes the full specification. Each panel shows results across the entire sample period (2013–2023) and two distinct phases: Phase 3 (2013–2020) and Phase 4 (2021–2023).

**Panel A. In-Sample**

| | Whole | | Phase 3 | | Phase 4 | |
|---|---|---|---|---|---|---|
| | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ |
| Carbon | 7.737 | 7.644 | 7.921 | 7.846 | 7.227 | 7.083 |
| Oil | 32.690 | 32.680 | 35.456 | 35.438 | 23.840 | 23.858 |
| Total | 25.323 | 25.303 | 27.409 | 27.386 | 18.695 | 18.685 |

**Panel B. Out-of-Sample**

| | Phase 3 (IS) | | Phase 4 (OOS) | | Phase 3 (OOS) | | Phase 4 (IS) | |
|---|---|---|---|---|---|---|---|---|
| | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ | $\mathcal{M}_1$ | $\mathcal{M}_2$ |
| Carbon | 7.953 | 7.945 | 10.071 | 8.771 | 9.118 | 8.667 | 6.934 | 6.870 |
| Oil | 35.424 | 35.367 | 24.648 | 24.474 | 52.302 | 51.980 | 20.579 | 20.546 |
| Total | 27.389 | 27.345 | 19.822 | 19.432 | 40.151 | 39.867 | 16.258 | 16.222 |

Table 3: The event study analysis.

This table presents the cumulative abnormal returns of short- and long-term carbon factors in response to EU ETS policy announcements. We calculate the CAR for each event based on all the event combinations listed in Table B1 using Equation (17). Then, we average the CARs for all events in the same category. The column 1 shows results for the [$-1$,0] window and the column 2 shows cumulative return for the [$-2$,2] window, which spans from three days before to three days after the announcement. Panel A reports the cumulative abnormal returns for the short-term carbon factor, separated by positive and negative events. Panel B presents the cumulative abnormal returns for the long-term carbon factor. Statistical significance is indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

| | [-1,0] | [-2:2] |
|---|---|---|
| Panel A. Short-term carbon factor | | |
| Positive | 0.277 | 1.368* |
| Negative | -1.551* | -1.950** |
| Panel B. Long-term carbon factor | | |
| Positive | 0.306 | 0.481 |

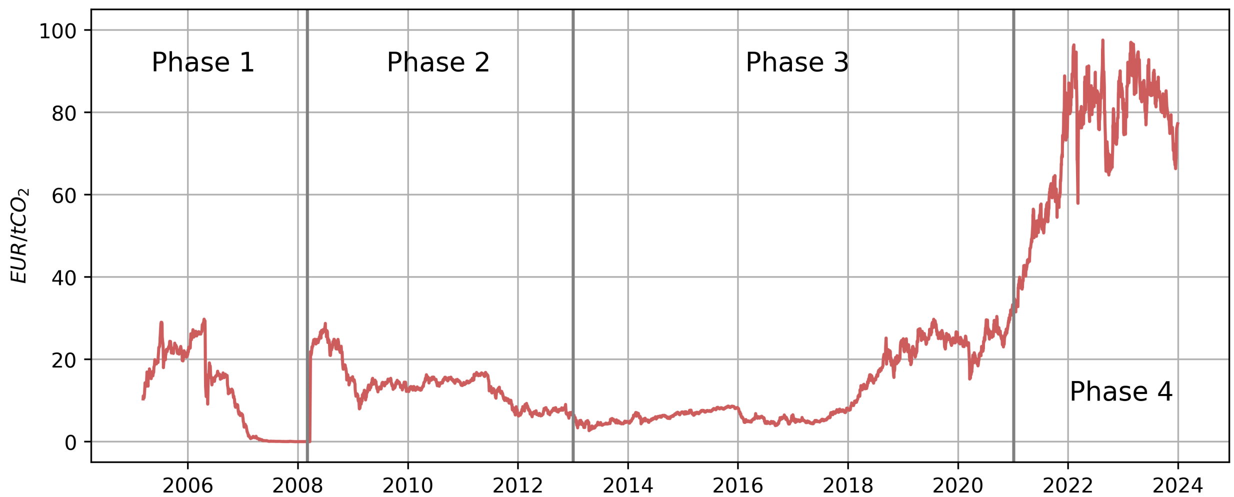
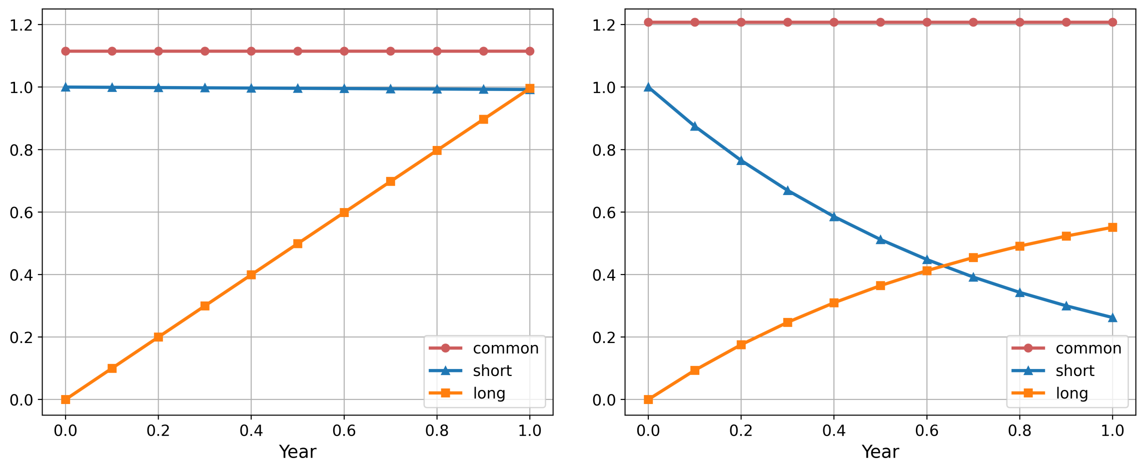



Figure 1: The EUA spot price. This figure shows the time series of EUA spot prices, spanning across various phases of the EU ETS: Phase 1 (2005–2007), Phase 2 (2008–2012), Phase 3 (2013–2020), and the initial years of Phase 4 (2021–2023).

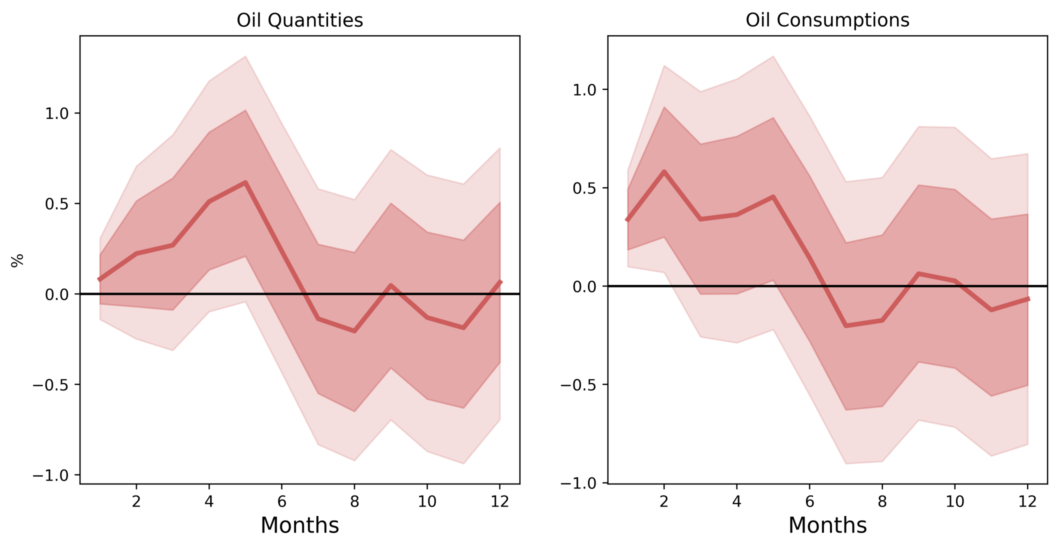

Figure 2: EUA and Brent oil futures. This figure shows the time series of commodity futures prices in the short term (2M) and the long term (12M). The top panel shows EUA futures and the bottom panel shows Brent oil futures. The data period covers different phases of the EU ETS: Phase 1 (2005-2007), Phase 2 (2008-2012), Phase 3 (2013-2020) and the first years of Phase 4 (2021-2023).



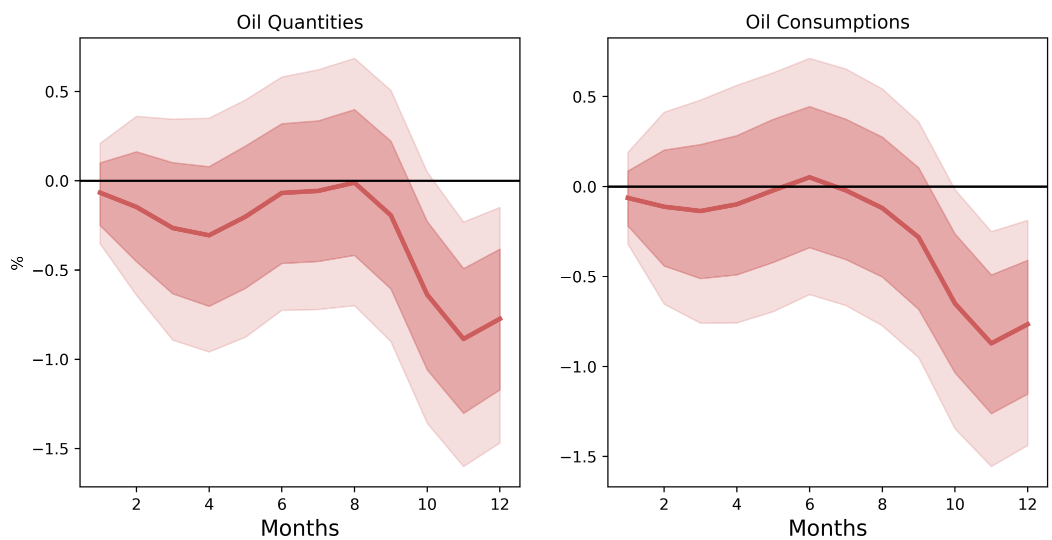

(a) Factor loadings of carbon futures

(b) Factor loadings of oil futures

Figure 3: The factor loadings. This figure shows the factor loadings across various futures expiry dates within the pricing formula. The left panel illustrates the factor loadings for the common factor, short-term carbon factor, and long-term carbon factor in the carbon futures pricing model. The right panel presents the factor loadings for the common factor, short-term oil factor, and long-term oil factor in the oil futures pricing model.




(a) Impacts of short-term carbon factor shocks




(b) Impacts of long-term carbon factor shocks

Figure 4: Results of impulse response function. This figure presents the impulse response functions (IRFs) of oil quantity and oil consumption in response to shocks from short-term and long-term carbon policy factors. The top panel illustrates the IRFs following a shock to the short-term carbon factor, while the bottom panel shows the IRFs following a shock to the long-term carbon factor. Solid lines represent point estimates, with dark and light shaded areas indicating 68% and 90% confidence intervals, respectively, based on 10,000 bootstrap replications. All shocks are standardized to a 1 standard deviation.

# Appendix A Futures Pricing

To derive the pricing formula for commodity futures, we first make some preparations for the dynamic process of $X_t$ under a risk-neutral measure. By Itô's lemma, we have the closed-form solution to Equation (1), that is:

$$X_T = e^{B^{\mathbb{Q}}(T-t)} X_t + \int_t^T e^{B^{\mathbb{Q}}(T-s)} A^{\mathbb{Q}} ds + \int_t^T e^{B^{\mathbb{Q}}(T-s)} \Sigma dW_s^{\mathbb{Q}}. \tag{A1}$$

We then calculate the conditional mean and variance of state variables as follow:

$$\mathbb{E}^{\mathbb{Q}} \left[ X_T | \mathcal{F}_t \right] = e^{B^{\mathbb{Q}}(T-t)} X_t + \int_t^T e^{B^{\mathbb{Q}}(T-s)} A^{\mathbb{Q}} ds; \tag{A2}$$

$$\mathrm{Var}^{\mathbb{Q}} \left[ X_T | \mathcal{F}_t \right] = \int_t^T e^{B^{\mathbb{Q}}(T-s)} \Sigma \Sigma' \left( e^{B^{\mathbb{Q}}(T-s)} \right)' ds \tag{A3}$$

Therefore, we recall Equation (8), the fundamental of the futures price, which indicates that the futures price is a martingale under a risk-neutral measure:

$$\begin{aligned} F(t,T) &= \mathbb{E}^{\mathbb{Q}} \left[ e^{s_T} | \mathcal{F}_t \right] \\ &= \mathbb{E}^{\mathbb{Q}} \left[ e^{\delta^{i'} X_T} \middle| \mathcal{F}_t \right] \\ &= \exp \left( \delta^{i'} \mathbb{E}^{\mathbb{Q}} \left[ X_T | \mathcal{F}_t \right] + \frac{1}{2} \delta^{i'} \mathrm{Var}^{\mathbb{Q}} \left[ X_T | \mathcal{F}_t \right] \delta \right) \\ &= \exp \left( \mathcal{A}^i(t,T,\Theta^{\mathbb{Q}}) + \mathcal{B}^i(t,T,\Theta^{\mathbb{Q}}) X_t \right) \end{aligned} \tag{A4}$$

# Appendix B Regulatory Events

Table B1: The regulatory events.

| Date | Event | Term | Impact |
|---|---|---|---|
| 2013/2/28 | Free allocation of 2013 aviation allowances postponed | short | positive |
| 2013/3/25 | Auctions of aviation allowances not to resume before June | short | positive |
| 2013/3/27 | Commission moves forward on climate and energy towards 2030 | long | positive |
| 2013/4/16 | Commission reacts to European Parliament back-loading vote The European Parliament today voted against the Commission's back-loading proposal for the auctioning of allowances in phase 3 of the EU ETS | short | negative |
| 2013/12/18 | Commission gives green light for a first set of Member States to allocate allowances for calendar year 2013 | short | negative |
| 2013/12/19 | EU Climate Change Committee meets on 8 January 2014 to decide on back-loading details | short | positive |
| 2014/1/8 | EU Climate Change Committee agrees back-loading | short | positive |
| 2014/1/22 | Commission sets our 40% target by 2030, LRF increase to 2.2% from 2021 onwards and MSR | long | positive |
| 2014/2/5 | Parliament adopts resolution on 2030 framework | long | positive |
| 2014/2/27 | Back-loading: 2014 auction volume reduced by 400 million allowances | short | positive |
| 2014/3/14 | Commission approves first batch of international credit entitlement tables | short | negative |
| 2014/3/21 | Council conclusions on 2030 framework | long | positive |
| 2014/4/4 | Update on Commission approval of international credit entitlement tables | short | negative |
| 2014/4/14 | Commission approves four more international credit entitlement tables | short | negative |
| 2014/4/23 | Commission approves final international credit entitlement tables | short | negative |
| 2014/6/4 | Auctioning of aviation allowances to restart in September | short | negative |
| 2014/7/4 | Commission publishes first status update for New Entrants' Reserve (NER) and impact of cessation rules | short | positive |
| 2014/10/9 | 2015 auction calendars for general and for aviation allowances published | short | positive |
| 2014/10/27 | European Commission adopts the carbon leakage list for the period 2015-2019 | short | positive |
| 2014/11/3 | EU Climate Action and Energy Commissioner Miguel Arias Cañete: "The science is clear. The time to act is now" | long | positive |
| 2015/7/15 | Revised emissions trading system will help EU deliver on climate goals | long | positive |
| 2016/6/23 | Commission to modify cross-sectoral correction factor for 2018 to 2020 | long | positive |
| 2017/1/24 | Commission adopts Decision to implement Court ruling on the cross-sectoral correction factor in the EU Emissions Trading System | long | positive |
| 2018/1/15 | Commission publishes status update for New Entrants' Reserve | short | positive |
| 2018/5/7 | 2018 auction calendars for aviation allowances published | short | negative |
| 2018/5/8 | Commission Notice on the preliminary Carbon Leakage List for the EU Emissions Trading System for Phase 4 (2021-2030) | long | positive |
| 2018/5/14 | Member States' emission reduction targets for 2021 to 2030 adopted | long | positive |

**Table B1 – continued from previous page**

| Date | Event | Term | Impact |
|---|---|---|---|
| 2018/5/15 | ETS Market Stability Reserve will start by reducing auction volume by almost 265 million allowances over the first 8 months of 2019 | long | positive |
| 2018/9/12 | Draft amendment to ETS Auctioning Regulation available for stakeholder feedback: renewed opt-out platform for Germany and arrangements for auctioning of 50 million allowa | short | negative |
| 2018/10/30 | Emissions Trading: Commission adopts amendment to ETS Auctioning Regulation | short | negative |
| 2018/12/7 | 2019 auction calendars of the common auction platform published | short | positive |
| 2019/5/15 | ETS Market Stability Reserve to reduce auction volume by almost 400 million allowances between September 2019 and August 2020 | short | positive |
| 2019/7/11 | 2020 and revised 2019 auction calendars of the common auction platform published | short | positive |
| 2020/5/8 | ETS Market Stability Reserve to reduce auction volume by over 330 million allowances between September 2020 and August 2021 | short | positive |
| 2020/7/1 | 2020 revised auction calendars published | short | positive |
| 2020/11/17 | Start of phase 4 of the EU ETS in 2021: adoption of the cap and start of the auctions | long | positive |
| 2020/12/11 | Further information on the start of phase 4 of the EU ETS in 2021: emission allowances to be issued for aircraft operators and the Market Stability Reserve | short | positive |
| 2021/5/12 | ETS Market Stability Reserve to reduce auction volume by over 378 million allowances between September 2021 and August 2022 | short | positive |
| 2021/6/29 | Commission publishes the national allocation tables of Member States for EU ETS stationary installations eligible to receive free allocation in the period 2021-2025 | short | negative |
| 2022/2/16 | Revised 2022 auction calendar for general allowances published | short | negative |
| 2022/5/12 | ETS MSR to reduce auction volume by over 347 milion allowances between Sep. 2022 and Aug 2023 | short | positive |
| 2023/5/15 | ETS MSR to reduce auction volume by over 272 milion allowances between Sep. 2023 and Aug 2024 | short | positive |
| 2023/7/28 | Adoption of the Commoission decision on the Union-wide quantity of allowances for 2024 | short | positive |
| 2023/10/25 | Commission adopts new ETS Union Registry Regulation for Fit for 55 | long | positive |
| 2023/10/31 | Adoption of the Commission Decision on the total quantity of allowances to be allocated in respect of aircraft operators in the EU ETS 2024 | short | positive |
| 2023/10/31 | Implementation of EU ETS for shipping makes progress | long | positive |
| 2023/11/16 | Notice of provisional EU ETS 2024 auction volume of general and aviation allowance | | |