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Structural Vector Autoregression Analysis:
Carbon Policy Impacts on Macroeconomic Variables - Belgium

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Introduction and Research Question

This report presents a Structural Vector Autoregression (SVAR) analysis examining the dynamic relationships between carbon policy measures and macroeconomic indicators in Belgium. Using monthly data, impulse response functions are estimated in order to trace the effects of carbon policy surprises and shocks on inflation (HICP), energy prices (HICP-E), industrial production, and unemployment rates. The analysis includes robustness checks across different models to check the strength of the assumptions made.

The primary objective of this study is to analyze the macroeconomic transmission mechanisms of carbon policy interventions. Specifically, to investigate:

1. How do carbon policy surprises and shocks affect key macroeconomic variables?
2. What are the dynamic adjustment patterns following carbon policy interventions?
3. How robust are these relationships across different model specifications?

Data

Carbon Shocks estimated by Diego Känzig	**Eurostat Data - Belgium All indexed by 2015 = 1**
Surprise: Monthly carbon policy surprises, aggregated by summing over daily surprises. Shocks: Carbon policy shock, identified using the external instruments VAR using the surprise series as an instrument for the energy price residual. (As defined by the source material)	Harmonized Index of Consumer Prices Harmonized Index of Consumer Prices - Energy Industrial Production Unemployment

Method used

Before being able to estimate a model and interpret results the data needs to be processed, assumptions need to be made, alongside which statistical tests can help facilitate generating the model specifications.

The span of the data was limited to the time frame of the carbon shocks. Out of convenience, the full extent of time for the Eurostat data was used, since the limiting time frame comes from the shock data. The final data spans from July 1999 to December 2019, with 246 observations.

1. Log-transforming variables

The first step was to take the logarithm of the variables. The transformation was applied to HICP, HICP-E, and Industrial production. The Unemployment rate variable is a percentage, making a log transformation not necessary. The Surprise and Shock are also non-modified, since these are already estimated from a VAR.

2. Testing for Stationarity

Before using the variables in a VAR, stationarity is an important statistical property for being able to estimate coefficients. Using the Augmented Dickey-Fuller Test, it is determined that Belgium's macroeconomic variables are not stationary. Therefore, the first difference of these variables was taken.

3. Reduced-form VAR without trend

As an initial model, a VAR is estimated. No trend is added to the model seeing as the variables are stationary, so this trend information is already removed from the variables. This reduced form model only includes a linear function of a variable's own lags and the lags of all other variables in the system, plus an error term. This model is limited due to it not being able to model contemporaneous effects, which have importance in economic modelling when shocks can influence a market in a very short time frame.

This is especially true for data observed on a monthly basis, where price shocks can influence a market equilibrium within a same day.

4. Determining lag length for the model

Time series modelling comes with a tradeoff between information captured and model complexity. The goal is to explain the most variance within a model without having issues like overfitting or not having enough data for estimating parameters, leading to high standard errors. Using the AIC and BIC, below is an output of these metrics compared to lag length of the model. In order to balance efficiency and complexity, optimal lag length was chosen at the point where there is less marginal benefit from adding more lags. This point is determined as 6 lags.

MATLAB output of AIC and BIC as a function of Lag Length:

Lag	AIC	BIC
1	-13.625	-13.523
2	-14.443	-14.252
3	-14.847	-14.568
4	-15.572	-15.203
5	-16.802	-16.345
6	-17.626	-17.078
7	-18.021	-17.382
8	-18.388	-17.658
9	-18.608	-17.786
(...)		

5. Ljung-Box test to test for autocorrelation in the residuals

Having autocorrelation within residuals would indicate that there is information not captured by the model. Due to the nature of VAR models specifically modelling for autocorrelation, the model can be expanded to include this information. The model is expanded one lag at a time until the P-value for the Ljung-Box test of all variables is above 0.05. This would indicate no information is left in the residuals. From testing this with the previous model with 6 lag, and increasing the length of the model, there is no more autocorrelation present at a lag length of 9.

6. Variable Ordering and Cholesky Decomposition

To choose the order of the variables it is important to understand the economic links between them. The goal of the order will be to apply a Cholesky decomposition to then estimate a Structural VAR. The order of the variables matter since the model allows for contemporaneous effects. If two closely linked variables are far from each other in order, the SVAR loses its advantage compared to a regular VAR.

Impulse response functions were identified using Cholesky decomposition with the following recursive ordering:

1. Carbon Policy Surprises
2. Carbon Policy Shocks
3. Energy Prices (log difference)
4. Industrial Production (log difference)
5. HICP (log difference)
6. Unemployment Rate (difference)

This ordering assumes that carbon policy variables are most exogenous, followed by energy markets, then real economic activity, general prices, and finally labor markets.

Economic Rationale for Ordering + Expectations

Policy Instrument Differences:

Carbon policy surprises(unexpected announcements) are expected to have more immediate market reactions, while policy shocks (implementation effects) may show more persistent impacts.

Carbon Policy Transmission Channels:

1. Energy Prices: Carbon policies, such as taxes or emission caps, increase the cost of fossil fuel usage. Since energy markets respond quickly to input cost changes, these policies lead to an immediate rise in energy prices. Suppliers adjust prices quickly to maintain margins, making this effect contemporaneous.

2. Industrial Production: Higher energy costs increase production expenses, especially for energy-intensive industries. As energy is a significant input, firms may reduce output or temporarily halt production to manage costs. Because firms adjust production relatively quickly in response to input price changes, this effect is also contemporaneous in monthly data.

3. General Inflation (HICP): Rising energy prices and declining production feed into consumer prices through higher production and distribution costs. However, due to sticky prices caused by contracts, menu costs, and pricing strategies, firms take time to pass these costs onto consumers. Therefore, general inflation responds with a lag.

4. Unemployment: As firms scale down production and revenues decline, they eventually reduce their labor force. However, employment decisions are less flexible due to hiring and firing costs, regulatory frictions, and uncertainty about whether energy price shocks are temporary. Thus, unemployment increases more slowly, lagging behind both industrial production and general inflation.

SVAR Response Function Plots

It can be seen in Figure 1, for the estimated SVAR model that the most notable impulse response functions (IRF) are for the first two carbon price related variables. The explanation for this behavior can be attributed to the Cholesky decomposition. The first “Surprise” variable can contemporaneously affect all others, while the second “Shock” can contemporaneously affect variables 3-6. These two drive the cause of the IRFs and could be the reason for which the SVAR model is not attributing response functions between Belgium’s economic variables. Other variables (Energy, Industrial Production, HICP, Unemployment) could be more reactive than proactive.

These response functions raise questions about the transmission mechanisms of carbon pricing to Belgium's economy. While the strength of carbon price shocks could reflect their economic importance, it may also indicate that the recursive identification scheme is not fully capturing the relationships between Belgium's macroeconomic variables. The limited response of Belgian economic variables could suggest either weak transmission channels from carbon pricing policies or potential identification issues.

The IRFs amongst Belgium’s economic variables are constant, especially when considering the confidence bands. Interpreting these as not being significantly different from 0 with the 68% and 90% two-sided confidence bands. An interesting observation is the effect of uncertainty over time. The IRFs for these variables get widening confidence bands after 1 to 3 periods, depending on the order of the variable. This at least shows the ordering of the variables is reflected within the model.

From the first column are the response functions of all variables from the Surprise variable. At t = 0, contemporaneously to a Surprise increase, the Carbon price shock also increases, which is consistent with the expected positive correlation between policy surprises and actual carbon price movements in the market. No other variables are affected by these two during the same month.

One period after the surprise and carbon shock there is a large upwards spike in unemployment. While economically speaking, an increase in carbon price is expected to lead to higher unemployment as explained in the previous section, it is unusual to observe this phenomenon after only one time lag. However, adhering to economic theory, the succeeding time period shows a decrease in unemployment, followed by a stabilisation over time.

The plots for the effect of the exogenous carbon price variables on energy prices are erratic, and hard to draw a conclusion from. It can be seen that spikes upwards between these 2 are correlated and contemporaneous. This pattern reinforces the strong link between the two carbon price variables.

Industrial production seems to be affected cyclically by the carbon price shock. The period of which is 6 months, suggesting that manufacturing sectors may follow a semi-annual adjustment cycle in response to carbon pricing changes.

Consumer price index gets affected 3 months after the shocks. Positively by the carbon price shock, but negatively by the surprise variable. This could indicate that anticipated carbon price increases (shocks) gradually feed through to consumer prices via higher energy and production costs, while unexpected policy announcements (surprises) initially create deflationary pressures through reduced economic activity. One period after the shocks, the direction of the respective plots revert back to 0, and stabilize over time, suggesting that while carbon pricing policies have temporary inflationary effects, the Belgian economy shows quick price adjustment mechanisms that prevent continuous inflation.

Robustness Checks

Linear Trend Specification

By adding a trend to the model, sensitivity to the assumption of the model not needing a trend is tested to deterministic trend assumptions. This model was implemented by adding a linear trend term to baseline VAR specification. No other variables were changed, the lag length of the model remained 9.

The Ljung-Box test results with trend keeps all p-values above 0.05. In Figure 2, comparing the initial plot with the trend one, differences in the IRFs can be observed. A reason for these drastic differences is the fact that the data was already stationary. Adding the possibility of a trend in the model interfered with the coefficients, and therefore the cholesky decomposition to identify shocks.

Alternative Lag Lengths

A reason to add different lag lengths would be to see how sensitive the model is to having more or less data, in order to verify results are not driven by specific lag choice. Implementing the strategy was done by estimating SVARs with 6, 12, and 24 lags, and comparing these to the first 9-lagged model.

Results from Figure 3 are again very erratic. Either due to high sensitivity to lag length, or a miscalculation when estimating the model. The variables involved in the cholesky decomposition and ordering of these were double checked many times.

Alternative Variable Orderings

The aim of testing different variable orderings is to test sensitivity to the identifying assumptions in Cholesky decomposition.

Three Orderings Tested:

Original: Surprise → Shock → Energy → IndProd → HICP → Unemployment

Alternative 1: Surprise → Shock → Unemployment → HICP → IndProd → Energy

Alternative 2: HICP → Unemployment → IndProd → Energy → Surprise → Shock

The rationale for the first alternative is to reverse the economic factor ordering to test the effect of contemporaneous effects, with the opposite order of what economic theory would suggest. The second alternative reverses the order of all variables, with a similar reason to the first alternative, with the added effect of moving the exogenous carbon price variables to the end. This tests whether carbon pricing responds to economic conditions rather than driving them.

Results from Figure 4 differ widely again, perhaps due to the fundamental sensitivity of the Cholesky decomposition to variable ordering assumptions, which suggests that the recursive identification scheme may not be appropriate for this particular system of variables. The dramatic changes across different orderings indicate that the contemporaneous restriction structure imposed by the Cholesky decomposition is likely misspecified for the relationships between carbon pricing and Belgian macroeconomic variables. This sensitivity suggests either that simultaneous relationships exist among the variables that cannot be captured by a SVAR model, or that the underlying economic relationships are more complex than the linear.

Conclusion

This SVAR analysis examined the dynamic relationships between carbon policy measures and key macroeconomic indicators in Belgium. While the study successfully implemented the technical framework for analyzing carbon policy transmission mechanisms, the results reveal methodological challenges that limit the economic interpretations.

The analysis identified several notable patterns in the impulse response functions. Carbon policy surprises and shocks demonstrated the strongest effects within the system, consistent with their role as exogenous variables in the model. Belgian macroeconomic variables showed mixed transmission patterns. The limited and inconsistent responses of these macroeconomic variables to carbon policy interventions could reflect either genuine weak transmission channels or, more likely, identification problems within the modeling framework.

The robustness checks revealed fundamental weaknesses that significantly undermine confidence in the results. The SVAR model demonstrated extreme sensitivity to specification choices, with dramatic changes in impulse response functions across different lag lengths, trend specifications, and variable orderings.

While this work provides a step by step technical framework for SVAR analysis of carbon policy effects, the methodological limitations and sensitivity of results prevent drawing reliable conclusions about macroeconomic impacts in Belgium. The analysis demonstrates the challenges inherent in identifying causal relationships in complex economic systems despite having introduced an economically backed structure to the classic VAR model.

Figures (MATLAB Output)

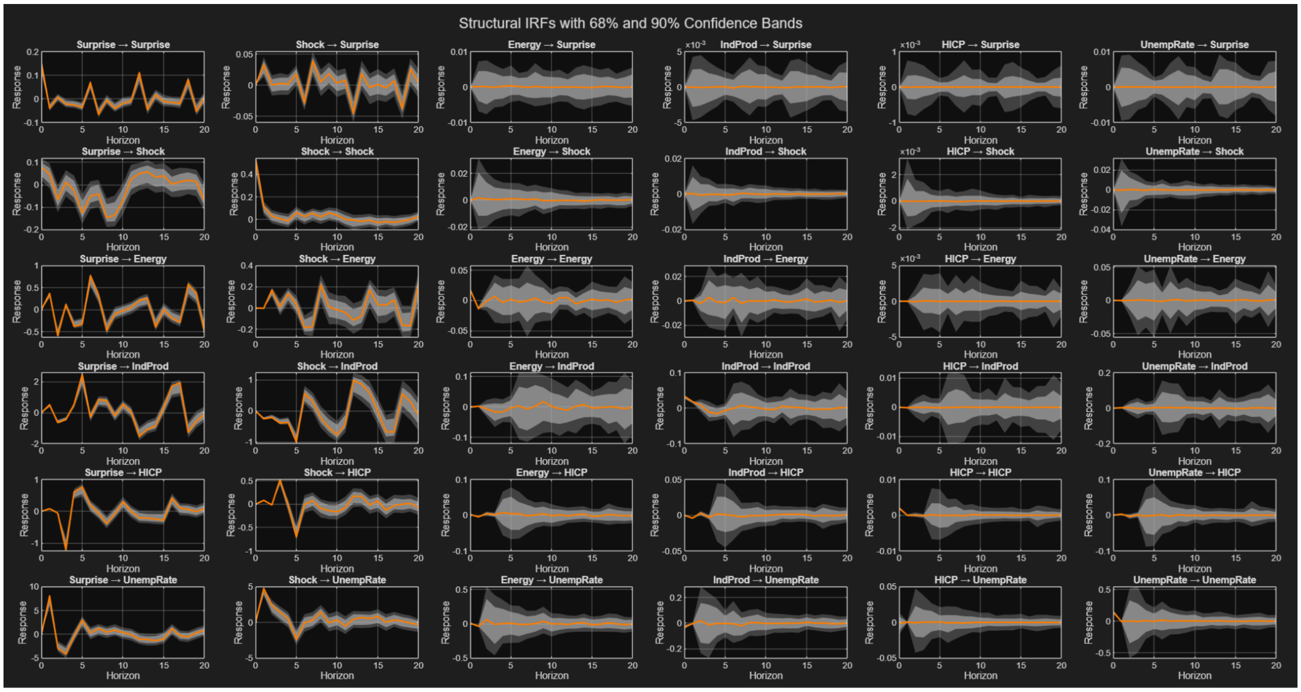

Figure 1: Structural IRFs with 68% and 90% confidence Bands

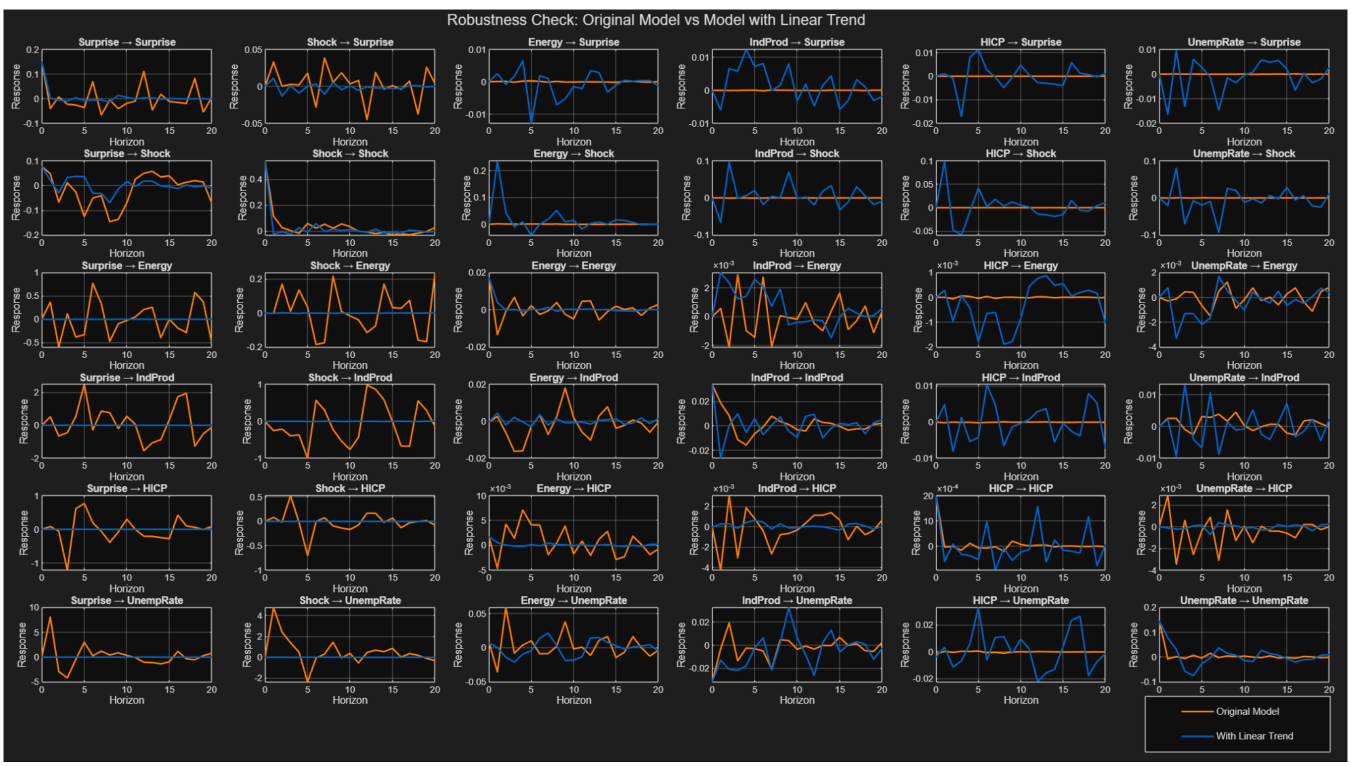

Figure 2: Original model vs. Model with Trend

Figure 3: Original model vs. Models with Lags 6, 12, and 24.

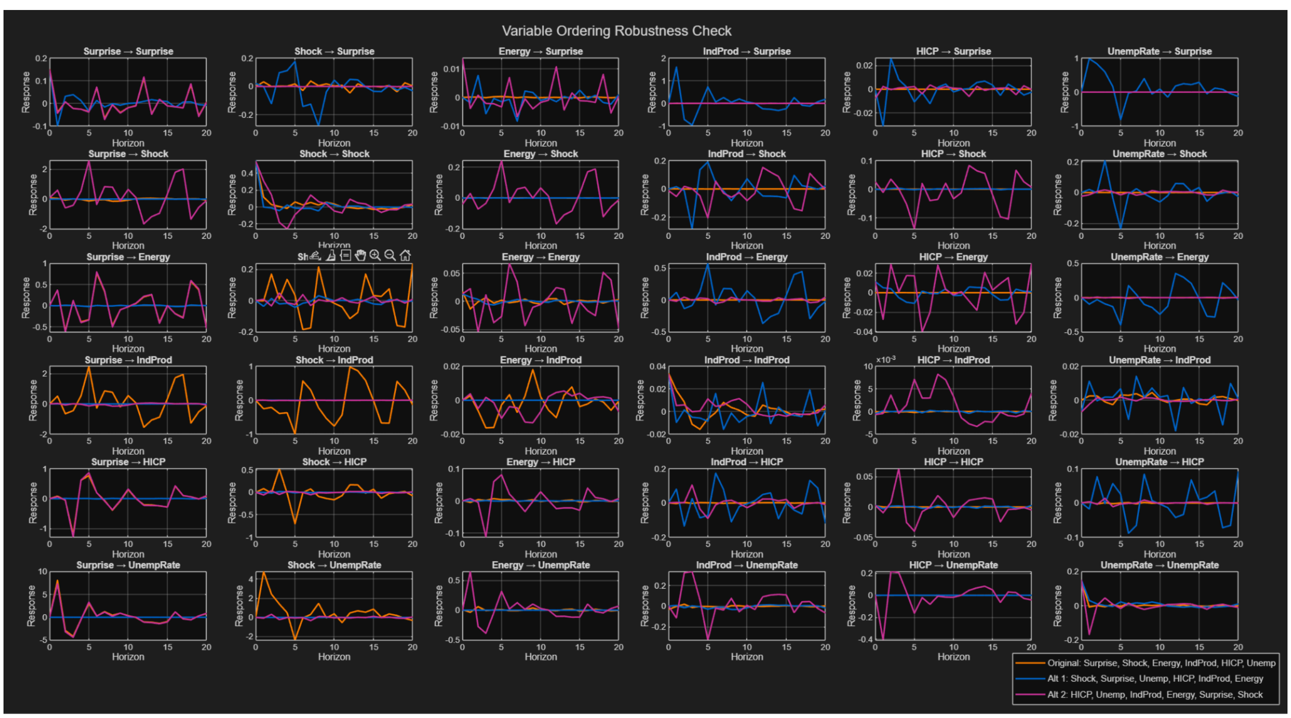

Figure 4: Original model vs. Models with Reordered Variables

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I declare that the work presented is entirely my own. No outside person was consulted for this work. The use of AI was limited to debugging code and help with MATLAB notation, and matrix multiplication. AI tools, namely Claude Sonnet 4 and ChatGPT, were used as a tool to get my ideas coded properly. The report was entirely produced by hand.

Anton Cronet July 31, 2025 - Magdeburg