European carbon pricing in boom and bust times

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January 2024

Preliminary version

Abstract

In this study, we explore the relationship between European carbon prices, energy prices and the macroeconomy in boom and bust times. Utilizing a smooth transition structural VAR model, we analyze monthly data spanning from 2006 to 2023. Our model benefits from identification through non-Gaussianity and the correlation with external carbon and energy shock series. Notably, our analysis reveals heterogeneous effects observed across two distinct regimes of economic activity and when considering the cost pass-through to the transport sector specifically. Furthermore, our findings support that crises affect carbon prices, but challenge the notion of a strengthened linkage between carbon prices and economic performance in recent periods. Linking carbon price dynamics to the business cycle allows to discuss the role of a flexible emission cap in enhancing the effectiveness of carbon pricing across various economic conditions. This is particularly relevant for the recent extensions of the EU ETS to sectors like road transportation.

Keywords: Structural VAR, non-Gaussian identification, carbon pricing, industrial production, EU ETS, business cycle

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I'm indepted to Hannes Rohloff for providing most ST-SVAR codes and many valuable comments. I thank all who have commented on the model and on European carbon pricing in various seminar settings.

1 Introduction

In recent years, the European Union has intensified its commitment to combat climate change by implementing various measures. Carbon pricing has emerged as a pivotal tool in reducing greenhouse gas emissions [Metcalf, 2009]. Understanding how carbon pricing performs with regard to the business cycle is crucial to properly implement future extensions to the transport and building sectors and regulations as, e.g., the Market Stability Reserve. In this paper, we analyse EU-level carbon pricing, the EU ETS, by means of a smooth-transition structural vector autoregressive (SVAR) model. This allows to study the causal effects both towards and from carbon pricing in interaction with the macroeconomy and energy prices in boom and bust times. The causal effects are identified by a flexible identification techniques based on non-Gaussianity.

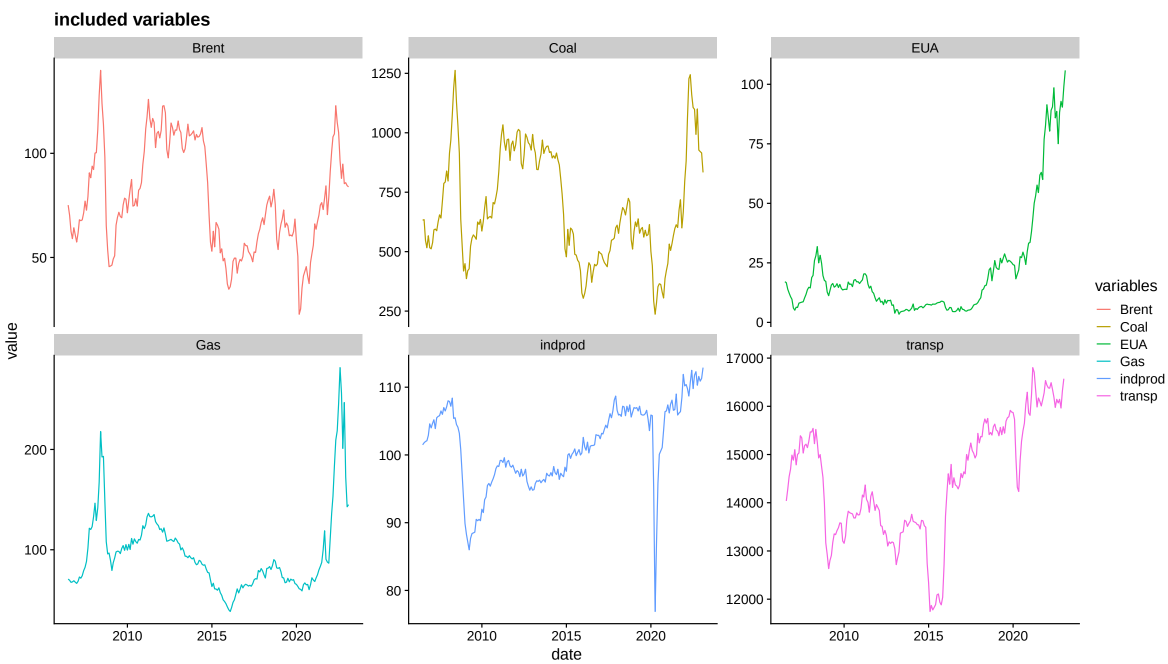

Figure 1: Potential series for the VAR model: Oil prices ($Brent$), coal price ($Coal$), carbon prices (EUA), gas price (Gas), industrial production ($indprod$) and deseasonalized average total road freight transport ($transp$).

The EU ETS has been introduced in 2005 and since then, has undergone several phases: 2005-2007, 2008-2012, 2013-2020 and the current phase 2021-2030. At the same time the economy has experienced two major crises (2008 and 2020) with additional disruptions in energy prices (e.g., the steady increases until 2008 followed by a sharp drop, see, e.g., Kruse and Wegener [2020]). Respective series of energy prices, i.e. Brent oil, coal and gas prices, industrial production, transportation and the carbon price series are shown in Figure 1. Specifically highlighting discussions on the endogeneity of the emission cap inducing a 'green paradox' through the Market Stability Reserve (MSR) [Gerlagh et al., 2021], it is interesting to carefully distinguish between the exogeneous and endogeneous parts of carbon prices. Studying the endogeneous carbon price series, the empirical literature, e.g. Chevallier [2011], Aatola et al. [2013], Friedrich et al. [2020], Zheng et al. [2021], have identified nonlinear relationships of carbon prices with determinants as energy prices and financial markets. Such nonlinearities might be sourced in economic expansion and recession regimes. Carbon pricing is discussed with regard to the business cycle by, e.g., Fischer and Springborn [2011], Doda [2016], Lintunen and Vilmi [2021], Annicchiarico et al. [2022]. While emissions are found to be procyclical [Doda, 2014], related policy discussions question whether carbon pricing tools should respond to the business cycle [Bel and Joseph, 2015]. On the other side, theoretical and empirical works have discussed the effects and effectivness of carbon pricing in Europe, see, e.g. Böhringer et al. [2009], Dissou and Karnizova [2016], Arlinghaus [2015] and, most recently, Känzig [2023]. Sector-specific impacts are analyzed based on micro data, for instance, on EU level by Abrell et al. [2011] and Dechezleprêtre et al. [2023]. Further studies focus on specific country settings and analyse the impact of carbon taxes, e.g., on manufacturing in the UK [Martin et al., 2014] or transportation in Sweden [Andersson, 2019]. On EU level the effects on non-covered sectors like transportation are, for instance, studied by analysing the cost pass-through of carbon prices [Cludius et al., 2020]. We add to the literature by empirically studying (sector-specific) impacts on EU level while conditioning on the business cycle covering both crises in 2008 and 2020.

Structural VAR models have widely been applied to study the implications of macroeconomic policy setting, mainly in the context of monetary and fiscal policies [see, e.g., Killian and Lütkepohl, 2017]. Once an SVAR model is identified properly, it allows to study the instantaneous, mid- and long-term effects of disruptions by impulse response functions, historical decompositions and the like. In the present context, SVARs are useful to draw a more concrete picture of the interaction of past carbon price changes with the macroeconomy and energy prices, which helps to provide guidance for future policy setting. For assessing the identification problem and potential endogeneity, the SVAR literature has been developing a vast force of economic and statistical identification techniques [cf e.g. Killian and Lütkepohl, 2017, for an overview]. For instance, Känzig [2023] accounts for endogeneity of carbon prices by means of a structural VAR model identified by a generated carbon policy shock series from regulatory events. In difference in our study, we approach the series from the data itself, identify carbon price shocks without prior economic assumptions based on non-Gaussianity and can verify them with exogeneous related policy events afterwards. We proceed analogouesly for energy prices which we can verify with oil and gas event series generated by Känzig [2021] and Alessandri and Gazzani [2023], respectively. In that sense, we focus on statistical identification driven by the uniqueness (up to scaling and permutation) of non-Gaussian structural shocks [see, e.g., Lanne et al., 2017, Herwartz, 2018b] and apply the procedure used in Maxand [2020] for identification.

We apply the smooth-transition SVAR to monthly EU-level data in the period of 2006M8-2023M2. This allows for the following findings: we find non-linearity of the interaction between carbon and energy prices depending on the macroeconomic regime. The results indicate a more uncertain response of economic performance to an increase in carbon prices in recession times compared to expansions which is mostly statistically negligible. During the observation period the EU ETS covers greenhouse gas emissions from power stations, energy intensive industries and (partly) commercial aviation. When diving into different economic sectors, namely manufacturing, aviation, construction and road transportation, we find no significant effect in the covered sector manufacturing but an effect on aviation and an analogue cost pass-through of carbon prices to road transportation which is positive in recessions and negative in expansions. Additionally, we identify economic crises to have a negative impact on carbon prices. An increased coupling between carbon prices and gas prices in recent time periods is supported and a coupling to the macroeconomy rejected. In that sense, the results support regulation mechanisms implemented along the ETS that ensure effectiveness of carbon pricing in strong crisis, specifically, if the crises are characterized by a drop in carbon intense industries.

The paper proceeds as follows: We first discuss the SVAR methodology in Section 2 and present the data and the results of the SVAR application to the European carbon market in Section 3. Section 4 concludes.

2 The empirical model

In order to analyse EU-wide monthly data, we follow the literature [Chevallier, 2011, Friedrich et al., 2020] and account for non-linear relations by applying a smooth-transition VAR. We study the interaction of carbon prices, macroeconomy and energy prices in a four-dimensional model

$$y_t = G(z_{t-1})A_l(L)y_{t-1} + (1 - G(z_{t-1}))A_h(L)y_{t-1} + u_t, \tag{1}$$

$$u_t \sim (0, \Omega), \tag{2}$$

where y_t is the four-dimensional vector of endogeneous variables, $A_\bullet, \bullet = h, l$ are the autoregressive matrices for the higher and lower regime, respectively. The matrix Ω is the covariance matrix of the error terms u_t and $G(\cdot)$ is the transition function depending on smoothness parameter γ, location parameter c and transition variable z_t in the following way

$$G(\gamma, c, z_t) = \frac{exp(-\gamma z_t - c)}{1 + exp(-\gamma z_t - c)}, \gamma > 0, Var(z_t) = 1, E(z_t) = 0. \tag{3}$$

Estimation of the model proceeds by maximum likelihood estimation via NLS regime dependent AR similar to Herwartz and Rohloff [2018]. For the calculation of impulse response functions (IRFs) and for structural identification, the model is transformed in the following way

$$\begin{aligned} &\Pi_t(L)y_t = u_t, \\ \text{with } \Pi_t(L) =& [I - G(z_{t-1})A_l(L)L - (1 - G(z_{t-1}))A_h(L)L]. \\ \Rightarrow y_t =& \Phi_t(L)B\varepsilon_t, \text{ with } \Phi_t(L) = \Pi_t(L)^{-1}. \end{aligned}$$

Similar to Herwartz and Rohloff [2018], the following analysis is based on dynamic responses assumed to be linear conditional on the regime $G(\cdot) = 0$, $G(\cdot) = 1$ or quantiles thereof. This implies impact matrices $BB' = \Omega$ forming covariance matrix Ω which is constant over time and there exist regime dependent IRFs from time horizon $h = 1$ onwards. This consequently defines the IRFs as $\Phi_l(L)B$ in the low regime and $\Phi_h(L)B$ in the high regime.

In this sense, we assume that non-linearity is modeled in the reduced form estimation and the error terms are 'smoothed out', but might contain remaining heteroskedasticity. Bruns and Piffer [2021] discuss that modelling a smooth transition variance and autoregressive structure simultaneously is computational challenging. They circumvert it with the inclusion of an external instrument which would need manual construction and thus, additional economic assumptions [cf. Känzig, 2023]. However, in the current setting we assume and verify non-Gaussianity of the residuals, in which case identification based on non-Gaussianity outperforms the identification based on external instruments in terms of the MSE of the estimated matrix B [shown in a simulation study in Crucil et al., 2023]. Alternatively, the model presented in Crucil et al. [2023] would allow for combination of both methods. The resulting model performs better for a relative large correlation between instrument and shock to be identified. We lack such an instrument, thus, leave the model free from external assumptions and make use of a flexible independent component analysis (ICA)-based approach to identify the non-unique matrix B to obtain the uncorrelated $\varepsilon_t = B^{-1}u_t \sim (0, I_K)$. Identification based on ICA has the advantage that it performs equivalent well to identification based on heteroskedasticity if heteroskedasticity is present in the error terms [Herwartz et al., 2022]. Economic identification is installed as a second step.

2.1 Statistical and economic identification of structural shocks

For identification, the assumption of at most one Gaussian shock in the vector ε_t implies a structural matrix B which is unique up to scaling and ordering [Comon, 1994]. Following principles of independent component analysis (ICA) this can be used for identifying structural VAR model. Multiple methodological approaches have developed to use this general ICA results for idenfication, i.e. by alternative recursive ordering and dependencies [Moneta et al., 2013], by non-Gaussian (Pseudo) Maximum Likelihood [Lanne et al., 2017, Gouriéroux et al., 2017], by GMM estimation [Lanne and Luoto, 2021, Keweloh, 2020] or by nonparametric dependence criteria [Herwartz, 2018a, Maxand, 2020]. Due to the flexibility of non-Gaussian identification [Herwartz et al., 2022], we rely on this approach and, more specifically, apply identification based on a nonparametric dependence criterion in the following, e.g., Maxand [2020].

In order to find the matrix B which minimizes the nonparametric dependence criterion of $\hat{\varepsilon}_t = B^{-1}\hat{u}_t$, we use Givens rotation matrices and proceed in the following way:

1. Compute the Choleski decomposition C of OLS estimate $\widehat{\Omega}$.
2. Compute $B(\theta) = CQ(\theta)$ with a set of Givens rotation matrices $Q(\theta)$ determined by

rotation angles θ.

3. Choose the rotation angle θ, i.e. decomposition $B(\theta) = CQ(\theta)$, such that the dependence in $\hat{\varepsilon}_t(\theta) = B(\theta)^{-1}\hat{u}_t$ is minimal.

The distance covariance $dCov$ measures the distance between the joint characteristic function and the product of the marginal characteristic functions [Matteson and Tsay, 2017] and is used to identify $\widehat{B} = B(\hat{\theta})$ in terms of $\hat{\theta} = \text{argmin}_\theta dCov(\hat{\varepsilon}_t(\theta))$.

The identified structural shocks $\hat{\varepsilon}_t(\hat{\theta})$ are unique in statistical sense, but do not necessarily hold an economic interpretation. Shock labelling, or economic identification, can proceed by means of different tools. We are specifically interested in studying the form and structure of the carbon policy and energy shocks. The following criteria help us to identify one of the resulting structural shocks as the carbon policy shock:

(i) Quantitatively and statistically significant contemporaneous reaction of the associated variable,

(ii) Dynamic responses in comparison to theory-based sign patterns,

(iii) Correlation to external shock series and comparison of the resulting shock to narrative events.

Verifying the economic reasonability of the shocks by correlation with an external shock series is similar to proxy-SVAR modelling or the combination of statistical and proxy identification as, e.g., in Schlaak et al. [2023], Crucil et al. [2023], but in difference we exploit the data in the first step and account for economic identification in the second step. After considering the additional criteria of the shock series $\hat{\varepsilon}_t(\hat{\theta})$, we claim to have identified the structural shock series and can interpret the resulting impulse responses. Details on the performed steps are described in the results section.

Next to impulse response functions, historical decompositions of the involved series provide a tool for interpreting the interconnections. For the present nonlinear VAR we follow Wong [2017] by defining the related historical decomposition. Wong [2017] writes the VAR process in companion form

$$Z_t = H\mu + A_t Z_{t-1} + HB\varepsilon_t,$$

where

$$Z_t = \begin{pmatrix} y_t \\ \vdots \\ y_{t-p+1} \end{pmatrix}, A_t = \begin{pmatrix} A_{1,t} & \dots & A_{p,t} \\ I_{K(p-1)} & & 0_{K(p-1)\times K} \end{pmatrix}, H = \begin{pmatrix} I_K \\ 0_{K(p-1)\times K} \end{pmatrix}.$$

From this equation, he defines the historical decompositions of the variables in Z_t depending on the contribution from the structural shocks, the initial conditions and a steady state component:

$$Z_t = \underbrace{HB\varepsilon_t + \sum_{j=0}^{t-(p+1)} A^j HB\varepsilon_{t-j}}_{\text{Contribution from shocks}} + \underbrace{A^{(t-p)} Z_p + \left\{ \sum_{j=0}^{t-(p+1)} A^j \right\} H\mu}_{\text{Baseline projection}}.$$

An indication of the effect of an unexpected change in one of the variables can displayed by comparing the effect in the first part of the right hand side to the overall estimated series which equals Z_t minus the remaining exogeneous component [Wong, 2017].

3 European carbon pricing in boom and bust times

We utilize the described ST-SVAR model to examine carbon pricing in the EU. We present the variable selection for the SVAR model, provide a concise overview of the technicalities for model selection, and subsequently discuss the obtained results in terms of resulting shock series, impulse response functions and historical decompositions.

The candidate variables for the model set up were displayed in Figure 1 above. Out of the three series of energy prices, i.e. oil, coal and gas prices, we drop the series of coal prices due to its high correlation to the oil price series (robustness is discussed in Subsection 3.2.4). The resulting VAR model is four dimensional involving carbon prices, two energy price series and one series representing economic output. Our main model involves overall industrial production as the economic output variable. We analyse sector-specific impacts later on. Following Chevallier [2011], the vector y_t of our main SVAR model contains monthly data for $t = 2006M9 - 2023M2$ of

dindprod Industrial production (in log-diffs),

$dEUA$ EUA carbon price futures (in log-diffs), *dBrent* Brent oil futures (in log-diffs),

dGas Gas futures (in log-diffs).

In this sense, we cover all three phases of the ETS. The data for the carbon and energy futures are taken from Datastream Refinitiv. The industrial production data comes from OECD. All time series in Figure 1 display non-stationary patterns which leads us to include all variables in log diffs into the model. We can identify clear high and low regimes, especially for carbon prices, gas prices and production. After 2020 the series of energy and carbon prices show the beginning of the recent price increases. We study if the recent price increases predominate the whole model by checking for robustness in a model for the sub-period until the end of 2019 in Subsection 3.2.4. In our main model we use the full time period as we see the recent increase in gas and carbon prices and the crisis period as an interesting time, especially with regard to future developments.

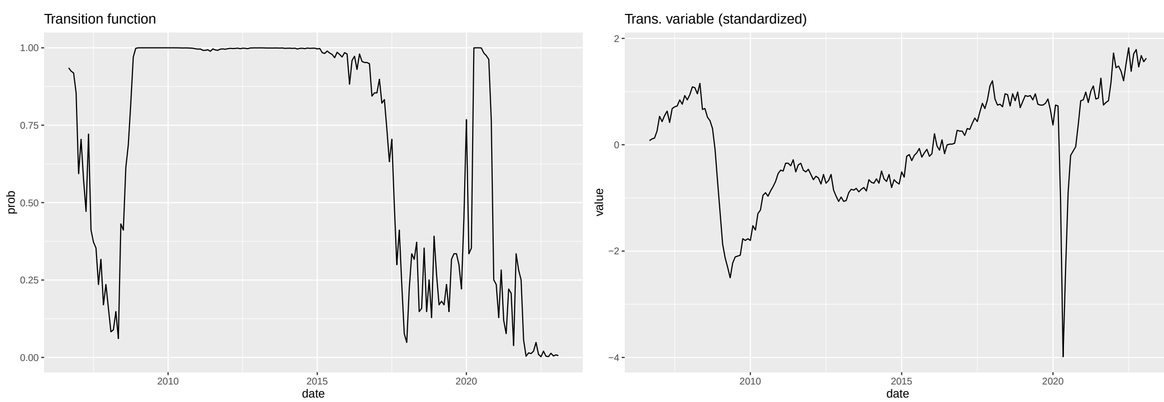

Figure 2: Transition function and the related transition variable 'industrial production'.

3.1 Technicalities

In the sense of a smooth transition model we are interested in effect differences over different regimes determined by the transition variable. For setting up the smooth transition model for $y_t = (dindprod_t, dEUA_t, dBrent_t, dGas_t)$ we need to define this transition variable (denoted by z_t in (3)). As we are interested in the interactions over the business cycle, we choose industrial production as transition variable. Next to industrial production ((i)) we can further identify nonlinearity over three additional potential transition variables: (ii) carbon prices to investigate whether there are different mechanisms at play in regimes of higher prices, which

Lags	SIC	AIC			JBstat	pvalue
VAR1	-21.05	-21.39		$\widehat{\varepsilon}_1$	44.37	2.3e-10
VAR2	-20.71	-21.32		$\widehat{\varepsilon}_2$	97.78	0.00
VAR3	-20.35	-21.23		$\widehat{\varepsilon}_3$	3742.95	0.00
VAR4	-20.06	-21.21		$\widehat{\varepsilon}_4$	182.05	0.00

Table 1: AIC and SIC values for different lag length choices (table on the left), separate Jarque Bera test results for the error series (table on the right).

would especially provide hints for future developments, (iii) the output gap; (iv) the time. We additionally check for overall stability of all models and stability of the higher and lower regimes separately. We find instability for option (ii) and (iii) which is due to a small number of observation in one of the regimes. We discuss the results for industrial production as the transition variable in our main model and display additional results for other transition functions in the Appendix. The estimated transition function $G(z_{t-1})$ with the standardized transition variable industrial production z_{t-1} are displayed in Figure 2. We can identify clear regimes of higher and lower industrial production (which are upside down in the graphic due to the negative sign in the transition function in Equation (3)) and periods where the model is in transition between the two regimes as, e.g., between 2018 and 2020.

Additionally, we find that AIC and BIC values are in fact lower for the ST-VAR compared to the linear counterpart without regime switches which provides additional reasoning for nonlinear transmissions. For the choice of the lag order we also rely on the information criteria (AIC and SIC suggest 1, see Table 1) and we end up with using $p = 1$ lags when additionally checking the model residuals. We include a constant as deterministic term in the model. For identification based on non-Gaussianity, we need to verify that the shock series are actually non-Gaussian [c.f., Maxand, 2020]. We run Jarque Bera Gaussianity tests on the shock series separately and find that all shocks are non-Gaussian with very small p-values. The test results are collected in Table 1.

3.2 Results

From the identified model we derive the impulse response functions (IRFs) for the high and low regime with industrial production as transition variable. The IRFs for the log differenced variables with 16% and 84% wild bootstrap confidence intervals based on 200 draws are displayed in Figure 3. The grey shaded area belongs to the expansion period, i.e., high industrial production, and the blue area refers to recession periods, or more precisely, low industrial production. While generating the bootstrap samples we add a stability control restriction and kick out unstable draws. The resulting IRFs in Figure 3 correspond to the stable draws. The comparison between the model with and without stability control is shown in Figure A5 in the Appendix. We find that the confidence bands for both models are largely identical.

We order the responses in the way that the variable associated to each shock shows the largest (and statistically significant) response. We suspect the second shock to be the carbon price shock from its impact on the carbon price series. Additionally, we claim to have identified the effect of oil and gas prices in column three and four of Figure 3. In order to further interpret the IRFs, we first need to discuss the proper identification and interpretation of the structural shocks.

3.2.1 Economic shock identification

After applying the statistical identification technique, the resulting shocks are least dependent and represent independent sources of the fluctuations in the model variables. For turning the shocks into an economically reasonable source and identifying them as carbon or energy price shocks, we study their characteristics in more detail and relate them to event series from the literature.

The carbon price shock

As described in Section 2.1, after statistical identification of independent shocks, we economically reason the carbon policy shock by its correlation with an external shock series, i.e., the series of regulatory events generated by Känzig [2023]. We additionally identify crucial narrative events for which we expect the shock to be either positive or negative. We find a medium correlation with the external shock series, especially during certain historical events

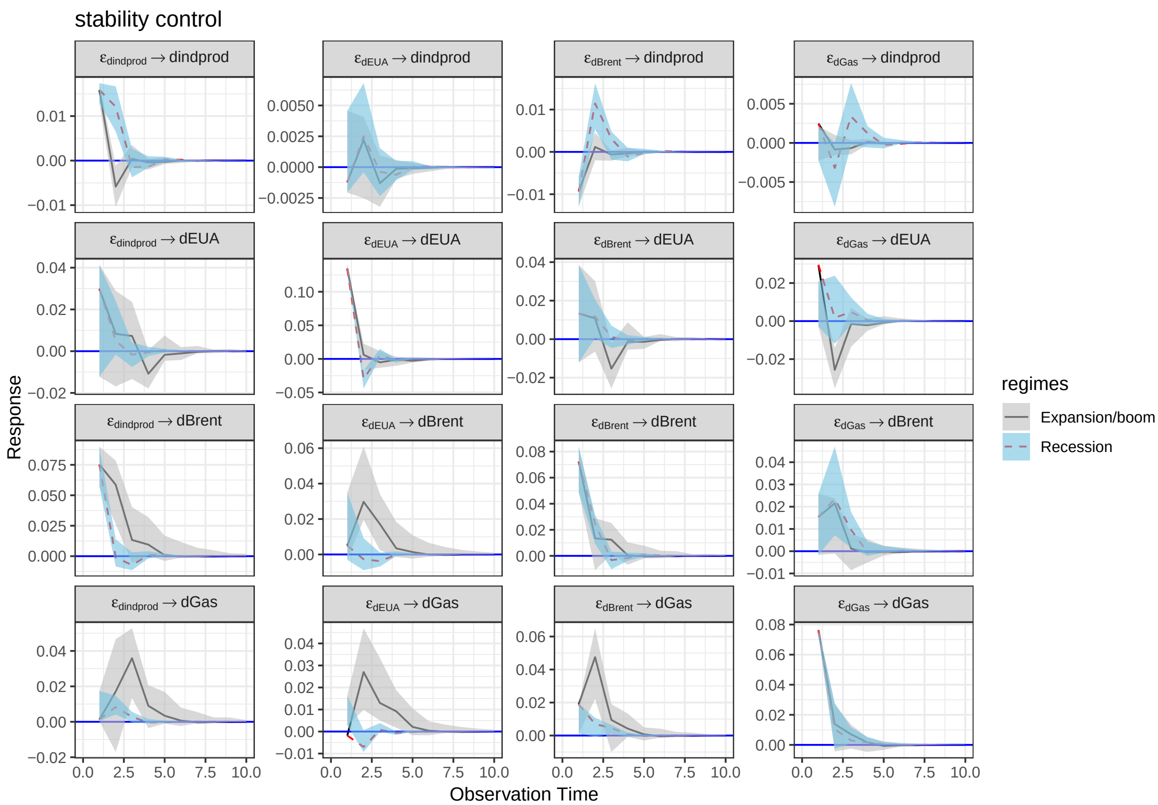

Figure 3: IRF with wild bootstrap confidence intervals for both regimes with transition variable *indprod* after stability control.

and discuss the results in the following.

Känzig [2023] manually constructs a series of regulatory events containing mostly supply side news on emission allowances. He generates a carbon policy surprise series based on the daily change in carbon prices relative to the wholesale electricity price on the day before the event. The surprise series is aggregated to monthly events from 2005 to 2019. In Figure 4 we display the correlation of our resulting structural shocks with the shock series from Känzig [2023]. We compare our shock to the shock series consisting of regulatory events (`Kzg_surpr`) and the shock series identified in Känzig [2023] as a carbon policy shock (`Kzg_shock`). The correlation of our carbon policy shock shows a correlation of 0.35 with the news surprise series (without prior assumptions) while the shock `Kzg_shock` shows a correlation of 0.26. When plotting our shock series against the news surprise series we find that our series covers most of the main disruptions in carbon prices as, e.g., large peaks as the vote against the back-loading proposal in April 2013 or the news on the auction volume in 2019 [Känzig, 2023]. We, thus,

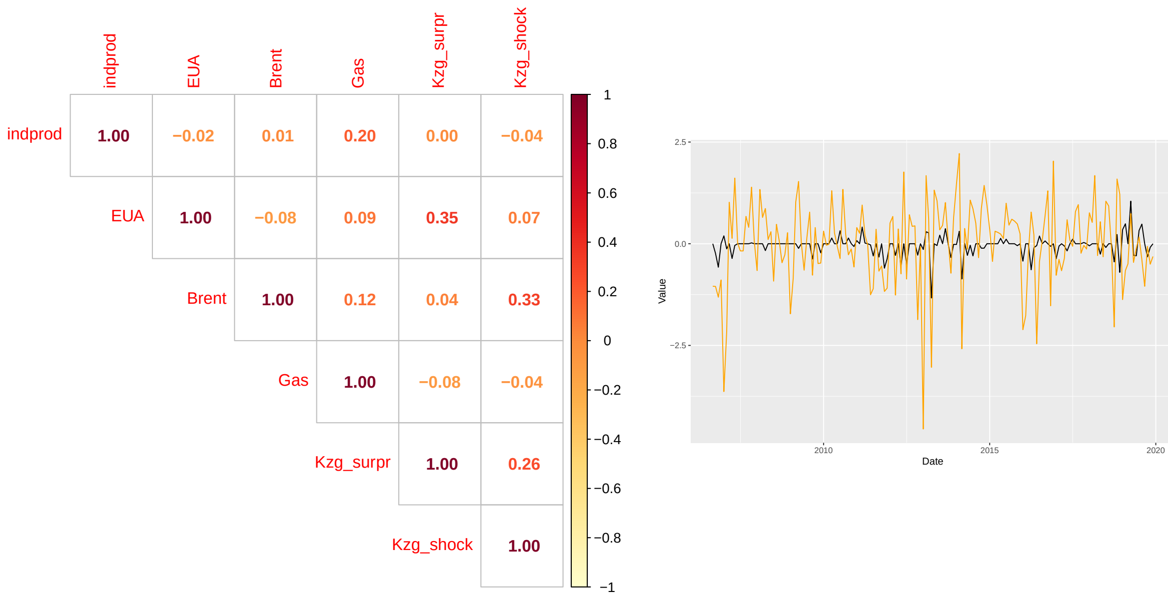

Figure 4: Correlation of the resulting structural shocks $\hat{\varepsilon}_t$ and the two shock series from Känzig [2023] (left); the series of collected regulatory events (black line) and the resulting structural shock from our model (upper panel) and the one from Känzig [2023] (lower panel).

label our shock as a *carbon price shock*. Furthermore, our identified oil price shock shows a small correlation to the news surprise series but a stronger correlation of 0.33 to the identified carbon shock series from Känzig [2023]. This is in line with the original study by Känzig [2023] which also finds a correlation to oil supply shocks. This might be due to the fact that his shock covers more disruptions important for oil producers. We next study our oil price shock in more detail and find it largely correlated with the oil news shock from Känzig [2021].

The energy price shocks

In general, energy price shocks might arise from supply, demand or expectation disturbances [Kilian, 2009]. During the observation period 2006-2023, several disruption have occured in all dimensions. Especially, the spike in oil prices in 2008 and the explosion of gas prices in recent times might base on external events. In the following, we verify our resulting shocks based on disruptions that have been discussed in the literature. The energy shocks which result from the model are related to the event series of oil supply news of Känzig [2021] and the series of gas supply events of Alessandri and Gazzani [2023].

With regard to oil prices, different proxy event series have been applied in the literature to identify an oil supply, surprise or demand shock [see, e.g., Stock and Watson, 2012, for a discussion]. In the following, we use the series of oil supply news generated from OPEC announcements by Känzig [2021] to discuss our identified shock series. The series is build from OPEC press releases in the period of 1983-2017. On his webpage, Diego Känzig provides the updated supply news series up to 2023 which we use to compare our shock series. Disentangling expectations-driven components of oil supply and demand, the supply news series allows to isolate news about future oil supply. We find our identified shock series well correlated with the oil supply news shock (30%) and even stronger with the shock series identified by Känzig [2021] (51%), see Figure 4. Plotting the identified series against each other we find them largely comoving while our series is partly more volatile. Important events like, for instance, the drop in 2008 and 2015 are captured by our series. The drop in 2015 is discussed by Känzig [2021] to correspond to the OPEC announcement that oil production levels stay unchanged. We infer that our identified shock contains widely similar information as the oil supply news shock series of Känzig [2021]. However, as we can not disentangle the supply news from other channels of demand or supply disruptions, we identify our shock as an combined *oil price shock* and can specify effects of the supply and demand side in the associated historical decompositions later on. A further comparison to the shock series from Degasperi [2023] might be interesting.

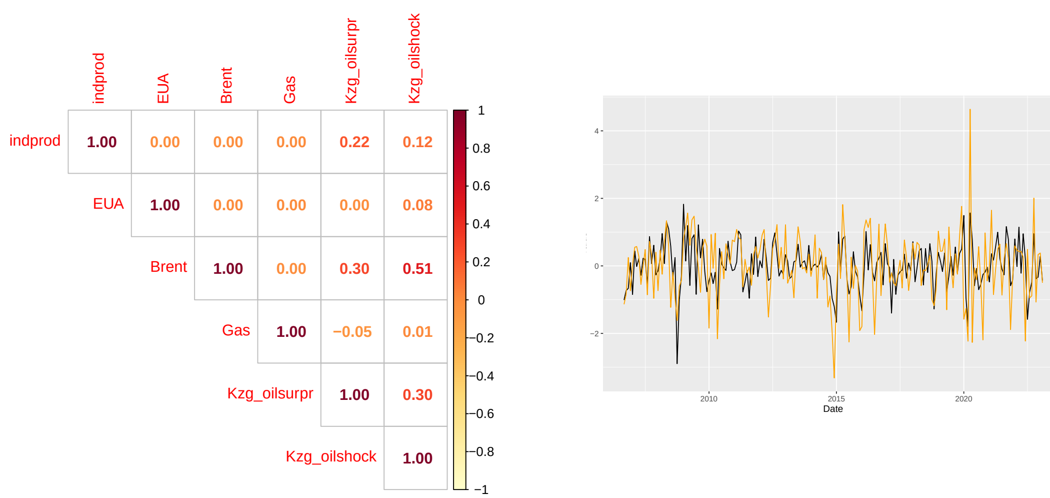

Figure 5: Correlation of the oil news event series $Kzg_{oilsurpr}$ from Känzig [2021] with the identified model shocks (left) and joint plot of the oil supply news shock series ($Kzg_{oilshock}$) and $\hat{\varepsilon}_{Brent,t}$ (right).

Focusing on the gas prices, Alessandri and Gazzani [2023] study the most recent increases in prices. They generate a news event series for the time period 2010 to 2022 by selecting relevant days and news related to 'Title Transfer Facility', 'Liquid Natural Gas' and/or 'Gazprom'. The resulting series contains 50 daily supply shocks of which 26 daily events are displayed in their Table 2. To compare it to our series, we aggregate the 26 events to 10 monthly disruptions. For some months, this means that positive and negative events, that occur in the same month, largely cancel each other out. The correlation of the resulting series and our statistically identified structural series are displayed in Figure 6. We find that the shock from Alessandri and Gazzani [2023], gas_{AG}, shows the highest correlation of 0.29 with the resulting gas price shock from our model $\widehat{\varepsilon}_{Gas,t}$. The correlation to all other shocks is negative and below 10%. The right-hand side of Figure 6 displays the energy shock series in orange and the news events in black. Given the schematized event series, this correlation is quite high. Our shock series covers disruptions as the increasing conflicts between Russia and Ukraine in 2014 and recent positive events related to the Nordstream pipeline in mid 2022 and the negative event of Gazproms reassurance to provide Europe with gas. Our identified *gas price shock* might still contain demand side disturbances as mentioned in the case of the oil prices. We point to such events when studying the historical decompositions.

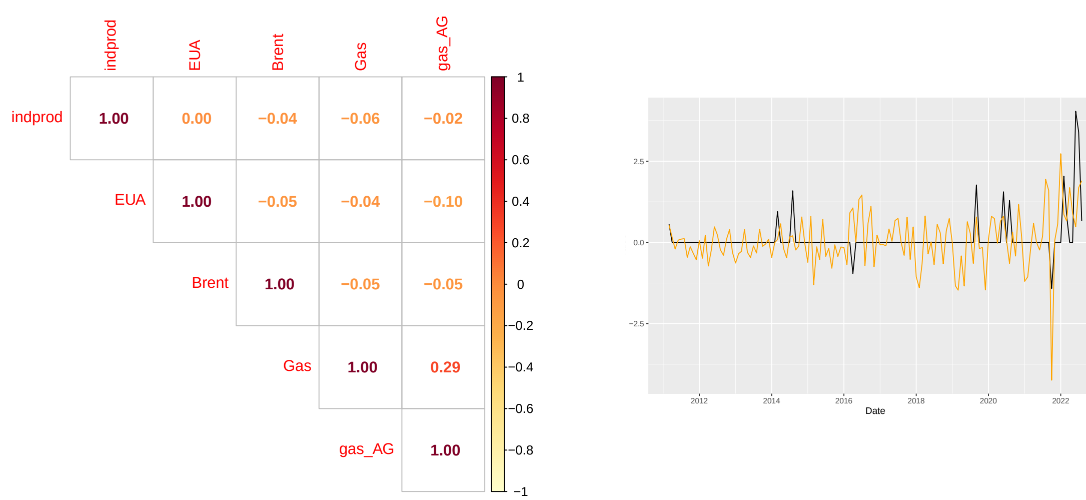

Figure 6: Correlation of the gas supply event series gas_{AG} from Alessandri and Gazzani [2023] with the identified model shocks (left) and joint plot of the event series and $\widehat{\varepsilon}_{Gas,t}$ (right).

3.2.2 Dynamic causal relations & historical decompositions

The impulse responses in Figure 3 are useful to analyse the dynamic causal effects of the identified shocks. The main results concern differences in expansion and recession times as well as the endogeneous interaction of carbon prices with production and energy prices. Based on the historical decompositions in Figure 7, we can identify the role each shock plays in the development of the log differences of the variables over time. We mainly focus on the decomposition of growth rates of industrial production and of carbon prices and can state several results.

To further verify that the IRFs displayed in Figure 3 are reasonable, we first consider the interaction between the energy prices and industrial production. Such interactions should be similar as in previous studies like, e.g., the sign pattern in Kilian and Murphy [2012] and effects in Känzig [2021], Degasperi [2023] who study diverse oil supply (and demand) news effects on the world and US industrial production. We find that industrial production has a positive impact on the oil and gas price that is larger in expansionary times compared to recession times. This means that the positive effect of demand shocks is larger in boom times. Reversly, oil price shocks have a negative instantaneous effect on industrial production in both regimes [cf. Kilian and Murphy, 2012]. The effect is positive after a few periods in recession times which highlights the role of demand shocks in recessions. Gas prices show an opposite pattern which is in recession times similar to the one in Alessandri and Gazzani [2023]. In the historical decompositions, we find that industrial production is largely driven by productivity shocks itself (which might be interpreted as aggregated shocks of factors important for economic performance). The second largest factor is the oil price shock which often counteracts the growth rate of production. This aligns with the instantaneous negative effect visible in the IRFs in Figure 3. The periods of negative growth rates after 2008 and in 2020 are driven largely by productivity shocks and are only to a certain extent explainable by oil and gas prices. We see largest contribution of oil prices around 2016. Towards the end of the sample in and after the 2020 crisis the oil prices seem less important. When zooming in the period after 2022, the growth rates of industrial productuion are a mix of all four shocks with increasing importance of the gas price shock as discussed in Alessandri and Gazzani [2023].

We are further interested in the nonlinear sources and effects of the carbon price series.

Figure 7: Historical decomposition of all variables with respect to all shocks calculated following Wong [2017].

In our model this accords to the relation to energy prices and industrial production. The impact of energy prices on carbon prices is positive (and significant for an oil price shock) in recession times and negative in expansion times. This is in line with the results of Friedrich et al. [2020]. In their nonlinear model they find a positive relation of oil prices on carbon prices which is less strong for the recession period located after 2009. Our model additionally allows for identifying the effect in the oposite causal direction: the effect of carbon price shocks on energy prices. Boer et al. [2023] and references therein point to a negative effect of demand-side climate policies on fossil energy prices. We find such negative effects of an increase of carbon prices in recession times. In expansion times the increase of carbon prices is positively coupled to fossil energy prices as oil and gas. We can find more evidence in the historical decompositions in Figure 7. When studying growth rates of carbon prices, we find that the series is mostly driven by external carbon price shocks. The decrease after 2008 is partly driven by industrial production and gas prices. This adds to the results of Koch et al. [2014] who identify the demand side channel as a determinant for the decrease during that time. The crisis period in 2020 with an additional drop in carbon prices shows that the prices react to external economic crises. This means that allowances are cheaper during that time. Implemented in 2018, the market stability reserve (MSR) is supposed to counteract allowance supply imbalances linked to business-cycle shocks. After the covid crisis, we do not find an increased coupling of carbon prices to industrial production which might support the effectiveness of the MSR. We instead find that carbon prices are stronger influenced by gas prices. Such an increased coupling plays an increasingly important role in recent months after the observation period.

3.2.3 Effects across different economic sectors

To precise the effects of an increase in carbon prices on economic production we substitute industrial prodution by the sector-specific performance of four major sectors of which two are covered by carbon pricing, manufacturing and aviation, and two are indirectly affected via cost pass-through, construction and transport [Cludius et al., 2020]. Monthly data series are taken from the OECD database and Eurostat and the log differenced data is used. The rest of the model set up remains unchanged, meaning that we build the models around the aggregate industrial production level as transition function. For the road transport data, aggregated data on European level is not available. Instead, we consider the country-specific data, which is available on monthly level, namely the 'Total road freight transport' for Germany, Spain, Czech Republic, Bulgaria, Poland and France. We average over the available data and deseasonalize and smooth the series. The resulting series is shown as a part of Figure 1. In that sense, we use these variables to get an indication of the interplay between the transport sector, energy and carbon prices. The seize of the effects, however, are per se interpretable only to a certain extent as not all European countries are covered. To cover the sector of aviation transport, we use total aviation passengers which is available on EU level from 2008. The corresponding model, thus, covers a shorter time period.

	Correlation between shocks:		
econ var	$(\widehat{\varepsilon}_{EUA},\, Kzg_{surpr})$	$(\widehat{\varepsilon}_{Brent},\, Kzg_{oilsurpr})$	$(\widehat{\varepsilon}_{Gas},\, gas_{AG})$
manufacturing	0.34	0.21	0.28
construction	0.34	0.23	0.26
aviation	0.38	0.38	0.29
road transport	0.34	0.36	0.31

Table 2: Correlation between statistically identified shocks $\widehat{\varepsilon}_{EUA}$, $\widehat{\varepsilon}_{Brent}$ and $\widehat{\varepsilon}_{Gas}$ and the external shock series Kzg_{surpr}, $Kzg_{oilsurpr}$ and gas_{AG} from Känzig [2023], Känzig [2021] and Alessandri and Gazzani [2023], respectively. The first column indicates which economic variables is included in the model.

In terms of model identification, we find that the carbon and energy shocks are similarly well identified compared to the main model. We summarize the correlations in Table 2. Thus, we assume that we can interpret the effects of oil, gas and carbon prices as in the main model. In the following we focus on the response of the sector-specific production to a carbon price shock which are displayed in Figure 8. For manufacturing and construction the remaining IRFs are largely in line with the results from the model including industrial production. For the road transport and aviation sector the full 4x4 matrix of IRFs is shown in the Appendix.

In Figure 8 we can see that manufacturing and construction react both similarly to a carbon price shock as aggregated industrial production in the previous model. The response is insignificant in both regimes. Overall zero effects might be interpreted as efficiency gains: The prices increase but the amount of production remains unchanged. For manufacturing, this is in line with the results of Martin et al. [2014] for the UK who find higher efficiency but

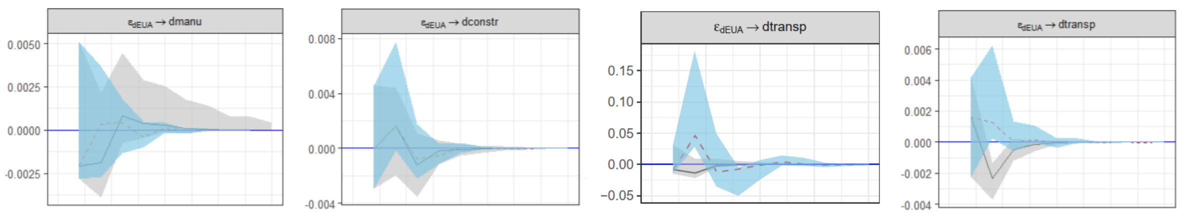

Figure 8: Reaction of manufacturing, construction, passenger aviation and freight transportation volume to a carbon price shock. The response with blue confidence intervals corresponds to recession times, grey to expansion times as in Figure 3.

no effect on revenues resulting from an increase in carbon taxes. Also Dechezleprêtre et al. [2023] find no or even a positive effect of the EU ETS on revenues in several sectors. The positive effect is visible in the medium- to long-term response displayed for manufacturing in Figure 8, which tends to be positive. In our aggregated model we can follow that there is no significant cost pass-through for the construction sector [Cludius et al., 2020, similarly find a medium sized pass-through for cement and glass, for instance].

When studying the response of the aviation and road transportation sector we find significant impacts on the average transportation in the six European countries. The effect is instantaneously insignificant but positive after some month in bust times and negative in boom times. This aligns with the results of cost pass-through of refineries to the consumers of Diesel found in Cludius et al. [2020] and a negative effect on emissions in the aviation sector in Fageda and Teixidó [2022]. The negative impact on the road transport sector is much stronger as in the manufacturing sector and thus, calls for a careful extension of the ETS on the transport sector which pays the costs of both their direct and indirect emissions. It hints at an effective carbon pricing system when studying the intermediate sectors. The large positive effects in recession times might be due to the fact that the crises in 2020 had a strong effect on the aviation sector (with an external flight stop in 2020). Thus, the response to a carbon price shock is heavily influenced by the second recession period.

3.2.4 Robustness

We have run various modifications of the baseline model to study its robustness. As a first modification, we have substituted the Brent oil price series by the respective series for coal. The resulting transition function is displayed in Figure A3. We find that the transition function looks largely similar to the model run for the oil price series. It is slightly less pronounced in the extreme regimes. The IRFs of this model are shown in Figure A4. While the interaction between the other variables stays largely unchanged, the coal series interacts less pronounced with industrial production, carbon prices and gas prices compared to the series of oil prices. On impact, most responses are insignificant but we find a slightly significant response of industrial production to the carbon policy shock after some month in recession times. Robustness with respect to coal prices in the Appendix confirm the relation between industrial production and carbon prices. Due to instability of the higher regime we need to plot the 70% quantile of the transition function. Additionally, we run the model for the shorter time period until 2019 only. This allows to better compare the results to the study of Känzig [2023] and study the influence of the recent recession period on the overall results. The results appear largely similar with less pronounced effects when considering, e.g., the interaction of oil prices and industrial production.

3.3 European carbon policy and the way ahead

From the results of this empirical exercise we can draw some important conclusions on European carbon policy. Focusing on heterogeneous effects in boom and bust times allows us, on the one side, to control for differences when calculating historical decompositions and, on the other side, explicitly quantify the differences when studying IRFs for both regimes. From the historical decompositions we find that the recent crisis has affected carbon prices stronger which is underlined by the strong interaction of aviation amount and carbon prices in recession times in the IRFs. These results indicate that the specific nature of a crises might be taken into account before drawing conclusions on carbon price effects. This is, for instance, in line with discussions in Annicchiarico et al. [2022] and Doda [2016] who specifically highlight the importance of country conditions and sources of crises when implementing tools coupled to the business cycle. While Heutel [2012] suggest an adaptation of emission caps to GDP growth deviations, our results rather support to take more detailed indices coupled to productivity into account when adapting to the business cycle.

Our observations cover effects on the aggregate level and sector-specific effects. When interpreting the effects it is important to discuss how the sectors interact with carbon prices due to emission coverage, free allowance allocations (e.g., in the aviation sector) or a cost pass-through. In this context, taking other carbon pricing tools into account is crucial as it allows to study the intertwined effects of different initiatives. For instance, Annicchiarico et al. [2022] study the development of intensity standards, emissions cap, and emissions tax over the business cycle. Along these lines, the European ETS might lead to less economic volatility compared to carbon taxation as it has a built-in dampening effect on business cycles. However, studying the increased effect heterogeneity in recession regimes in our IRFs might hint to the fact that the effects on output and price volatility might be interesting to study in a next step. When specifically focusing on the transportation sector, stringency of the emission cap might be overreacting in recession times visible in the positive coupling. While this sector is not specifically covered in the cap-and-trade system, its reaction calls for studying (1) the interaction of hybrid carbon pricing tools as present in the EU, and, (2) a careful implementation of the extension of EU ETS in the next years.

With regard to the implementation of the MSR, our results provide several indications. In order to avoid a green paradox introduced by the MSR, Gerlagh et al. [2021] proposes hybrid price-quantity-based regulation mechanism instead of quantity- or price-based only. The positive effect of carbon prices on transportation (and in contruction, see Figure 8) in recession times after some month might provide support of the statements in Gerlagh et al. [2021] that due to the banking of allowances in the MSR price increases might lead to a lagged positive response in economic activity.

The data is studied on an aggregated level analysing the European ETS. Considering carbon leakage, which has been increasingly studied in the literature [see, e.g. Annicchiarico and Diluiso, 2019], it appears additionally reasonable to study sectors separately as the risks are different dependening on their leakage potential. We find less strong effects in the manufacturing and builiding sector where the production of materials might partly be relocated which is not possible in the same extent in the transportation sector.

4 Conclusions

In this paper, we investigate carbon pricing on the EU level in recession and expansion times. We study a schematic four dimensional SVAR model identified by non-Gaussianity which is extended by smooth transitions and external shock correlation measures. We find correlation of the statistically identified shocks with oil, gas and carbon instrument series from the literature which confirms the model set-up. Overall the analysis provides us with insights on how carbon prices are coupled to the business cycle, more specifically, how they are related to energy prices and industrial production depending on the status of the economy. This becomes especially important when discussing regulation methods as the MSR or the extension to sectors like road transportation.

We find that carbon prices react to economic crises, specifically, if such crises lead to low performances of carbon intense sectors (as aviation in the 2020 crisis). Additionally, the road (and aviation) transportation sector react to carbon prices in boom and bust times. Thus, cost pass-through should be overall taken into account when extending the coverage of the ETS even more importantly in its unequal impact on the society.

For assessing future policy implications, these results can serve as a guidance but are not transferable one to one, as the changing macroeconomic settings and further redistribution and substitution policies need to be taken into account. Additionally, due the proceeding financialisation of the European carbon market further measures to study the financial market need to be taken into account in future studies of the carbon market. A further explicit comparison of the effects of EU carbon prices and carbon taxes might be not easy to assess empirically, but important in order to separate intertwined policy effects.

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A Appendix: Robustness Checks

A.1 Different economic output variables

Figure A1: Resulting IRFs when including aviation amount instead of industrial production. The rest of the model stays unchanged.

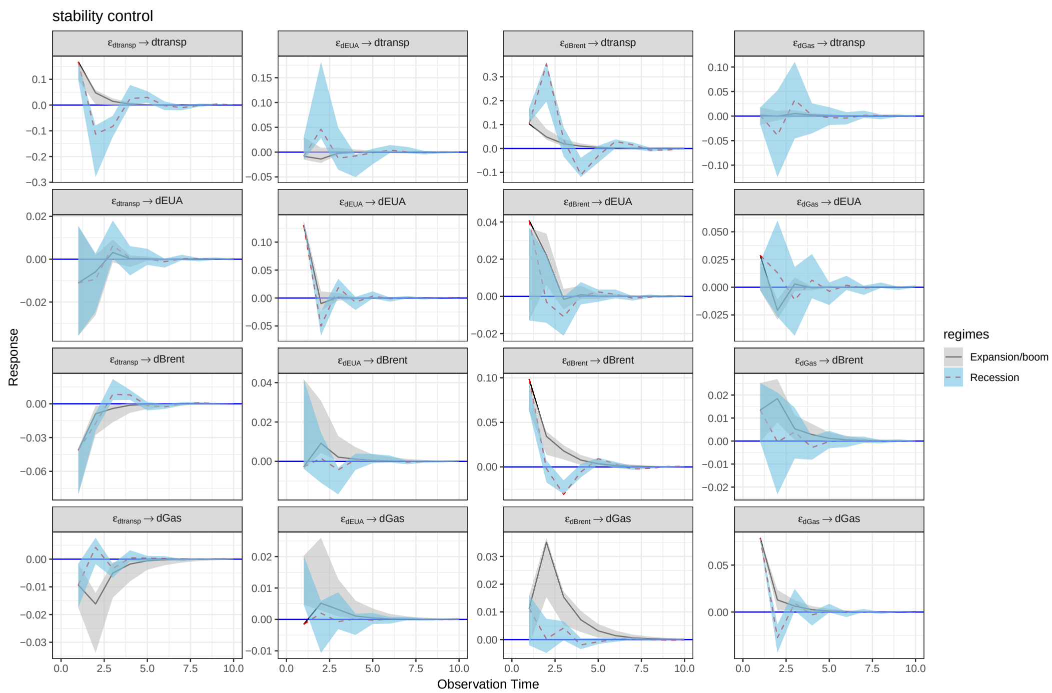
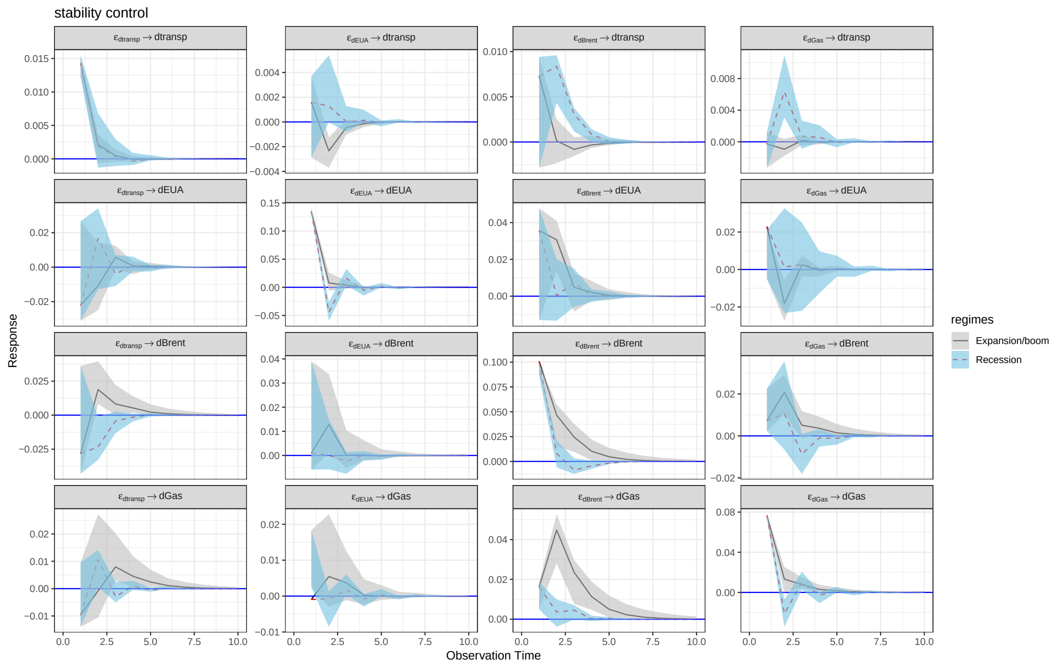


Figure A2: Resulting IRFs when including road transport amount instead of industrial production. The rest of the model stays unchanged.



A.2 Substituting oil prices by coal prices

Figure A3: Transition function for transitions variable *indprod* when including coal instead of oil prices.

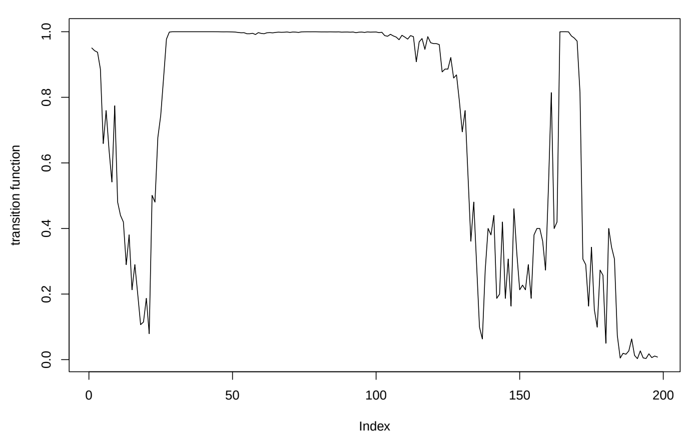
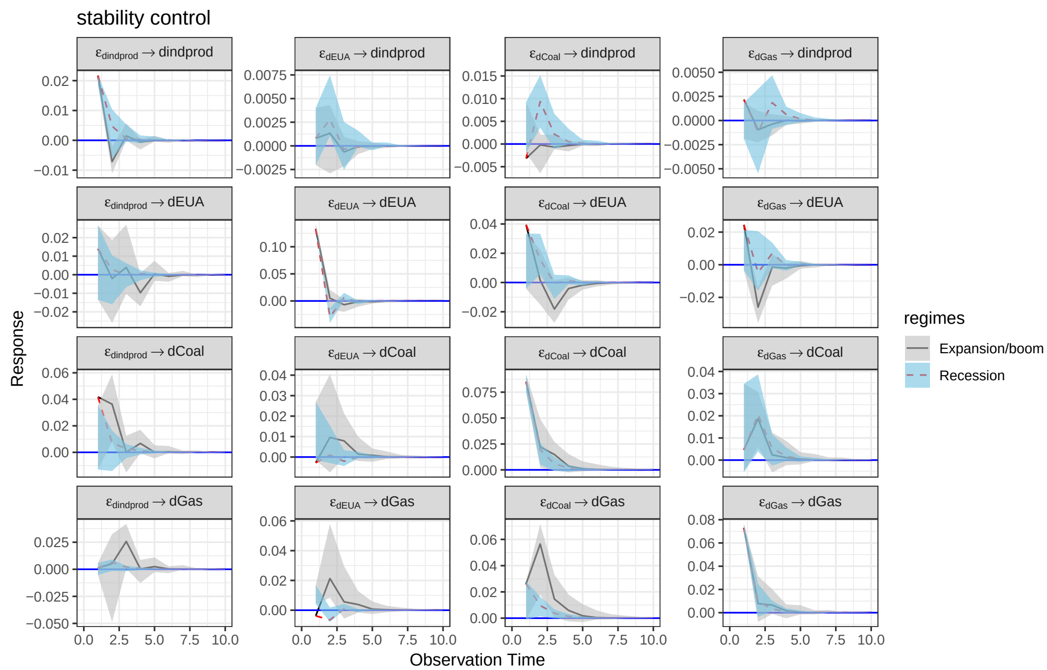
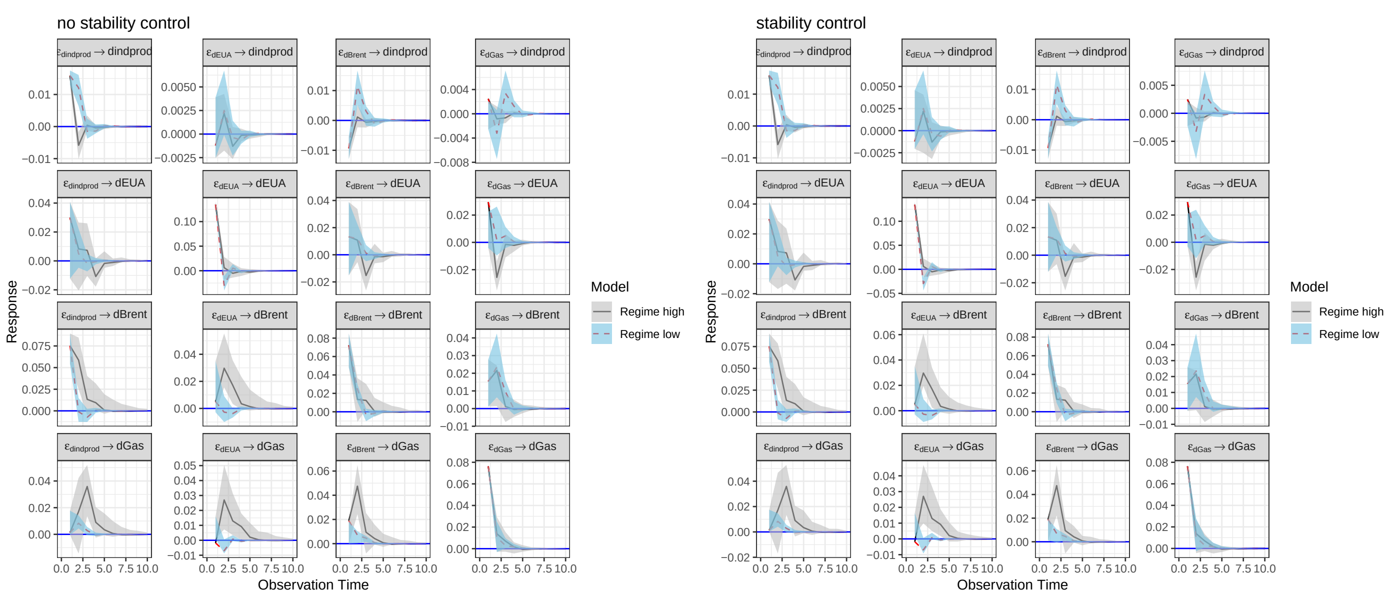


Figure A4: Resulting IRFs when including coal prices instead of oil prices. The rest of the model stays unchanged.



A.3 Bootstrap intervals with and without stability control

Figure A5: IRFs for transition variable *indprod* and full time period with and without stability control for the bootstrap iteration



A.4 Time period until 2019M12

Figure A6: Transition function and the related transition variable 'industrial production' for the time period until December 2019.

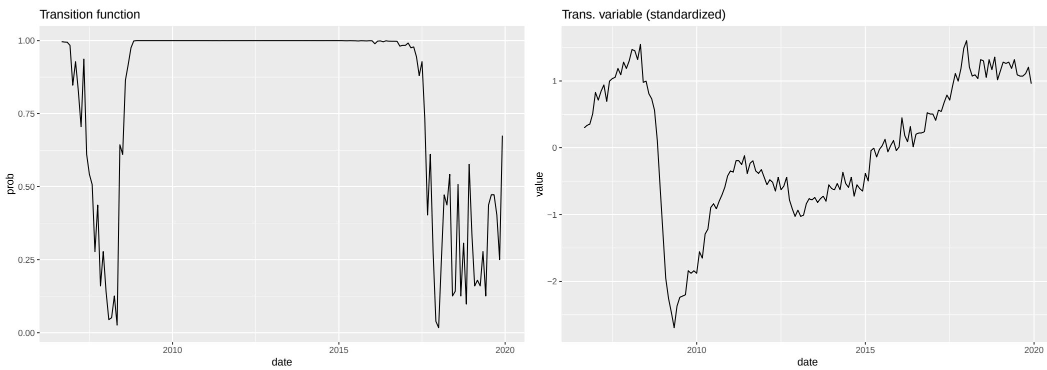


Figure A7: IRF with wild bootstrap confidence intervals for both regimes with transition variable *indprod* after stability control for time period until December 2019.