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**CARBON PRICING IN THE EU: FUNDAMENTALS OR MARKET SENTIMENT?**

by Andrea Gazzani* and Marco Taboga**

**Abstract**

The determinants of secondary-market price changes in EU emission allowances (EUAs), the main carbon-pricing tool in the European Union, are still largely unknown. Using a VAR model that combines data at different frequencies and exploits shock-based restrictions, we investigate the role of four potential drivers: i) EUA supply and, more in general, the EU's carbon policy; ii) the business cycle; iii) the emission intensity of output; iv) market sentiment or financial factors. According to our model, carbon policy and financial factors explain the bulk of the variability in EUA prices, while the business cycle and the emission intensity play a more marginal role.

**JEL Classification**: E32, Q41, Q58.

**Keywords**: EU allowances, emission trading scheme, VARs, real-time decomposition.

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# 1 Introduction[1]

The European Union Emissions Trading System (EU ETS) is a cornerstone of the EU's policy to combat climate change and a key tool for reducing greenhouse gas emissions cost-effectively. Established in 2005, the EU ETS operates on a cap-and-trade principle, where a cap is set on the total amount of certain greenhouse gases (mostly $CO_2$) that industries covered by the system can emit. Within this cap, companies receive or buy emission allowances, which they can trade with one another as needed. The cap is reduced over time so that total emissions fall.

The price of EU emission certificates, also known as EU Allowances (EUAs), is a critical indicator of the system's effectiveness and has significant implications for the behavior of regulated entities, market participants, and policymakers. Understanding the drivers behind the price fluctuations of EUAs is essential for assessing the stability and predictability of the EU ETS, and for designing policies that enhance its efficiency.

The market for EUAs has exhibited considerable price volatility since its inception, influenced by several factors, including regulatory changes, economic conditions, and market expectations. This paper analyzes the determinants of EUA price changes.

We distinguish between four key types of shocks that potentially drive EUA price changes. First, a *business cycle* shock: when economic activity increases (decreases), so do energy consumption and $CO_2$ emissions; as a result, the demand for EUAs rises (falls), driving up (down) their prices. Second, an *emission intensity (greening or transition)* shock: over time, there are changes in the amount of emissions generated by a given level of production (the so-called emission intensity). For example, advances in non-fossil energy adoption and energy efficiency reduce emission intensity, and hence the demand for EUAs. Third, a shock to the *supply of allowances (carbon policy)*: policy-driven adjustments, such as the introduction of the Market Stability Reserve, change the supply of EUAs and have an impact on their price. Finally, a *market sentiment* shock: speculative and precautionary demand for allowances may change due to non-fundamental factors such as shifts in risk aversion and liquidity needs, with

[1] We thank Fabrizio Ferriani, Gianluca Fusai, Giovanni Veronese, Riccardo Cristadoro, and participants at "Measuring, managing and hedging indirect climate-transition risk" in Politecnico di Milano for useful feedback. The views expressed in this paper do not necessarily reflect those of the Bank of Italy or Eurosystem.

a direct impact on EUA prices.

A dynamic model and a sound identification strategy are essential to disentangle these factors because they can simultaneously influence the price of EUAs. A further complication arises from the availability of verified emissions data only with a considerable lag at the annual frequency, which hinders econometric exercises based on these measurements.

In a motivating exercise, we use a simple accounting identity to decompose EUA price changes in intuitive factors at the annual frequency. This exercise suggests that components unrelated to current fundamentals play a significant role in the EUA market.[2]

We then propose a dynamic model to disentangle the EUA price drivers in a more timely and comprehensive way by exploiting high-frequency information and forward-looking variables. We use the real-time SVAR methodology proposed by Gazzani et al. (2024). Unlike traditional SVAR models that rely on low-frequency data with significant publication lags and revisions, a real-time SVAR includes in its set of endogenous variables only daily data (e.g., prices of assets and commodities). This allows the model to be updated in real time and to provide timely insights into the drivers of EUA price changes.

We include in the VAR the prices of EUAs, fossil fuels (oil, natural gas and coal) and electricity, an industrial equity index, and long-term interest rates. Traditional sign restrictions (Faust, 1998; Canova and Nicolo, 2002; Rubio-Ramirez et al., 2010) could offer a potential identification strategy for the VAR. However, this approach requires economically motivated restrictions, which increase quadratically with the number of variables and shocks that one aims at identifying. As our VAR includes several financial variables to fully capture the potential explanatory power of non-fundamental factors in the ETS market, we would need a very large number of sign restrictions to achieve a sharp characterization of the structural shocks of interest.

As we are not confident in a full-set of sign restrictions, we instead identify the VAR model through *shock-based restrictions* (Ludvigson et al., 2020, 2021). These restrictions require the identified shocks to exhibit a certain sign during specific periods (corresponding to well-understood historical events) and a sufficiently high correlation with certain variables

[2]By fundamentals, we mean the business cycle, the emission intensity and the supply of EUAs, while we consider market sentiment a non-fundamental factor.

external to the VAR that should be informative about the shocks of interest. The external variables we use are *i)* measures of the business cycle, *ii)* data about electricity production from fossil and non-fossil sources, *iii)* low-frequency measurements of carbon intensity, *iv)* Känzig (2023) carbon policy surprises, *v)* a measure of EUA supply and *vi)* two variables that capture market sentiment (a proxy of risk aversion and an index of speculative interest in emission allowances).

We find that business cycle oscillations and changes in the carbon intensity of output (both current and expected) have minor effects on EUA prices. Instead, much of the price variation is explained by changes in carbon policy and market sentiment. Importantly, shifts in expectations about the future carbon-policy stance, in a context of heightened climate policy uncertainty (Gavriilidis et al., 2023), appear to play a major role. The finding that changes in emissions (caused by variations in output and carbon intensity) are not a major source of price variability aligns well with the simple observation that verified emissions decreased at a relatively steady and predictable pace in our sample, while EUA prices were extremely volatile (approximately three times as volatile as an EU industrial equity index).

Our main contribution is to provide estimates that – thanks to a new methodology – simultaneously leverage high-frequency data from commodity and financial markets and lower-frequency data about macroeconomic trends and the functioning of the ETS system (issued, surrendered and unsurrendered allowances, and verified emissions). The proposed dynamic model can be updated in real time; it can incorporate information that is available only for some parts of the sample period, and it can easily be extended to new variables thanks to the flexibility of the external-restrictions methodology of Ludvigson et al. (2021).

**Relation with the literature.** Our findings contribute to the literature that studies EUA prices. Känzig (2023) provides an influential contribution by building a measure of carbon policy shocks based on the EUA price changes generated by the announcements of policy interventions on the ETS system. We exploit his series of surprises as an external variable that is informative for the identification of EUA supply shocks. Notably, his surprises allow us to capture the forward-looking component related to the future carbon policy stance in the EU. Bjørnland et al. (2023) decompose the drivers of EUA prices into three components (EUA supply, business cycle, and transition), using a monthly VAR model. Our approach relates to their paper as we also consider multiple sources of fluctuations in EUA prices. Two main features distinguish our analysis from theirs. First, our model is specified at the daily frequency and allows us to inform policy-makers in real-time on ETS market developments; second, we investigate the role of financial factors in the ETS market, also by constructing a proxy of speculative interest in carbon-related financial instruments.

Our work also contributes to a more policy-focused debate on the role of financial factors and speculation in EUA price formation (Friedrich et al., 2019; Ampudia et al., 2022; ESMA, 2022; Quemin and Pahle, 2023). Several commentators voiced concerns that the significant volatility in EUA prices, mainly since 2018, may have been caused by speculative activity unrelated to market fundamentals. The debate spurred some research aimed at disentangling the effects of speculation. Contrary to our findings, Lovcha et al. (2022) provide evidence that fundamentals explain up to 90% of EUA price variability, although their results hinge on the identification assumption that speculative shocks produce only short-lived effects. In contrast, Lucia et al. (2015) analyze data on EUA derivatives and find high degrees of speculative behavior in the early years of the ETS system. Ampudia et al. (2022) regress EUA prices on some commodity prices and find statistically significant regression coefficients, which they interpret as evidence of a strong relation between EUA prices and market fundamentals; however, the R squares in their regressions reveal a large fraction of unexplained variance. Koch et al. (2014) find that 90% of the variability in EUA price changes is not explained by abatement-related fundamentals. Overall, the findings in the literature are mixed and mostly about the earliest phases of the ETS system. Our findings underscore a relevant role for non-fundamental financial factors in driving EUA prices and can provide policy-makers with important information for the design and potential reform of the ETS system.

**Structure of the paper.** The rest of the paper is organized as follows. Section 2 describes the potential determinants of EUA prices and Section 3 presents the data. Sections 4 and 5 illustrate the evidence from the static model and the SVAR respectively. Finally, Section 6 concludes.

# 2 Institutional background and determinants of EUA prices

This section describes in detail the four types of shocks that affect the pricing of EUAs and that we seek to identify. The first two, the business cycle and emission intensity, are shocks that determine the current and future level of emissions and, hence, the demand for EUAs to be surrendered. The third shock relates to carbon policy and the supply of EUAs, that is, the number of allowances issued. These first three shocks concern the "fundamentals" of the ETS system and capture not only changes in current fundamentals, but also shifts in expectations about their future evolution. For example, supply shocks include reactions to announcements about changes in carbon policy that will affect the future supply of EUAs, and emission intensity shocks may comprise revisions in expectations about the pace of green-technology adoption. In other words, each kind of shock can include forward-looking components. The fourth shock is a market sentiment or financial shock that is unrelated to ETS fundamentals but stems from changes in the risk aversion or liquidity needs of investors holding EUAs in their portfolios for speculative purposes. Finally, our most sophisticated model includes a residual component that includes all the sources of fluctuations in EUA prices that cannot be directly related to the four shocks described so far.

## 2.1 Business cycle

Greenhouse gas emissions are highly correlated with cyclical fluctuations (Sheldon, 2017; Khan et al., 2019; Doda, 2024). During periods of economic expansion, industrial production, transportation, and overall consumption increase. These activities are energy-intensive and often rely on fossil fuels, which release $CO_2$ when burned. On the contrary, in a recession companies produce less, and factories may operate at reduced capacity or shut down temporarily, which leads to a significant drop in energy consumption and, consequently, $CO_2$ emissions.

This relationship can be seen through the lens of the identity

$$\text{Emissions} = \text{Output} \cdot \frac{\text{Energy}}{\text{Output}} \cdot \frac{\text{Emissions}}{\text{Energy}} \tag{1}$$

which equates carbon dioxide emissions to the product of output, the energy intensity of output, and the emission intensity of energy (Kaya, 1989). The identity can be also expressed in the simpler form

$$\text{Emissions} = \text{Output} \cdot \frac{\text{Emissions}}{\text{Output}} \tag{2}$$

where the ratio between emissions and output is the emission intensity of output.

We define a business-cycle shock as one that affects the current or expected future level of output but is orthogonal to emission intensity, as well as to the other shocks defined below.

## 2.2 Emission intensity

The second category of shocks encompasses all the fluctuations that mainly affect emission intensity. We also call them "greening shocks". They include several distinct components.

First, *shifts to greener (or browner) energy sources.* For example, an increase in the proportion of electricity produced from renewable sources, such as wind and solar, is a positive greening shock that decreases emissions. Not only electricity generation has been the single most important source of emissions historically (especially among the sectors covered by the ETS system), but its greening has been a major contributor to emissions reductions in the EU (Ember, 2024). It is important to note that shifts in the proportion of green electricity are driven not only by long-term factors such as investment in new renewable generation capacity, but also by short-term ones, such as coal-to-gas switching, the variability of hydropower generation due to precipitation, and temporary shutdowns of power plants (e.g., for maintenance). Second, *other technological changes that reduce emissions* without negatively impacting economic activity. For example, a more widespread adoption of energy-saving devices (provided that the money saved on energy bills is spent elsewhere). Third, *changes in preferences* that do not affect the overall level of economic activity but determine re-allocations of production and demand from more polluting to less polluting activities. An example could be a reduction in business travel motivated by environmental concerns, and compensated by less polluting corporate expenditures (e.g., on IT infrastructure). Fourth, *the offshoring of more polluting production activities*, if compensated by an increase in less polluting onshore ones. This kind of greening, however, becomes ineffective/irrelevant once a well-functioning Carbon Border Adjustment Mechanism is in place.

Thus, we define greening shocks as fluctuations in current or future expected emission intensity orthogonal to the other shocks, such as the business cycle shock.

## 2.3 EUA supply

Since the EU ETS was established in 2003, its rules have been changed multiple times, primarily to reduce the surplus of emission allowances and create additional scarcity in the market.[3]

The main changes regarded seven factors. First, *the percentage of annual issuance allocated via auctions*. For example, in 2018 a cut in free allocations was decided (starting in 2021).[4] Second, *the programmed reduction in the annual issuance of new allowances*. The European Commission has been regularly tightening the market with higher reduction rates. The initial rate was 1.74% per year. The current rate is 4.3%, and it will increase to 4.4% in 2028. Third, *programmed delays in the issuance of allowances*, also called back-loading. Fourth, *the Market Stability Reserve* (MSR), a mechanism used to adjust the supply of EUAs by transferring to the reserve allowances withheld from auctions and either releasing or canceling them at a later stage. The MSR was created in 2015, amended in 2018, and became operational in 2019.[5] The entry into force of some of its rules was staggered (e.g., the cancellation of allowances has been possible since 2023). Fifth, *the treatment of offsets* originally allowed in the EU ETS.[6] Introducing offsets into the system was economically equivalent to increasing the supply of allowances. Rules concerning offsets became progressively more restrictive over time, and their use has been disallowed since 2021. Sixth, *the scope of the ETS system*, which was progressively enlarged to encompass more industries (e.g., airlines since 2012 and shipping since 2024) and importers (through the so-called Carbon Border Adjustment Mechanism). Finally, *the links to foreign ETS systems* like the link to the Swiss ETS since 2020.

[3] Directive (EU) 2003/87/EC.

[4] This is different from the allowances allocated for free to sectors deemed at risk of carbon leakage.

[5] Decision (EU) 2015/1814 and Directive (EU) 2018/410, respectively.

[6] I.e., carbon credits from projects that reduce, avoid, or remove emissions. Offsets can be used as substitutes of emission allowances.

Long and complex public negotiations and consultations preceded legislative changes. Moreover, they were often implemented in a staggered and delayed manner. This process created not only variability in the supply of EUAs, but also an almost continuous "news flow", relevant for forecasting future supply and hence able to produce an impact on prices.

In line with these considerations, we define an EUA supply shock as one that pertains to actual or expected changes in ETS rules, with consequent shifts in the supply of EUAs.

## 2.4 Market sentiment

The fourth category of shocks we consider are financial in nature and so in principle unrelated to market fundamentals in the ETS. These shocks, dubbed "market sentiment" shocks, include two main components.

First, changes in *speculative demand* by EUA traders and investors that do not surrender allowances to pay for generated emissions but hold them for speculative and investment purposes. Speculative demand may be influenced by multiple factors that are unrelated to fundamentals, such as changes in risk aversion and liquidity needs. For example, financial tensions that induce intermediaries and investors to liquidate risky assets may also have repercussions on EUA prices. The creation of investment vehicles (such as ETFs) that facilitate EUA trading may increase investors' participation in the market for EUAs.

Second, shifts in *precautionary demand by industrial players not driven by fundamentals.* Some industrial players may decide to hold stocks of allowances that go beyond their immediate surrendering needs for precautionary motives. These players may alter their stock of allowances because they anticipate future changes in fundamentals. Ideally, we would like to classify this kind of shock under the previous three categories of EUA price determinants. However, shifts in precautionary demand may also be induced by changes in risk aversion or more concretely, risk-management practices. We classify these changes, which are unrelated to fundamentals, as market sentiment shocks.

Thus, we define a market sentiment shock as one that alters the willingness of investors and firms to hold EUAs but is unrelated to current and expected future fundamentals.

# 3 Data

We use data from various sources. We present them in this section, grouped by frequency.

**Daily data.** We use the daily prices of the main energy commodities. We focus on European benchmarks: Brent oil 1-month futures prices, TTF natural gas 1-month futures, API2 coal 1-month futures, the average of day-ahead electricity baseload prices on the EEX Phelix, Powernext, GME, and OMEL markets (for Austria/Germany, France, Italy and Spain, respectively), EUA 1-month futures. Moreover, we use the following series from non-energy markets: a Datastream industrial equity index for the EU, the yield to maturity of German 10-year benchmark government bonds, and the BEX Risk Aversion Index (Bekaert et al., 2022). All the daily series, which start on 1-Jan-2008 and end on 31-May-2024, are displayed in Figure A1.

**Monthly data.** We employ the seasonally-adjusted volume of industrial production in the euro area computed by Eurostat, the business confidence indicator for the euro-area manufacturing sector as published by the Directorate General for Economic and Financial Affairs of the European Commission, the volume of electricity production in the European Union (separated between fossil and non-fossil sources) computed by Ember.[7] We also employ the EU baseline carbon-policy shocks estimated by Känzig (2023). Finally, we exploit an index that measures investors' interest in carbon allowances, obtained by combining Google Trends data (volume of searches for financial instruments related to allowances), a proxy of the amount of EUAs held by exchange-traded funds (ETFs), and a measure of trading volume on the EUA futures market. The methodology for constructing the index is described in the Appendix. Not all the monthly series cover the entire period spanned by the daily series (see Figure A2 for details), but this is not an issue thanks to the flexibility of the methodology involved.

**Yearly data.** The following EU ETS yearly data, referred to all stationary installations, is sourced from the EU Transaction Log (EUTL) and aggregated across countries: total allocated allowances (i.e., the overall amount of emission certificates issued in a given year, both via free allocations and by auctions and other mechanisms), surrendered allowances

[7]We perform a denoising seasonal adjustment by removing the components with periodicities below one year from the spectral decomposition of the series.

(i.e., the number of certificates used by firms in a given year to pay for their emissions), verified emissions (i.e., the amount of emissions generated by the firms participating in the ETS system). We compute the total supply of allowances in each period by summing the allowances allocated in that period to those allocated but not surrendered in previous periods. These yearly series are displayed in Figure A3. When inspecting the the figure, it is helpful to remind that, in the first years of life of the ETS system, the amount of surrendered allowances was often much lower than the amount of allocated ones because large quantities of offsets were surrendered in place of the allowances. This led to the accumulation of a significant stock of unsurrendered allowances, which contributed to the build-up of supply.

# 4 Motivating evidence from an accounting identity

In this section, we perform a first exercise providing evidence that changes in current fundamentals (output, emission intensity, and EUA supply) are not a primary driver of EUA prices, and – instead – the bulk of price variability is likely to be generated by shifts in expectations about future fundamentals and market sentiment.

We use the following accounting identity:

$$ln\left(P_t\right) = \ln\left(Y_t\right) + ln\left(\frac{E_t}{Y_t}\right) - ln\left(S_t\right) + ln\left(\frac{P_t}{E_t/S_t}\right) \tag{3}$$

where $P_t$ is the price of EUAs at the end of year $t$, $Y_t$ is the yearly volume of industrial production, $E_t$ is the amount of verified emissions, $S_t$ is the supply of allowances equal to the sum of all allowances allocated in year $t$ and those allocated and not surrendered in previous years.

The identity above separates the price of EUAs into four components that can be mapped to the four sources of price shocks discussed in Section 2: i) $\ln\left(Y_t\right)$ is the component associated to business-cycle oscillations; ii) $\ln\left(\frac{E_t}{Y_t}\right)$ is the component associated to changes in the emission intensity of output $E_t/Y_t$ (the lower this term, the greener production is); iii) $-ln\left(S_t\right)$ is the supply component; iv) $\ln\left(\frac{P_t}{E_t/S_t}\right)$ is a log valuation ratio that tells us how pricey EUAs are relative to their scarcity, measured by the ratio $E_t/S_t$. This component captures market sentiment and shifts in expectations about future fundamentals.

The fourth component is equal to the logarithm of a time-varying elasticity-of-demand parameter $\theta_t$ in a stylized static model in which prices are determined by the demand equation

$$Q_t = \theta_t \frac{E_t}{P_t}$$

where the quantity of certificates demanded $Q_t$ is assumed to be proportional to emissions[8] and inversely proportional to prices.[9]

In an equilibrium, the demand $Q_t$ is equal to the supply $S_t$, and we can write

$$P_t = \theta_t \frac{E_t}{S_t}$$

By taking the natural logarithm of both sides, adding and subtracting $\ln(Y_t)$ from the right side, and re-arranging terms, we obtain:

$$\ln(P_t) = \ln(Y_t) + ln\left(\frac{E_t}{Y_t}\right) - ln(S_t) + ln(\theta_t) \tag{4}$$

which is equal to the previously shown accounting identity once we replace $\theta_t$ with its value derived from the equilibrium condition in equation (3).

Thus, in the framework above, the fourth component of EUA prices can be interpreted as not related to the current value of market fundamentals (output, emission intensity, and supply), but to other factors (such as preferences and expectations) that determine how firms and investors value current fundamentals.

Figure 1 displays the yearly changes (first differences) in the four components, whose sum equals the change in the log-price of EUAs (itself an approximation of percentage price changes). From the figure, it is apparent that market sentiment (and expectations) explain the bulk of the variability in the EUAs prices. The standard deviations of the contributions of output, emission intensity, EUA supply, and the residual valuation component are 0.061, 0.041, 0.126 and 0.424 respectively. Their variances as a proportion of total variance are 1.7%, 0.8%, 7.3%, and 83.4%, respectively (the proportions do not sum to 1 because contributions

[8]Note that in this simple model emissions are taken as exogenous, which is a realistic assumption in the short-run, when firms are unable to adjust their technology.

[9]As in a classical demand equation derived from the optimization of a Cobb-Douglas utility function.

are not orthogonal).

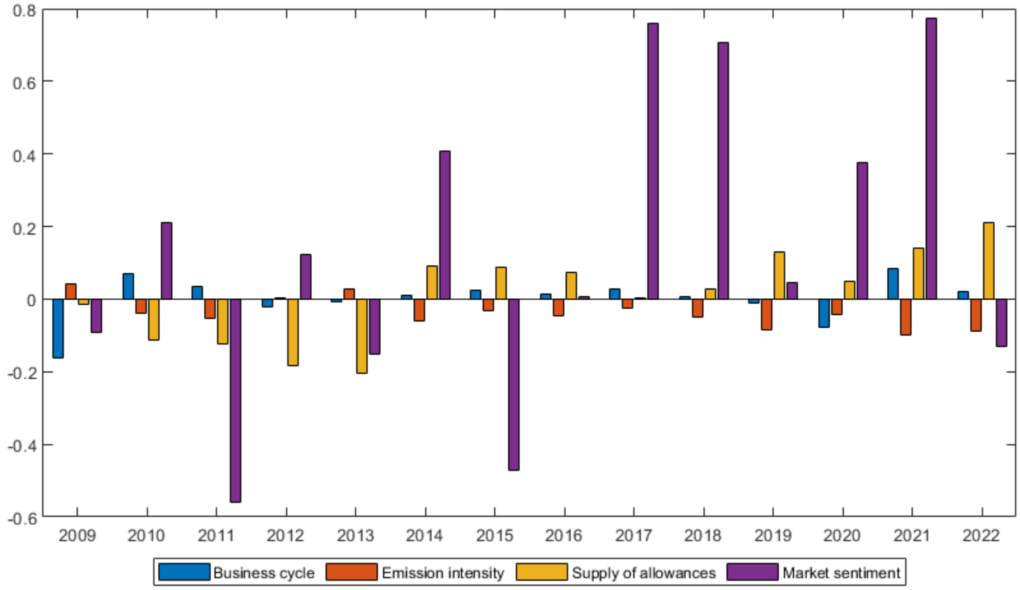


Figure 1: Static model decomposition

*Note. The figure reports the decomposition of EUA prices according to the static model.*

# 5 VAR-based evidence

The main theoretical drawback of the decomposition presented in the previous section is that it is static and, as such, it does not allow us to disentangle expectations about future fundamentals from market sentiment.

This section proposes a dynamic model featuring the same four components of EUA prices previously discussed. However, in this model, the three fundamental components potentially incorporate changes in both current and future fundamentals. Therefore, the fourth component (market sentiment) is explicitly identified rather than obtained as a residual, thus moderating any concerns that results may driven by model mis-specification. A fifth stochastic component, a proper residual one, can also affect EUA prices.

## 5.1 The VAR setting

First, we estimate the reduced-form vector auto-regression (VAR) model defined:

$$Y_t = \mu + \sum_{l=1}^{p} A_l Y_{t-l} + \Sigma z_t \tag{5}$$

where, given an integer dimension $n$, $Y_t$ is a $n \times 1$ vector of endogenous variables, $\mu$ is an $n \times 1$ constant vector, $p$ is the number of lags, $A_l$ are $n \times n$ constant matrices, $\Sigma$ is an $n \times n$ lower-diagonal matrix with positive diagonal entries, and $z_t$ are serially independent and identically distributed $n \times 1$ random vectors with zero mean and identity covariance matrix.

The vector $Y_t$ includes several variables observed at daily frequency that are informative about the four shocks of interest. Some of them (e.g., financial-market variables and the prices of storable energy commodities) are also known to be forward-looking: they may incorporate traders' expectations about the future dynamics of the fundamentals. The VAR includes: log of the EUA price, log of the oil price, log of the natural gas price, log of the coal price, log of the the electricity baseload price (as weekly moving average due to its extreme volatility), log of the industrial equity index, 10-year bond yield.

We set the number of lags to $n = 2$, and we use a ridge estimator of the parameters of the model.[10] Results are, however, pretty insensitive to these choices (i.e., they are quite stable if we use ordinary least squares instead of ridge, or if we add more lags to the specification of the model).

## 5.2 Identification strategy

We aim at identifying the four structural shocks described in Section 2 but, as it is well known, an infinite number of structural representations of the VAR compatible with the reduced-form representation exist.

Let $Q$ be any orthogonal $n \times n$ matrix, and $Q^T$ be its transpose. Then,

$$\Sigma z_t = \Sigma Q Q^T z_t = B \varepsilon_t \tag{6}$$

[10] The ridge regression is performed after rewriting the model in such a way that the dependent variable is $Y_t - Y_{t-1}$ and all variables are standardized (zero mean and unit variance). The regularization parameter is set equal to 100.

where $B = \Sigma Q$, and $\varepsilon_t = Q^T z_t$ is a vector of orthogonal shocks (zero mean and unit variance) that can be interpreted as structural shocks.

The identification of the model is performed by searching for matrices $Q$ such that the first four entries of $\varepsilon_t$ are interpretable as the four fundamental shocks of interest: i) business cycle, ii) emission intensity, iii) EUA supply, iv) market sentiment).

We randomly draw matrices $W$ whose entries are mutually independent standard normal random variables. Then, we compute their QR decompositions $W = QR$, where $Q$ is orthogonal and $R$ is upper-triangular with positive diagonal entries. The orthogonal matrices $Q$ thus obtained are kept and used in subsequent analyses only if they – together with the associated shocks $\varepsilon_t$ – satisfy a set of identification constraints. Otherwise, they are discarded. The draws stop when the number of kept matrices reaches a pre-defined threshold. These matrices are then used to derive probability distributions for quantities of interest such as impulse-response functions, variance, and historical decompositions.

The main tool we use for the identification of the model are the *shock-based restrictions* proposed by Ludvigson et al. (2021), which impose that the shocks $\varepsilon_t$ satisfy two sets of constraints. First, a set of *event constraints* based on unusual historical episodes that offer unambiguous economic narratives and, thus clear implications for the structural shocks of interest. Second, a set of *external variable constraints* that require the VAR shocks to display non-zero correlations with some variables external to the VAR. In our framework, these constraints are particularly useful because they connect our daily model based on asset and commodity prices with low-frequency macroeconomic variables and measurements of carbon emissions.

We also impose a small and incomplete set of sign restrictions that are deemed completely safe. Conversely, we deliberately refrain from imposing complete sign restrictions based on theoretical considerations due to the complexity of the analysis at hand and to the limited theoretical insights from the literature. First, the empirical evidence about correlations and causal relationships in carbon pricing markets is still very limited and often mixed (Rickels et al., 2015; Fan et al., 2019; Ampudia et al., 2022; Shi et al., 2023; Wang et al., 2024). Second, the balance among opposing effects of carbon pricing is not yet well understood. For example, a lower supply of EUAs might incentivize producers to switch from coal to less polluting fuels, and thus put downward pressure on the price of coal. However, this effect might be partially or more than compensated by other effects: a lower supply of EUAs might discourage investment in coal production capacity, making coal scarcer in perspective and incentivizing storage; it might encourage investment in capital-intensive green technologies, spurring economic activity and increasing the demand for energy resources (including coal) in the short-run; it might increase the cost of the energy that is used to extract and deliver coal, with a positive impact on the final price. Which of all these effects prevail is not clear. This is just an example, but it is indicative of the fact that a more agnostic approach to shock identification seems preferable to a tight sign identification scheme.

### 5.2.1 Event constraints

For each of the four shocks of interest, we select three historical events in which the sign of the given shock is unambiguous according to the prevailing narrative. Thus, we impose a total of twelve event constraints, reported in Table 1.

Most of the proposed event constraints concern announcements or data releases that provided indications about the future evolution of regulation, energy markets, or the economy. Therefore, the constraints force the shocks to include forward-looking components.

Events related to the business cycle shock are associated with surprises in the state of economic activity. The events linked to the emission-intensity shock are instead associated with developments in the nuclear energy sector that affect the level of emissions. EUA supply shocks are constrained through policy events similarly to Känzig (2023). For example, on February 1, 2013, the 6th meeting of the Carbon Market Forum was convened to provide indications about a possible response to the European Commission consultation on EU ETS restructuring options. The Background Document for the meeting was immediately made public and clearly pointed at low carbon prices, excesses of EUA supply, and the need for carbon-policy tightening. EUA prices rose by 27% on that day. We interpret this narrative as an unambiguous indication that the EUA supply shock was positive, and we therefore impose $\varepsilon_{t,3} > 0$ (representing a decrease in supply) for $t = 2013/02/01$. Finally, market sentiment shocks are disciplined via events originating in financial markets.

| Start date | End date | Event | Constraint |
|---|---|---|---|
| 2008-11-21 | 2008-11-21 | Euro Area flash manufacturing PMI much below expectations due to Great Financial crisis (actual 36.2 versus expected 40.5) | Business cycle shock $< 0$ |
| 2020-03-24 | 2020-03-24 | Euro Area flash manufacturing PMI much above expectations in spite of Covid-19 pandemic (actual 44.8 versus expected 40.1) | Business cycle shock $> 0$ |
| 2020-04-23 | 2020-04-23 | Euro Area flash manufacturing PMI much below expectations as Covid-19 effects hit the economy (actual 33.6 versus expected 38.7) | Business cycle shock $< 0$ |
| 2010-10-28 | 2010-10-29 | Germany approves a moratorium on the shut-down of some nuclear plants. | Emission-intensity shock $< 0$ |
| 2022-08-01 | 2022-08-31 | Most French nuclear reactors are shut down or operate at reduced capacity because of maintenance, heat, and drought. | Emission-intensity shock $> 0$ |
| 2022-11-03 | 2022-11-04 | French utility EDF announces a downward revision to expected electricity output from nuclear plants. | Emission-intensity shock $> 0$ |
| 2013-02-01 | 2013-02-01 | The Carbon Market Forum background document highlights the need for a strong carbon-policy tightening. EUA prices rise by 27% on the day of release. | EUA supply shock $> 0$ |
| 2013-04-16 | 2013-04-16 | The EU parliament votes against a proposal to backload EUA issuance. | EUA supply shock $< 0$ |
| 2019-02-15 | 2019-02-15 | The EU Commission decreases the number of sectors exposed to carbon-leakage risks and entitled to allocations of free allowances. | EUA supply shock $> 0$ |
| 2018-02-05 | 2018-02-06 | A sudden large spike in equity volatility ("Volmageddon") leads investors to liquidate risky assets and causes a flight-to-safety. | Market-sentiment shock $< 0$ |
| 2020-03-10 | 2020-03-18 | "Dash for cash": investors sell assets across the board to increase cash holdings due to Covid-19. | Market-sentiment shock $< 0$ |
| 2023-03-08 | 2023-03-10 | Silicon Valley Bank faces a liquidity crisis and is declared bankrupt, triggering financial turbulence. | Market-sentiment shock $< 0$ |

Table 1: Events constraints

### 5.2.2 External variable constraints

The second subset of shock-based restrictions is a set of external variable constraints. As explained by Ludvigson et al. (2020): "*the data alone are often quite informative about the quantitatively important shocks that have occurred in the sample*". What they propose is to require the identified shocks to exhibit at least a small positive correlation with certain variables external to the VAR that should be informative about the shocks of interest. The methodology is predicated on the idea that "*a credible identification scheme should produce estimates that are congruent with our ex-post understanding of historical events and/or with broadly accepted economic notions of a shock's defining properties*".

The external variable constraints require that the daily shocks, once appropriately cumulated, are positively correlated with low-frequency changes in some observed external variables. The latter are conjectured to be good proxies of current and expected trends in the business cycle, emission intensity and EUA supply, as well as market sentiment, and help to link the daily-financial shocks with physical counterparts.

We impose two external variable constraints for each shock, which amount to eight constraints on the correlations. We impose the constraints by requiring a correlation larger than 0.1.[11] Ex-post, the average correlation across draws and constraints is found to be equal to 19.7%. The constraints are displayed in Table 2.

| Shock | Variable | Sign |
|---|---|---|
| Business cycle (monthly sum) | monthly % change in industrial production | + |
| Business cycle (monthly sum) | monthly change in business confidence | + |
| Emission intensity (monthly sum) | monthly change in electricity share from fossil fuels | + |
| Emission intensity (yearly sum) | yearly change in emission intensity of industrial production | + |
| EUA supply (monthly sum) | monthly Känzig (2023) shocks | + |
| EUA supply (year sum) | yearly change in annual supply | - |
| Market sentiment (weekly sum) | weekly change in BEX risk aversion index | - |
| Market sentiment (monthly sum) | monthly change in investors' interest in EUA | + |

Table 2: External variables constraints

The advantages of the methodology are twofold. First, it allows us to use external variables that are forward-looking (such as business confidence and Känzig's shocks). Second, the correlation constraints are very flexible, as they can be imposed on external data that is at lower frequencies than that of the VAR, and is not available for all sample covered by the VAR.

### 5.2.3 Ancillary constraints

To sharpen the identification and to ensure a consistent definition of shocks, we also impose a small set of sign restrictions mainly for computational purposes. Those constraints are imposed on the the VAR impact matrix $B$:

[11] We observe that moderately higher thresholds (e.g., 0.11) do not change results significantly (although they increase the computational burden of the exercise). In comparison, much higher thresholds (e.g., 0.15) tend to lead to empty identification sets.

- *a positive business-cycle shock increases the prices of EUAs, natural gas, and the 10-year yield;*
- *a positive emission intensity shock, i.e., an increase in emission intensity of production, raises the prices of EUAs;*
- *an EUA supply shock, representing a decrease in EUA supply, raises the price of EUAs;*
- *a market sentiment shock, representing an improvement in sentiment, raises the price of EUAs.*

Thus, we impose six sign constraints. The four regarding EUA prices ensure that positive and negative shocks are defined consistently across draws: a positive shock is always defined as raising EUA prices. The other two constraints, which help to identify business-cycle shocks, impose two well-known economic mechanisms on the system: when either current or expected future economic activity increases, agents anticipate tighter monetary policy and higher short-term interest rates, whose trajectory is incorporated in long-term bond yields; furthermore, higher activity requires more energy resources, putting upward pressure on their prices. We impose the latter restriction on the price of natural gas, whose market is geographically segmented and therefore likely to be affected more markedly by EU-specific shocks (as compared, for example, to the oil market).

Finally, we impose *bounds on the forecast error variance* (see for instance Volpicella, 2022). Our VAR includes seven variables and seven shocks, but we identify only four of the structural shocks. From a theoretical standpoint, these four perturbances should explain the bulk of the forecast error variance in EUA prices, net of potential other (minor) shocks that may affect EUA prices and measurement error. We thus impose a further constraint, requiring that the contribution to the (impact) forecast variance of EUA prices by the unidentified shocks should not exceed 20%.

#### 5.2.4 Computational aspects

The computational burden of identification procedures based on draws of random orthogonal matrices tend to increase exponentially with the number of variables included in the VAR (and with the identified shocks), due to high rejection rates. For this reason, these identification procedures are typically employed with small-scale VARs or few identified shocks.

Our 7-variable VAR is no exception to the empirical rule that computational requirements increase exponentially with the number of variables. In fact, to obtain 100 accepted draws, we had to perform approximately half a trillion draws. By parallelizing the random extraction and rejection procedure on two low-end GPUs (RTX 3060), we managed to complete the identification procedure in about three days.[12]

We stress that the computational burden of the identification does not prevent the use of the model in real time. Once the extracted $B$ matrices are saved, they can be re-used to update the model at the daily frequency, at virtually no computational cost.[13]

## 5.3 Empirical Results

### 5.3.1 Impulse Response Functions

Figure 2 reports the impulse-response functions (IRFs) from the four shocks of interest identified in our VAR system.[14] Several remarks are in order.

The IRFs show that the economic consequences of each shock are distinct from those of the other shocks. The economic interpretation of the IRFs is completely straightforward for both the business-cycle and the greening shocks. A positive business cycle shock raises interest rates and natural gas prices, as imposed in our identification scheme, and increases coal, electricity, and equity prices. The response of the oil price is not significantly different from zero, which may be due to oil prices being expressed in euros in the model but quoted in dollars in practice (a positive business cycle shock may determine an exchange rate appreciation). A greening slowdown shock increases the prices of all fossil fuels and electricity. This is expected, for example, when lower-than-forecast electricity production from green sources forces utilities to burn more fossil fuels to keep up with electricity demand. Coherently with

[12] A companion paper describing the parallelization procedure and sharing the codes will be soon made available.

[13] Adding a few daily observations to a dataset that covers over 4000 trading days is highly unlikely to change the set of accepted matrices significantly, if at all. However, the model can be re-estimated every once in a while (e.g., quarterly) to address potential concerns about the stability of the identification set.

[14] The whole set of IRFs are reported in Appendix. Here we report quantiles simply for graphical purposes.

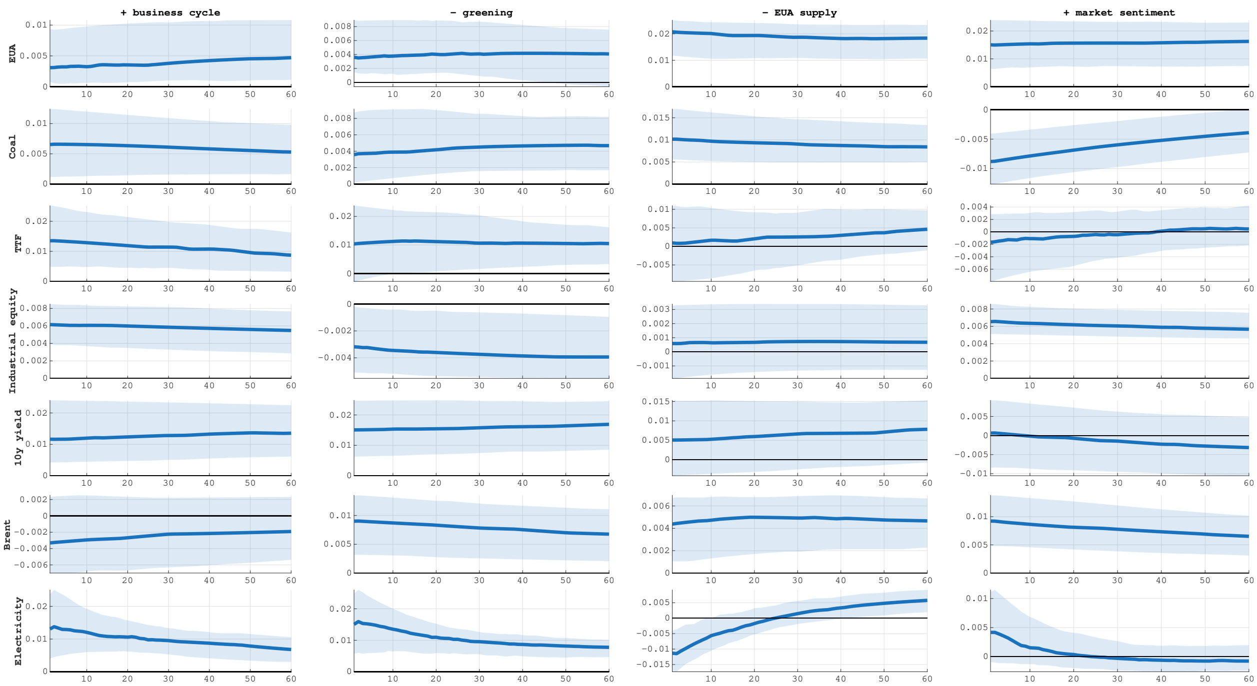


Figure 2: Impulse responses

*Note. The figure reports the IRFs of all endogenous variables (rows) to the four shocks of interest (columns). The solid line represents the median response and the shaded areas report the 68% set.*

the inflationary nature of the shock, interest rates rise. Finally, equity prices decrease, which may be explained by the higher energy costs firms pay.

The effects of a restrictive EUA supply shock are broadly in line with those found by Känzig (2023). They are inflationary, leading to an increase in interest rates, and muted for equity prices. Interestingly, the reaction of electricity prices is at first negative and then positive over the longer run, pointing to possible strategic behaviors and intertemporal optimization in selling dispatchable renewable energy (see for instance Bonacina and Gulli, 2007; Chernyavs'ka and Gulli; Hintermann, 2017, for an analysis of the pass-through of carbon prices in the presence of market power).[15] Finally, a positive market sentiment shock has the distinctive feature of causing a significant increase in equity and oil prices while it depresses coal prices. The latter finding might be explained by a "green preference" component driving investors' interest towards carbon-instruments.

[15]We also note that the first differences of log EUA and electricity prices are slightly negatively correlated in our sample.

### 5.3.2 Variance Decomposition

We report the forecast error variance decomposition to gauge the quantitative relevance of each shock as a driver of the endogenous variables. For each draw of the impact matrix of the shocks, we compute the variance decomposition of the unpredictable component of EUA price changes. Figure 3 displays the proportion of variance explained by the four identified shocks for each endogenous variable.

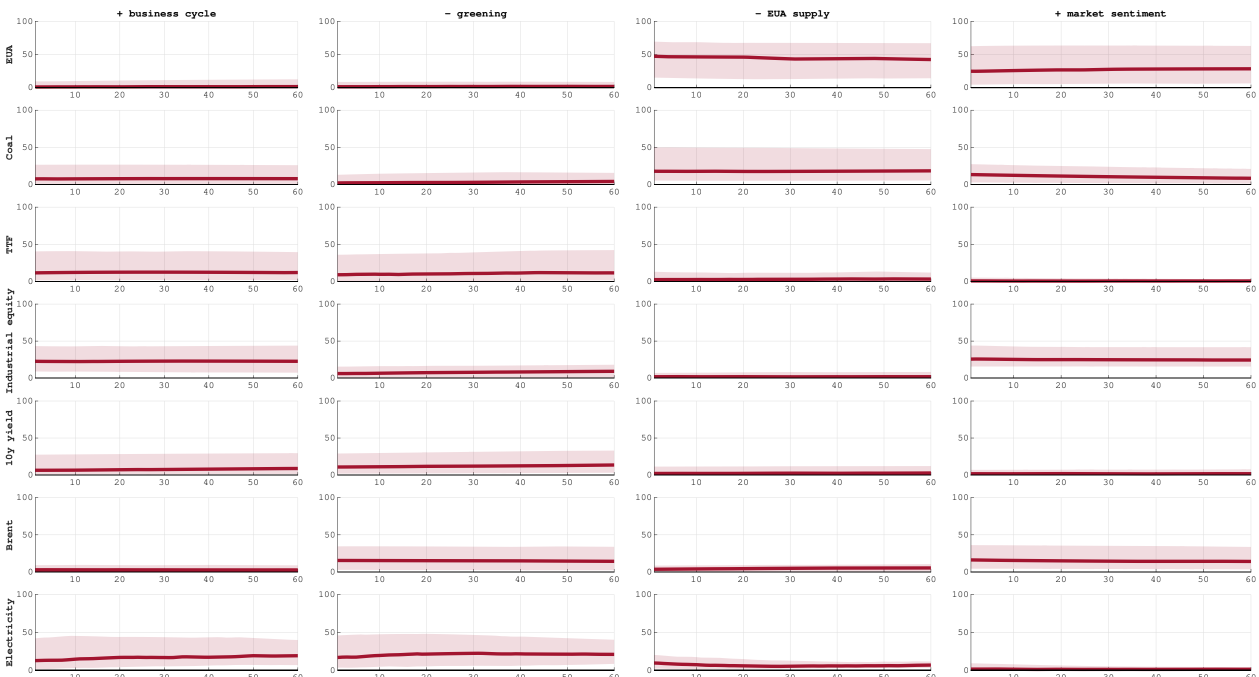


Figure 3: Variance decomposition

*Note. The figure reports the FEVD of all endogenous variables (raws) to the four shocks of interest (columns). The solid line represents the median response and the shaded areas report the 68% set.*

The variance decomposition confirms the findings of the static model regarding the business cycle and emission intensity: although these two shocks now potentially incorporate forward-looking components, they explain only a modest portion of EUA price variance (4.4% and 2.1% respectively at the one-year horizon). Even if we look at the right tail of the distribution of variance shares, they never explain a substantial portion of variance. We note that this finding is not to be interpreted as evidence that the significant reduction in emission intensity observed over our sample (see Figures A2 and A3) played a minor role in carbon pricing. Simply, this process might have been more predictable and therefore less relevant for explaining fluctuations in daily EUA prices.

EUA supply explains almost 40% of the variance at the 1-year horizon. As our EUA supply shock is forward-looking and it measures changes in the carbon policy stance, this finding is complementary to those of Känzig (2023), who shows that carbon-policy shocks generate a significant fraction of the variability of energy prices.[16] Finally, we find that market sentiment explains more than 30% of the variance of EUA prices, in line with other studies that provide evidence of a large role of speculative shocks in EUA markets (Lucia et al., 2015; Friedrich et al., 2019).[17]

### 5.3.3 Historical Decomposition

This section focuses on the historical decomposition of the EUA price that provides economic insights into the drivers of EUA prices from a historical perspective. The decomposition descends directly from the moving-average representation of the VAR according to:

$$Y_t = \varphi_t + d_{1,t} + d_{2,t} + d_{3,t} + d_{4,t} + e_{5,t} \tag{7}$$

$$d_{j,t} = \sum_{s=2}^{t} b_{t,j,s}\varepsilon_{s,j} \tag{8}$$

$$e_{5,t} = \sum_{j=5}^{7} d_{j,t} \tag{9}$$

where $\varphi_t$ is a deterministic component that depends on the initial value $Y_1$ and on the parameters of the model; the column vectors $d_{1,t}$, $d_{2,t}$, $d_{3,t}$, $d_{4,t}$ are the components of the observed variables that depend only on previous and current business cycle, emission intensity, EUA supply and market sentiment shocks respectively; $e_{5,t}$ are the residual unidentified components; the column vectors of coefficients $b_{t,j,s}$ are functions of the parameters of the

[16] Although he does not compute the variance decomposition of EUA prices, as they are not included in his VAR.

[17] We note that there is significant variability around the figures just reported, given the agnostic nature of the exercise and the objective difficulties in disentangling unobservable variables such as expectations and sentiment-risk aversion. For example, if we consider the lowest quartile of the distribution of variance proportions, the fraction of variance explained by market sentiment decreases to 16%. If we take the highest quartile, the explanatory power of EUA supply increases to 57%. Despite the ample confidence bounds, the role of market sentiment and EUA supply is always economically significant, while that of emission intensity and the business cycle is always marginal.

model.

The historical decomposition highlights that the contribution of the business cycle and emission intensity shocks to EUA price fluctuations is meaningful. However, these components matter mostly at lower frequencies as they are more stable than the emission supply and market sentiment components. The latter explain a larger share of the volatility of EUA prices because they are relevant for both low- and high-frequency movements in EUA prices. Business cycle shocks visibly contributed to a fall in EUA prices during the Covid. The emissions intensity shock exerted a negative effect on EUA prices during the 2010s but this tendency reverted during the 2020s in the aftermath of the Covid crisis, the European energy crisis (due to gas-to-coal switching), and the reduced nuclear electricity production due to policy and contingent reasons. The contribution of EUA supply oscillates during our sample, where EUA Phase IV (staring in 2021) marks a clearcut period of positive contribution to EUA prices. Finally, the market sentiment component depressed EUA prices during the global financial crisis in 2009, the Euro sovereign debt crisis, and the Covid-19 pandemic. In contrast, a significant positive effect characterizes the latest part of the sample.

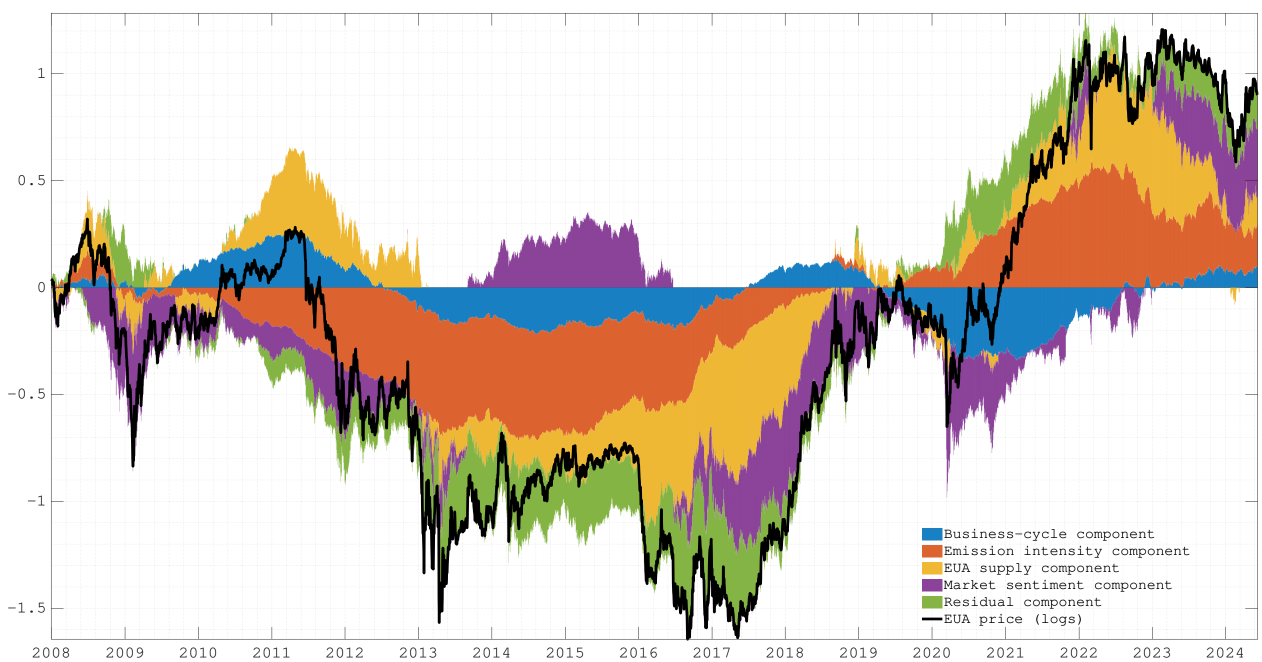


Figure 4: Historical decomposition

*Note. The figure reports the historical decomposition of EUA prices in deviation from the deterministic component of the VAR.*

# 6 Conclusions

Two main obstacles hinder a reliable identification of the drivers of EUA prices. First, the low frequency and the paucity of observations of some fundamental drivers (e.g., verified emissions and the supply of allowances). Second, the difficulty of measuring changes in the expectations about these quantities.

We have proposed a dynamic model that allows us to partly circumvent the above difficulties by leveraging a significant amount of high-frequency and forward-looking data.

Shifts in current and expected carbon policy and in the supply of EUAs seem to be the primary drivers of price changes. This finding is consistent with the fact that EU carbon policy has been revised multiple times, and legislative changes were preceded by long and complex public negotiations: these two factors created not only variability in the supply of EUAs, but also an almost continuous "news flow", relevant for forecasting future supply and hence able to produce an impact on prices.

The second most important contributor to price variability is a financial factor unrelated to developments in emissions and carbon policy, which we dub market sentiment. This factor is related to risk aversion, liquidity needs, and the willingness of financial players to hold allowances for investment or hedging purposes.

We find that changes in current and expected future emissions (caused by variations in output and carbon intensity) are not a major source of price variability. This finding aligns with the simple observation that verified emissions decreased at a relatively steady pace in our sample, while EUA prices were extremely volatile (approximately three times as volatile as an equity index). However, we do not interpret our results as evidence that the significant reduction in emission intensity observed over our sample played a minor role in carbon pricing. Instead, we conjecture that the greening process might have been more predictable and therefore less relevant for explaining short-term fluctuations in EUA prices.

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### A1. The index of investors' interest in carbon allowances

We build a composite index of investors' interest in carbon allowances, obtained by combining Google Trends data (volume of searches for carbon-allowance-related financial instruments), a proxy for the volume of EUAs held by exchange-traded funds (ETFs) and a measure of trading volumes on the EUA futures market.

While the single series used to build the composite indicator are noisy, they show broadly similar dynamics (in particular, they spike around the end of 2021). The noise is removed by averaging the three series and denoising the result.

We download three distinct time series from Google Trends measuring the worldwide volume of searches for financial instruments related to carbon allowances (not necessarily EU). The financial instruments may be the allowances (or credits) themselves or futures and exchange-traded funds having the allowances as underlying. The queries used are as follows:

- "EUA price" + "EUA prices" + "carbon credit price" + "carbon credit prices";
- "EUA future" + "EUA futures" + "carbon future" + "carbon futures" + "carbon credit futures";
- "carbon credit ETC" + "carbon credit ETF" + "carbon ETF" + "carbon ETC".

As the three series are downloaded simultaneously, they are standardized by a unique value and they can therefore be aggregated (by taking a cross-sectional sum) to produce a single series of search volumes.

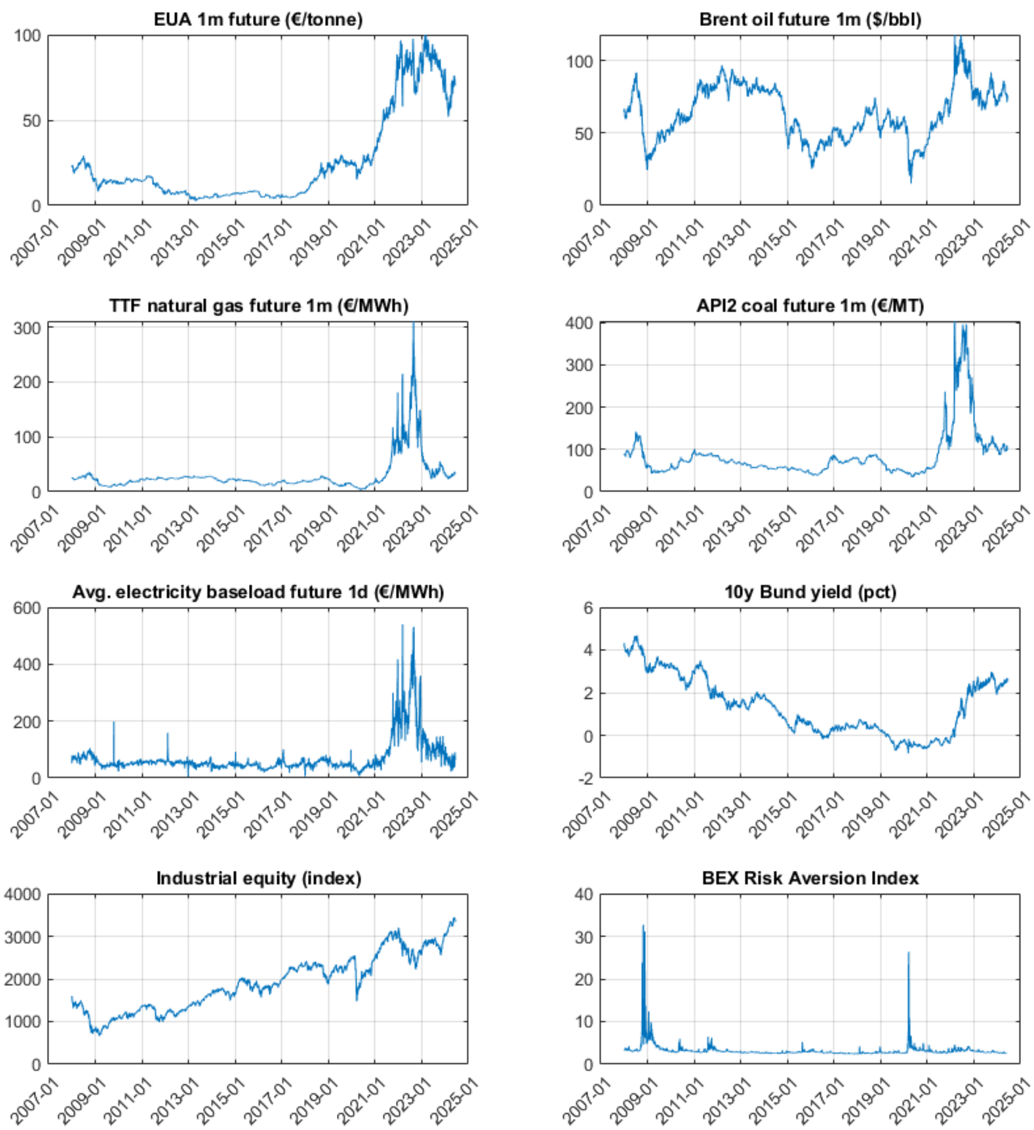
We then build a database of exchange-traded funds that invest uniquely or prevalently in EUAs. For each of them, we download the total assets under management and divide them by the price of EUAs to obtain a proxy of the amount of allowances held by the funds. We then aggregate the series thus obtained to form a unique proxy of the total amount of allowances held by ETFs.

As a third measure of investors' participation / interest in allowances, we use the volume of trading in front-month EUA futures.

The three time series obtained (Google Trends, allowances held by ETFs, EUA-futures trading volume) are standardized (demeaned and divided by their standard deviation) and then averaged to produce a unique composite indicator. As both Google searches and future trading volumes are highly seasonal, we also perform a denoising seasonal adjustment by removing the components with periodicities below one year from the spectral decomposition of the series. The raw index and its denoised version are plotted in Figure A2.

## A2. Figures and tables

### Figure A1 – Daily data



## Figure A2 – Monthly data

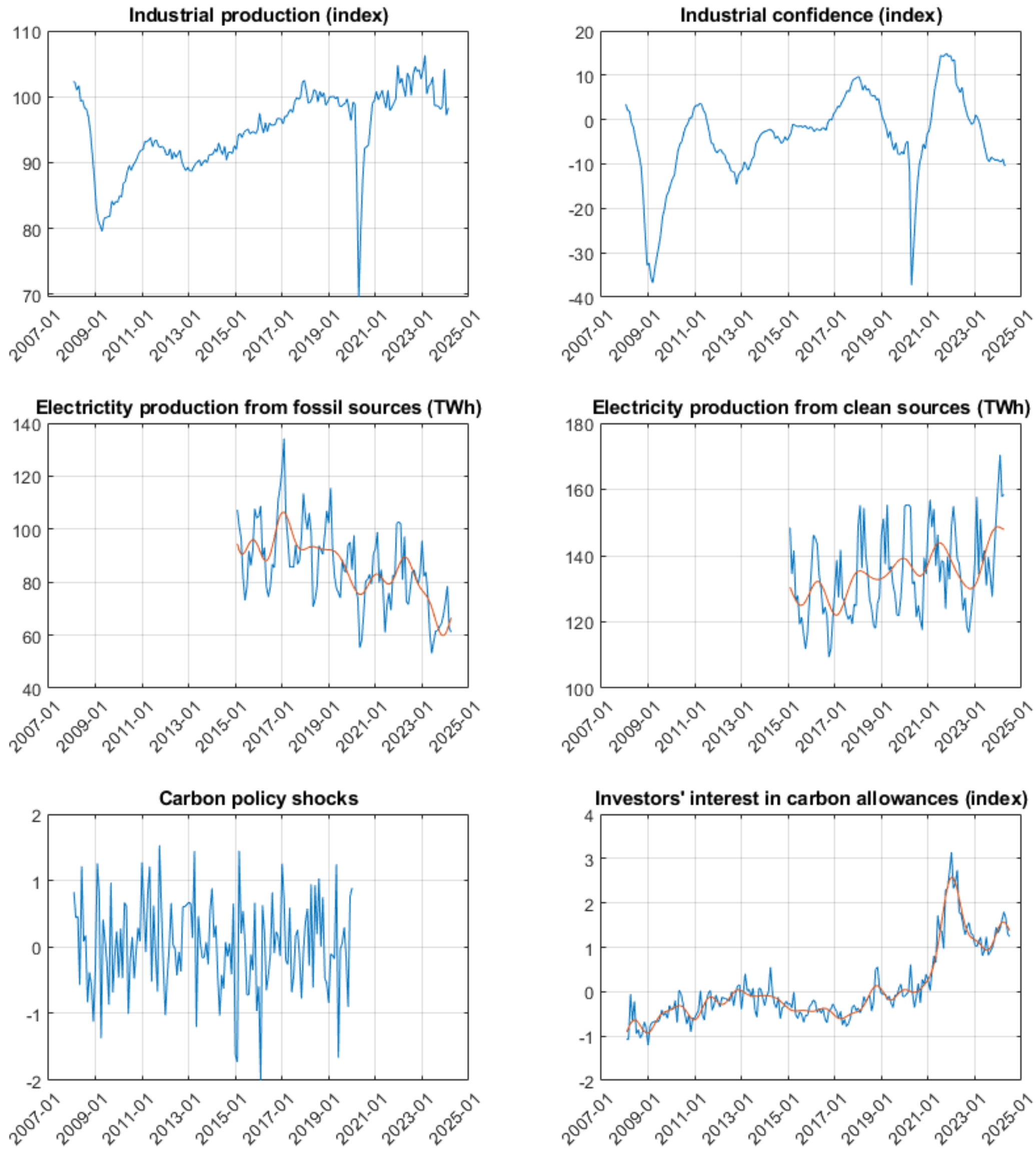
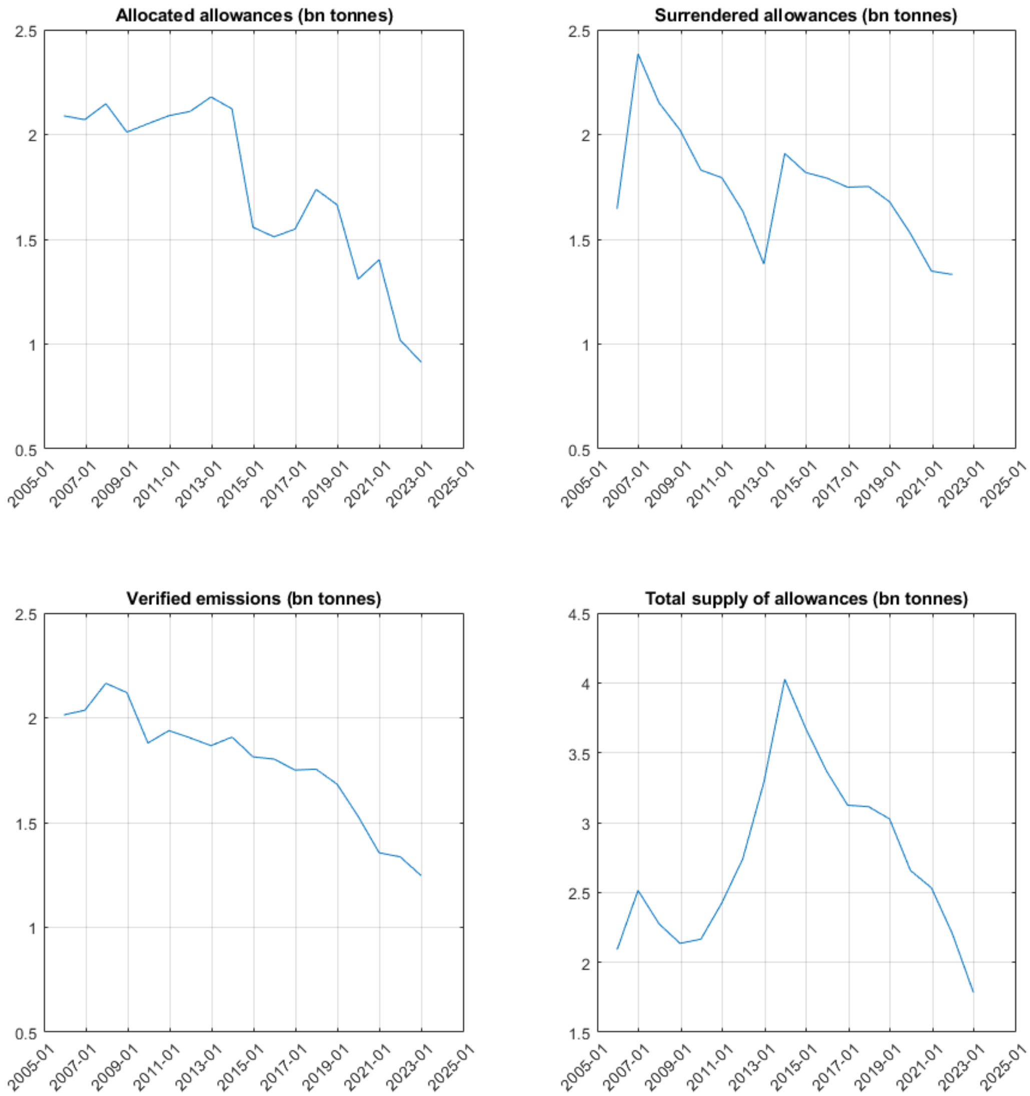


**Figure A3 – Yearly data**



## Figure A4 – IRFs from each draw